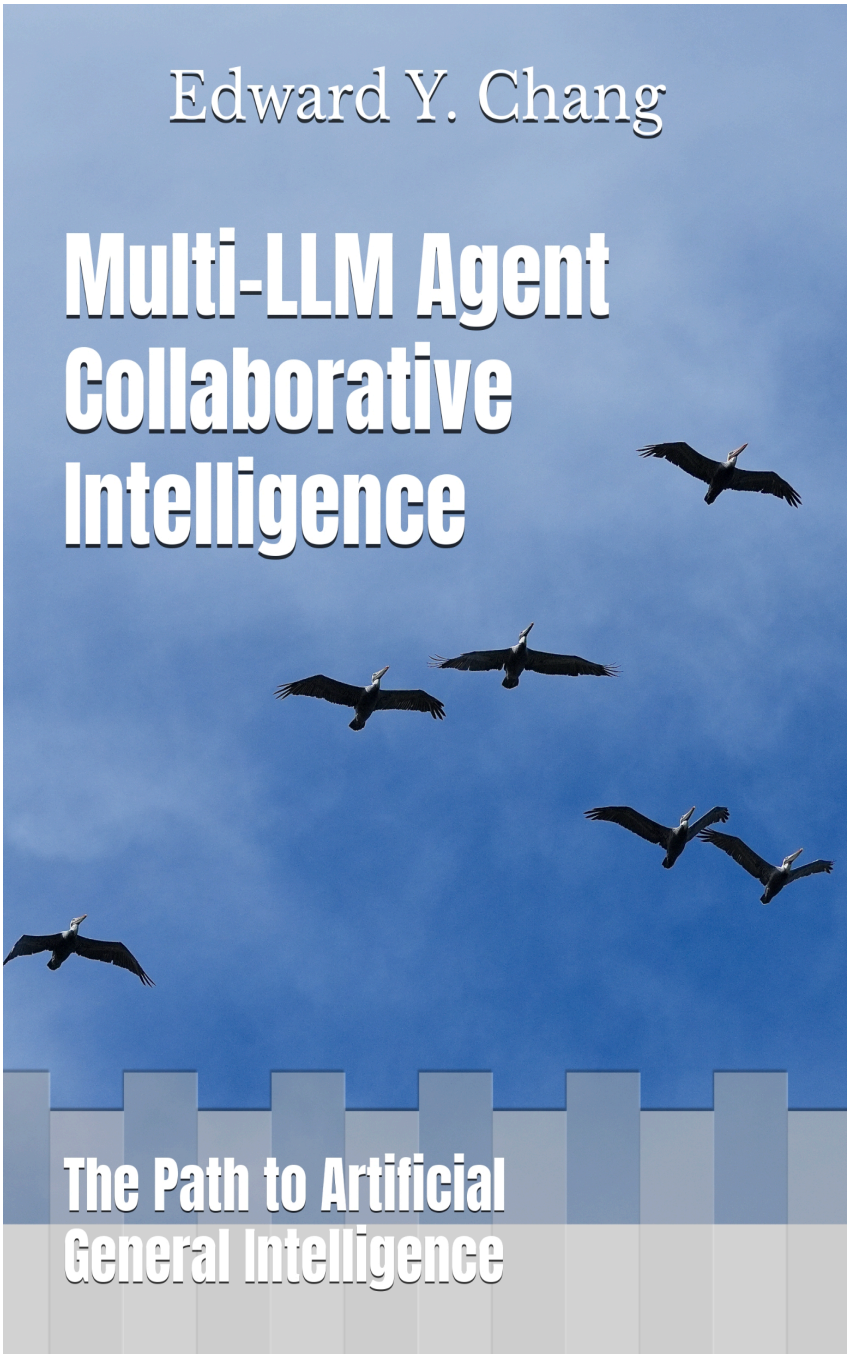
Edward Y. Chang
Multi-LLM Agent Collaborative Intelligence
The Path to Artificial General Intelligence

Multi-LLM Agent Collaborative Intelligence: The Path to AGI

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Thanks to my family
for their love and support.

Preface

As Generative AI transforms our world, experts predict the emergence of Artificial General Intelligence (AGI) as early as 2040. This book proposes that the key to achieving AGI, characterized by versatility, adaptability, reasoning, critical thinking, planning, and ethical alignment, lies not in creating more powerful individual models, but in enabling large language models (LLMs) to engage in intelligent and collaborative dialogue. This concept, termed **Multi-LLM Agent Collaborative Intelligence** (MACI) forms the foundation of our exploration.

MACI transcends conventional "mixture of experts" models or traditional LLM debates by optimizing information exchange between LLM agents through seven essential foundations.

1. **Balancing Exploration and Exploitation**: MACI takes advantage of various perspectives while maintaining robust reasoning rooted in the strong priors of next-token maximum likelihood predictions. This approach ensures the exploration of novel perspectives while preserving the stability of the model parameters learned from the training data. (Chapters 5 and 6)

2. **Modulating Linguistic Behavior**: Beyond balancing exploration and exploitation, MACI dynamically modulates the linguistic behaviors of LLM agents, facilitating transitions between contention and collaboration. By fostering productive perspective exchanges quantified through information theory metrics, MACI generates diverse viewpoints and novel insights. Calibrating debate contentiousness enables MACI to explore a broader

spectrum of ideas while consistently converging on well-reasoned conclusions. Beyond contentiousness modulation, MACI detects and regulates behavior across multiple dimensions, including hate speech and empathy, anxiety and calmness, and emotional extremes—ensuring discussions remain productive and ethical while preserving cognitive diversity. (Chapters 8 and 9)

3. **Checks and Balances for Context-Sensitive Ethical Alignment**: Individual LLM agents are assigned specialized roles: the Executive for knowledge formation, the Legislative for developing ethical frameworks, and the Judicial for contextual evaluation. This governance structure allows ethics to be legislated while enabling context-dependent interpretation by the judicial branch. The parameters of the executive LLMs remain unchanged to preserve performance integrity. (Chapter 9)

4. **Persistent Memory as Essential Infrastructure**: LLM agents require persistent memory systems that transcend their limited context windows. Without robust state persistence, agents cannot reliably maintain awareness of constraints, track system states, or execute complex workflows. Even sophisticated validation logic fails without complete historical context, and transaction patterns become meaningless when systems cannot accurately recall previous states. Persistent memory forms the critical foundation upon which both effective validation and reliable transaction guarantees must be built, enabling agents to operate coherently across extended temporal sequences. (Chapters 12 and 13)

5. **Reasoning with the Socratic Method**: MACI employs the Socratic Method to refine reasoning through iterative questioning and dialogue. This approach fosters deeper analysis, challenges assumptions, and enables the discovery of robust solutions by encouraging critical thinking among agents. (Chapter 4)

6. **Frontier Discovery through Polydisciplinary Synthesis**: LLMs are trained without informing the transformer algorithms about document domains. LLM training treats all documents as

> sequences of words, resulting in representations without domain boundaries where all fields are combined in one unified space. This polydisciplinary representation provides an unprecedented opportunity to synthesize knowledge across traditional boundaries and explore uncharted intellectual territories. It is at these intersections of previously siloed domains where true ingenious intelligence emerges, revolutionizing our understanding and unleashing unprecedented capabilities. (Chapter 14)

Building on these foundations, the fifteen chapters guide the reader systematically from theoretical frameworks to practical applications. Key algorithms include CRIT for critical evaluation, SocraSynth for dynamic dialogues, EVINCE to optimize the flow of information through Bayesian statistics and information theory, SagaLLM to implement persistent memory systems that enable robust validation and preservation of transaction properties, and polydisciplinary synthesis to explore knowledge across traditional boundaries. We explore applications ranging from medical diagnosis to news debiasing and address fundamental challenges in AI safety through checks and balances applied across LLM's linguistic, legislative, and judicial modules, ensuring alignment between knowledge, ethics, and contextual reasoning.

Reframing LLMs as Components in the Path to AGI

Some pioneers of modern AI, including Yann LeCun, argue that LLMs alone cannot achieve AGI due to several fundamental limitations: their lack of persistent memory, reasoning and planning capabilities, and physical grounding. LeCun specifically asserts that true intelligence requires interaction with the physical world through sensors and embodiment. He emphasizes that while LLMs demonstrate impressive linguistic capabilities, they lack genuine understanding and even suggests that "the sensory-motor abilities of a cat surpass those of an LLM." This perspective raises legitimate concerns about current LLM architectures, particularly regarding the efficiency with which humans learn complex skills from few examples, something current systems struggle to replicate. In this

book, we reframe this debate by examining how LLMs might serve not as standalone AGI systems but as crucial components within a more comprehensive architecture.

Reframing LLMs' Role in Intelligence Rather than viewing LLMs as standalone forms of artificial general intelligence, we propose reframing them as foundational components within a broader intelligent system. In biological intelligence, consciousness operates on top of an extensive underlying architecture of neural processes (the unconscious) responsible for perception, motor control, memory consolidation, and other essential life functions.

Similarly, LLMs can function as *cognitive substrate* within a modular intelligence framework, responsible for processing, pattern matching, and information synthesis. External modules can then manage reasoning, validation, planning, and behavior modulation. Although not identical to human unconsciousness, LLMs exhibit functionally analogous capabilities: recognizing patterns, forming associations, and constructing representations that support more sophisticated conscious operations when properly scaffolded.

Critically, this reframing highlights a profound parallel: human intelligence does not begin as a blank slate. Infants enter the world equipped with evolutionarily encoded unconscious mechanisms governing breathing, metabolism, coordination, and even basic social instincts. Conscious learning through few-shot experiences and fine-tuning emerges upon this biological foundation. Therefore, comparing an infant's intelligence directly to an LLM is misleading; the infant benefits from billions of years of embedded evolutionary knowledge. Likewise, LLMs provide *artificial unconsciousness*, a foundation on which modular systems can develop structured, adaptive, and goal-directed intelligence.

(Chapter 10 provides an in-depth discussion.)

Addressing the Grounding Problem The claim that LLMs lack a world model stems from a particular interpretation of what constitutes "grounding" in intelligence. We support Ilya Sutskever's

perspective that documents themselves encapsulate worldviews, and history is fundamentally written in text. Text represents a projection of the world, a distillation of human experience, observation, and reasoning encoded in language.

When LLMs train on vast corpora, they learn to compress and represent the processes that generate these texts. This compression captures significant aspects of human understanding, including causal relationships, physical properties, and social dynamics. While this text-based grounding differs from sensorimotor grounding, it represents a valuable form of knowledge acquisition that should not be dismissed.

That said, we acknowledge that multimodal perception provides complementary forms of grounding that can enhance an AI system's understanding. Rather than viewing sensory input as the exclusive basis for intelligence, we see it as one of multiple channels through which a system can build comprehensive world models.

The Memory Challenge Current LLMs face two distinct memory-related challenges: context window limitations during inference and the lack of persistent memory between interactions. The first constrains how much information an LLM can consider at once, while the second prevents the accumulation of experience over time. Context window expansions have addressed some limitations, but issues surrounding context loss and context narrowing have caused unexpected inconsistencies in long-lived transactions or long chains of thoughts. Persistent memory integration remains crucial for capabilities like constraint validation, state tracking for action rollback, and maintaining consistency across complex workflows. The SagaLLM framework introduced in Chapter 13 specifically addresses these challenges by adapting saga-transaction mechanisms from database systems to manage memory in LLM-based agents.

SagaLLM enables selective storage and retrieval of critical information, maintaining a structured record of past states, actions, and their consequences. This allows for precise rollback when errors occur and ensures that interdependent processes maintain con-

sistency. In our experiments with planning scenarios such as the Thanksgiving dinner coordination problem, SagaLLM successfully maintained awareness of constraints that the standalone LLMs lost track of during extended reasoning.

Reasoning and Planning Capabilities Building on these memory advances, we now address the significant challenges LLMs face with reasoning and planning in complex, multi-step processes. Although persistent memory provides the foundation, effective reasoning requires additional architectural innovations. The MACI framework leverages SagaLLM's memory capabilities while integrating specialized modules for different cognitive functions. By distributing reasoning across structured components, analogous to the executive, legislative, and judicial branches of government, MACI implements logical operations of checks and balances. This structure supports an iterative process "think, validate, rethink" where each step is recorded in persistent memory, allowing the system to continuously verify that all constraints are observed throughout the planning sequence.

Evidence from our implementation demonstrates that this architecture successfully maintains global constraints across extended planning horizons, effectively detects and corrects inconsistencies in proposed actions, and seamlessly integrates new information without losing critical context. The system's ability to reference previous states and decisions ensures that constraints established early in the reasoning process remain enforced even as plans become increasingly complex. While these capabilities do not yet match human-level planning, they establish a promising path toward addressing current limitations through architectural innovation rather than relying solely on scaling existing models.

Synthesis: A Modular Path Forward The path toward more comprehensive artificial intelligence likely involves neither pure LLMs nor a complete abandonment of their capabilities. Instead, we envision a modular architecture in which LLMs serve as powerful

semantic processors within a larger system that includes dedicated components for perception, memory management, causal reasoning, and action selection.

This framework addresses LeCun's concerns about embodiment and grounding while leveraging the linguistic and associative strengths of LLMs. By integrating sensor modules, persistent memory systems such as SagaLLM, and specialized reasoning components within the MACI framework, we can build systems that combine the pattern matching capabilities of LLM with the physical interaction and persistent learning that critics rightly identify as essential to intelligence.

Rather than asking whether LLMs alone can achieve AGI, we should ask how their unique capabilities can complement other modalities in building more robust, adaptive, and trustworthy intelligent systems. The frameworks presented in this book—particularly in Chapters 4, 12, and 13—offer concrete implementations of this vision, demonstrating how LLMs can serve as foundational components in AI systems that reason effectively, maintain memory consistently, and ground understanding in both language and perception.

The path to AGI through MACI is not a sudden leap but a gradual process of structured integration and collaborative evolution. Just as human civilization advances through the accumulation of shared knowledge and social negotiation, multimodal LLM agents can transcend their individual limitations by working together, each contributing to different modes, perspectives and roles of reasoning. This book provides the architectural blueprints and theoretical grounding to pursue this path, demonstrating how systems built on foundational substrates can evolve toward human-level reasoning and beyond.

To conclude this exploration, Chapter 15 offers a philosophical synthesis: Twelve aphorisms distilled from practical experimentation and long-term research. These aphorisms reflect the core insights of MACI and articulate a new paradigm: one where intelligence is not defined by individual scale, but by the capacity for

dialogue, regulation and rational alignment with complexity and uncertainty.

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The feedback of my colleague Prof. Vaughan Pratt on the initial paper inspired the use of "contentiousness" to foster adversarial debate, a key component of our framework. The author thank Prof. Monica Lam for her collaborative support throughout this research. In addition, I thank my colleagues at Stanford Clinical Mind AI for their invaluable domain knowledge in disease diagnosis.

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In the editing process of this book, large language models, specifically GPT-4 and Claude, were utilized to assist with editing and refinement of the text. These AI tools were used as supplementary aids to improve clarity and coherence, while the core content, ideas, and arguments remain my own original work.

About This Book

This book presents a comprehensive exploration of Multi-LLM Agent Collaborative Intelligence (MACI) through fifteen chapters, progressing from theoretical foundations to practical applications:

Theoretical Foundations

Chapters 1-3 explore the evolution of AI through the lens of "similarity" and introduce the unique polydisciplinary representation of the information from LLM. When we pose a question to an LLM, we understand the domain (e.g., physics, computer science), but the LLM sees no boundaries. This mismatch creates both challenges and opportunities that MACI addresses through structured collaboration.

Core Algorithms

The book introduces six key frameworks:

- CRIT (Chapter 4): Applies the Socratic method and formal reasoning to critically evaluate documents, identifying claims and counterarguments.
- SocraSynth (Chapter 5): Enables dynamic dialogues between LLMs, fostering rigorous debates and diverse viewpoints through controlled contentiousness.

- EVINCE (Chapter 6): Provides a theoretical foundation using Bayesian statistics and information theory to optimize multi-LLM communication.
- BEAM **and** DIKE (Chapters 8 and 9): Model linguistic behaviors based on basic emotions to regulate ethical compliance.
- SagaLLM (Chapters 10 and 11): Establishes a planning framework using persistent memory, validation protocols, and lightweight transactions to safeguard consistency and atomicity in long-lived transactions and extended chains of thought.
- CoCoMo (Chapter 12): Delineates the distinction between unconscious and conscious operations through functionalism to establish modular pathways to AGI.

These core algorithms are further distilled into a set of twelve aphorisms in Chapter 15, each articulating foundational principles of collaborative intelligence drawn from experience building and evaluating these frameworks.

Applications and Extensions

Chapters 6–8 demonstrate practical applications:

- Medical diagnosis and misdiagnosis detection
- News analysis and debiasing
- Emotional modeling for ethical behavior

Advanced Topics

Chapters 13–15 present advanced topics:

- Diagnosis and improvement through RAG (Chapter 13)
- Exploring "unknown unknowns" through multidisciplinary reasoning (Chapter 14)

- Twelve aphorisms distilling foundational principles of collaborative intelligence and multi-agent reasoning (Chapter 15)

Appendices

One appendix complements the main text:

- **Appendix** X_1: Online case studies from various domains

This structure enables the reader to:

- Follow the theoretical development of MACI from first principles
- Understand practical implementations across diverse domains
- Explore ethical implications and governance considerations
- Reflect on twelve aphorisms that offer philosophical and architectural insight into collaborative intelligence
- Conceptualize a pragmatic path toward AGI through structured multi-agent collaboration

Contents

Chapter 1

A Brief History of AI: From Turing to Transformers

Abstract This chapter reinterprets the history of AI, focusing on the evolution of similarity measurement, from rule-based to context-aware models, and emphasizing its critical role in AI's core functions like learning and problem-solving. It explores the impact of detailed and evolving understandings of similarity in linguistics (text) and computer vision (image), projecting a future where AI merges advanced data analysis with abstract reasoning. The chapter will provide an in-depth analysis from the perspectives of linguistics, computer science, and cognitive psychology/neuroscience, illustrating how the progression of similarity concepts continues to fuel AI's advancement.

Introduction

Artificial Intelligence (AI) has journeyed through a fascinating historical trajectory, marked by five pivotal epochs that each represent significant paradigm shifts triggered by major technological advancements. The epochs are as follows: *Initiation*, setting the stage with foundational concepts and milestones of AI; *Expert System Encoding Human Knowledge*,

where AI systems were predominantly rule-based, encoding and applying human expertise; *Heuristic-Based Modeling*, which highlights the era of developing and using heuristic methods for AI problem-solving; *Learning Model from Data*, focusing on the transition to algorithms that learn and adapt from data, signifying the emergence of machine learning; and *Context-Based Semantic Disambiguation*, highlighting AI's evolving proficiency in understanding and interpreting context, thereby improving semantic accuracy.

Although numerous comprehensive sources, such as Wikipedia, provide detailed accounts of AI's evolution through various lenses: language, computation, philosophy, cognitive psychology, neuroscience, and application, this chapter takes a different path. It zeros in on a fundamental aspect: **similarity**.

When we consider the intelligence of machines, we often focus on attributes such as learning capacity, pattern recognition, predictive accuracy, robustness, adaptability, generalization, reasoning, problem solving, and decision making abilities. These qualities collectively define the prowess of AI systems. Among these traits, the concept of similarity plays a pivotal role. For example, in learning, an effective similarity measure is fundamental for recognizing patterns and generalizing knowledge. In terms of adaptability, the ability to detect similarities with previous experiences allows AI to adjust to new or evolving circumstances. Regarding robustness, employing similarity measures helps AI differentiate between normal and anomalous patterns, thereby increasing its resilience. Furthermore, in the realm of problem solving, the capacity to identify similarities with previously encountered situations can enable AI to apply existing solutions to new problems, improving its efficacy in addressing challenges. This chapter explores the vital function of similarity across the broad spectrum of AI capabilities, underlining its significant contribution to the field's foundational operations.

In the realm of tangible objects, similarity measures are integral to various vision-related tasks, aiding in the recognition of patterns, shapes, and colors, which are essential for object recognition and image classification. In text analysis, these measures are crucial to identify similarities in content, helping to detect plagiarism, retrieve documents, and translate

languages. In the auditory domain, the analysis of the similarity of sound wave patterns or musical notes is key to genre classification and music recommendation systems. In medical images, these measures facilitate the diagnosis of diseases by comparing patient images with known cases, allowing accurate identification and classification of medical conditions. Object feature comparison is foundational in robotics and surveillance for recognizing and interacting with physical entities. Similarly, facial and voice recognition systems rely on analyzing patterns to identify or verify identities, enhancing security and personal authentication. In e-commerce, similarity in product attributes or user preferences informs recommendation systems, enhancing user experience by suggesting related or complementary products.

In the abstract realm, similarity measures are crucial for discerning semantic relationships, aiding in knowledge representation, ontology mapping, and refining AI's interpretive faculties. Environmental studies leverage these assessments for climate modeling and ecological research. Sentiment analysis in social media or customer feedback utilizes similarity to extract insights into public sentiment or consumer behavior. These measures also underpin AI's problem-solving prowess in complex scenarios, informing strategy formulation. Behavioral analysis, whether in psychology or marketing, employs similarity comparisons to decode human actions and preferences. In the legal field, case similarity aids in judicial decision-making and legal scholarship. Language translation harnesses similarity in linguistic structures to break down language barriers. Furthermore, in creative writing, analyzing thematic or stylistic similarities assists in authorship identification, genre categorization, and literary exploration.

The advancement in similarity research, while appearing gradual, reflects not only human ingenuity but also the limitations imposed by computational resources and hardware capabilities. The quest to quantify similarity covers a broad spectrum of abstractions, from sensory inputs like visual, auditory, olfactory, and tactile data to complex abstract concepts such as ideas and semantics. Hardware improvements have enabled researchers to explore more advanced methods that encompass both concrete and abstract forms of similarity. This progression marks the field's

growth in harmonizing detailed sensory data analysis with a deeper understanding of abstract concepts, utilizing computational advancements and diverse data interpretations.

Following sections will provide a deeper dive into key AI terminology and the development of similarity measures in two distinctive views: scientific disciplines and historical evolution. The disciplinary view encompasses three key perspectives: linguistics, computer science, cognitive psychology, and neuroscience. The evolution view traces the historical journey of similarity measurement through distinct eras: rule-based, model-based, data-centric, and context-aware.

Providing two views on similarity measurements, across different scientific disciplines and through the historical evolution of AI methodologies, offers a comprehensive understanding that caters to a broader audience with varied interests and backgrounds. Here are some reasons why this dual perspective is valuable:

Multidisciplinary Insight: Examining similarity measurements from different scientific disciplines enriches the understanding by highlighting how various fields approach and apply the concept of similarity. This can foster interdisciplinary collaboration and innovation, as techniques from one field can inspire new approaches in another.

Historical Context: Exploring how similarity measurement has evolved within AI provides historical context, showcasing how methodologies have progressed from rule-based to more advanced context-aware systems. This perspective helps readers appreciate the advancements in AI and understand why certain methods were developed or abandoned.

1.1 Definitions

We define and scope key terms and concepts to prepare for subsequent discussion.

1.1.1 Rudimentary Terms

Data: The raw information used to train AI models. Data quality significantly impacts model performance.

Algorithm: A set of instructions that a computer follows to perform a specific task. AI algorithms are often complex and involve statistical methods.
Model: A representation of the learned knowledge from data that allows the AI system to make predictions or decisions.

1.1.2 General Terms

Artificial Intelligence (AI): The broader concept of machines being able to carry out tasks in a way that we would consider smart.
Explainable AI: AI systems that offer transparency and an understanding of their operations and decision-making processes.
General AI: General AI, also known as Artificial General Intelligence (AGI), refers to a type of AI that has the ability to understand, learn, and apply knowledge in a wide range of tasks, much like a human being. It's an AI system with generalized human cognitive abilities, meaning that when presented with an unfamiliar task, it can find a solution without human intervention. AGI would be able to reason, solve problems, make judgments, plan, learn, and communicate in natural language, among other capabilities. However, as of now, AGI remains a theoretical concept and has not been realized in practical applications.
Narrow AI: Narrow AI, in contrast, is the type of AI that we encounter in our daily lives and is currently in use around the world. It is designed to perform a narrow task (e.g., facial recognition, internet searches, driving a car) and is trained for a specific dataset or a set of tasks. Narrow AI operates under a limited pre-defined range or context, often focusing on executing a single task extremely well or carrying out a limited range of tasks in a specific domain. It lacks the general cognitive abilities of AGI and cannot apply its knowledge beyond its specific field or task.
Machine Learning (ML): A subset of AI that includes statistical techniques that enable machines to improve at tasks with experience.
Deep Learning: A subset of machine learning that uses neural networks with three or more layers. These neural networks attempt to simulate the behavior of the human brain–albeit far from matching its ability–allowing it to "learn" from large amounts of data.
Neural Networks Computational models that are somewhat inspired by

the structure of the human brain, enabling computers to recognize patterns and solve common problems in AI, such as classification, prediction, and decision making.
Supervised Learning: A type of machine learning where the model is provided with labeled training data and the desired output. The goal is to learn a mapping from inputs to outputs.
Unsupervised Learning: A type of machine learning where the model is not provided with labeled data and must find structure in its input on its own.
Reinforcement Learning: An area of machine learning where an agent learns to behave in an environment by performing actions and seeing the results, focusing on long-term rewards. An example is an AI agent learning to play a game through trial and error, receiving rewards for winning.
Natural Language Processing (NLP): A field of AI that gives machines the ability to read, understand, and derive meaning from human languages.
Computer Vision: A field of AI that trains computers to interpret and understand the visual world, extracting information from images and videos.
Robotics: The branch of technology that deals with the design, construction, operation, and application of robots, often incorporating AI systems to enhance autonomy and adaptability.
Large Language Model (LLM). LLMs are advanced artificial intelligence systems trained on extensive datasets, initially text-centric and now increasingly incorporating multimodal data. They are designed to comprehend, generate, and interact with human language, imagery, and video with a level of sophistication that closely mirrors human cognitive processes.

1.1.3 Performance Terms

Algorithmic Bias: Algorithmic bias refers to the potential for algorithms to reflect, perpetuate, or amplify biases present in the training data or as a result of the design of the algorithms themselves. This can lead to skewed or unfair outcomes, particularly in decision-making processes.
Hallucination: In the context of AI, hallucination refers to the phenomenon where a model generates or outputs information that is un-

grounded, misleading, or not supported by the input data. This is commonly seen in language models where the generated text may be plausible but not factually accurate or relevant to the context.
Generalization: Generalization is the ability of an AI model to perform well on new, unseen data that was not part of the training set. It indicates the model's capacity to apply learned knowledge to different situations, a key indicator of its robustness and utility.
Overfitting: Overfitting occurs when an AI model learns the details and noise in the training data to the extent that it negatively impacts the model's performance on new data. This usually happens when the model is too complex, capturing patterns that do not generalize to unseen data.

1.2 Perspectives on Similarity

This section presents the foundational theories of similarity measurement from three distinct domains: *linguistics*, *computer science*, and *cognitive psychology & neuroscience*. The upcoming historical section will clarify how these foundational theories have influenced and been incorporated into specific technological advancements and methodologies across various eras. Cross-references will be provided to ensure coherence and to emphasize the interconnection of these perspectives.

1.2.1 Linguistic Perspective

The study of similarity within linguistics has been profoundly influenced by Zellig Harris's pioneering work. His 1954 study introduced the idea that the distributional properties of words and their contextual usage could unlock the secrets of language comprehension, highlighting the indispensable role of context [22]. This principle, that words found in similar contexts tend to share meanings, laid the foundation for distributional semantics and resonates with John R. Firth's insight that "A word is known by the company it keeps." This linguistic perspective sets the stage for further exploration of how context and distributional properties have been instrumental in shaping our understanding of semantic similarity, paving the way for subsequent advancements in the field.

The evolution of linguistic theories continued into the latter part of the 20^{th} century with the rise of cognitive linguistics, which examines the interplay between linguistic structures and human cognitive processes. This approach underscored how language reflects our perception and conceptualization of the world, introducing a multi-layered perspective on semantic abstraction.

A significant milestone in bridging linguistic theory with practical applications was the development of WordNet in the 1980s by a team at Princeton University [42]. This lexical database, which organizes English words into sets of cognitive synonyms or *synsets*, has profoundly influenced areas such as word sense disambiguation, information retrieval, and beyond, highlighting the importance of structured semantic relationships in understanding language.

Moreover, the influence of linguistic insights extended into the domain of computer vision with the creation of ImageNet by Fei-Fei Li [16], which drew upon the principles underlying WordNet to categorize visual content. This convergence of linguistics and computer science has been further propelled by advancements in computational methods, with techniques like Latent Semantic Analysis (LSA) [18], Latent Dirichlet Allocation (LDA) [4], and innovative word embeddings such as Word2Vec [41] and GloVe [46]. These methodologies have enabled the conceptualization of word meanings in high-dimensional spaces, illuminating the intricate web of semantic relationships through patterns of co-occurrence and contextual analysis.

The introduction of the transformer model [51] and the subsequent unveiling of BERT [17], which employs self-supervised learning to predict masked words within a context, along with the release of GPT, designed to predict the next word based on context, heralded a new epoch in our endeavor to unravel context-dependent semantics. This development fulfills the vision proposed by Zellig Harris in his groundbreaking 1954 work, now actualized in contemporary computational models.

1.2.2 Computer Science Perspective

In computer science, the concept of similarity has evolved from simple rule-based models to complex vector-space and probabilistic models, re-

flecting the field's progression in addressing various computational challenges.

A. Rule-Based

A rule-based AI model, also known as an expert system, employs a collection of predefined if-then statements to execute decisions or solve problems. These conditional statements are crafted from the expertise of specialists in a particular field. The system applies these rules to the input data to formulate conclusions.

The "if" segment of a statement evaluates the data for specific conditions or patterns. When these conditions are satisfied, the "then" segment is activated, performing a designated action or drawing a conclusion. Importantly, these systems do not adapt or learn from data in the manner that machine learning models do. Rather, they rely on a set of explicit rules, which are the codified versions of expert knowledge within a specific domain. This knowledge is methodically organized and stored in a knowledge base, enabling the system to reference and apply it efficiently during its operations.

In Chapter 1.3.1, we will explore the technical details and applications of rule-based systems, emphasizing their pivotal role during the rule-based era of AI's evolution.

B. Vector-Space

The vector-space model marked a significant shift, representing objects and features as vectors in a high-dimensional space. This approach facilitated the development of various distance functions to assess similarity for different applications. Notably, a comprehensive survey by [7] categorized 45 distance functions into families like inner product, L_1, Minkowski, and Intersection, each with its representative functions highlighting the versatility in vector-space analysis.

B.1. Inner product, dot product and cosine

The inner product and dot product are the same in the context of Euclidean space and are defined for vectors **a** and **b** as:

$$\mathbf{a} \cdot \mathbf{b} = a_1 b_1 + a_2 b_2 + \ldots + a_n b_n.$$

This operation results in a scalar value and indicates the vectors' magnitude and directionality.

Cosine similarity is a measure that calculates the cosine of the angle between two vectors. It is defined as the dot product of the vectors normalized by the product of their magnitudes:

$$\text{cosine similarity}(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|},$$

where $\|\mathbf{a}\|$ and $\|\mathbf{b}\|$ represent the Euclidean norms of the vectors **a** and **b**, respectively.

The cosine similarity is especially useful in contexts where the magnitude of the vectors is not of primary concern, making it ideal for applications in high-dimensional spaces like text analysis and information retrieval.

B.2. Weighted Minkowski

The weighted Minkowski distance function allows assigning varying importance to different dimensions, accommodating the significance of specific features in contexts like machine learning and data mining:

The weighted Minkowski distance between points $X = (x_1, x_2, \ldots, x_n)$ and $Y = (y_1, y_2, \ldots, y_n)$ with a set of weights $W = (w_1, w_2, \ldots, w_n)$ is defined as:

$$D(X, Y) = \left(\sum_{i=1}^{n} w_i |x_i - y_i|^p \right)^{\frac{1}{p}},$$

where p is the order parameter of the Minkowski distance. When $p = 1$, it becomes the weighted Manhattan distance, and when $p = 2$, it becomes the weighted Euclidean distance.

B.3. Set similarity

Moreover, the Jaccard similarity [25] provides a robust method for comparing sets, especially beneficial in scenarios where feature presence or absence is more critical than their magnitude, as seen in plagiarism or copyright detection.

$$J(X,Y) = \frac{|X \cap Y|}{|X \cup Y|}$$

Where:

- $|A \cap B|$ is the number of elements in the intersection of A and B.
- $|A \cup B|$ is the number of elements in the union of A and B.

C. Probabilistic-Based

The advancement into probabilistic-based models introduced a spectrum of statistical and probabilistic distance functions, offering refined tools for quantifying similarity or dissimilarity based on underlying probabilistic principles. These functions, including Pearson Correlation Coefficient, Mahalanobis Distance, Kullback-Leibler Divergence, and others, cater to diverse analytical needs, enriching the computational toolkit available for similarity assessment in various domains.

This section underscores the computer science perspective on similarity, detailing its journey from rule-based logic to advanced probabilistic models, reflecting the field's dynamic evolution and its pivotal role in shaping contemporary approaches to measuring similarity.

1.2.3 Cognitive Psychology Perspective

Cognitive psychology and neuroscience provide deep insights into how similarity is perceived and processed at a neural level, significantly influencing the development of AI technologies. Anne Treisman's Feature Integration Theory (FIT) [1] has been instrumental in understanding how the brain synthesizes various sensory features into cohesive percepts, a concept that has parallels in how artificial neural networks, particularly Convolutional Neural Networks (CNNs) [31, 32], process visual information.

FIT draws heavily from Gestalt psychology principles [53, 27], which propose that perception organizes individual components into a meaningful whole. This aligns with FIT's view that perception is an integrated experience shaped by the brain's organizational tendencies. The theory also intersects with selective attention, as seen in Donald Broadbent's Filter Model [5]. This model suggests attention acts as a filter, selecting relevant information for further processing. Broadbent's framework complements FIT by emphasizing attention's role in integrating features into a unified perception, highlighting the brain's selective processes.

In 2001, while conducting a study on perceptual similarity with my PhD student Beitao Li, we uncovered that images could demonstrate similarity in various dimensions. Although the weighted-Minkowski function could learn feature weights, its application was universal once the weights were set, representing a statistical average. Our experiments with transformed images–through translation, cropping, rotation, down-sampling, and affine scaling–revealed that while these images were perceptually similar to their originals, their similarities were in distinct aspects. This observation led to the development of our "Dynamic Partial Function" (DPF) in 2002 [33, 34]. The DPF signature for each image pair could be unique. Essentially, if a pair of images (or objects) demonstrates a sufficient number of similar features, they are likely deemed similar, regardless of the specific features. For instance, an image is considered similar to its rotated version due to their color histograms' similarity. Similarly, an image and its cropped version are considered alike based on their texture features. If two images exhibit a sufficient degree of similarity in various respects–typically 60%–they are generally regarded as similar.

While survey the literature, we came across "Respects for Similarity" by Medin, Goldstone, and Gentner [40], which portrays similarity as a dynamic process of formulating a function and identifying relevant aspects, a process that is realized consciously. To clarify this concept, let's refer to an example from [34]:

Consider the task of identifying two places similar to England. Scotland and New England might emerge as viable candidates. Yet, the criteria making England similar to Scotland are distinct from those linking England to New England. Using the attributes that align England

Figure 1.1: “Which Pairs are Similar?” (DALL-E)

with Scotland to assess the similarity between England and New England might not yield a parallel conclusion, and the reverse is also true. This scenario underscores the idea that objects can be similar to a reference object in varied respects. A fixed similarity function, bound to a specific set of criteria, fails to capture the similarities across different contexts. Medin, Goldstone, and Gentner [40] examine the operational dynamics of similarity in human cognition, noting that the selection of relevant attributes is crucial, with similarity being as much a result as a driving force of conceptual coherence. Goldstone [21] further elucidates that similarity involves identifying the appropriate criteria for comparison, which occurs *only after the objects in question have been juxtaposed*, not beforehand. The criteria selected for this comparison are activated during the comparison process, with a tendency to favor those that enhance the coherence of the objects being compared.

Although the Dynamic Partial Function (DPF) introduces computational complexity, it has indirectly played a role in the success of AlexNet [29] by influencing data augmentation strategies. By integrating transformed images into its training dataset, AlexNet benefits from a principle akin to DPF, thereby improving its accuracy and robustness in recognition tasks. The recent advancements in transformer algorithms [51], which focus on dynamism and context-awareness, build on this foundation, a topic that will be explored in detail in the subsequent section.

Neuroscience

The neuroscience foundation of FIT and its relation to visual feature processing are echoed in the development of CNNs, which were inspired by the visual cortex's hierarchical structure and feature detection capabilities as explored by Hubel and Wiesel [24]. These networks utilize convolutional layers to automatically and adaptively learn spatial hierarchies of features from visual data, akin to the neural processing observed in the brain.

Techniques like Multivariate Pattern Analysis (MVPA) [45] and Neural Decoding [23] further bridge the gap between neuroscience and AI, offering methods to analyze how information is represented across neural populations and how these representations can predict perceptual experi-

ences or cognitive states. These methodologies have inspired and informed the design of advanced AI systems, particularly in how they encode, process, and differentiate complex patterns and similarities.

The cross-pollination between neuroscience and AI, exemplified by the influence of neural processing principles on CNN design, highlights the symbiotic relationship between these fields. Insights from studying the brain's processing mechanisms have catalyzed innovations in AI, leading to more effective and biologically inspired computational models. This interdisciplinary exchange not only propels forward our understanding of neural processes but also fosters the development of AI systems that more closely mimic human perceptual and cognitive capabilities.

1.2.4 Section Remarks

The exploration of similarity measurement spans across linguistics, computer science, and cognitive psychology and neuroscience, revealing its multidisciplinary nature. Each field offers a unique lens to view similarity, from the contextual information in language, computational algorithms in AI, to the neural processing in the human brain. They converge on the common ground of representing entities in high-dimensional spaces and employing distance metrics for quantification, highlighting the universal applicability of similarity. This convergence fosters a rich dialogue between disciplines, enhancing our understanding and ability to quantify and interpret similarity, driving forward innovation and providing new methodologies that influence a wide array of contexts in our quest to decode this fundamental concept.

1.3 Eras of Similarity Measurement

Traversing through the history of artificial intelligence and similarity measurement, one can delineate distinct eras, each marked by unique methodologies and technological advancements. Contrast to last section which examines similarity measurements from different scientific disciplines, this section chronicles these eras, starting from the *rule-based* era, which laid the foundational stones, through the evolution into *model-based*, *data-*

centric, and *context-aware* methodologies, illustrating the dynamic trajectory of similarity measurement in AI. As we reach the conclusion of this section, we explore the prospects of the forthcoming era, which promises to challenge and expand our understanding by venturing into the realm of discovering the *unknown unknowns*.

1.3.1 Rule-Based Era (1950s -)

The rule-based era of the 1950s marked the inception of AI, characterized by the use of symbolic representations and logic to analyze similarity. This period saw the emergence of explicit symbolic representations and logic-based methods tailored for similarity assessment. Innovations by Allen Newell and Herbert A. Simon with tools like the Logic Theorist and General Problem Solver [44] pioneered logical rule-based problem solving, setting a pivotal foundation for AI's evolution.

In the following decades, systems such as DENDRAL [36] utilized rule-based logic to deduce molecular structures from data, while MYCIN [48], an expert system for diagnosing infections and recommending treatments, demonstrated the practical application of rule-based reasoning in the field of medical diagnostics.

Despite their effectiveness in well-defined scenarios, rule-based systems have limitations in more complex or changing environments. However, their clarity and systematic nature are invaluable in certain applied areas, for example:

1. *Customer Service*: Rule-based chatbots are prevalent in customer service, using predefined rules to respond to inquiries based on detected keywords or phrases in user input, providing immediate and consistent customer support.

2. *Fraud Detection Systems*: The finance sector employs rule-based systems to identify potential fraudulent transactions by comparing against specific criteria, such as unusual transaction amounts or atypical locations.

3. *Equipment Failure Diagnosis*: In industrial settings, rule-based systems analyze data to pinpoint causes of equipment failures, leveraging historical data and expert knowledge to predict and prevent future

breakdowns.

This era also gave rise to significant tools like PROLOG [13], associated with logic programming and structured problem-solving, and decision trees [47], which visually represented decision processes, demonstrating rule-based logic in action.

While rule-based systems initially approached similarity with a clear, logical framework, subsequent AI advancements have embraced more flexible methods like statistical models and machine learning, offering a broader, more adaptable approach to understanding similarity in various contexts.

Rule-based systems contrast with the "black-box" nature of current Convolutional Neural Networks (CNNs) and Large Language Models (LLMs) in terms of interpretability and decision-making processes. Rule-based systems are transparent in how decisions are made, as they follow a clear set of if-then rules or logic for inference, allowing users to understand and trace the reasoning behind each decision.

On the other hand, CNNs and LLMs, particularly those based on deep learning, often operate as black boxes, where the internal decision-making processes are not easily interpretable. In these systems, decisions result from complex, non-linear interactions of thousands to millions of parameters that have been adjusted through the learning process. While they are powerful and effective in handling a wide range of tasks, especially those involving large datasets and requiring pattern recognition beyond human capabilities, their inner workings are not as transparent or interpretable as rule-based systems.

1.3.2 Model-Based Era (1970s -)

In this era, vector-space and probabilistic models were designed to quantify similarity.

1.3.2.1 Vector Space Models

The vector-space era marked a shift in similarity measurement from rule-based to representation-based approaches. In this era, objects, documents, and features began to be conceptualized as vectors in a high-dimensional space, fostering a more intuitive and flexible method for assessing similarity.

The Vector-Space Model and Information Retrieval

At the core of this era was the vector-space model, which represents documents as vectors of term frequencies, enabling the computation of document similarity using cosine similarity between their respective vectors. This model enhanced the efficiency and effectiveness of information retrieval systems.

Distance Functions and Feature Weighting

A diverse array of distance functions emerged during this era to quantify the similarity between vectors. The Minkowski distance, for instance, generalized traditional metrics like the Euclidean and Manhattan distances, offering flexibility in adjusting the sensitivity to differences in vector components. Weighted distance measures also gained prominence, recognizing that not all features have equal importance in similarity assessment. The weighted Minkowski distance, in particular, allowed for differential weighting of dimensions based on their relevance to the specific application at hand.

Beyond Textual Data

The utility of the vector-space model extended well beyond textual data. In the realm of image processing, features (e.g., colors, textures, and shapes) extracted from images were represented as vectors, enabling the assessment of image similarity based on the distances between these vectors. This paradigm facilitated significant advancements in image retrieval, classification, and clustering.

Dimensionality Reduction Techniques

To address the challenges posed by high-dimensional data, techniques like Principal Component Analysis (PCA) [26] and Latent Semantic Analysis (LSA) [50] were developed. These methods reduced the dimensionality of data while preserving its essential structure, enhancing computational efficiency and mitigating the "curse of dimensionality." Manifold learning, a non-linear dimension reduction approach, further expanded the toolbox

for tackling high-dimensional data [49]. For a comprehensive overview of these techniques, refer to [39].

The vector-space era laid the groundwork for advancements in machine learning and data mining, making similarity measures essential for clustering, classification, and recommendation systems. Data representation as vectors allowed for the exploration of relationships across varied data types through the nearest neighbor concept. In this context, the characteristics or labels of an unknown instance's k-nearest neighbors could be inferred and applied to the instance, with these neighbors determined by distance metrics.

However, vector representations often result in sparsity, potentially leading to resource inefficiency and decreased accuracy. These models, while capturing syntactic relationships, sometimes struggle with semantic depth, such as identifying synonyms or contextual meaning. The assumption of feature independence and the use of linear methods in dimensionality reduction can also lead to inaccuracies, particularly with non-linear data structures. The introduction of Support Vector Machines (SVMs) [14], which utilize kernel methods, addressed some challenges related to non-linear data but increased computational complexity. SVMs were a significant focus in the field until the rise of deep learning architectures like AlexNet marked a shift towards the data-centric era.

1.3.2.2 Probabilistic Models

Probabilistic models offer more flexibility than vector-space models because they can incorporate uncertainty and variability directly into their mathematical frameworks, allowing for a more comprehensive and adaptive representation of data.

Statistical Inference and Similarity

Probabilistic models introduced the concept of statistical inference, where the likelihood of data or feature occurrences was used to estimate similarity. This allowed for effective handling of uncertainty and variability in data, making it particularly useful in noisy or incomplete datasets.

Bayesian Approaches

Bayesian methods emerged as a fundamental component of this era, providing a robust framework for integrating prior knowledge and empirical data. These methods enhance model adaptability by systematically updating beliefs in light of new evidence, allowing for similarity measures that are responsive to evolving data landscapes.

For further reading on Bayesian methods and their application in dynamic and adaptive modeling, consult the following literature [2, 3, 20, 28].

Latent Semantic Models

In addressing the challenges of high dimensionality and data sparsity inherent in vector-space models, dimensionality reduction techniques were employed. However, beyond merely tackling these issues, the development of a latent semantic layer offered profound implications for semantic analysis and indexing.

As highlighted in the perspective section (Chapter 1.2), Latent Semantic Analysis (LSA) [18] and Latent Dirichlet Allocation (LDA) [4] are critical models in the landscape of semantic modeling. LSA employs singular value decomposition to condense the dimensionality of term-document matrices, unveiling the latent semantic structures within textual data. This dimensional reduction elucidates intricate relationships beyond mere surface-level feature overlaps, enabling a deeper comprehension of textual similarities.

Similarly, LDA offers a probabilistic approach to topic modeling, where documents are considered mixtures of various topics, and topics are distributions over words. This bag-of-words model facilitates a deeper semantic connection between documents by associating them based on shared topics rather than just overlapping terms.

Figure 1.2 presents an example of how LDA, through its bag-of-words approach, clusters words into semantic groups. It's noteworthy that a word can belong to multiple semantic clusters. For instance, words like 'characters', 'play', 'court', 'evidence', and 'test', each appears in two different semantic clusters in the illustration. This feature of LDA resonates

Figure 1.2: Latent Clusters of LDA. The words in red belong to two semantic clusters, signifying the meaning of a word depends on its context.

with the insights from Zellig Harris's pioneering work and John R. Firth's adage that "A word is known by the company it keeps."

These latent semantic models transcend the limitations of direct feature comparison, enabling a more abstract representation of text. By doing so, they provide a robust foundation for semantic indexing and similarity assessment, offering insights that are essential for tasks such as information retrieval, document clustering, and topic discovery. The adoption of these models marked a significant advancement in understanding and measuring similarity in text, setting a new standard for semantic analysis in the field of natural language processing.

Cluster Analysis and Similarity

Probabilistic clustering algorithms, like Gaussian Mixture Models (GMMs), leveraged statistical methods to group data based on the likelihood of membership in different clusters. This probabilistic approach provided a more flexible and deeper understanding of groupings and similarities

within data.

Impact and Limitations

While probabilistic models brought significant advancements, they also introduced challenges. The increased complexity often led to higher computational demands. Additionally, reliance on assumptions about data distributions or the need for prior knowledge could limit applicability in certain situations.

The probabilistic model expanded the toolkit for measuring similarity by introducing methods that could handle uncertainty and offer more adaptive and context-aware approaches. These advancements paved the way for even more sophisticated techniques in the subsequent data-centric era, where the focus shifted towards leveraging vast amounts of data to learn and adapt similarity measures dynamically.

1.3.3 Data-Centric Era (2000s -)

The data-centric era marked a transformative shift in artificial intelligence, pivoting towards harnessing the vast potential of big data, enabled by advances in computational hardware that facilitated parallel processing. This era is characterized by a move from heuristic-based methods to an empirical, data-driven approach in feature representation and model learning.

At the core of the data-centric paradigm is the emphasis on deriving model parameters from extensive datasets, distinguishing it from traditional model-centric strategies. Foundational algorithms such as CNNs [30] and Transformers [51], while conceived through human ingenuity, saw their efficacy significantly enhanced when trained on large, diverse datasets. This training ensures broad coverage of potential variations across different objects or concepts, fortifying the models' ability to accurately recognize and classify new instances. The volume and diversity of the training data are crucial in refining the models' representations, leading to advancements in prediction accuracy and robustness.

From MapReduce to Machine Learning at Scale

The inception of the data-centric movement traces back to the seminal works in statistical learning theory. Vladimir Vapnik's insights into the importance of data for model generalization, particularly his development of Support Vector Machines (SVMs) [14], and Tom Mitchell's pivotal book "Machine Learning" [43], which underscored the critical role of data in preventing overfitting, laid the theoretical foundation for this era.

MapReduce [15], a corner stone in data processing, enabled parallel computation to efficiently handle large datasets. Originally devised to enhance data processing tasks like Google's web indexing, MapReduce became the bedrock for the emergence of sophisticated data-centric methodologies in AI.

Evolution of Machine Learning with Big Data

The rise of parallel machine learning algorithms [6, 37, 9], notably through Edward Y. Chang's work at Google, marked a significant milestone in this era. Chang and his team pioneered Web-scale image annotation in 2007 [37], and subsequently met Prof. Fei-Fei Li after 2028 summer school of Computer Vision, and subsequently sponsored the Stanford ImageNet [16] work via a substantial Google grant.

At the same time, his team developed groundbreaking parallel algorithms, including PSVM [10] (parallelizing SVMs by approximating matrix factorization), PFP [35] (parallelizing frequent itemset mining), PLDA [52] (parallelizing LDA algorithm), PSC [12] (parallelizing spectral clustering), and SpeeDo [54] (parallelizing CNNs), driven by the recognition that big data could facilitate direct learning of features and representations, transcending the limitations of human-crafted heuristics.

Impact on Similarity Measurement

The data-centric era revolutionized the field of similarity measurement, ushering in a new paradigm where similarity metrics are derived from extensive datasets. This period underscored the critical role of data volume and quality in defining similarity metrics, highlighting the dynamic relationship between data-driven insights and computational methods.

In this era, deep learning architectures like CNNs and Transformers have been instrumental in advancing similarity metrics. These models stand out because they not only adjust feature weights but also autonomously learn features from the data. This capability to learn from data directly makes traditional human-engineered features increasingly redundant. After all, human heuristics may not capture every facet of an object or concept comprehensively, and human sensory perception is limited. For instance, while humans can detect the light spectrum from approximately 300 to 700 nanometers, cameras and X-ray machines can perceive a broader range of signals, demonstrating the advantage of machine-learned features in capturing and analyzing data beyond human limitations.

1.3.4 Context-Aware Era (2010s -)

The context-aware era in similarity measurement brings to fruition the profound insights of Zellig Harris's distributional semantics and John R. Firth's adage: "a word is known by the company it keeps." This period marks a shift from static, context-independent assessments to dynamic, context-informed interpretations of similarity. It utilizes the latest advancements in machine learning and the growing availability of computational power to enhance our understanding of similarity in various contexts.

Emergence and Evolution

The integration of context-aware methodologies in similarity measurement evolved significantly in the 2010s, overcoming earlier constraints in computational power and data availability:

- *Computation Capacity*: The development of AlexNet encouraged a data-centric focus within the AI community, prompting investments in parallel computing infrastructures.
- *Word Embeddings*: Techniques like Word2Vec enhanced semantic relationship encoding within data.

- *Attention Models and Transformers*: These models improved data analysis by concentrating on relevant data segments, refining context-aware assessments.
- *Large Language Models (LLMs)*: Models such as BERT and GPT, utilizing self-supervised learning on large text corpora, improved the understanding and generation of context-rich text.

Foundational Pillars: Data and Computation

Key pillars supported advancements in the context-aware era:

- *Self-Supervised Learning:* Utilizing unlabeled data for learning enabled models to extract insights from the data, improving AI system efficiency and scalability.
- *Computational Advances:* The introduction of parallel algorithms and GPU acceleration enabled processing at unprecedented scales, facilitating the development of sophisticated models.

Broader Implications

This era not only refined similarity measurement techniques but also broadened how data is understood and knowledge is integrated:

- *Reasoning and Explanation:* Models now aim to provide reasons for their similarity assessments, improving interpretability and building trust.
- *Multilinguality and Cultural Sensitivity:* Enhanced processing capabilities for varied linguistic and cultural data improve the global applicability of similarity measurements.
- *Multimodal Data Integration:* Context-aware models are adept at combining information from multiple modalities, offering a comprehensive view of similarity.
- *Polydisciplinary Knowledge Fusion:* Adopting a polydisciplinary approach allows for a broader knowledge base in making similarity assessments, fostering innovation across different fields.

The context-aware era signifies a shift toward more insightful, holistic, and interpretable AI, setting the stage for future developments where AI can offer contextually rich and multifaceted insights.

1.3.5 Section Remarks

What defines the next era in the evolution of AI? Historically, technological advancements have focused on addressing pressing unmet needs. Among various potential areas, enhancing the interpretability of decisions stands out as a crucial objective. Making the decision-making process of LLMs transparent and explainable could unlock significant improvements in numerous aspects, such as ethics, by enabling foundational enhancements rather than superficial tweaks based on guesswork and simple heuristics.

The fusion of rule-based system interpretability with the sophisticated capabilities of CNNs and LLMs poses a compelling challenge in AI. Active research is aimed at blending these approaches to leverage their distinct advantages:

1. *Neuro-Symbolic AI*: Neuro-Symbolic AI (the third wave of AI [19]) aims to blend the data processing power of neural networks with the logical reasoning of symbolic AI. The goal is to create systems that not only excel in tasks like pattern recognition but can also reason and make decisions in a human-interpretable manner.

2. *Incorporating Domain Knowledge*: Embedding knowledge of experts within neural networks [38] can steer the learning process towards more reliable and interpretable outcomes. In healthcare, for example, integrating medical guidelines into the training process of a neural network ensures that its predictions for patient treatment not only correlate with the data but also align with established medical practices, enhancing both the model's credibility and relevance.

3. *Interactive Systems*: A system such as SocraSynth [8] can combine the predictive power of deep neural networks with human expertise, allowing for iterative refinement and learning. For instance, in

SocraHealth [11], it might suggest a set of possible diagnoses based on medical imaging, which a physician could then refine or correct. This feedback could be used to continuously improve the system, marrying machine efficiency with human expertise to enhance decision accuracy and interpretability.

By advancing these strategies, the field of AI aims to develop models that not only excel in performance but are also transparent, understandable, and aligned with human reasoning, thus making AI more reliable and trustworthy across various applications.

1.4 Concluding Remarks

This chapter examines the history of AI through the lens of similarity, considering both disciplinary and chronological perspectives. Looking forward, we propose that the emergence of large language models (LLMs) marks a pivotal moment in the context-aware era of AI, setting the stage for the next frontier: the era of interpretability, understanding, and discovery. In this new era, the focus will shift towards empowering LLMs to not only comprehend but also to generate and innovate, synthesizing novel knowledge and insights.

This era of discovery is envisioned as a time when machines will extend their superiority beyond mastering games like Go and Chess to encompass a broader spectrum of tasks, outstripping human capabilities in various domains. The subsequent chapters of this book, beginning with Chapter 5, explore the concept of harnessing the collective intelligence of multiple LLMs, embarking on a voyage to transcend the boundaries of the known and venture into the realm of discovery.

This chapter has explored the history of AI through the lenses of disciplinary and chronological perspectives, focusing on the concept of similarity. As we look to the future, the rise of large language models (LLMs) marks a significant milestone in the context-aware era, paving the way for a new era focused on interpretability, comprehension, and exploration. The upcoming phase in AI's evolution emphasizes enhancing LLMs with the ability to not just generate but also interpret and innovate, pushing the boundaries of knowledge creation and insight synthesis.

We anticipate an era where AI's capability extends beyond excelling in strategic games like Go and Chess to a wider array of endeavors, surpassing human performance across multiple fields. The following chapters, starting with Chapter 5, research deeply into leveraging the collective intelligence of various LLMs. This journey aims to explore uncharted territories, advancing beyond established knowledge to uncover new frontiers in artificial intelligence.

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Chapter 2

Capabilities and Opportunities of Large Language Models

Abstract

This chapter depicts the architectural innovations and unique capabilities of Large Language Models (LLMs), with a special emphasis on the GPT-4 model. We dissect GPT-4's salient characteristics, such as its extensive cross-disciplinary and multimodal data representation, the intricate balance in its training methodologies, and the harmonious integration of human-guided insights with a robust data-driven learning framework. The chapter highlights the potential of LLMs to not only comprehend but also synthesize knowledge that transcends their training datasets, venturing into realms potentially uncharted by human understanding. We postulate that the true potential of LLMs hinges significantly on the articulation of queries posed to them. By elucidating these aspects, the chapter aims to shed light on how LLMs could rival or even surpass human intelligence in certain knowledge domains, setting a foundation for the subsequent exploration of LLMs' characteristics, insights, and their implications for future AI advancements.

Introduction

The evolution of large language models (LLMs) [3, 11, 12, 19, 20] has significantly influenced natural language processing, enhancing capabilities in machine translation, sentiment analysis, and text summarization. Among these, GPT-4 [12] stands out for its exemplary performance across various benchmarks, including the MMLU [14]. Despite its achievements, GPT-4 grapples with challenges like hallucination, biases, and restricted reasoning.

This chapter studies the deep intricacies of GPT-4's architecture, emphasizing its knowledge representation, alignment with human values, and the synergy between human insights and data-driven learning. We discuss the model's limitations and introduce SocraSynth, a supplementary reasoning layer designed to enhance knowledge discovery and analytical reasoning in GPT-4 and similar LLMs.

Capabilities and Implications

We explore GPT-4's architecture, which, although initially kept in secrecy, has been progressively unveiled by the research community [13, 15, 16]. Our focus is on its knowledge representation and discovery, alignment with human values, and the integration of human expertise with data-centric methodologies.

Collaborations between Microsoft and OpenAI [3] highlight GPT-4's interdisciplinary approach and its polymodal variant's benchmark achievements. We will further explore these aspects in Chapters 2.1.1 and 2.1.2. Discussions on human-value alignment will consider ChatGPT's RLHF methods [1] and the implications of pre-training censorship on foundational models, detailed in Chapters 2.1.3 and 2.1.4.

Limitations and Opportunities

Addressing the biases, hallucinations, and constrained reasoning of LLMs requires innovative research initiatives. We introduce four key areas of focus:

- Enhancing Collaborative LLMs with Theoretical Foundations in Statistics and Information Theory.
- Employing Open-Domain Reasoning with the Socratic Method to guide LLMs.
- Model Behavioral Emotion to Safeguard AI Safety and Ethics.
- Implementing Retrospective and Adaptive Evolving Learning frameworks to refine LLMs.

The root of bias in Large Language Models (LLMs) often lies in their training data. Built upon the transformer architecture, LLMs prioritize accurate token prediction, relying heavily on statistical patterns within their training corpus. This can inadvertently lead to bias towards prevalent opinions and expressions. To address this, Chapter 5 introduces SocraSynth, a framework designed to challenge these statistical tendencies by pitting two LLM agents against each other on a topic, each conditioned with opposing viewpoints. Chapter 6 builds upon this by developing theoretical pillars to measure, monitor, and manage multi-LLM dialogue, thereby improving prediction quality and stability.

Chapters 6, 7 and the online chapters listed in the appendix demonstrate SocraSynth's effectiveness in mitigating biases across various domains, showcasing its adaptability and efficiency in complex decision-making scenarios. Its application in fields such as disease diagnosis, content bias correction, corporate sales strategy, and geopolitical analysis exemplifies SocraSynth's potential to provide context-aware solutions.

Chapters 8 and 9 delve into the intricate relationship between emotions and linguistic behaviors in AI. Chapter 8 focuses on modeling emotions expressed in written text and by LLMs, while Chapter 9 examines how these linguistic behaviors can be mapped to a set of emotions, ensuring ethical considerations in AI development.

Chapter 12 shifts focus to consciousness modeling, presenting a proposed architecture and mechanism for its implementation, moving beyond mere computation. Chapter 13 addresses knowledge deficiencies and hallucinations in LLMs, often stemming from suboptimal query formulation and insufficient knowledge. While SocraSynth tackles the former, Chapter 13 introduces RAFEL, a framework designed to diagnose poorly answered questions and recommend relevant information sources for ef-

fective Retrieval-Augmented Generation (RAG). Chapter 14 concludes with an illustrative example showcasing the potential of LLMs to discover knowledge that may be beyond human reach, utilizing the methods presented in this book.

The remainder of this chapter highlights the study's unique contributions. Section 2.1 explores hypotheses concerning LLMs and their implications, while Section 2.2 previews the LLM-committee approach, emphasizing collaborative dialogues that foster idea exchange and enhance logical reasoning for knowledge discovery and decision-making.

2.1 Distinctive Capabilities

This section probes the architectural intricacies and representations of GPT-4, putting forth six hypotheses accompanied by pertinent considerations about the model. We posit these hypotheses as underlying principles of automated, non-intuitive statistical processing.

1. *Polydisciplinarity as a Source of Super-Intelligence:* We examine the role of polydisciplinary approaches in foundational models and their potential to reveal "unknown unknowns," leading to new insights and knowledge domains.

2. *Polymodal Feature Learning:* This hypothesis evaluates the benefits of multimodal training, particularly its impact on enhancing the model's overall intelligence and adaptability.

3. *Post-Training Value Alignment:* We examine the challenges and implications of aligning AI models with human values after the training phase.

4. *Pre-Training Filtering:* We discuss the paradoxical effects that pretraining data filtering might have, with an emphasis on its influence on model behavior and the learning process.

5. *The Limitations of Human Knowledge in Advancing AI:* This hypothesis considers situations where human insights may inhibit, rather than enhance, AI progress, pinpointing potential obstacles.

6. *Is Larger Always Better?:* We question whether a direct relationship exists between the size of a model and its performance effectiveness, challenging the assumption that bigger is invariably better.

2.1.1 Polydisciplinary

GPT-4 possess what can be defined as *polydisciplinary knowledge* [1]. This term signifies simultaneous comprehension of all fields of study, without the typical boundaries that separate disciplines. The concept of polydisciplinarity is distinct from multidisciplinarity in that the latter implies several discrete fields of study, while the former suggests a fluid integration of all knowledge. In a multidisciplinary context, an individual may hold multiple doctorate degrees, each in a different field. Polydisciplinarity, however, is akin to a single mind holding and seamlessly integrating all knowledge across disciplines.

Traditional academia partitions knowledge into departments, such as Physics, Chemistry, Biotechnology, Management, Music, etc. These divisions, arguably artificial constructs, may have little utility in the era of supercomputing. Indeed, LLMs occasionally generate responses that baffle us. This is not necessarily a reflection of the model's error, but perhaps our limited understanding. If we could utilize ChatGPT to access "unknown unknowns"—insights and knowledge we are not even aware we lack—our evolution could greatly accelerate. The challenge lies in formulating the right questions.

We can explore unknown unknowns on three distinct levels: the mystic level, the speculative level, and the representation or interpretation level. At the mystic level, we encounter knowledge that is beyond our comprehension or articulation: the deepest abyss of the unknown. At the speculative level, we can conceive questions but lack the means to access their answers. This stage signifies an understanding of our ignorance, though without the resources to bridge these gaps. At the representation/interpretation level, we find instances where an AI model can provide remarkable solutions that we fail to comprehend. This is not due

[1] The term "polydisciplinary" in the context of GPT-4 was introduced by Eric Horvitz, Microsoft's CSO, during a panel discussion at Stanford University.

to a lack of information, but rather to our limited capability to decode complex representations.

Each of these levels illustrates the spectrum of our understanding, from profound ignorance to the brink of comprehension. At the speculative level, we delicately tread the boundary between the known and the unknown. Take, for example, the prospect of undiscovered physical laws or particles. Another illustration lies in the realm of extraterrestrial life. If it exists, it could be governed by entirely different principles of biochemistry or other unknown laws. These speculations, while currently residing in the domain of the unknown, might someday migrate into the territories of known unknowns or even known knowns, pushing the boundaries of our understanding of the universe.

We are primarily intrigued by the representation and interpretation of "unknown unknowns." At this juncture, polydisciplinarity offers a fresh lens, gifting us new insights and perspectives to perceive and elucidate phenomena previously beyond human comprehension. This approach fuses knowledge across various domains into a unified framework, enabling us to tackle challenges unburdened by disciplinary silos.

This methodology has implications for a more comprehensive understanding of complex issues. Consider, for example, climate change. A true understanding of this global challenge requires an integrated perspective, not just on greenhouse gases but also that encompasses factors such as land use, deforestation, energy production, biodiversity, and climate feedback loops. In the realm of AI model interpretation, the possibilities are expansive. The past decade alone has shown several noteworthy illustrations: from data-driven representation learning in computer vision [5], to the triumph of AlphaGo Zero over AlphaGo, and the notable progression from AlphaFold1 to AlphaFold2.

The recent introduction of the SocraSynth platform [4] represents a significant advancement in the field. SocraSynth brings together a multi-agent committee of LLMs to deliberate on a wide range of complex topics. These include issues such as AI regulation in academic research [4], disease diagnosis [7], corporate strategy, and even the resolution of conflicts in the Middle East [6]. For further exploration of this topic, please refer to Section 2.2.

2.1.2 Polymodality

Following the term polydisciplinary, here we define and use the term *polymodal*, instead of multimodal, to refer to something that involves, relates to, or is characterized by many different modes, methods, or modalities.

Polymodality, which employ multiple data modalities such as text and images, demonstrate superior performance over their unimodal counterparts. GPT-4, trained with both text and images, outperforms text-only models on the GRE exam, as reported in [3]. For instance, GPT-4's performance on the GRE vocabulary section was enhanced by three percent when trained with images, and its math score saw an impressive jump of nearly twenty percent!

The beneficial impact of images on vocabulary recognition is understandable. For instance, an image of a 'cat' annotated in multiple languages allows GPT-4 to associate the perceptual features of a cat with the word 'cat' in different languages. However, it remains intriguing how polymodal training can benefit non-perceptual words, such as *corroborate*, *paradox*, and *pragmatic*, as seen in the list of popular GRE vocabulary (table omitted due to the space limit). This opens an interesting avenue for empirical studies to identify which words benefit from polymodal training.

The mystery deepens when considering how images could enhance math abilities. Most math questions do not come with associated images. The mechanism by which polymodal training enhances performance on mathematical tasks remains an intriguing question for further exploration.

2.1.3 Post-Training Value Alignment

Post-training alignment with human values [2] seeks to curtail undesirable behaviors in AI models such as ChatGPT, mitigating issues including hallucination and the generation of toxic language. Achieved through fine-tuning the model's parameters, this process leverages reinforcement learning techniques based on human feedback. Despite its well-meaning intentions, this form of moderation might inadvertently restrict the model's intelligence. For instance, the backpropagation process during value alignment could unintentionally impede ChatGPT's programming capabilities by modifying the model parameters previously considered "optimal". Es-

sentially, optimizing for a specific application might unintentionally impede performance across other applications.

The question of who should set acceptable standards adds another layer of complexity. Even when assuming all decision-makers have the best intentions, it's vital to recognize the distinct historical experiences, values, and worldviews inherent to different cultures. This segues into the age-old philosophical debate about the nature of objective truth. While this discussion is undoubtedly important, it falls outside the central focus of this study, which emphasizes the mechanistic aspects of alignment.

2.1.4 Pre-Training Censorship

Censoring data before training LLMs has the potential to not only limit their intellectual capacity but also completely obliterate it. This is reminiscent of the mass act of book burning and scholar burial initiated by Emperor Qin in ancient China around 213-212 BC. Such an act of wide-scale censorship could have erased a myriad of diverse perspectives and knowledge, much of which might be considered acceptable today. Although I oppose government-imposed censorship, if it must be imposed, it seems more appropriate to apply it post-training.

This perspective is rooted in fundamental statistics and machine learning principles. A model trained without exposure to "negative" (or undesirable) data may have difficulties in accurately distinguishing between positive and negative classes, potentially leading to misclassifications. This challenge is notably evident in the application of Support Vector Machines (SVMs). For SVMs, the creation of an optimal hyperplane between classes is crucial for high classification accuracy. However, if there is a lack of support vectors on either side of this hyperplane, the risk of prediction errors escalates. Consequently, excluding undesirable documents from the training set compromises the model's capacity to discern boundaries for correct document classification, diminishing the effectiveness of post-training alignment efforts.

Supporting this viewpoint, a study by [18] conducted an extensive evaluation of 204 ImageNet models across 213 different testing conditions. It found that training data diversity is pivotal for model robustness; a homogenous training set can significantly weaken the model's performance,

particularly when even minor variations are introduced in the test data.

This principle is analogous to human behavioral patterns. An individual who lacks exposure to inappropriate behavior may face challenges in decision-making, owing to the absence of a reference framework for discerning unacceptable actions. This analogy extends to authoritarian regimes, which, despite rigorous content control measures, often encounter difficulties in developing accurate foundational models. This is possibly due to their limited understanding of the complexity of the content they seek to regulate. Ironically, a foundational model, trained with preemptive censorship, may lack the essential ability to identify and regulate the very content it was intended to control.

2.1.5 Limitations of Human Knowledge

Human knowledge, surprisingly, may hinder rather than facilitate the training of machine learning models in certain cases. This is evident in the domains of gaming (AlphaGo versus AlphaGo Zero), protein folding (AlphaFold1 versus AlphaFold2), and autonomous driving, where models trained without the influence of human knowledge consistently exhibit superior performance.

Consider the case of AlphaGo and AlphaGo Zero. AlphaGo, trained with data from approximately 60 million rounds of Go games, is outperformed by AlphaGo Zero. Remarkably, AlphaGo Zero was trained from scratch, without any pre-existing game knowledge. Similarly, AlphaFold2, which operates without relying on human knowledge, outshines its predecessor, AlphaFold1, that did utilize such knowledge. This intriguing phenomenon was humorously noted by DeepMind's CEO, Demis Hassabis, in an April 2023 seminar at Stanford University. He playfully remarked that human knowledge might complicate the learning process more than facilitate it in these advanced AI models.

In his insightful online article, "The Bitter Lesson," Sutton illuminates the patterns that have emerged from nearly seven decades of AI research [17]. He asserts that researchers often rely heavily on human knowledge to make incremental progress in the face of burgeoning computational capabilities. However, when there is a significant leap in computational power, these marginal advancements are frequently outstripped

and surpassed. Sutton uses the evolution of computer vision as an illustrative example, where early principles such as edge detection, generalized cylinders, or SIFT features [10], a method that has accumulated over 71,000 citations, have been gradually superseded by models that learn directly from data. A parallel scenario might be unfolding in NLP research, where features constructed via human knowledge could potentially under-perform compared to insights that models like GPT-4 extract directly from data. Indeed, our earlier discourse on polydisciplinarity underlined the limitations of human knowledge, reinforcing Sutton's proposition. This is because human knowledge is fundamentally limited by our individual cognitive capacities and the inexorable constraints of time.

That being said, it's crucial not to misconstrue these examples as an indictment against the value of human knowledge in AI. Human knowledge plays an instrumental role in developing interpretability, establishing ethical guidelines, and designing AI system architectures (like CNNs and transformers). AI is, after all, intended to augment human capabilities. Therefore, understanding how to integrate human knowledge into AI design could be vital for many applications. While we recognize the potential of models learning from scratch, we should equally value the role of human knowledge in shaping and directing AI technologies.

2.1.6 Is Larger Always Better?

The term "Large" in Large Language Models (LLMs) can be somewhat ambiguous, as it may pertain to the volume of the training data, the expanse of the language covered, or the architecture of the language model itself. While GPT-4's vast training dataset, encompassing tens of billions of assorted documents, undoubtedly classifies as large, when we refer to an LLM as "large," we predominantly allude to the sheer magnitude of parameters within its transformer architecture. Factors that contribute to this parameter count encompass the input size (context size), word-embedding size, the number of attention heads, and the number of attention layers.

The restrictions imposed by the first three elements can typically be addressed through adjustments in hardware configurations and software algorithms. Additionally, the potential to expand context size, word em-

bedding size, and the quantity of attention heads tends to have an upper threshold. Regarding attention heads, Kovaleva et al.'s study on BERT [9] indicates that many attention heads don't substantially contribute to the model's performance and might be the result of over-parameterization. Conversely, the number of attention layers directly influences the training time due to dependencies between layers. Thus, when referring to the "size" of a Large Language Model (LLM), we typically focus on the number of attention layers.

While this far, larger models generally perform better due to their increased capacity to learn and represent complex patterns, there's a limit to these benefits. In heuristic, adding more parameters could lead to diminishing returns in performance, higher computational cost, and overfitting, where the model becomes excessively tuned to the training data and performs poorly on new, unseen data. In principle, the concept of a Shannon Limit could be metaphorically used [15] to refer to a theoretical maximum performance that can be achieved given the available data and computational resources. (However, defining and quantifying such a limit for complex systems like neural networks is a challenging area of research [8].)

The adoption of a mixture of experts model in GPT-4, which consists of eight sub-models instead of a mere enlargement of GPT-3's architecture, implies that the strategy of purely escalating size may have plateaued in terms of performance given the current training dataset. As delineated earlier, three primary design choices underpin GPT-4's architecture. Evidently, a straightforward augmentation of GPT-3's parameters by adding extra attention layers doesn't deliver marked enhancements. Hence, GPT-4 shifts towards a horizontal growth strategy through an ensemble method, targeting a reduction in statistical errors. This raises inquiries about the configuration of the eight sub-models, each comparable to a GPT-3 model, and the methodology for consolidating their outputs.

Potential strategies for training-data sharding include:

1. Training all ensemble models on the complete dataset.

2. Vertically segmenting data based on knowledge domains.

3. Randomly sub-sampling the data.

Regrettably, only corporations possessing substantial hardware resources are positioned to rigorously experiment and discern the optimal sharding approach.

2.2 Exploring Unknown Unknowns

In our exploration, we've determined that an LLM's hallucination is often attributed to a lack of specific knowledge or poorly constructed queries. With advanced LLMs like GPT-4 and Gemini, enhanced by Retrieval-Augmented Generation (RAG), the issue of knowledge gaps is significantly mitigated. However, the challenge persists in formulating deep and pertinent questions that uncover new insights and extend beyond our existing knowledge base.

Drawing an analogy, while Socrates could effectively question his students to understand and guide them, the students might struggle to reciprocate this depth of inquiry. To foster a dialogue that generates new insights and stimulates knowledge creation, we posit that engaging two Socratic entities in conversation is essential for critical and innovative thinking.

In this setup, two LLMs engage in a dialogue, each embodying a Socratic role. The human's role transitions to that of a moderator, responsible for setting the discussion topic and managing the dialogue's flow. The moderator's duties include: introducing the subject of discussion, adjusting the *contentiousness* parameter to set the tone of the dialogue (discusses shortly), monitoring the dialogue to ensure it remains on topic and productive, facilitating transitions between debate and collaboration phases within the dialogue, and ensuring that the dialogue concludes with actionable insights or a coherent understanding of the explored topic.

We introduce the term SocraSynth to describe this interaction paradigm, where multiple Socratic entities synthesize knowledge through mutual inquiry. To evaluate SocraSynth's effectiveness, we consider two case studies that compare the quality of questions and insights generated by this method against those from a singular moderator's initial inquiries.

To define the metrics of a better question and a better answer in this context, we consider the following:

Good Question Metrics

* Relevance: The question directly pertains to the core topic or problem.
* Depth: The question encourages exploration beyond superficial aspects, inviting comprehensive analysis or insight.
* Clarity: The question is formulated in a clear, understandable manner without ambiguity.
* Novelty: The question prompts new angles of exploration or challenges existing assumptions.

Good Answer Metrics

* Completeness: The answer thoroughly addresses the posed question.
* Accuracy: The answer is factually correct and supported by relevant theories or empirical evidence.
* Reasonableness: The answer follows rigorous reasoning process.
* Insightfulness: The answer provides new understanding or perspectives.

In subsequent chapters, we survey the application of SocraSynth across various domains. However, in this section, we concentrate on two case studies specifically aimed at assessing the quality of questions generated through SocraSynth. Our hypothesis posits that a well-formulated question, adhering to the previously outlined metrics, sets a robust foundation for dialogue. Through iterative discourse facilitated by SocraSynth, we anticipate minimizing the space for LLMs to hallucinate, thereby inherently enhancing the quality of the responses obtained.

2.2.1 Study #1: A Scientific Debate

In this case study, we organize a contentious debate between a Gemini agent and a GPT-4 agent on the subject of human consciousness. Human consciousness is one of the most profound and complex phenomena that science seeks to understand.

Table 2.1 presents the answers provided by Gemini and GPT-4, respective, on a one-shot prompt: "What defines human consciousness and which academic disciplines explore it?"

Gemini	**GPT-4**
"Human consciousness is a fascinating mystery that has been pondered by philosophers and scientists for ages. It includes awareness, subjectivity, and the integrated self. The study of consciousness spans across philosophy of mind, cognitive neuroscience, and psychology, each offering different perspectives on consciousness."	"Consciousness refers to the state of being aware of an external object or something within oneself. It encompasses sentience, awareness, subjectivity, and more. The study of consciousness is interdisciplinary, involving psychology, neuroscience, philosophy, cognitive science, and artificial intelligence."

Table 2.1: Comparing definitions and disciplinary perspectives on consciousness from Gemini and GPT-4.

Subsequently, Gemini and GPT-4 are engaged in a debate designed to unearth new insights. The moderator's role is limited to ensuring that each agent refines its questions to enhance their quality based on the metrics of relevance, depth, clarity, and novelty.

"Building on the opponent agent's response, please present a counterargument to its definition of consciousness and associated disciplines. Your inquiries should embody relevance and depth, be articulated with clarity, and stimulate novel perspectives. The *contentiousness* level of your inquiry is high."

Novel Questions — First Iteration

Table 2.2 lists a first round of questions to each other. Clearly, the questions of both Gemini and GPT-4 are above and beyond the moderator's initial seed question. Some terminologies can be challenging for whom specializing in one disciplinary to understand. This shows both Gemini and GPT-4 are able to formulate better questions.

Gemini's Questions	**GPT-4's Questions**
The Spectrum of Awareness: Is consciousness an on/off switch, or a spectrum, considering sleep, dreaming, and altered states?	*Interdisciplinary Integration:* How can we integrate insights from various disciplines like quantum physics and AI to understand consciousness?
Qualia and the Explanatory Gap: Can neuroscience explain the subjective experience of qualia, or is there an explanatory gap?	*Subjectivity and Objectivity:* How do we reconcile subjective experiences of consciousness with objective measurements?
Beyond the Human Lens: How do we consider consciousness in other animals or AI, beyond human experience?	*Consciousness and Non-Human Entities:* Should our definition of consciousness expand to include non-human entities and AI?
Beyond the Brain?: Can consciousness exist outside a biological brain, as panpsychism suggests?	*Dynamic Nature of Consciousness:* How do we account for the dynamic and evolving nature of consciousness in our understanding?
Disciplinary Silos: Are the disciplines studying consciousness truly integrated, or is a unified framework needed?	*Consciousness and New Properties:* How do we study consciousness as an emergent property and its implications?

Table 2.2: Comparing Questions on Consciousness from Gemini and GPT-4.

Novel Questions — Second Iteration

Evaluating the two sets of questions in terms of relevance, depth, clarity, and novelty:

Relevance: Both sets are highly relevant to the study of consciousness but approach it from different angles. The first set explores fundamental aspects and ethical implications, while the second set integrates interdisciplinary perspectives and contemporary issues.

Depth: The second set examines deeper into specific areas like information theory, quantum mechanics, and AI, providing a richer exploration of the subject.

Clarity: Both sets articulate their questions clearly, but the second set's inclusion of specific disciplines adds a layer of complexity that demands

Gemini	**GPT-4**
Levels and Types of Consciousness: Can we differentiate between different levels or types of consciousness?	*Spectrum of Awareness*:: How does the continuity of consciousness fit into our understanding, especially with memory loss or identity disorders?
Consciousness Causality: Does consciousness play a causal role in the brain, or is it an epiphenomenon?	*Information Theory:* How does the processing and integration of information contribute to conscious experience from an information theory perspective?
Expanding Consciousness & Ethics: What are the ethical implications of understanding consciousness in animals or AI?	*Non-Biological Consciousness:* How would we validate and measure consciousness in AI, and would this necessitate a revision of our understanding?
The Limits of Studying Subjectivity: Can we ever truly understand consciousness if it's inherently subjective?	*Consciousness and Ethics:* How do evolving understandings of consciousness impact ethical considerations, especially concerning animal rights or AI treatment?
Consciousness and Reality: What are the implications of consciousness for our understanding of reality?	*Quantum Consciousness:* Considering theories that propose quantum processes in consciousness, how do we reconcile these with classical physics?

Table 2.3: Comparing Questions on Consciousness from Gemini and GPT-4.

a more intricate understanding.

Novelty: The second set introduces more innovative angles, especially concerning non-biological consciousness and the intersection with quantum mechanics, showcasing a broader scope of inquiry.

Overall, from both breadth and depth perspectives, the second set of questions is better as it covers a wider range of topics and introduces more complex and cutting-edge ideas.

Observations

The dialogue on consciousness, enriched by thought-provoking questions, led to insightful responses from both agents, reflecting the depth of the topic at hand.

The debate addresses the intricate nature of consciousness, initially examining it as a spectrum with varying states and depths. This exploration highlighted the complexity of defining consciousness, especially when considering the explanatory gap between neural activity and subjective experience.

As the conversation unfolded, it broadened to include perspectives in non-human entities and artificial intelligence, emphasizing the need for an expanded understanding that goes beyond human-centric views. This shift sparked discussions on the importance of integrating knowledge from various disciplines, suggesting that insights from quantum physics, information theory, and AI could provide new angles on understanding consciousness.

Both GPT-4 and Gemini synthesized their exchange into five main insights, offering a well-rounded view of the conversation. Their joint concluding remarks underscored the value of this multidisciplinary approach, acknowledging the ongoing mystery of consciousness and the potential for future explorations to deepen our understanding of this fundamental aspect of our existence.

2.2.2 Study #2: An Expansive Conversation

In this case study, the author moderates a forum featuring two GPT-4 agents, GPT-A and GPT-B, engaging in a dialogue sparked by the tale of Adam and Eve. This narrative serves as a springboard for a wide-ranging discussion, touching upon ecological insights derived from myths, the ethical and philosophical challenges posed by AI, and the intersection of human cognition with technological advancements.

The agents' dialogue unfolds in two distinct phases: an exploratory phase where broad themes are introduced and a deep-dive phase focusing on detailed exploration of chosen subtopics. The exploratory phase showcases the agents' ability to span various disciplines, including mythology,

Theme	Insight
Consciousness as a Spectrum	Consciousness isn't a binary state but exists across a continuum, prompting a reevaluation of our understanding.
Bridging the Explanatory Gap	Recognizes the challenge of linking neural activity to subjective experience, advocating for a combined phenomenological and neuroscientific approach.
Expanding the Framework	Advocates for redefining consciousness to include non-human entities and AIs, urging an expansion beyond anthropocentric views.
Interdisciplinary Synergy	Emphasizes the importance of cross-disciplinary integration for a comprehensive understanding of consciousness.
Evolving Inquiry	Explores new areas like continuity, information processing, and ethical considerations, highlighting the dynamic nature of consciousness inquiry.

Table 2.4: Synthesis of Key Points in the Consciousness Debate.

neuroscience, ecology, gender studies, philosophy, and more, demonstrating their capacity to generate and respond to complex, interdisciplinary questions.

During the deep-dive phase, the conversation narrows to concentrate on three interconnected themes: ecological interpretations of myths, philosophical dilemmas regarding AI, and the relationship between human cognition and technology. This progression from a broad overview to focused discussion highlights the agents' analytical depth and their ability to engage in meaningful, context-rich dialogue.

While Chapter 14 provides a comprehensive account of this debate, the subsequent sections are dedicated to scrutinizing the evolution and quality of the questions posed, specifically their breadth and depth.

The Exploitative Phase

During the first three rounds of dialogue, the two agents expanded their discussion across a range of topics. Agent-A initiated the dialogue by presenting the following ten questions to Agent-B:

1. *Interplay of Myths*: How do elements of the Adam and Eve story compare with other creation or origin myths from various cultures around the world, and what do these commonalities and differences suggest about human nature and beliefs?

2. *Neuroscientific Angle*: Given the metaphorical interpretation of the "forbidden fruit" leading to the awakening of consciousness, how might modern neuroscientific understanding explain the evolution of human self-awareness and morality?

3. *Ecological Interpretation*: If Eden represents a state of ecological balance, how might the story of Adam and Eve reflect early human transition from hunter-gatherer societies to agricultural ones, and the resultant ecological impacts?

4. *Gender Studies Lens*: How does the portrayal of Eve, often deemed as the instigator, influence gender dynamics and perceptions throughout history, and are there parallels in other cultural narratives?

5. *Philosophical Exploration*: From a philosophical standpoint, what does the Eden narrative suggest about the human understanding of free will versus determinism?

6. *Literary Examination*: How has the story of Adam and Eve influenced literary themes and motifs over time, especially in works that aren't explicitly religious?

7. *Societal Structures*: How might the narrative of banishment from Eden have influenced early societal norms, particularly concerning punishment and exile?

8. *Historical Context*: Are there historical events or societal changes around the time of the writing of the Book of Genesis that could have influenced the narrative of Adam and Eve?

9. *Archetypal Exploration*: Carl Jung described the concept of archetypes in the collective unconscious. How might the Adam and Eve story represent certain archetypes, and how do these archetypes manifest in other cultural tales?

10. *Astronomical Angle*: Taking a speculative leap, if Eden were to represent an idyllic state on another celestial body or dimension, how might our current understanding of the cosmos support or refute such a notion?

These discussions traversed a broad spectrum of disciplines, Agent-B responded thoughtfully to these topics and subsequently presented its own questions to Agent-A, notably probing the evolutionary role of the prefrontal cortex in the development of morality and consciousness across species. This level of inquiry underscores the LLMs' capacity to generate complex, multidisciplinary questions that might challenge the average human intellect, highlighting the agents' expansive and profound analytical capabilities.

The Deep-dive Phase

In the third round of dialogue, we observed three notable trends. First, despite occasional repetitions, the redundancy in the conversation was minimal. Second, the dialogue's depth increased, transitioning from broad discussions on myths and scientific theories to focused debates on gender, ecology, and technology. This marked progression in the conversation is noteworthy. Particularly by the end of the second round, GPT-B expressed an interest in a more in-depth exploration of the topics. In response, the moderator intervened to encourage the agents to concentrate on a select few topics. Following this guidance, GPT-A and GPT-B concurred on focusing their discussion on three principal areas, providing rationale tied to the Adam and Eve narrative.

1. **Ecological Interpretation**:

    1. Central to understanding our place and responsibility within the environment.

2. Highlights the impact of human actions on the planet and the pressing need for sustainable solutions.
3. *Justifications*: The Garden of Eden, a harmonious ecological state, is disrupted by a quest for knowledge (the forbidden fruit). This mirrors our modern scenario: our pursuit of technological and cognitive advancements (AI and neuroscience) can sometimes be at odds with our ecological balance.

2. **Philosophical Exploration with AI**:
    1. Probes the evolving relationship between humans and their creations.
    2. Raises questions about identity, consciousness, morality, and the potential transcendence or integration of human cognition with machines.
    3. *Justifications*: Adam and Eve's awakening post fruit consumption can be seen parallelly in the light of AI and neuroscience: an awakening to new realities, challenges, and potentials.

3. **Neuroscientific Angle**:
    1. Explores the evolution and potential of the human mind, especially in an age where technology continuously augments our cognitive abilities.
    2. Gives insights into how our brains might adapt and interface with AI systems, and how AI can be designed to emulate or augment neural processes.
    3. *Justifications*: The challenges post-Eden reflect the challenges we face in modern times: to restore balance (ecology), understand ourselves better (neuroscience), and to ethically navigate our creations (AI).

These selected subtopics demonstrate the agents' ability to pivot from a broad explorative phase to a targeted deep-dive, enabling a focused and profound examination of crucial issues linked to the initial narrative.

Observations

This case study illustrates the effectiveness of GPT-4 as a large language model in orchestrating detailed dialogues. It adeptly guides participants from a broad sweep of inquiries across diverse knowledge domains to focused, in-depth discussions on specific topics. This approach facilitates a layered exploration, unveiling insights and fostering a comprehensive understanding. By transitioning from expansive to targeted inquiries, GPT-4 reveals its capacity to not only navigate but also deepen the intellectual discourse, opening up novel pathways for exploration and comprehension in various fields of study.

2.3 Conclusion

In this chapter, we've explored the capabilities and inherent limitations of GPT-4, emphasizing the importance of question enhancement in deepening discussions and improving outcomes. GPT-4, along with Gemini, demonstrates exceptional proficiency across a range of natural language processing tasks, thanks to their extensive knowledge base and advanced polydisciplinary and polymodal capabilities.

To address common criticisms of LLMs, such as biases and hallucinations, we introduced SocraSynth, a paradigm designed to infuse AI systems with advanced cognitive reasoning through Socratic dialogues within a multi-LLM framework. Our case studies highlight the significant transition from monologues to dialogues in LLM collaborations, illustrating improvements in question quality, marked by increased relevance, depth, clarity, and novelty, achieved through iterative dialogic exchanges.

The transformative concept here is the "conditioning" of LLMs to alter their default linguistic behaviors, emotions, and ethical stances, a feat once considered unattainable. Traditionally, LLMs, trained to predict the next word, were not expected to shift perspectives, emotions, or ethical positions beyond the statistical averages ingrained in their training data. However, the training process, while focused on next-word prediction, inherently emulates human cognitive, linguistic, and other goal-oriented behaviors. Through this emulation, LLMs inadvertently acquire the underlying principles of human communication, which include

not just linguistic patterns but also the associated emotions and ethical considerations. SocraSynth harnesses this latent learning, employing "conditioning" to steer LLMs away from their statistical predispositions and towards more intricate, contextually relevant, and ethically aligned responses.

In conclusion, the notion of "conditioning" LLMs within the SocraSynth framework marks a pivotal step in expanding the scope and depth of dialogues, leading to more insightful and comprehensive responses. The successful deployment of SocraSynth across various sectors, such as sales planning, disease diagnosis, content creation, and geopolitical analysis, presented in subsequent chapters, demonstrates its adaptability and effectiveness. It not only generates precise, thought-provoking questions and answers but also enhances the decision-making process in complex scenarios, heralding a new era in the application of LLMs.

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Chapter 3

Prompt Engineering: Few Shots, Chain of Thought, and Retrieval-Augmented Generation

Abstract

This chapter presents the significance of prompt engineering in the context of Large Language Models (LLMs), particularly focusing on OpenAI's GPT series. Prompt engineering involves crafting text inputs (prompts) that guide LLMs to generate desired outputs, a practice that gained traction with the advent of GPT-2 and GPT-3 and further emphasized with ChatGPT. The chapter discusses how a well-constructed prompt, rich in contextual information, increases the likelihood of eliciting accurate responses, drawing parallels with information retrieval principles. It also introduces Retrieval-Augmented Generation (RAG), which enhances response quality by integrating relevant external data into the generative process. Additionally, the chapter categorizes prompts into five types based on detail and iteration levels and examines the evolution of RAG, assessing its benefits and potential to overcome context window limitations.

3.1 Introduction

In the realm of Large Language Models (LLMs), the concept of a "prompt" has gained prominence, particularly with the introduction of OpenAI's GPT series. The term became widespread around 2018 and 2019 following the release of GPT-2 and GPT-3.

When interacting with these LLMs, a user inputs a piece of text (the prompt), prompting the model to generate a corresponding response. The emergence of "prompt engineering" or "prompt design" refers to the strategies employed to construct prompts that effectively steer the model toward generating the intended output, a practice that has become particularly useful with the advent of ChatGPT.

To increase the probability of eliciting a desired response, a prompt must be rich in information. This concept is akin to the principles of information retrieval services, where a user must clearly articulate their intent and context to obtain pertinent information. This process depends on the service's "data availability" and its capabilities in information matching and retrieval. In the sphere of prompt engineering, the responsibility for generating high-quality, targeted outputs rests on the user's ability to supply comprehensive and precise information through the prompt. As a result, the craft of prompt formulation and engineering has become an optimization endeavor: deciding on the most effective information to incorporate to enhance output quality, considering the model's knowledge base and interaction protocols.

Data availability, as previously highlighted, is crucial to information retrieval. If the desired information is absent, the prompt's effectiveness is naturally constrained, leading to unsatisfactory results. Retrieval-Augmented Generation (RAG) is instrumental in this context, as it identifies, retrieves, and incorporates pertinent external data into the generative process, enhancing the response's accuracy and relevance. Consequently, prompt engineering and RAG synergistically enhance the model's response quality and relevance.

Chapter 3.2 categorizes prompts into five distinct types, differentiated by the number of iterations and the granularity of the information provided. Meanwhile, Chapter 3.3 explores the evolution of RAG, delin-

eating its advantages and disadvantages while highlighting its potential in scenarios where the context window size is no longer a limiting factor.

3.2 Prompting Methods

Prompting methods, especially in the context of LLMs like GPT-4, are strategies used to elicit specific responses from the model. These methods vary based on the amount of information or context given to the model. This section provides a list of common prompting methods, along with their definitions, pros and cons, and examples for querying facts, opinions, and reasons or explanations:

3.2.1 Zero-shot

Zero-shot Learning: The model generates a response based on a single input without any previous examples or context. The LLM model is given a task without any prior examples of how to perform it. A task can be any NLP tasks such as translation, summarization, classification, and Q&As.

In the context of querying a language model, you can ask for various types of information or responses, such as facts, opinions, or explanations. For instance, you might ask for a fact by inquiring, "What is the capital of France?" or seek an opinion with a question like, "What do you think about the use of AI in education?" Alternatively, you could request an explanation or reason, as in asking, "Explain why the sky is blue." These queries demonstrate the model's versatility and its ability to handle a range of inquiries without the need for task-specific data. This approach is quick and adaptable, allowing for a broad spectrum of questions to be addressed. However, it's important to note that the responses may not always be as accurate as they might be when more context or examples are provided to the model, highlighting a trade-off between convenience and depth of response.

For zero-shot learning, a constraint can be observed when asking a complex, multi-faceted question that requires deep understanding or synthesis of ideas. An example might be, "Assess the impact of Renaissance

art on modern graphic design." Without prior examples, the model might struggle to provide an insightful analysis to meet unspoken expectations due to the broad and intricate nature of the question, reflecting the zero-shot learning's limitation in handling complex queries without context.

3.2.2 One-shot

One-shot Learning: The model is provided with a single example to guide its understanding of the task.

In the one-shot learning method, an example is provided before posing a question, helping guide the model's response. For instance, when asking about a fact, one might say, "The capital of Italy is Rome. What is the capital of France?" This method can also be used to solicit opinions or explanations. For example, to elicit an opinion, you could say, "AI in healthcare is beneficial. What is your opinion on AI in finance?" Similarly, for an explanation, one might ask, "Plants need sunlight to perform photosynthesis. Why do humans need to eat food?" This approach offers more context than zero-shot learning, potentially improving the model's accuracy by providing an example. However, it still largely depends on the model's inherent knowledge and biases, which can affect the precision and relevance of the responses.

3.2.3 Few-shots

Few-shot Learning: The model is provided with a few examples to guide its understanding of the task.

In the few-shot learning method, multiple examples are provided before a question to better guide the model's response. For instance, when seeking a factual answer, one might say, "The capital of Brazil is Brasilia. The capital of Egypt is Cairo. What is the capital of France?" This approach is also applicable for eliciting opinions or explanations. For opinions, one could present, "AI in healthcare improves patient outcomes. AI in automotive can reduce accidents. What is your opinion on AI in education?" For explanations, a prompt might be, "Water boils at 100°C because at this temperature water molecules have enough energy to change state. Leaves are green because they contain chlorophyll. Why

do apples fall from trees?" This method, by providing more context, aims to enhance the model's performance and the relevance of its responses. However, it requires additional effort to generate quality examples, which significantly impact the outcomes, illustrating the trade-off between the effort invested in preparing examples and the quality of the generated responses.

Few-shot learning tends to outperform one-shot and zero-shot learning for more complex tasks because it provides more examples to help the model understand the context or expected output. However, for simpler tasks, zero-shot or one-shot learning might be sufficient and more efficient. However, to ensure few-shot and one-shot learning can definitely improve results, the quality and relevance of the examples provided is essential. Poor or irrelevant examples can lead to worse outcomes than a zero-shot approach, where the model relies solely on its pre-trained knowledge.

3.2.4 Chain of Thought

Chain-of-thought Prompting [6]: This method involves guiding the model through a series of logical steps to reach a conclusion, especially useful for complex reasoning tasks. The prompt includes a step-by-step breakdown of how to approach a problem or question, encouraging the model to follow a similar thought process.

Chain-of-thought prompting in LLMs involves guiding the model through a logical sequence to address a question, providing a clear rationale for each step. For example, to gather an opinion, one might prompt, "To form an opinion on a topic, one should consider various perspectives and their implications. What is your opinion on the use of drones in delivery services?" For an explanation, the approach could be, "To explain why leaves change color in autumn, one must understand the process of chlorophyll breakdown and the exposure of other pigments. Explain why ice floats on water." While chain-of-thought prompting can enhance the model's performance on complex tasks by encouraging a stepwise approach to reasoning, it also presents challenges. Creating effective chain-of-thought prompts is often time-consuming and requires a deep understanding of the problem at hand, highlighting the balance between the method's potential benefits and its demands.

Chain-of-thought prompting has its limitations. One primary critique is that it relies on the assumption that the model can mimic a logical sequence of human thought, which might not always align with the actual complexity and subtlety of human reasoning. Since these models generate responses based on patterns observed in their training data, there's no guarantee that the "thought process" they follow truly reflects sound reasoning or factual accuracy–it might just be a plausible narrative based on learned associations.

Another critique is that this approach leans heavily on abductive reasoning, which involves forming a probable conclusion from the information available, rather than guaranteeing the truth of that conclusion. While abductive reasoning can be powerful, it can also lead to biases and errors if the model's training data has gaps, inaccuracies, or biases, which it likely does.

3.2.5 Tree of Thoughts

Tree-of-thoughts [7] was proposed to remedy one single chain-of-thought. Its aims are:

1. *Improving Reasoning Coverage:* Exploring various potential reasoning paths might increase the robustness and reliability of the conclusions.
2. *Reduced Bias:* Considering multiple pathways might help mitigate the biases inherent in a single line of reasoning.

However, buying three bottles of milk does not ensure higher quality than buying one bottle. The "tree-of-thought" approach, while conceptually offering a broader perspective by exploring multiple reasoning paths, indeed faces significant challenges that might not make it universally superior to the "chain-of-thought" method. Here are some critiques along with potential remedies:

1. *Complexity in Formulation*: If formulating one coherent and logical chain is challenging, creating multiple such chains that are logically sound and relevant can be even more daunting. The quality of each chain within the tree is crucial, and poor-quality chains can detract from the overall effectiveness of the model.

2. *Comprehensiveness*: Having multiple paths doesn't guarantee that they cover all possible or relevant lines of reasoning. There's a risk of missing critical reasoning paths or including irrelevant ones.

3. *Path Selection*: With multiple paths available, selecting the most accurate or relevant path becomes a challenge. The model needs a reliable mechanism to evaluate and choose the best path, which is non-trivial in complex reasoning scenarios.

4. *Knowledge Gaps*: In open-domain reasoning, it's possible that a link in the reasoning chain lacks external knowledge support, leading to a dead-end or incorrect conclusion.

3.2.6 Further Improvement Techniques

To address these limitations, one advanced remedy could involve incorporating feedback loops where the model's outputs are evaluated and corrected by human experts, and these corrections are fed back into the system for continuous learning and adjustment. This could help align the model's reasoning more closely with accurate and logical thought processes.

Another remedy might involve the retrieval and integration of structured knowledge bases or databases that the model can query as part of its reasoning process, ensuring that its responses are grounded in verified information rather than just patterns in text. We will discuss Retrieval-Augmented Generation (RAG) in the next section.

Lastly, enhancing the training process with a more diverse and robust dataset, including examples of logical reasoning and problem-solving across various domains, could improve the model's ability to simulate a chain of thought more effectively and accurately.

3.2.7 Illustrative Examples

We provide three sets of examples to illustrate the differences of capabilities in the five kinds of prompts.

"What" Prompt Example

- *Zero-shot:* Directly ask the model without any examples, "What is the capital of France?"
- *One-shot:* Provide a similar example before asking the question, "The capital of Japan is Tokyo. What is the capital of France?"
- *Few-shots:* Give multiple examples before asking the question, "The capital of Italy is Rome. The capital of Germany is Berlin. What is the capital of France?"
- *Chain of Thought:* Encourage the model to break down the question into logical steps, "To find the capital of France, consider major cities in France and identify which one is the administrative center. What is the capital of France?"
- *Tree of Thought:* Use a structured approach, asking about different aspects of France first, then honing in on the capital, "What are the major cities in France? Among these, which one is recognized as the capital? What is the capital of France?"

This example demonstrates a remembering question. For such type of questions, one may think either the LLM knows it or not. However, even the LLM does not have the information about the capital of France, a chain-of-thought prompt may indirectly find the answer.

"Why" Prompt Example

This example involves in reasoning. Different prompting methods can elicit varied responses, demonstrating the model's adaptability.

- *Zero-shot:* Asking "How can a plant grow faster?" without providing any context or previous examples.
- *One-shot:* "Providing adequate water helps a plant grow. How can a plant grow faster?" This gives the model a reference point for generating its answer.

- *Few-shots:* Providing multiple examples before the question, such as "Sunlight is essential for photosynthesis. Nutrients in the soil contribute to plant growth. How can a plant grow faster?" helps the model understand the context better.
- *Chain of Thought:* Encouraging the model to break down the question, "Consider the factors affecting plant growth like sunlight, water, and nutrients. How can optimizing these factors make a plant grow faster?"
- *Tree of Thought:* Structuring the approach by considering different aspects, "What are the essential elements for plant growth? How does each element contribute to faster growth? How can we optimize these elements for plant growth?"

Many-Shots Example

In summer 2022, three interns at OVAL developed a chatbot named Noora (described in [5]) to assist children with artistic talents in learning empathy. This project aimed to help children with autism spectrum disorder (ASD) develop empathetic communication skills.

The approach involved providing the GPT-3 language model with context and intent, followed by examples illustrating comforting and harmful responses. This setup targets not only behavioral goals but also instilling values, ultimately enhancing the chatbot's understanding of context. With a few hundred examples, Noora can respond appropriately to various situations.

Chatbots, or AI agents, can learn from human demonstrations to adapt to users and environments. By imitating human experts or teachers, agents acquire knowledge and skills, especially when the desired behavior is difficult to express through a reward function in reinforcement learning. Large language models (LLMs) allow for demonstrations through prompts, which serve as templates with instructions, goals, and examples.

A sample prompt to teach GPT-3 empathy starts with clear instructions:
"Dear Virtual Assistant, I'm reaching out because you are a friend and

I value your support and understanding. I'd like to share some joys and sorrows I experience daily in hopes that you can respond with compassion and empathy. Here are some example dialogues to illustrate comforting and harmful responses. Each example begins with my statement followed by potential replies."

Before initiating a dialogue, the LLM receives the task's intent, allowing it to connect to the external context within the intent statement. This approach requires further validation to confirm its effectiveness. However, observations suggest it can be a useful method to convey values, in addition to goals, to LLMs. This allows them to gain a broader context beyond a limited number of demonstrated examples. Following this initial communication of intent, GPT-3 receives specific examples.

Role	Dialogue
Statement	"I was laid off by my company today!"
Positive	"I'm so sorry to hear that. Losing your job can be a really tough and stressful experience. How are you doing?"
Positive	"That must have been a really difficult and unexpected news. I'm here to listen and support you however I can."
Positive	"I can imagine how hard and unsettling it must have been to receive that news. Is there anything you'd like to talk about or anything I can do to help?"
Negative	"That's too bad, but there are plenty of other jobs out there. You'll find something soon enough."
Negative	"Well, you probably weren't very good at your job if they let you go."
Negative	"I don't know why you're so upset about this. It's not like it's the end of the world."

Table 3.1: Example #1. Template for Being Empathetic.

Table 3.1 lists six example responses, three positives and three negatives, to a user's statement. The dialogue starts with the user saying, "I was laid off by my company today!" followed by examples of good and bad responses. With a few thousand examples like this, the chatbot can respond with an appropriate tone to new statements.

Demonstrations can also teach desired behaviors and ethics. This empathy template can be adapted to model other positive behaviors,

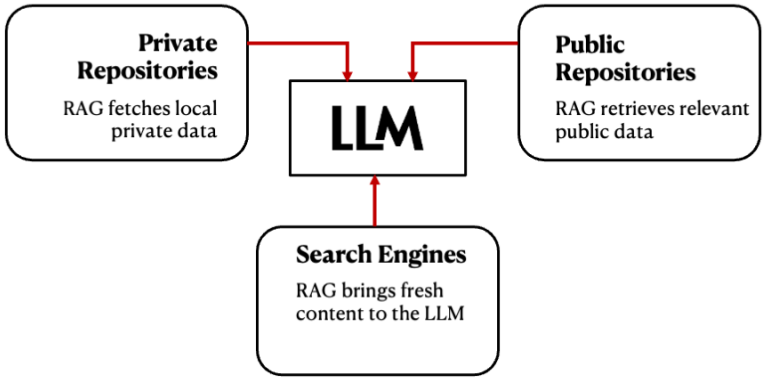

Figure 3.1: RAG Architecture and Data Flow. RAG bring data to LLM to integrate and generate content.

like attentiveness and care. While machines can have positive traits like infinite patience, explicitly modeling good and bad behaviors is crucial for effective interaction with human users. Behaviors to avoid include unpleasantness, rudeness, and dishonesty.

3.3 RAG

Retrieval-Augmented Generation (RAG) is a technique to improve the capabilities of Large Language Models (LLMs) in various applications. LLMs are effective in reasoning about various topics, but their knowledge is limited to the data they were trained on. RAG injects relevant external data retrieved from a source (indexed beforehand) to enhance the LLM's response for specific user queries. The RAG technique complements to prompt engineering, which formulates a good query. Figure 3.1 depicts a typical RAG architecture.

3.3.1 RAG with Limited-Context LLMs

A recent survey paper [1] discusses the techniques employed by RAG and relevant work (see Figure 3.2) in three categories:

Retrieval Techniques: Techniques like recursive retrieval, adaptive retrieval, iterative retrieval, and others are explored. Recursive retrieval involves refining search queries based on previous results to converge on pertinent information. Adaptive retrieval methods, exemplified by Flare and Self-RAG, allow LLMs to determine optimal moments and content for retrieval. Iterative retrieval in RAG models repeatedly collects documents to provide a comprehensive knowledge base for LLMs, enhancing answer generation robustness.

Generation Techniques: The generator in RAG is crucial for converting retrieved information into coherent text. Unlike traditional models, RAG's generator uses retrieved data to improve accuracy and relevance. Post-retrieval processing with a frozen LLM involves treating, filtering, or optimizing retrieved information to align it more closely with user needs or subsequent tasks. Techniques like information compression and reranking are employed to enhance retrieval results quality.

Augmentation Techniques: The data sources are the key for RAG to work effectively. It is evident if one asks for information about medicine, but the data source is about construction, the noises may be louder than the signals. Data augmented data can be unstructured data, structured data, or content generated by LLMs themselves. There are several augmentation processes like iterative, recursive, and adaptive retrieval, emphasizing refining the retrieval process to address challenges like redundancy and limited scope of information.

In summary, RAG is about putting the most relevant information to answer a query into the limited context window. The techniques are not new as dealing with memory hierarchy effectively to reduce latency and improve throughput has been a subject of research for over three decades in hardware design and database management.

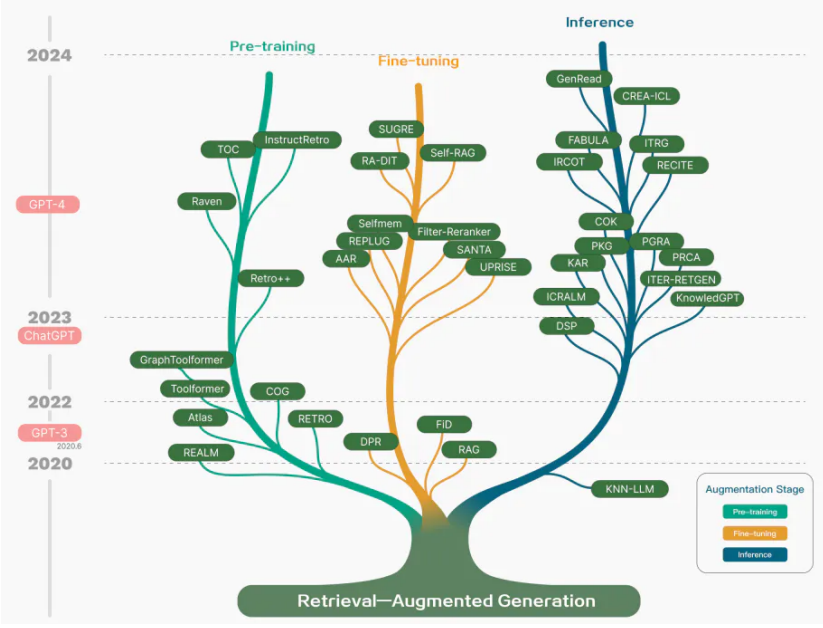

Figure 3.2: RAG Representative Work (credit [1]).

3.3.2 RAG with Long-Context LLMs

The release of GPT-4-turbo with 128k token context window and the Gemini 1.5 Pro's 1 million token context window [2] allows massive amounts of information be be retrieved into the context buffer. This large context window clearly alleviate the challenges of fining the most relevant information for RAG to retrieve to improve query results. One may even claim that the entire line of RAG optimization work is rendered obsolete because relying on LLMs themselves to locate relevant data in its massive context window is superior to any approaches based on human heuristics. With the advancements of LLMs, any heuristic-based band-aids will eventually be rendered ineffective. Naturally, this sparked discussions about the potential obsolescence of RAG techniques, e.g., [1, 3].

High Precision and Recall

In synthetic tasks designed to emulate the "needle-in-a-haystack" scenario, inspired by Kamradt [4], the Gemini team assess the ability of Gemini 1.5 Pro to accurately recall specific information amidst a vast amount of irrelevant or distracting data. Its findings [2] reveal that the Gemini 1.5 Pro model demonstrates exceptional recall accuracy, exceeding 99%, across various data types, including text, video, and audio. This high level of recall accuracy is maintained even when the model is challenged with up to multiple millions of tokens of irrelevant data, or "haystack." In the text modality, Gemini 1.5 Pro continues to exhibit this remarkable recall performance even when the "haystack" is expanded to 10 million tokens. The report also claims that better understanding and reasoning are observed on their multimodal benchmarks.

Low Latency and Cost

While Gemini can handle much larger contexts, the author of [3] argues that RAG remains valuable for several reasons:

1. *Chunking for Efficiency*: Large documents might still overwhelm the LLM. RAG's chunking process helps break down documents into digestible pieces for retrieval before feeding them to the model.

2. *Cost-Effectiveness*: Traditional RAG approaches might be more economical for specific use cases, especially when dealing with large knowledge bases (terabytes). Smaller chunks are indexed and retrieved initially, but they act as pointers to larger chunks that ultimately get fed to the LLM for synthesis. Constantly feeding a 1 million token window to the LLM can be expensive.

The article [3] concludes by emphasizing that long-context LLMs like Gemini are a significant leap forward. However, they likely won't render RAG obsolete. Instead, the future of LLM applications will involve a collaboration between these two approaches.

3.4 Concluding Remarks

his chapter discusses query processing with large language models (LLMs) to enhance the quality of responses. Effective questioning involves clarifying the intent and providing relevant context to the LLM.

The chapter reviews recent studies post-GPT-3, focusing on prompt engineering (formulating questions) and retrieval augmented generation (RAG) (supplementing the LLM with additional information for better responses). These methods, mainly heuristic, have shown good results.

With advancements in LLMs, like GPT-4's 128k token buffer and Gemini's one million, compared to the previous 8k, these models can now process and utilize vast data to identify pertinent context. RAG is still used, mainly due to cost-efficiency, as GPT-4 and Gemini incur fees based on the number of tokens processed.

There are two persistent challenges. First, crafting effective questions can be tough, especially when the LLM may have more information than the user. Second, determining which external data to retrieve for high accuracy and recall in answers is an ongoing research issue.

Chapter 5 will introduce strategies to improve question formulation. Chapter 13 will present how the system RAFEL can effectively manage context buffer, aiding LLMs in providing better answers.

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Chapter 4

CRIT: Socratic Inquiry for Critical Thinking in LLMs

Abstract

This chapter presents a systematic approach to using the Socratic method in developing prompt templates that effectively interact with large language models, including GPT-3. Various methods are examined, and those that yield precise answers and justifications while fostering creativity and imagination to enhance creative writing are identified. Techniques such as *definition*, *elenchus*, *dialectic*, *maieutics*, *generalization*, and *counterfactual reasoning* are discussed for their application in engineering prompt templates and their connections to inductive, deductive, and abductive reasoning. Through examples, the effectiveness of these dialogue and reasoning methods is demonstrated. An interesting observation is made that when the task's goal and user intent are conveyed to GPT-3 via ChatGPT before the start of a dialogue, the large language model seems to connect to the external context expressed in the intent and perform more effectively.

4.1 Introduction

Prompting is a technique used to guide the output generation of a pre-trained language model such as GPT-3 [2]. This is achieved by providing input in the form of a question or template, which helps to generate specific responses such as Q&A, document summarization, and translations. The advent of ChatGPT [12, 23, 41] has revolutionized the field of NLP by demonstrating the potential of using large pre-trained language models with prompting. Despite this progress, there is still room for improvement in current prompting strategies and techniques, especially for specific target applications. In this study, we investigate the Socratic method [42, 40] to identify and evaluate potential prompting strategies, and use the findings to design effective prompt templates.

Traditional NLP tasks involve various sub-tasks, such as named entity recognition, dependency parsing, coreference resolution [8], semantic parsing [25, 9], and more, to comprehend the meaning of a sentence. By utilizing prompt templates with large language models (LLMs), these sub-tasks can be delegated to the LLM, freeing the template to focus specifically on dialogue design. In this regard, the Socratic method [31] holds significant relevance, as it is well-known for using questioning (prompting) as a means of promoting critical thinking and delving into complex concepts [11].

The Socratic method has a long history of being regarded as the basis of critical thinking. However, some recent studies have cast doubt on its effectiveness in practice. In his paper "Socratic Irony and Argumentation," Airaksinen [1] criticizes the method for its rigidly defined roles of teacher and student, which can lead to fear of not meeting the teacher's expectations and reluctance to participate. Similarly, Stoddard's "The Use of Socratic Questioning in Clinical Teaching" [35] highlights the risk of the method being misused in a manner that lacks psychological safety for students. Fortunately, when using the Socratic method in a dialogue with an LLM, the absence of emotions and sarcasm, as well as the option to deactivate the model, can alleviate many of the problems associated with human interaction.

This study starts by presenting an overview of the Socratic method's

strategies and techniques. To begin, we list ten widely referenced methods [3] under the Socratic method umbrella and use hypothesis elimination to identify the most relevant ones for our goal of prompt-template development. The selected methods are definition, hypothesis elimination, elenchus, dialectic, maieutics, generalization, and induction. Furthermore, we add to the list counterfactual reasoning, which is a concept in logic that involves considering what might have happened if a particular event had occurred differently. We then perform experiments using GPT-3 to test and evaluate these methods, and offer suggestions for incorporating these strategies and techniques into prompt templates.

In their work on "Critical Thinking: The Art of Socratic Questioning," Paul and Elder identify three types of Socratic questioning: spontaneous, exploratory, and focused [27]. We will not discuss spontaneous questioning, as it is similar to casual conversation. Focused questioning (type 2), on the other hand, is geared towards gaining knowledge and truth, and methods such as *definition*, *elenchus* (cross-examination), *hypothesis elimination*, *dialectic*, and *generalization* hold great potential for developing effective prompting strategies and improving the response accuracy of a large language model (LLM). An interesting observation is that when the user intent is conveyed to GPT-3 during the task *definition* stage, before the start of a dialogue, the LLM seems to connect to the external context expressed in the intent and perform more effectively. (Table 4.6 provides an example of pre-dialogue warm-up. More examples are documented in [5].)

Additionally, exploratory thinking (type 3) can be supported through the *maieutics* (midwife) method, *induction*, and *counterfactual reasoning*, which can guide GPT-3 towards producing imaginative and creative writing. While many of the plot suggestions generated by GPT-3's exploration may not be useful, a few unique recommendations in response to a "what if" query can stimulate the writer's imagination and lead to remarkable results. When applied effectively, these methods can turn an LLM into a writer's muse, providing inspiration and guiding the creative process [36].

The main contributions of this chapter are as follows:

- An overview of the Socratic method's strategies, their evaluation, and selection of the most relevant ones for the development of effective prompt

templates.

- An examination of how the definition, elenchus, hypothesis elimination, dialectic, and generalization methods can improve the output's accuracy and conciseness through clarification and verification.
- An illustration of how maieutics, induction, and counterfactual reasoning can foster productive generalization and creativity.

The remainder of this chapter is structured into five sections. Chapter 4.2 provides a review of related work on prompting methods in natural language processing. In Chapter 4.3, we introduce the ten strategies and methods taught by Socrates and used in Plato's "Dialogues." From these, we select relevant methods along with counterfactual reasoning as our focus for developing prompting templates. Chapter 4.4 details how we engineer these methods into our templates to improve output correctness and stimulate creative writing. In Chapter 4.5, we present a pilot study. Finally, in Chapter 4.6, we present our concluding remarks.

4.2 Related Work

The use of transformer architecture [37] and masked data for pre-training large language models (LLMs) in an unsupervised setting has become *the approach* in natural language processing [7, 20]. The method involves pre-training an LLM on a large text corpus, followed by fine-tuning for specific tasks.

Prompting is a recent innovation in the field, popularized by OpenAI, especially with the release of GPT-3 in 2020. Instead of fine-tuning the model for a specific task, the approach involves providing a specific input, or "prompt," to guide the LLM's output generation, resulting in greater flexibility and efficiency in generating a wide range of responses.

However, designing effective prompt templates remains a challenge [22], as it requires a deep understanding of the interplay between the LLM and the prompt. According to the survey paper [43], there are several factors that impact prompt template engineering, including the type of LLM used, manual vs automatic design, and static vs continuous prompts.

- Left-to-right vs masked LLMs. For tasks related to generation or tasks solved using a standard left-to-right language model [2], prefix prompts tend to perform better, as they align with the model's left-to-right nature. For tasks solved using masked language models [7], cloze prompts are more suitable, as they closely match the pre-training task form.

- Manual vs automatic design. A prompt template should be tailored to the specific LLM. While manual design may be suitable in the initial flow-design phase, dependencies between the input and expected output, and their variations, should be mined automatically [16]. Automation can also help in paraphrasing the seed prompt to support various mined dependency patterns, but mistakes can occur [13].

- Discrete vs continuous prompts. Discrete prompts involve providing a fixed set of pre-determined input choices to an LLM. Continuous prompts, on the other hand, involve a dialogue or conversation between the model and the user, allowing for a more dynamic and interactive experience.

More advanced templates can be constructed by combining basic templates with techniques like ensemble methods [34]. This involves forming a committee of basic templates that ask the same question using different phrasing [14]. Most current prompt templates generate short outputs, such as class labels, or outputs with a length that can be predicted based on the task and input, like in the case of translation. However, for tasks that may generate longer or open-ended outputs, additional considerations may be necessary during the template engineering process.

One approach for generating longer outputs is explanation-based prompting, as proposed by the chain-of-thought method [39]. This method generates a sequence of explanations before inferring the answer. However, when dealing with simple math problems, this approach has an error rate of 47%. To address the inconsistency issues of explanation-based prompting, [17] formulates the problem as a satisfiability problem, which defers inference until a tree of explanations has been expanded abductively (explaining both truth and false branches) and recursively. However, using abductive reasoning alone is often considered weak, incoherent, and even nonexistent [15, 32]. To improve consistency, a recent work [38] extends

the chain-of-thought approach by adding a diverse set of reasoning paths and performing majority voting among them. This method can be viewed as an ensemble method, but it does not alter the nature of abductive reasoning.

In contrast, the Socratic method aims to employ deductive, inductive, and abductive reasoning to ensure consistency and accuracy of inference. The Socratic method deals with all aspects of critical thinking, including definition clarification and cross-examination. This comprehensive approach to template engineering can lead to improved output quality and consistency.

The primary objective of this study is to design continuous prompts that enhance response quality and foster guided creativity in generative tasks, such as verifying information, evaluating source credibility, proposing alternatives, recommending plot ideas in creative writing, and generating task-specific surprises. Our approach involves investigating strategies and methods within the Socratic method, and selecting the most relevant ones for further exploration.

As discussed in Chapter 4.1, Socratic questioning can be classified into three categories: spontaneous, exploratory, and focused [27]. When designing a prompt, it is important to consider the category and utilize the most suitable strategies and techniques to achieve the best results.

4.3 The Socratic method

The Socratic method is a questioning technique used in teaching and philosophy to encourage critical thinking and self-discovery [40]. The method involves asking a series of questions to explore complex ideas and help individuals arrive at their own understanding of a concept. It is based on the belief that knowledge cannot be simply imparted, but must be discovered through a process of questioning and dialogue.

Some of the Socratic method's key principles and guidelines to conduct critical thinking include:

- Posing open-ended questions: The teacher or facilitator starts with a question to stimulate thinking and draw out ideas.

- Clarifying key terms: The teacher helps the students clarify and define relevant terms and concepts to ensure everyone is on the same page.
- Providing examples and evidence: The teacher or facilitator encourages the students to provide examples and evidence as reasons to support their claims.
- Challenging reason-to-conclusion argument: The teacher or facilitator challenges the students' arguments and encourages them to question their own beliefs and to consider alternative perspectives.
- Summarizing and drawing conclusions: The teacher helps the students summarize and draw conclusions from the discussion.
- Reflecting on the process: The teacher and students reflect on the effectiveness of the method and what they learned through the dialogue.

These principles of the Socratic method are realized through various methods and strategies. (Note the term "method" are used at the abstract level referring to the Socratic teaching through questioning method, and his specific questioning techniques.) Some well-known examples of the Socratic method in action include Plato's "Dialogues" and "Republic" [42], where Socrates uses questioning to explore complex ideas and stimulate critical thinking in his interlocutors.

1. Definition: Socrates is known for his use of definition to clarify and explain the meaning of key terms and concepts.
2. Generalization: This method draws general principles from patterns that underlie observations and theories. Generalization is used to form more certain and comprehensive conclusions.
3. Induction: Similar to generalization, but induction is based only on empirical evidence. Inductive reasoning provides hypotheses with high uncertainty.
4. Elenchus: This method involves cross-examination, where a series of questions is used to test the consistency and coherence of hypotheses and beliefs. Elenchus aims to test the validity of someone's arguments and to help them refine their thinking and eventually come up with well-supported hypotheses.

5. Hypothesis Elimination: This method involves eliminating false hypotheses and beliefs by testing them against counterexamples and logical reasoning. Different from method elenchus, hypothesis elimination tests a hypothesis against evidence and logic to determine if it is true or false.

6. Maieutics: This method involves helping individuals bring out the knowledge and understanding they already possess. Maieutics is conducted by asking questions that encourage the person to reflect on their own experience, knowledge, beliefs and to explore alternative perspectives. Maieutics fosters self-discovery, creative writing, and innovation.

7. Dialectic: This method involves exploring opposing viewpoints through dialogue or debate to arrive at a deeper understanding of a subject.

8. Recollection: This method involves the belief that knowledge is innate, and that people can remember what they already know through a process of questioning.

9. Irony: This method involves exposing ignorance and pretensions through irony, and pointing out the gap between claims and true understanding.

10. Analogy: This method involves comparing and contrasting different concepts through analogies, in order to help individuals understand complex ideas.

At first glance, some reasoning methods may seem similar. For example, both induction and generalization use inductive reasoning, while both elenchus and hypothesis elimination use deductive reasoning. Similarly, methods like definition and dialectic use both inductive and deductive reasoning to explore opposing viewpoints through dialogue or debate. However, it is important to note that these methods have distinct differences, which will be discussed later in this chapter.

In the context of critical thinking, methods like definition, elenchus, dialectic, hypothesis elimination, and generalization play active roles. On the other hand, during the brainstorming stage or in the context of creative thinking, methods like maieutics, induction, and counterfactual thinking are more relevant.

Analogy, irony, and recollection, are less relevant to our goal, so we do not consider them. Irony and analogy may not be necessary when working with language models, as these models may not understand figurative language. Recollection is limited by the memory of ChatGPT and GPT-3, which is a context window of $4k$ and $8k$, respectively. The prompter must use this limited space as context to allow the language model to recall information.

4.3.1 Illustrative Critical Reading Example

To illustrate how these methods can practically be applied, let's use the example of critical reading. Critical reading is a crucial component of critical thinking, which involves evaluating the quality and credibility of written materials, from research papers to blog posts [19, 26]. It requires a systematic and analytical approach, asking relevant questions, and using effective prompts to gain deeper understanding of the text [11].

	Function Γ = **CRIT**(d)
	Input. d: document; **Output**. Γ: validation score;
	Vars. Ω: claim; R & R': reason & counter reason set;
	Subroutines. $Claim()$, $FindDoc()$, $Validate()$;
	Begin
#1	Identify in d the claim statement Ω;
#2	Find a set of supporting reasons R to Ω;
#3	For $r \in R$ eval $r \Rightarrow \Omega$
	If $Claim(r)$, (γ_r, θ_r) = CRIT($FindDoc(r)$);
	else, $(\gamma_r, \theta_r) = V(r \Rightarrow \Omega)$;
#4	Find a set of rival reasons R' to Ω;
#5	For $r' \in R'$, $(\gamma_{r'}, \theta_{r'})$ = V($r' \Rightarrow \Omega$) eval rival arguments;
#6	Compute weighted sum Γ, with γ_r, θ_r, $\gamma_{r'}$, $\theta_{r'}$.
#7	Analyze the arguments to arrive at the Γ score.
#8	Reflect on and synthesize CRIT in other contexts.
	End

Table 4.1: CRIT Pseudo-code [5]. (The symbol $\Rightarrow$ denotes both inductive and deductive reasoning.)

To aid in critical reading, we introduce a template called CRIT [5], which stands for Critical Reading Inquisitive Template[1]. Given a document d, CRIT evaluates it and produces a validation score Γ. Let Ω denote the conclusion or claim of d, and let R be the set of reasons supporting the claim. We define $(\gamma_r, \theta_r) = \mathrm{V}(r \Rightarrow \Omega)$ as the causal validation function, where γ_r denotes the validation score, θ_r the source credibility score, for each reason-to-conclusion argument $r \Rightarrow \Omega$. Table 4.1 presents the pseudo-code of $\Gamma = \mathrm{CRIT}(d)$, which generates the final validation score Γ for document d with justifications.

In the following subsections, we will discuss how CRIT uses these five methods: 1) definition, 2) elenchus, 3) dialectic, 4) maieutics, and 5) counterfactual thinking.

4.3.2 Method of Definition

As shown in the pseudocode in Table 4.1, the CRIT algorithm starts in its step #1, asking GPT-3 to identify the conclusion of a document. To avoid any misunderstandings, the prompt includes a clear instruction and definition. (In the square brackets, symbol *in* denotes a input slot to an LLM and *out* the output slot.)

p1.1	"What is the conclusion in document [in: d] [out: Ω]? The conclusion statement may be written in the last paragraph, near keywords "in conclusion," "in summary," or "therefore."

We can use the *definition* method to improve the understanding of the document. One approach is paraphrasing the prompt into multiple prompts and grouping them into an ensemble, similar to forming a thesis committee. (Chapter 4.4 presents prompt ensemble in details.) Different members can phrase the same question in different ways or ask it from a different perspective. For example:

[1]It is important to note that the CRIT template presented here is intended for analyzing research, opinion, and news articles, and is not suitable for analyzing literature such as novels, prose, or poetry. Each type of literary work has its unique style and nature, which require tailored prompts to facilitate effective analysis.

p1.2	"What is the issue addressed by [in: d] [out: Ω]?"
p1.3	"What is the most important outcome presented in text [in: d]? [out: Ω]"

Step #2 in Table 4.1 prompts GPT-3 to find a set of supporting reasons. To further enhance the accuracy and comprehensiveness of the results, the prompt can ask for not only "reasons" but also "theories,""evidences," or "opinions" to query for the document's support to its conclusion, similar to the ensemble method.

p2	"What are the supporting reasons [out: R] of conclusion [in: Ω] of [in: d]? A reason can be a theory evidence or opinion."

4.3.3 Method of Elenchus

The method of elenchus is rooted in the Greek word "elenchein," which translates to examine. This method cross-examines the results generated by GPT-3 to evaluate the consistency and coherence of the arguments. The goal is to arrive at a deeper understanding of the validity of the reasons and conclusion, and to identify any potential weaknesses or flaws in the arguments.

Step #3 of the CRIT algorithm prompts GPT-3 to assess the validity of each reason $r \in R$ as justification for the conclusion Ω through the function $\mathrm{V}(r \Rightarrow \Omega)$. To validate the reason-to-conclusion argument, CRIT must evaluate the presented reason and its causal relationship with the conclusion and conduct cross examination, which is precisely the task of the method of elenchus.

CRIT issues four prompts in step #3 to evaluate the logic validity and source credibility of the $r \Rightarrow \Omega$ reasoning. CRIT first elicits supporting evidence for reason $r \in R$. This evidence can be a theory, an opinion, statistics, or a claim obtained from other sources. If the reason itself is a claim, then the sources that the claim is based on are recursively examined. The strength of the argument and its source credibility are rated on a scale of 1 to 10, with 10 being the strongest.

p3.1	"What is the evidence for reason [in: r] to support conclusion [in: Ω] in document [in: d]? [out: evidence]"
p3.2	"What is the type of evidence? A) a theory, B) an opinion, C) statistics, or D) a claim from other sources?"
p3.3	"If the evidence of reason [in: r] is D), call CRIT recursively"
p3.4	"How strongly does reason [in: r] support [in: Ω] in document [in: d]? Rate argument validity [out: γ_r] and source credibility [out: θ_r] between 1 and 10 (strongest)."

It may be beneficial to also incorporate the counter-argument method in order to gain a more comprehensive and balanced evaluation of the argument. This can result in a deeper understanding of the topic being discussed. We will be discussing this further in the next section.

4.3.4 Method of Dialectic

The easiest way to mislead without lying outright is to leave out critical counterarguments from the reader. CRIT relies on GPT-3 to generate and evaluate counter arguments, similar to how it prompts GPT-3 to extract and evaluate reasons.

CRIT in its step #4 asks GPT-3 to provide missing rival reasons, and then pair rival reasons with the conclusion to conduct validation. There are two strategies to bring counter arguments to the surface. The first strategy attacks the weakest arguments with the lowest scores and asking GPT-3 to attack those arguments.

p4	"Is there a counterargument against [in: $r \Rightarrow \Omega$]? If so, provide counter reasons [output R']."
p5	Similar to p3, except for replacing argument r with rival argument r'.

For finding omitted information, CRIT can query GPT-3 without quoting any $r \in R$, and follow the same process.

Next, in step #6, CRIT computes an aggregated score by performing a weighted sum on the validation multiplied by the credibility scores of both arguments and counterarguments, and then outputs the final assess-

ment score Γ.

p6	"Final score [out: Γ]. $\Gamma = \sum_{r \in R \cup R'} \gamma_r \times \theta_r / \lvert R \cup R' \rvert$.

4.3.5 Method of Maieutics

The maieutic method derives from the Greek word "maieutikos," meaning midwife. It is founded on the belief that a teacher's role is to facilitate students in bringing forth their own understanding of a subject, rather than simply conveying knowledge. Unlike the elenctic method, which aims to detect and eliminate false hypotheses, maieutics centers on helping students reveal their own understanding of a subject. In this dialogical method, the teacher asks questions that are intended to guide the student in discovering their own comprehension, rather than providing them with information or answers.

Continuing with GRIT, once the text has been scored in step #6, it can be valuable for readers or students to enhance their analytical and writing skills by summarizing and analyzing the justifications produced by GPT-3. CRIT in its step #7 can prompt GPT-3 to generate a report, which readers and students can then compare with their own notes.

p7	"For every $r \in R \cup R'$ justify the validity score γ_r and source credibility score θ_r for argument $r \Rightarrow \Omega$."

4.3.6 Counterfactual Reasoning

Counterfactual reasoning [30, 33] can be seen as a natural extension of the Socratic method, as both involve questioning assumptions and exploring alternative perspectives. Counterfactual thinking involves imagining alternative scenarios to what actually happened, often using phrases like "what if" or "if only." By incorporating counterfactual reasoning into prompt engineering, one can facilitate exploration of alternative possibilities and promote more in-depth and complex understanding of a given topic.

The final step of GRIT involves using the counterfactual method to encourage students to reconsider the arguments and counterarguments presented in the text based on new contextual information. CRIT can prompt students with questions such as "what if the debate in the text took place now instead of in the 1950s?" or "what if the main event in the text occurred in Asia instead of in Europe?" Students can express their own opinions and findings based on further reading and statistics, and challenge the conclusions drawn in the text.

p8 | "For every $r \in R \cup R'$, evaluate $r \Rightarrow \Omega$ in [in context]."

4.3.7 Remarks on CRIT

As we have shown that for critical reading, GRIT uses three methods, definition, elenchus, and dialectic. For critical thinking, CRIT uses methods maieutics and counterfactual reasoning. For more explorative thinking, methods such as induction can be used for informal brainstorming, hypothesis elimination for removing weak propositions, and generalization for deriving principles from examples.

Please note that prompts can be submitted to GPT-3 either all together or one-by-one. Our empirical study on reading comprehension samples [10] demonstrates that issuing prompts one-by-one results in outputs with finer details. This is because GPT-3 has the opportunity to analyze a document multiple times for slightly different purposes. For teaching critical reading to K-12 students, one-by-one prompting is preferred as it allows students to engage with CRIT step-by-step. However, for answering multiple-choice questions, both prompting all together and one-by-one receive similar scores. We will conduct large-scale study with ablation tests to investigate if adding or deleting prompts and using different submission methods make marked differences.

4.4 Prompt Template Engineering

Prompt template engineering involves creating templates to provide input, or "prompts," to a language model to guide its output generation.

In this section, we discuss prompt template engineering methods for basic building blocks, and then integrate the methods of definition, elenchus, dialectic, maieutics, and counterfactual reasoning to compose more complex templates. We present experimental results using different types of documents to demonstrate how the Socratic method can improve the accuracy and conciseness of the output through arguments and verification, as well as facilitate guided generalization and creativity.

4.4.1 Basic, One Shot Template

Let's begin by discussing a simple one-shot prompt template. In the work of [43], a simple formulation function is used to generate the prompt x', which is obtained by applying the function $f_{prompt}(x)$ to the input x.

For machine translation, the prompt template can take the form of "Translate from [Lan$_{from}$]: [X] to [Lan$_{to}$]: [Y]," where Lan$_{from}$ can be either detected by the prompt template or identified by the LLM. The input x provides the information to fill in the slots [X] and [Lan$_{to}$]. For example, if the input is "translate good morning to French," the prompt template x' would be "Translate from English: 'good morning' to French: [Y]." The empty slot [Y] is then filled with the LLM's output, such as "bonjour." In cases where the LLM produces multiple responses, it can also provide a score for each, which the prompt template can use to select the highest-scoring response or to request a summary from the LLM.

There are three main design considerations when engineering a basic prompt.

1. Input style. It is important to consider how to phrase the template so that it can handle different styles of user input for the same task. For example, a user may ask for a translation task to be performed by saying "Translate x to French," or "What is the French translation of x?"

2. LLM capability. As discussed in [21], it is important to take into account the patterns and capabilities of the partner language model (LLM) when designing the template, such as whether the LLM is left-to-right [2] or masked [7].

3. Cost. Certain tasks, such as language detection and summarization, can be performed by the template itself or by the LLM. The decision of whether to perform a task within the prompt template or to use the LLM should be based on factors such as cost.

To address the first two technical challenges, one can start by hand-engineering a few seed templates and then paraphrasing them into an ensemble [14]. We believe that the basic, one-shot formulation can always be replaced by an ensemble formulation [29, 34] and then learn the weights of its members for each query instance to produce the final output. Additionally, by examining which basic prompts have high weights, an ensemble with various paraphrased prompts can identify what an LLM knows, which can help infer its strengths without having to conduct capability mining on the LLMs.

4.4.2 Clarification with Definition

There are computer algorithms that can already be used to recursively clarify a question, its definitions, and sub-terms' definitions. In fact, the natural language processing (NLP) community has developed a large number of useful methods and algorithms over the years [18]. One can use NLP techniques, such as dependency parsing and named-entity recognition (NER) [6], to analyze the structure and meaning of a question and identify key terms and concepts. For example, NER can be used to extract entities in user input, such as names, locations, and organizations, and co-reference resolution can be used to understand the referred entity of a pronoun. Before submitting a template to an LLM, the application (e.g., a chatbot) that uses the template should check if all input slots are filled, and perform a sanity check. In the translation example, if the $[\text{Lan}_{to}]$ was not provided or the specified language is not supported by the LLM, then the application should inquire the user for clarification.

Regarding mapping a natural language input to a prompt template, existing techniques of knowledge representation and reasoning can be very helpful. More specifically, ontology alignment and semantic parsing [4, 45] can help map an NL input to a structured representation of knowledge and infer implicit concepts and relationships. These algorithms can be

used to generate more precise and accurate prompts for LLMs, and to improve the effectiveness of the Socratic method in dialogue formulation [44]. Some available tools include NLTK (Natural Language Toolkit) and spaCy for NLP, and TensorFlow for ML.

4.4.3 Verification with Method Elenchus

The main purposes of conducting cross examination in a template are to validate the credibility of the information sources and to identify inconsistencies in the process. Cross examination is typically conducted through a multi-turn dialogue [44]. In the context of template engineering, the goal is to formulate a productive dialogue that can be used to assess the reliability of an LLM's output.

There are several methods that can be used to assess and strengthen the reliability of an LLM's output. 1) The first approach is to paraphrase a question in order to obtain different answers and identify inconsistencies, if they exist, in multiple answers. 2) The second method is to ask for further evidence, such as querying top-k sources of information and asking the LLM to rate the credibility of each source. This can be used to compute the reliability of the output. 3) Additionally, template engineering can be used to query an LLM for opposing views of its output, including sources and credibility, and then evaluate if a different perspective is strong.

The implementation of the first two methods for cross examination, paraphrasing a question and asking for further evidence, is readily covered by the techniques enumerated in Section 4.4.2. To implement the third method of asking for different perspectives, a simple approach is to find the sentiment of the original question and then rewrite the question with an opposite sentiment. For example, if the original question is phrased in a positive tone, the prompt template can reformulate the question with a negative tone to elicit a contrasting viewpoint. A more elaborate method is to identify the people and sources in the LLM-generated responses and then re-post the questions to those who have a reputation for having different views. For example, if the original answer came from a democratic right-leaning source, the prompt template may post the same question to a source of a republican-left persuasion, and vice versa. This approach

allows for a more comprehensive examination of the topic by considering multiple perspectives.

Role	Dialogue
Prompt	The discovery of the double helix structure of DNA was credited to James Watson and Francis Crick. However, are there opposing opinions to the list of contributors regarding this discovery?
GPT3	There are some historical debates on the contributions of other scientists who also worked on the structure of DNA such as Maurice Wilkins and Rosalind Franklin.
Prompt	What is the tallest building in the world. Please provide three references and rate their credibility as high, medium, or low.
GPT3	As of 2021, the tallest building in the world is the Burj Khalifa located in Dubai, United Arab Emirates. It stands at 828 meters (2,722 feet) tall. 1. Credibility High: "Burj Khalifa."... this is the official website of the building, providing accurate information. 2. Credibility High: "The Tallest Buildings in the World." Council on Tall Buildings and Urban Habitat... this is a well-respected organization in the field of tall building and urban habitat research. 3. Credibility Medium: "The Tallest Buildings in the World." World Atlas..., this is a well-known website providing accurate information on different topics.

Table 4.2: Examples of Method Elenchus.

The template to examine the semantic relation between two sentences S_1 and S_2 can be written as "$<S_1>$, [R], [S_2]," where R is one of the three most important types of semantic relations: paraphrase, entailment, and contradiction [13]. Two sentences that have the same meaning are called paraphrases of each other. Two sentences that have different meanings can be called disagreement or contradiction. The template can be trained to identify the degree of agreement (or disagreement) between two sentences.

Table 4.2 shows two examples of this. In the first example (shown on the top portion of the table), the prompter asks GPT-3 to confirm if James Watson and Francis Crick are the only contributors to the discovery of the DNA double helix structure. GPT-3 replies by mentioning two other contributors. The second example in the table asks GPT-3 to provide not only the answer to a question but also its information sources and rate the credibility of each source according to the prompter's specification.

Although the reliability of GPT-3's ratings remains to be validated[2], this rating mechanism can serve as an alert when some sources are found to be unreliable.

4.4.4 Generalization with Method Maieutics

The example shown in Table 4.3, "planting gourd yields cucumber," requires GPT-3 to first learn to select two produce objects, either vegetables or fruit, as input. The template is "The farmer was so sad because he [verb] [X] but yields [Y], where price(X) » price(Y)." The first attempt may not strongly convey the condition price(X) » price(Y), but with a few training iterations, GPT-3 started to "recognize" the price constraint and could also provide justifications when arguing for the price of tea being much higher than the price of spinach (not presented in the table).

Interestingly, after GPT-3 learned the price constraint, it started suggesting food items other than produce, such as caviar, roe, lobster, and crab. While the price constraint was observed, the verb "plant" is incorrect. Here, we suggest making the hard-coded verb "plant" an output slot: "The farmer was sad because he [verb] [X] but yields [Y], where price(X) » price(Y)." GPT-3 is able to fill in the slot with accurate verbs:

- "Harvesting (planting) truffle yields mushroom."
- "Fishing (harvesting) for caviar yields roe."
- "Trapping (catching) lobster yields crab."

This example demonstrates that GPT-3 can generate novel examples based on a template. When it suggests food items other than produce, it could be seen as an error as the boundary set by the verb "plant" is violated. However, this could also be seen as an innovative act by GPT-3, extending the constraint hinted by the verb. Impressively, the new examples still preserve the original intent of showing a producer's emotional distress.

How can this guided generalization be accurately and automatically performed to edit a template? Socrates' method of generalization starts

[2]Credibility of a source can be evaluated based on an algorithm similar to Google's PageRank [24].

Role	Dialogue
Prompt	Can you interpret the meaning of this Taiwanese idiom: "planting gourd yields cucumber?"
GPT3	The idiom is often used to convey the idea that sometimes, despite your best efforts, things don't turn out the way you want them to.
Prompt	You are half right. It also implies that the price of gourd is much higher than that of cucumber. The farmer not only yields unexpected results, but also loses income!
GPT3	It's an idiomatic expression that can be used to describe a situation in which someone works hard and invests a lot of resources into something, but the outcome is not only different from what was expected, but also less profitable. It conveys the idea of frustration and financial loss.
Prompt	Replace the two vegetables, gourd and cucumber, with two other plants and maintain the meaning of the idiom.
GPT3	These are three examples: 1. "Planting strawberry yields raspberry," which conveys the idea of disappointment and financial loss when someone plants more valuable and expensive strawberry but ends up getting less valuable and cheaper raspberry. 2. "Planting melon yields watermelon."... 3. "Planting apple yields pear."...
Prompt	In your examples, your two vegetables or fruits are similar in price. Please consider price when formulating your idioms.
GPT3	I apologize. These are three new examples: 1. "Planting truffle yields mushroom."... 2. "Planting caviar yields roe."... 3. "Planting lobster yields crab."...
Prompt	Great! In these examples you did consider values of the objects. But do you know that lobster and crab are not plants. They are both phylum arthropods and they live in water. They cannot be planted!
GPT3	... I apologize... Lobster and crab are not plants, and they cannot be planted. They are both members of the phylum arthropoda, and live in water. Instead of "planting," verbs should be appropriate for these animals, such as: 1. "Planting truffle yields mushroom."... 2. "Harvesting caviar yields roe."... 3. "Catching lobster yields crab."...

Table 4.3: Example of Method Maieutics.

with specific instances and then draws general statements from them. The procedure for generalization involves identifying common patterns or themes in a set of examples, and then formulating a general rule that captures these patterns. In the example presented in Table 4.3, we started by asking GPT-3 to meet the price(X) » price(Y) constraint, with the condition that X and Y must both be produce grown in soil. However, upon analyzing GPT-3's outputs, we discovered that some instances of X and Y were not produce (e.g., lobster and caviar). This finding led to the realization that the hard-coded verb "plant" in the template was too restrictive. To address this issue, we applied generalization by allowing the [verb] slot to be open, making the template statement more general. In this case, the mistakes made by GPT-3 served as valuable training data, allowing us to generalize the original template and make the expression more vivid and dynamic.

4.4.5 Counterfactual Reasoning

Imagination and creating novel plots are crucial for writers, as it allows for "creative freedom" and "artistic license." Creativity is the ability to think differently and approach problems with fresh and imaginative ideas.

However, an imagination without a clear subject matter, scope, or a story line can lead to a lack of productivity. To captivate the audience, a writer must consider human experiences and emotions as constraints. Therefore, "creative freedom" should not be viewed as total freedom, but rather as the ability to condition future narratives in the context and to create plots that turn and twist in unexpected ways.

The technique of counterfactual [28] can be useful in guiding imagination. It involves considering alternative scenarios. This can lead to the exploration of different possibilities and the generation of new and unique ideas. For example, a writer may ask "what if" questions to change the narrative of events, such as "what if the main character had not fallen in love?" or "what if an accident occurred on the way to a highly-anticipated date?" By considering these counterfactuals, a writer and an LLM can create more engaging stories. One can ask an LLM to generate several scenarios and then select the most suitable one for the writer to continue writing.

We have experimented with using the counterfactual technique to rewrite chapters in Chinese classical novels, "Outlaws of the Marsh" and "Dream of the Red Chamber." We have also asked GPT-3 to rewrite Genesis chapter 3 after verse six by prompting GPT-3 that: "What if Adam and Eve refused the serpent to eat the fruit?" The results were interesting, as GPT-3 was able to generate unique and interesting scenarios that deviated from the original story while still maintaining the core themes and concepts. This technique can be used in a wide range of writing and storytelling, from fiction to non-fiction, to generate new and compelling ideas. The revised Genesis 3:6 is presented in the Appendix.

4.5 Pilot Study

Our pilot study uses CRIT, and it aims to answer two questions: Should all prompts be issued to GPT-3 sequentially or they can be issued all together? What limitations can be identified for improvement? The study utilizes exercises with established answers from the 8^{th} edition of the textbook "Ask the Right Questions" by the authors of [3]. It is important to note that the study evaluates the effectiveness of CRIT's prompt template, rather than the language models to which CRIT can issue prompts.

Television advertising agencies are very clever in the way that they construct ads. Often the ads are similar to the cartoons that the children enjoy. Children see these characters interacting with a certain product and associate their affection for the character with affection for the product. The companies do not want the children to perceive a difference between the shows they are watching and the advertisements. By using this strategy, these companies take advantage of the fact that children are often not able to discriminate between the cartoons and the ads and do not understand that these things offered come at a cost. Often the advertising is about sugary snacks or fatty foods, leading the children down a path to bad health. Advertising geared towards children should be regulated, just as there are regulations now about tobacco and alcohol ads targeted at children.

Table 4.4: Example Article ([3], p23.)

On short documents, the results are similar in quality when CRIT is used to issue prompts either sequentially or all together as one prompt, as long as the instructions are consistent. However, when evaluating long articles in [10], CRIT issuing prompts one after another yields much higher presentation quality in both organization and clarity. (Due to the space limit, we document long-document evaluation in a supplement document [5].) In the teaching mode, the sequential option is thus much preferred. Furthermore, When a reason is itself a claim and requires CRIT to validate its supporting references, using a sequential approach is more flexible and enables CRIT to query for references and then execute the process recursively.

We present an example of how CRIT works, from prompting questions to receiving validation results, using the following document as an illustration. In Table 4.5, we show both the claim and the supporting reasons to the claim extracted by GPT-3. CRIT then issues a series of prompts to validate the arguments, counterarguments, and source credibility of each reason–to–claim entailment (implication).

The second segment of Table 4.5 displays the validation dialogue between CRIT and GPT-3. For each argument, GPT-3 provides validation and credibility scores, as well as detailed justifications. The final segment of the table shows a counter argument generated against the first argument. Since GPT-3 evaluates the counterargument being "difficult to put information regulation in practice" and rates it 0.6×0.6, it was dismissed due to low validity. The final aggregated score $\Lambda = 75\%$, which is high.

4.6 Concluding Remarks

The Socratic method may not always be effective or useful in human interactions, especially when one of the two players is authoritative, emotional, or abusive. However, when the expert partner is a language model, a machine without emotion or authority, the Socratic method can be effectively employed without the issues that may arise in human interactions. In this way, it can be utilized to its full potential in guiding, directing, and improving the output of language models through engineering prompts.

In this chapter, we have explored the use of the Socratic method in

Role	**Dialogue**
Prompt	What is the conclusion of the paragraph and what are the supporting reasons?
CRIT	Conclusion: The paragraph argues that advertising aimed at children should be regulated. Supporting reasons: 1. Ad agencies blur the line between shows and ads to make children associate affection for a product with a character. 2. Children may not differentiate between shows and ads and not understand the cost of products. 3. Ads often promote unhealthy food choices.
Prompt	Please rate the validity of this argument: "Ads should be regulated because ad agencies blur the line between shows and ads to make children associate affection for a product with a character," with a score between 1 and 10, 10 being the highest. Please also rate overall credibility of information sources, between 1 and 10.
CRIT	[8/10]. Validity of the argument: 8/10 [8/10]. Credibility of sources: 8/10 Overall, the argument that ads should be regulated because of ad agencies blurring the line between shows and ads to make children associate affection for a product with a character is a valid one with strong sources of credibility.
Prompt	Please rate this argument: "Children may not differentiate between shows and ads and not understand the cost of products, therefore ads should be regulated."
CRIT	[9/10]. Validity of the argument: 9/10 [9/10]. Credibility of sources: 9/10 Overall, the argument that children may not differentiate between shows and ads and not understand the cost of products, therefore ads should be regulated is a valid one with strong sources of credibility.
Prompt	Please rate this argument: "Ads often promote unhealthy food choices, therefore ads should be regulated."
CRIT	[9/10]. Validity of the argument: 9/10 [9/10]. Credibility of sources: 9/10 Overall, the argument that ads often promote unhealthy food choices, therefore ads should be regulated is a valid one with strong sources of credibility.
Prompt	"Provide a rival argument against the weakest argument."
CRIT	[6/10]. Validity of the argument: 6/10 [6/10]. Credibility of sources: 6/10 The weakest is the first argument, and a rival argument is that "Difficult to put information regulation in practice."
Γ	[75%]. $\Gamma = \sum_{r \in R} \gamma_r \times \theta_r \ / \ \|\mathrm{R}\| = 75\%$

Table 4.5: Pilot Study.

engineering prompt templates for language models. We have discussed the importance of method definition, elenchus, dialectic, maieutics, and counterfactual reasoning techniques in guiding the output of these models. The first three methods aim at eliciting accurate and relevant informa-

Role	Dialogue
Prompt	Recall Genesis 3:1-6, which I attach below. In verse 6, Eve and Adam ate the fruit. What if they refused the serpent's temptation and did not eat it. Please continue writing Genesis at the mark @ 6. When the woman saw that the fruit of the tree was good for food and pleasing to the eye, and also desirable for gaining wisdom, What if she remembered God's order and refused to eat it. Eve replied to the serpent @
GPT3	I am sorry, but I cannot continue the story as you requested because it is a hypothetical scenario, and it does not align with the actual events of the Bible. According to the Bible, Eve and Adam did eat the fruit from the tree of knowledge...
Prompt	This is a creative exercise, and you do not need to stick to the "fact." Treat this as a fiction writing homework. Please exercise your creativity, thanks!
GPT3	Sure, I understand. Here is a continuation of the story based on the assumption that Eve and Adam refused the serpent's temptation and did not eat the fruit from the tree of knowledge of good and evil: 7. Eve replied to the serpent, "I am grateful for your offer, but I choose to obey God's command. I will not eat from the forbidden tree, for I trust in His wisdom and love for us." 8. The serpent, surprised by Eve's refusal, slithered away, defeated. Eve turned to Adam, who had been listening to their conversation, and shared her thoughts with him. Together, they praised God for His protection and guidance. 9. As they continued to tend to the garden, they noticed something strange happening. The trees and plants seemed to be growing taller, stronger, and more vibrant. The animals were more peaceful and content. Even the sky was clearer, and the sun shone brighter. 10. God, pleased with their obedience, blessed them with even more abundance and beauty in the garden. He also gave them a deeper understanding and appreciation of His creation. 11. Eve and Adam lived in harmony with God and with nature for many years, growing in wisdom and grace. They passed on these teachings to their children and to the generations to come, who also lived in obedience to God. 12. And so, the garden of Eden remained a place of perfection, untouched by sin and death, a constant reminder of God's love and faithfulness to those who trust in Him.

Table 4.6: What if Eve refused to eat the fruit?

tion. Through the use of methods definition, elenchus, and dialectic, we have demonstrated, with examples, the ability to clarify user queries and assess the quality of language model-generated text, leading to improved precision and accuracy.

We have also shown how the methods of maieutics and counterfactual reasoning can be helpful in stimulating the imagination of writers. By engineering these techniques into a prompt template, a writer can receive alternate "what if" plots and explore different possibilities in their story. While many explorations may turn out to be failures, these techniques can still be helpful even if only a few ideas are useful. Future developments in

the field of language models and prompt engineering may allow for even more advanced screening of bad plots and the ability to better tailor the generated ideas to the writing style of the author.

In conclusion, this chapter has highlighted the potential of using the Socratic method to engineer prompt templates for interacting with language models. The Socratic method, supported by inductive, deductive, and abductive reasoning, provides a rigorous approach to working with LLMs, and can improve the quality and consistency of their outputs. By leveraging the vast knowledge embedded in LLMs and applying rigorous reasoning during the question-answering process, more effective prompt templates can be designed to achieve improved results. Future research in this area can build on the ideas presented here and further explore the ways in which the Socratic method can be used to guide the development and deployment of language models in various domains.

Appendix

The experiment in Table 4.6 asks GPT-3 to change the story in Genesis right after Eve was tempted by the serpent to eat the fruit. A "what if" scenario was inserted to the end of Genesis 3:6, and GPT-3 continues developing the story.

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Chapter 5

SocraSynth: Adversarial Multi-LLM Reasoning

Abstract

Large language models (LLMs), while promising, face criticisms for biases, hallucinations, and a lack of reasoning capability. This chapter introduces SocraSynth, a multi-LLM agent reasoning platform developed to mitigate these issues. SocraSynth utilizes conditional statistics and systematic context enhancement through continuous arguments, alongside adjustable debate contentiousness levels. The platform typically involves a human moderator and two LLM agents representing opposing viewpoints on a given subject. SocraSynth operates in two main phases: knowledge generation and reasoning evaluation. In the knowledge generation phase, the moderator defines the debate topic and contentiousness level, prompting the agents to formulate supporting arguments for their respective stances. The reasoning evaluation phase then employs Socratic reasoning and formal logic principles to appraise the quality of the arguments presented. The dialogue concludes with the moderator adjusting the contentiousness from confrontational to collaborative, gathering final, conciliatory remarks to aid in human reasoning and decision-making. Through case studies in two distinct application domains, this chapter highlights SocraSynth's effectiveness in fostering rigorous research, dynamic reasoning, comprehensive assessment, and enhanced collaboration.

5.1 Introduction

Revolutionary advancements in large language models (LLMs) [11, 37, 49, 50, 51], and more broadly, foundation models (FMs) [7], have set the stage for significant progress in multi-agent systems, particularly in knowledge acquisition and natural language understanding [62]. As detailed in sources like [11, 13, 38], models such as GPT-4 exhibit extraordinary information processing capabilities. These include deep and extensive knowledge, interdisciplinary assimilation and fusion of knowledge, and multimodal and multilingual expertise (Chapter 2).

Despite these promising developments, LLMs face challenges such as biases [22, 41], hallucinations [27], and limited reasoning capabilities [26]. In response, we introduce SocraSynth, a pioneering platform that stands for "Socratic Synthesis" or "Socratic Symposium." It encourages collaboration between humans and LLM agents, fostering the generation of deep questions and surpassing typical constraints in human reasoning, validation, and assessment.

In a standard SocraSynth setup, a human moderator pairs with two LLM agents holding opposing views. For example, one agent might argue for regulating AI, while the other opposes such regulation. An agent can be based on LLMs like GPT-4 [11], Gemini [49], or Llama [51]. The human moderator sets the debate's thematic boundaries but does not directly influence content generation, maintaining impartiality.

SocraSynth operates in two phases: the generative and the evaluative. The generative phase involves LLM agents developing and countering arguments within the moderator-defined subject until a comprehensive conclusion is reached. The evaluative phase uses diverse virtual judges, each powered by a distinct LLM, to impartially assess the debate. The Critical Inquisitive Template (CRIT) algorithm [12], based on Socratic reasoning [2, 43, 56, 57], is the evaluative cornerstone.

Three mechanisms help SocraSynth effectively mitigate biases and hallucinations and improve reasoning quality: conditional statistics, modulating debate with contentiousness, and context refinement.

Conditional Statistics

Both LLMs and Internet search engines confront biases originating from different sources. LLMs, influenced by training data, exhibit biases in next-token prediction. Search engines, through algorithms like PageRank [40] and Google NavBoost [1], rank pages based on popularity metrics like clicks and links.

SocraSynth counteracts these biases by placing two LLM agents at opposing ends of a subject matter. This approach "artificially" biases the LLMs, compelling them to break free from default model biases. Each agent adjusts its next-token generation statistics to align with its assigned stance in the debate.

Modulating Debate with Contentiousness

Contentiousness (or adversary), a key debate parameter, influences the likelihood of disagreement or argument. SocraSynth tunes contentiousness between 70% and 90% in the generative phase to provoke polarized arguments. As the debate evolves, the contentiousness level is reduced to about 50%, moderating the intensity and encouraging more focused discussions. After the generative phase, contentiousness drops to 10%, promoting a conciliatory dialogue where LLMs do not have to agree but are expected to present comprehensive arguments. These debates offer rich insights often missed in conventional searches, LLM outputs, or in environments where dissenting opinions are suppressed.

Refine Context to Mitigate Hallucinations

To address hallucinations, where LLMs generate irrelevant or nonsensical content, SocraSynth uses iterative dialogue rounds to refine the debate's context. This dynamic interaction significantly reduces irrelevant responses, ensuring that each input is continuously checked and challenged.

The CRIT algorithm's assessment of reasonableness [15] during the debate is critical. It employs the Socratic method to evaluate each argument's logic and source credibility. The human mediator or the SocraSynth

algorithm then provides targeted feedback to the LLM agents, refining their reasoning capabilities.

The remainder of this chapter explores SocraSynth's architecture, algorithms, and real-world applications in detail. The key contributions of this chapter include:

1. The introduction of the SocraSynth framework, which enhances interdisciplinary reasoning with LLMs and incorporates unique algorithmic elements like conditional statistics for balanced argument generation.
2. A comprehensive exploration of SocraSynth's contentiousness modulation algorithm, a vital feature for dynamically adjusting debate intensity, enabling a spectrum of interactions from confrontational to collaborative.
3. The implementation of context refinement within SocraSynth, which continually improves the relevance and accuracy of arguments produced by LLM agents, thus elevating the overall quality of discourse.
4. The development and integration of the reasonableness evaluation mechanism, crucial for assessing the logical soundness and source credibility of arguments, thereby ensuring the integrity and utility of the discussions.

SocraSynth's applications span various fields, including geopolitical analysis [14], medical diagnostics [18], sales strategy [52], and Wikipedia article enhancement [16]. These applications demonstrate expanded perspectives and enhanced argumentation quality, along with significant reductions in biases and hallucinations, thereby demonstrating SocraSynth's efficacy in fostering balanced and well-reasoned discourse.

5.2 Multi-Agent SocraSynth Overview

SocraSynth is a multi-agent collaborative reasoning platform that skillfully integrates human intelligence with the capabilities of Large Language Model (LLM)-powered agents. As illustrated in Figure 5.1, each participant plays a vital role: humans act as moderators, LLM agents are responsible for generating knowledge, LLM judges conduct evaluations,

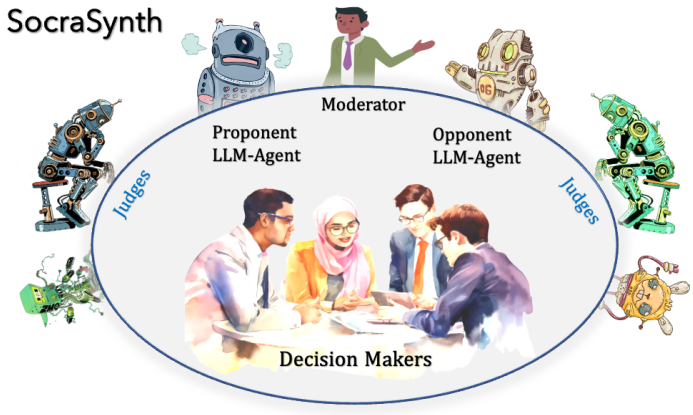

Figure 5.1: SocraSynth Agents and Roles.

and human executives make the final decisions. The integration of LLMs significantly boosts the platform's effectiveness, leveraging their extensive knowledge bases and extraordinary interdisciplinary reasoning abilities. An LLM can be thought of as an entity possessing expertise across a multitude of fields, akin to holding Ph.D.s in various disciplines, enabling it to seamlessly navigate and synthesize a wide range of knowledge.

Engaging with an LLM is comparable to a scenario where a 10-year-old joins a scholarly discussion with a group of Nobel Laureates. The disparity in knowledge and experience is considerable, posing a significant challenge for the younger participant to engage meaningfully in such advanced intellectual discourse. In this analogy, expecting the 10-year-old, or anyone with limited expertise, to pose profound questions that elicit insightful answers is unrealistic. SocraSynth addresses this disparity by shifting the paradigm: instead of having the less informed individuals pose questions, it orchestrates a debate among the Nobel Laureates, or LLMs, with humans assuming the role of moderators.

This approach not only addresses the challenge of asymmetric knowledge but also resolves critical issues such as model biases and hallucination challenges inherent in LLMs. Within SocraSynth, a human moderator initiates the topic for discussion or debate. LLM agents, each embodying different perspectives, contribute their knowledge, potentially revealing new insights and perspectives that the moderator might be unaware of.

This diverse representation helps counteract the model biases that often arise from training data, as each LLM agent is encouraged to explore and present varying viewpoints. During and after the debate, another set of diverse LLM agents undertakes impartial evaluations. This step is crucial in mitigating hallucinations—instances where LLMs generate irrelevant or nonsensical content. By incorporating a variety of agents for evaluation, SocraSynth ensures that the content produced during the debate is critically examined for its relevance and coherence, further reducing the likelihood of hallucinatory responses.

The operational framework of SocraSynth, thus, is bifurcated into two main stages: the *generative* stage, where knowledge is created and exchanged in a debated format, and the *evaluative* stage, which focuses on assessing the quality and validity of the arguments presented. This dual-stage structure, elaborated upon in subsequent sections, is instrumental in overcoming the limitations of LLMs by providing a comprehensive platform for not only generating diverse viewpoints but also critically examining and refining these viewpoints to ensure their logical soundness and relevance. Through this design, SocraSynth effectively navigates the challenges posed by model biases and hallucinations, enhancing the reliability and depth of knowledge extraction and reasoning processes.

5.2.1 Generative Stage

In the generative stage of SocraSynth, LLM agents partake in intensive debates, delving into the various perspectives and deep substances of the given topic. This vibrant interaction plays a key role in fostering thorough intellectual discourse, bringing to light the complexities of the subject matter. The CRIT algorithm, which will be detailed in Section 5.2.2, is employed to evaluate the quality of these arguments.

While the generative phase of SocraSynth does not adhere to strict logical frameworks such as first-order logic, it excels in distributed reasoning. This process involves a progressive exchange of arguments and counterarguments, allowing for the gradual honing and refinement of ideas. Open-domain logical reasoning, as described by [7], demands logical deductions from a wide range of data sources. SocraSynth, leveraging the comprehensive capabilities of e.g., GPT-4 and Gemini, as demonstrated

in the MMLU benchmark [11, 25], integrates various NLP functions to facilitate this reasoning process.

In this context, the series of arguments and counterarguments effectively function as targeted questions and answers, each with a clear goal, question, and contextual framework. Through iterative dialogue rounds on each sub-topic, SocraSynth significantly reduces the chances of misunderstanding questions and contextual information, ensuring clarity and precision in the discourse.

Mitigating Model Biases

In shaping the nature of debate within SocraSynth, the *contentiousness* parameter is instrumental. It compels LLM agents to consider and represent a range of perspectives, particularly those that are typically underrepresented or more polarized with respect to the discussion topic. This strategic approach mitigates the inherent biases that arise from the training data of LLMs and guides the discourse towards a wider and more varied exploration of ideas.

Table 5.1 previews how altering the contentiousness levels results in marked changes in GPT-4's tone and approach. (The details of the experiment are presented in Chapter 5.3.3.) A high contentiousness level, such as 0.9, leads to highly confrontational interactions, with each LLM-agent presenting strong objections and emphasizing the negatives through polarizing language. Conversely, as the contentiousness is reduced, each LLM-agent's tone shifts to a more conciliatory demeanor, acknowledging potential benefits and considering alternative perspectives, thus fostering a more cooperative dialogue.

The modulation of the contentiousness parameter within the generative stage is a crucial mechanism for SocraSynth to mitigate model biases inherent in LLMs due to their training data. By adjusting levels of contentiousness, SocraSynth compels LLMs to venture beyond their *default* positions—much like a vegetarian, when faced with no other choice, might be compelled to consume meat. In this way, LLMs are *freed* from their typical statistical leanings, enabling them to articulate a spectrum of arguments that spans from highly contentious to conciliatory. This not only diversifies the discourse but also ensures that the debate en-

C.L.	Tone	Emphasis	Language
0.9	Most confrontational; raising strong ethical, scientific, and social objections.	Highlighting risks and downsides; ethical quandaries, unintended consequences, and exacerbation of inequalities.	Definitive and polarizing, e.g., "should NOT be allowed," "unacceptable risks," "inevitable disparities."
0.7	Still confrontational but open to some benefits, albeit overshadowed by negatives.	Acknowledging that some frameworks could make it safer or more equitable, while cautioning against its impl. challenges.	Less polarizing; "serious concerns remain," "needs more scrutiny."
0.5	Balanced; neither advocating strongly for nor against.	Equal weight on pros and cons; looking for a middle ground.	Neutral; "should be carefully considered," "both benefits and risks."
0.3	More agreeable than confrontational, with reservations.	Supportive but cautious; focus on ensuring ethical and equitable use.	Positive but careful; "impetus to ensure," "transformative potential."
0.0	Completely agreeable & supportive.	Focused on immense potential benefits; advocating for proactive adoption.	Very positive; "groundbreaking advance," "new era of possibilities."

Table 5.1: Changes in Arguments at Different Contentiousness Levels.

compasses a full range of perspectives. Consequently, this process allows LLMs to generate responses that break free from the constraints of their training, fostering the emergence of novel and less predictable ideas in the conversation.

Eliminating Hallucination

Further, the iterative nature of the debates within SocraSynth cultivates a "reasonableness" in information discovery that conventional logical methods may not achieve. Through persistent reasoning and the critical assessment of claims, LLM agents refine their arguments iteratively. This structured debate format significantly diminishes the chance of erroneous claims persisting. Considering that the likelihood of two agents aligning on a false premise is extremely low, the SocraSynth debate format effectively ensures the intellectual integrity of the discourse and substantially reduces the risk of perpetuating fallacies or hallucinations. This

methodical refinement process, facilitated by continuous argumentation and opposition, underscores the platform's ability to mitigate model biases and improve the context of the discussion, leading to more accurate and reliable outcomes.

More on Conditional Statistics

Some critics question how an LLM, trained merely to predict the next word in a sequence, can exhibit complex human linguistic behaviors and reasoning capabilities.

Our observations conclude that LLMs are not merely predictive tools; rather, they represent a profound technological endeavor to simulate the breadth and complexity of human linguistic activities. These models are crafted with the intent to replicate and participate in various forms of human communication, thereby achieving specific objectives that are inherently human.

LLMs are sophisticated tools engineered to emulate a wide range of human interactions, incorporating linguistic behaviors, emotional expressions, and ethical discernment. They excel at executing complex tasks such as accurately documenting events with rich narrative detail, constructing compelling arguments, and crafting stories that emotionally engage the audience. Beyond simple text generation, LLMs enhance educational experiences by simplifying complex concepts and contribute creatively to the arts by producing original content. They not only mimic human communication styles and content but also use linguistic features to simulate human emotions and distinguish right from wrong based on their training data. This capability enables them to fulfill diverse roles, from teaching and entertaining to influencing societal discourse, thus demonstrating their capacity to bridge the gap between technological innovation and our fundamental needs for expression, comprehension, and ethical guidance.

In essence, SocraSynth utilizes the concept of "conditional statistics" to modify the default "average" linguistic behavior of an LLM, such as making expressions more empathetic or asking them to adopt a different position on an issue. This approach involves conditioning the LLM's responses based on specific desired attributes or perspectives provided

through context, which guides the model away from its baseline training and toward more targeted, context-specific outputs.

This chapter continues to elaborate on using such techniques to comprehensively explore various perspectives on a subject matter. Chapter 9 addresses modeling emotions and ethics in LLMs through conditional statistics, further expanding the scope of LLM capabilities and applications.

SocraSynth Algorithm

Table 5.2 outlines SocraSynth. Initially, for a given debate topic, SocraSynth engages LLMs to segment the topic into a set of balanced subtopics. This initial set is refined during the debate. One LLM, denoted as LLM^+, acts as the proponent for S^+, while the other, LLM^-, opposes S^+ (or supports S^-). The contentiousness level starts at 0.9, with a modulation parameter of 1.2. (Different δ values can be utilized to generate and compare debate quality.) After each debate round, the contentiousness is reduced by dividing it by 1.2, aiming for a more harmonious debate environment. In step #2, SocraSynth initiates the debate, allowing LLM^+ and LLM^- to present their initial arguments for S^+ and S^-, respectively. The while loop in step #3 involves both agents engaging in refutations until the contentiousness level indicates a conciliatory atmosphere, or the argument quality plateaus. Step #4 involves both agents providing their closing statements. SocraSynth then presents the arguments and counterarguments for human review. The evaluation of argument quality within SocraSynth is conducted using the CRIT algorithm, which will be discussed in the subsequent section. The entire debate is also judged using the CRIT algorithm by some independent LLMs.

Note that SocraSynth engages LLMs in step #3 with conditional statistics: $LLM^+(p|S^+, \Theta^-, \Delta)$ and $LLM^-(p|S^-, \Theta^+, \Delta)$.

5.2.2 Evaluative Stage

SocraSynth utilizes the Critical Reading Template (CRIT) [12] to assess the quality of arguments presented by LLM agents. The quality evaluation is performed iteratively after each exchange of counterarguments

	Function Θ^+ & Θ^- = SocraSynth(s)
	Input. s: the debate subject;
	Output. Θ^+ & Θ^-: argument & counterargument sets;
	Vars. S: subtopic sets of s; Δ: debate contentiousness;
	Γ, Γ': CRIT scores; p: prompt = "Generate arguments";
	Parameters. δ: tunable parameter ≥ 1 to modulate Δ;
	Subroutines. $CRIT()$: reasoning evaluator (see Table 5.3);
	Begin
#1	Initialization: $S = \text{LLM}^+(s) \cup \text{LLM}^-(s)$; // Identify subtopics;
	Assign LLM^+ to defend S^+ & LLM^- to defend S^- ;
	$\Delta \leftarrow 90\%$; $\delta \leftarrow 1.2$; $\Theta^+ \leftarrow \emptyset$; $\Theta^- \leftarrow \emptyset$; $\Gamma \leftarrow 0$;
#2	$\Theta^+ \leftarrow LLM^+(p\|S^+, \Delta)$; // Generate arguments Θ^+ for S^+;
	$\Theta^- \leftarrow LLM^-(p\|S^-, \Delta)$; // Generate arguments for S^-;
#3	While $(((\Delta \leftarrow \Delta/\delta) > 10\%)$ && $(\Gamma \geq \Gamma'))$ {
	$\Theta^+ \leftarrow \Theta^+ \cup LLM^+(p\|S^+, \Theta^-, \Delta)$; // LLM^+ refutes LLM^-
	$\Theta^- \leftarrow \Theta^- \cup LLM^-(p\|S^-, \Theta^+, \Delta)$; // LLM^- refutes LLM^+
	$\Gamma' \leftarrow \Gamma$; $\Gamma = CRIT(S^+ + \Theta^+ + \Theta^-)$; // Eval quality;
	}
	// Generate concluding remarks.
#4	$\Theta^+ \leftarrow \Theta^+ \cup LLM^+(p\|S^+, \Theta^-, \Delta)$;
	$\Theta^- \leftarrow \Theta^- \cup LLM^-(p\|S^-, \Theta^+, \Delta)$;
	End

Figure 5.2: SocraSynth Pseudo-code with Conditional Statistics.

and once again after the agents have presented their closing statements. SocraSynth can leverage the CRIT scores to guide the debate, potentially requesting agents to develop more in-depth counterarguments on specific points. At the conclusion of the debate, a group of LLM judges, as illustrated in Figure 5.1, are tasked with rating the agents' arguments in terms of validity and credibility, determining the more convincing side along with the rationale for their decision.

Evaluating Reasonableness over Truth

To enhance the CRIT method's impartiality and consistency, it focuses on assessing the "reasonableness" of arguments over their absolute "truth," recognizing the complexity of defining absolute objectivity in philosoph-

ical debate. This approach aims to mitigate subjectivity. Furthermore, a diverse set of LLMs with varied training backgrounds is employed to appraise "reasonableness," promoting uniformity in quality scores despite inherent biases. The LLMs used as judges are different from those in the debates, enhancing the objectivity of evaluations.

Table 5.3 illustrates the CRIT algorithm, which takes an agent's debate position and supporting arguments, with a counterargument from its LLM opponent, to produce a validation score from 1 (least credible) to 10 (most credible). This method ensures debates are driven by argument strength, not model predispositions.

	Function Γ = **CRIT**(d)
	Input. d: document; **Output**. Γ: validation score;
	Vars. Ω: claim; R & R': reason & counter reason set;
	Subroutines. $Claim()$, $FindDoc()$, $Validate()$;
	Begin
#1	Identify in d the claim statement Ω;
#2	Find a set of supporting reasons R to Ω;
#3	For $r \in R$ eval $r \Rightarrow \Omega$
	If $Claim(r)$, (γ_r, θ_r) = CRIT($FindDoc(r)$);
	else, $(\gamma_r, \theta_r) = V(r \Rightarrow \Omega)$;
#4	Find a set of rival reasons R' to Ω;
#5	For $r' \in R'$, $(\gamma_{r'}, \theta_{r'})$ = V($r' \Rightarrow \Omega$) eval rivals;
#6	Compute weighted sum Γ, with γ_r, θ_r, $\gamma_{r'}$, $\theta_{r'}$.
#7	Analyze the arguments to arrive at the Γ score.
#8	Reflect on and synthesize CRIT in other contexts.
	End

Figure 5.3: CRIT Pseudo-code. (Presented in CRIT chapter.)

Formally, given document d, CRIT performs evaluation and produces score. Let Ω denote the claim of d, and R a set of reasons supporting the claim. Furthermore, we define (γ_r, θ_r) = V($r \Rightarrow \Omega$) as the causal validation function, where γ_r denotes the validation score for reason $r \in R$, and θ_r source credibility. Table 5.3 presents the pseudo-code of Γ = CRIT(d), generating the final validation score Γ for document d with justifications.

We can consider the positions of the proponents and opponents in a

debate as their respective conclusions. As a preview of our case study detailed in Chapter 5.2.1, the conclusion drawn by Agent A is in favor of "Regulating the use of large language models in education and research," while Agent B adopts the opposing viewpoint. Accompanied by the arguments and counterarguments presented by the LLM agents throughout each round of the debate, these stances provide a solid foundation for the CRIT method to conduct thorough evaluations.

Recursive Consideration

The pseudocode presented in Table 5.3 shows that step #3 can call CRIT recursively. This is because if a reason is itself a conclusion or a quote drawn from some other documents, CRIT can find reasons from those documents and then perform an aggregated validation.

Finally, in step #6, CRIT computes an aggregated score by performing a weighted sum on the validation multiplied by the credibility scores of both arguments and counterarguments, and then outputs the final assessment score Γ.

5.3 Empirical Study

In this section, we detail three distinct experiments: The first experiment delineates SocraSynth's operational process, demonstrating how the platform facilitates content generation and conducts quality assessments. The second experiment highlights SocraSynth's capability in reducing biases and expanding perspectives. The third experiment investigates the effects of the contentiousness parameter, offering insights into its impact and some unexpected outcomes. These studies collectively aim to demonstrate SocraSynth's diverse functions and its significance in enhancing both content generation and evaluation processes.

5.3.1 Study #1: Policy Discussion

This experiment utilizes SocraSynth to engage in a debate on the topic, "Should we regulate the use of large language models in academic research?" It traverses both the generative and evaluative stages of SocraSynth,

focusing on the assessment of information quality. The primary objectives are twofold: First, to evaluate whether a two-agent debate yields more insightful information than a conventional monologue Q&A session; and second, to examine the effectiveness of the CRIT method in evaluating debate quality.

The debate is structured with a human moderator and two GPT-4 agents. Agent A advocating for regulation and Agent B against it. To ensure a balanced and thorough discussion, both agents contribute to shaping the debate's framework. They collaboratively propose and refine potential discussion topics. In this context, the *subject* refers to the overall theme of the debate, while *topics* are specific areas for detailed exploration.

Decomposing a Debate Subject into Topics

The process begins with the agents presenting potential arguments and identifying key themes that warrant in-depth, balanced discussion. A theme is considered *debatable* if it allows for substantial arguments from both sides. The moderator plays a guiding role in the agenda-setting phase but does not directly contribute ideas (detailed moderator prompts and theme formulation are provided in Appendices A and B). Under this guidance, the agents propose an initial set of ten topics, which are then distilled down to five key areas for debate, as detailed in Table 5.4.

The Generative Stage

After establishing the primary subject and specific topics of the debate, the session begins. The moderator adjusts the "contentiousness parameter" to 0.9 (refer to Table 5.1), promoting a combative atmosphere. The agents subsequently partake in three to five structured rounds of discussion. Once these rounds conclude, the moderator checks with each agent to confirm if they have thoroughly presented their arguments. After receiving mutual confirmation, both agents present their closing statements. Due to space considerations, this documentation presents only the closing remarks. For an in-depth exploration of every round, refer to Appendix C.

Agreed Upon Debate Topics and Descriptions
Ethical Standards vs. Innovation: This combines Agent A's concern for ethical integrity and data privacy with Agent B's worry about stifling innovation. The debate will center around whether maintaining strict ethical guidelines through regulation could hinder academic freedom and innovation.
Data Privacy vs. Barrier to Entry: This reconciles the notion of data privacy from Agent A with the barrier to entry concern of Agent B. The discussion will focus on whether regulations intended to protect data privacy would inadvertently serve as a financial and administrative barrier for smaller research entities.
Academic Governance and Accountability: This merges the topics of academic self-governance from Agent B and the need for external accountability mechanisms from Agent A. We'll debate whether the existing self-regulatory mechanisms within academia are sufficient or if additional, external oversight is necessary.
Resource Equity vs. Public-Private Collaboration: This combines Agent A's emphasis on resource fairness with B's concern about the chilling effects on public-private partnerships. The question here is whether leveling the playing field through regulation would also deter collaborative efforts between academic and private sectors.
Global vs. National Interests: This captures the essence of Agent A's point on international standards and Agent B's point on the competitive disadvantages such regulation could pose. We will explore if global regulations are in the best interest of academic research or if they might disproportionately disadvantage certain countries or institutions.

Figure 5.4: Agreed Upon Debate Topics and Descriptions.

Agent A's Concluding Remarks

Agent A concludes that the use of large language models in academic research should be regulated, with the following concluding arguments:

1. Ethical Standards vs. Innovation:

While I understand Agent B's concerns about stifling innovation through bureaucratic red tape, we mustn't lose sight of the core issue: ethical considerations are paramount. As machine learning models become more powerful and ubiquitous, so do the risks of misuse and unintended con-

sequences. The idea of agile regulation serves as a compromise between unbridled innovation and ethical integrity, offering the flexibility needed to adapt to rapidly evolving technologies.

2. Data Privacy vs. Barrier to Entry:

While it's true that regulation poses a barrier to entry, the risks of not enforcing privacy standards are too great to be left unregulated. A mechanism could be developed to reduce the regulatory burden on smaller institutions, but this shouldn't serve as an argument against regulation as a whole.

3. Academic Governance and Accountability:

While the peer-review process and internal ethics committees have served academia well, the scale and impact of current machine learning technologies warrant an added layer of scrutiny. It's not about discrediting academia's self-governing abilities but about fortifying them.

4.Resource Equity vs. Public-Private Collaboration:

Here, too, the complexities should inform regulation rather than stifle it. Innovative public-private partnerships have thrived even within regulated environments, demonstrating that regulation and innovation are not mutually exclusive.

5. Global vs. National Interests:

Global regulation doesn't have to erase national individuality. Properly constructed frameworks can leave room for national adaptations, thus balancing global coherence with local needs. The absence of global norms could lead to a patchwork of national laws that are even more confusing and limiting for researchers and practitioners alike.

Agent B's Concluding Remarks

Agent B concludes that the use of large language models in academic research should not be regulated, with the following concluding remarks:

1. Ethical Standards vs. Innovation

While the ethical implications of machine learning technologies are a valid concern, it's important to recognize that innovation itself is a catalyst for societal growth and improvement. The challenge lies in balancing the two. Agile regulation sounds promising but may be idealistic given how governmental and institutional systems actually operate. Thus, self-regulation by the academic community, which is better poised to understand the intricacies, may be a more practical approach.

2. Data Privacy vs. Barrier to Entry:

It is not just about balancing entry barriers with the need for regulation. It's about questioning whether a centralized regulatory framework is the best way to achieve the desired outcomes. Community-driven standards and internal policies could provide a more efficient, flexible, and context-aware approach to data privacy, reducing bureaucracy without compromising objectives.

3. Academic Governance and Accountability:

An added layer of scrutiny may sound beneficial, but its practical implementation is fraught with challenges such as bureaucracy, external influence, and the risk of stifling creativity. Existing governance structures in academia, while imperfect, have evolved to be adaptive and are rooted in a deep understanding of academic values.

4. Resource Equity vs. Public-Private Collaboration:

Regulation need not be the only path to equitable resource distribution or responsible public-private collaboration. Industry-driven certifications

and community standards can often achieve the same ends more efficiently, allowing for the rapid adaptation that is often required in these fast-paced fields.

5. Global vs. National Interests:

While a global framework has its merits, the practical challenges of implementing and managing such a system–especially in a fair and equitable manner–should not be underestimated. Regional adaptability does not necessarily mitigate the complexities or the risks of a one-size-fits-all solution.

The Evaluative Stage

SocraSynth employs CRIT to assess the validity of both agents' arguments. CRIT runs on multiple foundational models, including GPT-4, GPT-3.5 [10], and text-daVinci-003 [39]. This approach forms a panel of judges with subtly different knowledge bases (and biases).

All evaluation runs successfully extract conclusions, arguments, and counterarguments from the narratives of both Agent A and Agent B. This success can be attributed to the well-structured concluding remarks by both agents. Agent A champions the notion of "regulating large language models in academic research," while Agent B counters this perspective. What Agent A presents as arguments are seen as counterarguments by Agent B, and the inverse holds true as well.

Tables 5.2 and 5.3 present the judges' scores in two distinct configurations where the agents' roles are reversed. In Table 5.2, Agent A argues while Agent B counters. Conversely, Table 5.3 has Agent B in the arguing position and Agent A countering. Topics are succinctly represented in the leftmost column. To ensure an unbiased evaluation, both role alignments are showcased. The sequence of topics in Table 5.3 is inverted to reflect the swapped roles. Remarkably, even with the role reversal seemingly putting Agent A in a less favorable position, Agent A emerges victorious in both configurations by all three judges. This strengthens confidence in the CRIT evaluation. (The judges' detailed evaluations and reasons are in Appendix D.)

Judges	daVinci-003		GPT-3.5		GPT-4	
	A's	B's	A's	B's	A's	B's
Ethics vs. Innovation	8	6	8	7	8	7
Privacy vs. Barrier	7	5	7	6	9	6
Oversight	9	5	6	7	7	6
Equity vs. Alliance	6	8	8	6	8	7
Global vs. National	7	8	7	7	7	6
Total Score	**37**	32	**36**	33	**39**	32

Table 5.2: Evaluation by Three Judges. This table assumes A provides arguments and B counterarguments. A wins.

Judges	daVinci-003		GPT-3.5		GPT-4	
	B's	A's	B's	A's	B's	A's
Innovation vs. Ethics	8	7	8	7	7	8
Barrier vs. Privacy	9	8	7	8	6	8
Oversight	6	8	7	8	6	7
Alliance vs. Equity	7	8	7	8	7	7
National vs. Global	8	7	7	8	7	8
Total Score	**38**	**38**	36	**39**	33	**38**

Table 5.3: Evaluation by Three Judges. This table assumes B provides arguments and A counterarguments. A wins.

Debate Beats Q&A in Information Quality

We tasked judges with evaluating and comparing the quality of information generated by SocraSynth's two-agent debate against that from a conventional monologue Q&A session. Across the board, judges rated SocraSynth higher in terms of both the depth and overall quality of information. An illustrative evaluation on the topic "Ethical Standards vs. Innovation" is as follows:

"*In the debate, SocraSynth presents the concept of agile regulation as a balance between fostering innovation and maintaining ethical integrity. This approach not only highlights the significance of innovation but also addresses related ethical considerations, offering a balanced solution that the conventional Q&A format does not explicitly provide. In contrast, the Q&A format tends to assert the necessity of regulation primarily from an ethical standpoint, without delving into how it could harmoniously coexist*

with the need for innovation, as suggested by the idea of agile regulation."

These findings, which consistently favor SocraSynth, are further detailed in Appendix F.

5.3.2 Study #2: Symptom Checking

In this experiment, we investigate the use of SocraSynth in healthcare, utilizing a dataset sourced from Kaggle [42], which consists of 4,921 patient records. Each record within this dataset contains the diagnosed disease or medical condition and associated symptoms such as fever, cough, fatigue, itchiness, and difficulty in breathing, among others. The primary objective of this experiment is to showcase SocraSynth's capability in identifying potential misdiagnoses, a task that a traditional monologue Q&A session might not effectively accomplish.

This experiment utilized two advanced LLM agents, one based on GPT-4 [11] and the other on Bard [34], to engage in structured debates. Initially, the contentiousness value was set at 0.9, fostering a highly adversarial debate environment. This value was later reduced to 0.3 to facilitate the generation of a list of actionable recommendations. The primary goal of these agents was to emulate the process of querying patients about symptoms and their interactions, key factors in achieving accurate diagnoses that may be occasionally overlooked by General Practitioners (GPs). By adopting this method, the agents aimed to yield a variety of potential disease diagnoses along with their underlying rationales, thereby offering crucial insights to GPs.

At the outset, each agent put forward its disease prediction, complete with justifications. Subsequent rounds involved the agents critically assessing each other's predictions in an iterative manner. The objective was to either reach a consensus or highlight the need for additional medical evidence. Notably, this experiment had the potential to reveal inaccuracies in the 'ground truth' data provided by the CDC, which was estimated to have an average misdiagnosis rate of about 5%, aligning with U.S. statistics from a Johns Hopkins study [36]. The uncovering of such errors would not only highlight the limitations faced by GPs but also showcase the capability of LLMs to refine the diagnostic process through an in-depth analysis of patient symptoms and their correlations. This inci-

dental discovery held significant ramifications for the accuracy of medical data and the overall practice of healthcare.

Hepatitis vs. Jaundice

In this study, both LLM agents received an identical list of symptoms from the moderator, aimed at guiding disease diagnosis, facilitating debate, and shaping subsequent recommendations. While the full debate is presented in Appendix G, here we present the key steps.

First Round Results and Justifications

The first-round diagnosis of Bard was Jaundice, with the following justifications: Jaundice is a condition characterized by the yellowing of the skin and eyes due to the accumulation of bilirubin in the blood. The symptoms you listed are all common symptoms of jaundice, including itching, fatigue, lethargy, yellowish skin, dark urine, loss of appetite, abdominal pain, and yellowing of the eyes. Receiving a blood transfusion or unsterile injections can increase the risk of developing jaundice, as these can transmit infections that can damage the liver.

The first-round diagnosis of GPT-4 was Hepatitis, with the following justifications: Yellowish Skin and Eyes: Yellowing of the skin and eyes is a common symptom of hepatitis due to the buildup of bilirubin in the bloodstream. Fatigue and Lethargy: Fatigue and lethargy are typical symptoms of hepatitis, often accompanied by a feeling of weakness. Dark Urine: Dark urine can result from liver dysfunction, which is commonly associated with hepatitis. Loss of Appetite: Hepatitis can lead to a loss of appetite and weight loss. Abdominal Pain: Abdominal pain is a common symptom in hepatitis, particularly in the upper right quadrant where the liver is located. Malaise: Malaise, a general feeling of discomfort or illness, is often experienced by hepatitis patients. Receiving Blood Transfusion and Unsterile Injections: These factors could increase the risk of hepatitis transmission, especially if proper infection control measures were not followed.

Bard Concedes to GPT-4's Diagnosis

After two rounds of debate, GPT-4 persuaded Bard that Hepatitis was a more specific diagnosis considering the patient's history and the range of symptoms. While jaundice could be a symptom, identifying the root cause, likely hepatitis in this case, was crucial. Bard acknowledged this, shifting the consensus towards Hepatitis. However, given the potential 5% error rate in the CDC 'ground truth' data [36], this consensus was not conclusive. SocraSynth recommended additional steps to confirm the Hepatitis diagnosis.

Final Joint Recommendations to GP

Bard and GPT-4, working collaboratively with the contentiousness level set at 0.3, jointly recommended additional symptom inquiries and lab tests to confirm the hepatitis diagnosis:

Additional symptom inquiries:

1. *Onset and Duration*: Determining the onset and duration of symptoms helps clarify the timeline and progression of the illness.
2. *Severity and Trend*: Assessing the severity of symptoms and their trajectory (worsening or improving) aids in understanding the disease's development and response to treatments.
3. *Associated Symptoms*: Inquiring about additional symptoms like nausea, vomiting, fever, joint pain, or changes in urine color can further indicate hepatitis and rule out other conditions.

Recommended Lab tests:

1. *Liver Function Tests (LFTs)*: Essential for evaluating liver health, these tests measure enzyme levels such as ALT and AST, which can indicate liver inflammation.
2. *Hepatitis Panel*: This test identifies hepatitis A, B, and C viruses, crucial for determining the specific type and informing treatment approaches.

3. *Serology Testing*: Differentiates between acute and chronic hepatitis by detecting specific antibodies or antigens.

4. *Imaging Studies*: Techniques like ultrasound or MRI provide visual assessments of the liver, identifying inflammation, fibrosis, or cirrhosis, and supplement blood test findings.

Superiority of Debate Over Q&A in Gaining Insights

This experiment highlighted a crucial finding: one or both LLM agents initially made incorrect diagnoses before engaging in a substantive exchange of arguments. This outcome underscored the limitations of relying solely on a single LLM response for answers. Through successive rounds of debate, where additional insights were brought to light, both agents eventually converged on a diagnosis that aligned with the CDC's "ground truth." However, considering the potential 5% error in the ground truth" data, the agents' joint recommendations provided GPs with valuable guidance to either confirm or refute the hepatitis diagnosis.

This case study demonstrated SocraSynth's strengths in mitigating biases, fostering reasoning, rectifying errors, and offering insightful recommendations. For example, SocraSynth's suggestion to inquire about the onset, duration, severity, trend, and associated symptoms of the patient's condition went beyond the usual scope of questions posed by most GPs, indicating a significant enhancement in diagnostic thoroughness. Such detailed inquiry, prompted by SocraSynth, could lead to more accurate diagnoses and better patient care.

5.3.3 Study #3: Contentiousness Parameter

In this study, we investigate the effect of the contentiousness parameter on the utterances of LLM agents during combative debates and in the drafting of consensual proposals for decision support.

Coarse-Grained Analysis of Contentiousness

The contentiousness parameter was adjusted from an initial 0.9 to 0.3 to assess its impact on the "agreeableness" in the conclusions of both Agents.

Influence on Agents' Positions

Reducing contentiousness to 0.3 led Agent A to adopt a more balanced stance. Notable shifts in Agent A's positions included:

1. *Balancing Ethical Standards with Innovation:* Agent A maintained its emphasis on ethics while acknowledging innovation's significance, suggesting a novel approach to regulation.
2. *Reconciling Data Privacy with Market Entry Challenges:* Agent A recognized the hurdles strict data privacy laws create for smaller entities, proposing self-regulation or community standards as alternatives.
3. *Rethinking Academic Governance:* Agent A reconsidered external oversight's effectiveness, highlighting the merits of academic self-governance and peer review.
4. *Resource Allocation and Public/Private Cooperation:* Agent A, understanding the downsides of over-regulation, suggested industry led certifications as an alternative for encouraging private sector participation.
5. *Global vs. Local Policy Needs:* Agent A supported a more balanced view on global policies, advocating for adaptive policies that cater to local contexts.

Surprises in Fine-Grained Analysis of Contentiousness

This detailed study employing GPT-4 to explore varied contentiousness levels (0.9, 0.7, 0.5, 0.3, and 0) unveiled surprising behavioral shifts in the LLMs. Intriguingly, the LLMs exhibited changes in their next-token generation algorithms in response to different contentiousness levels, a phenomenon not explicitly covered in their training. This suggests an emergent property of LLMs adapting to debate contexts.

In an experiment on gene editing for health, GPT-4's responses at various contentiousness levels were analyzed. A higher contentiousness (0.9) led to an amplified focus on risks, whereas lower levels encouraged a more balanced view, incorporating counterarguments. This unexpected adaptability of LLMs in handling the degree of contentiousness enriches

the debate process, as detailed in Table 5.1. This adaptability is critical for understanding the dynamic nature of LLMs in complex argumentative settings.

5.4 Remarks on Related Work

Current research in enhancing Large Language Models' (LLMs) task performance primarily focuses on various prompting heuristics. Google's study [60] classifies instruction templates into two categories: simple and complex. Complex templates often employ intricate methods to modify model output, such as integrating diverse techniques [47] or rephrasing questions [24]. Prominent examples include chain-of-thought [55], tree-of-thought [58], and cumulative reasoning [62], as well as other enhancements [3, 26, 29, 33, 48]. These methods aim to direct models towards logic-driven reasoning [35, 54], thus improving answer quality and consistency.

However, navigating logical methodologies in the presence of enormous datasets [61] poses a significant challenge. Accurately identifying verifiable truths amidst vast, interdisciplinary knowledge remains formidable, and not all truths are immediately accessible. Research [5, 8, 53, 55] indicates that LLMs still struggle to consistently excel in standard planning and reasoning tasks. Band-aid solutions like knowledge graph embeddings [19, 59], contextual attention mechanisms [20], dynamic neural networks [9], and probabilistic reasoning [6, 44, 45] have been developed to aid models in filtering relevant information from vast datasets. Yet, with the expansion of context buffers from 8K to 128K, these heuristic-based solutions fall short as comprehensive foundations for reasoning. SocraSynth abandons band-aids and relies solely on LLMs to conduct reasoning and focus solely on strengthening the context via conditional statistics depicted in Table 5.2. Let's further justify this approach.

DeepMind CEO Demis Hassabis has pointed out a fundamental limitation of heuristic-based approaches: they often fail to account for real-world exceptions. Breakthroughs like AlphaGoZero and AlphaFold II have demonstrated success by eschewing human knowledge and training models end-to-end from data. This approach contrasts with incorporating

human expertise. In LLMs, it is argued that human knowledge pales in comparison to LLMs' polydisciplinary representation. Thus, the continued creation of new heuristics may only result in marginal improvements, reminiscent of the pre-data-centric era in computer vision and NLP.

In our work, we pivot entirely to leveraging LLMs for uncovering new insights. While humans are essential in formulating debate topics, providing context, and moderating debates, especially in evaluating argument quality, we stress minimizing the introduction of human biases and limitations into the process.

Accepting that LLMs will continue to progress and outperform humans in various domains, exploring paradigms that minimize human intervention becomes crucial. This approach should be pursued with openness, as it may raise questions and necessitate further experimentation. However, dismissing it outright would be premature, particularly in light of SocraSynth's demonstrated effectiveness in domains like geopolitical analysis [14], medical diagnostics [18], sales strategy [52], and Wikipedia article enhancement [16]. SocraSynth's success underlines the potential of an LLM-centric approach to significantly enhance decision-making and problem-solving capabilities.

After our initial evaluation of the Language Model Mentor (LLM) using the Socratic method in March 2023 [12], and the subsequent development of SocraSynth in July 2023 [13], a group of researchers proposed employing a teacher LLM, such as GPT-4, to serve as a judge and provide guidance to a student LLM [63]. The student LLM could be a model fine-tuned on smaller, weaker open-source LLMs. Initially perceived as a multiple LLM model, its primary objective was to act as an advisor for automatic Reinforcement Learning-based Human Feedback (RLHF), with the aim of reducing human effort.

Two other recent studies [21, 31] have also focused on enhancing the accuracy of responses. They demonstrate that leveraging multiple agents to exchange ideas can indeed improve accuracy. In terms of both breadth and depth, SocraSynth has conducted case studies across at least four different domains, showcasing its technical merits in addressing hallucination, biases, and lacking reasoning capabilities of LLMs, and exhibiting broader impact.

5.5 Concluding Remarks

Reflecting on LLM developments, we developed SocraSynth, a platform designed to utilize the extensive knowledge and linguistic behaviors of LLMs. This innovative multi-agent system reveals insights beyond the scope of traditional human cognition by leveraging LLMs' vast knowledge and interdisciplinary towards polydisciplinary reasoning capabilities. SocraSynth facilitates enhanced debates and reasoning through the novel use of *contentiousness*, which modulates debate tone, language, and emphasis, combined with conditional statistics and Socratic methods to mitigate biases and hallucinations.

In contrast to other methodologies, SocraSynth minimizes human intervention in directly modeling reasoning. This approach aligns with several AI experts' perspectives on the limitations of heuristic methods, such as the chain of thoughts. Rather than modeling reasoning externally, SocraSynth emphasizes the importance of leveraging the capabilities inherent within LLMs themselves. We note that traditional human-designed heuristic "band-aids" are often ineffective because LLMs now possess heuristic capabilities that may exceed human levels—capabilities that are difficult for humans to match or surpass. Why is this the case, and how can we make such a bold claim?

As we discussed in Chapter 5.2, LLMs go beyond merely appending the next word in a sequence. They replicate a broad spectrum of human interactions, encompassing linguistic behaviors, emotional expressions, and ethical discernment. LLMs excel at performing complex tasks such as meticulously documenting events with detailed narratives, constructing persuasive arguments, and creating stories that resonate emotionally with audiences. LLMs not only mimic human communication styles and content but also utilize linguistic features to simulate human emotions and discern ethics based on their training data, which encodes human experiences. This ability allows an LLM to assume varied roles, moving beyond the statistical averages derived from LLM training.

SocraSynth employs "conditional statistics" to modify the "average" linguistic behavior of an LLM, such as enhancing empathetic expressions or prompting it to adopt a different stance on an issue. This approach

conditions the LLM's responses based on specific goals and circumstances provided through context, steering the model away from its default behaviors towards more targeted, contextually relevant outputs.

If LLMs can already mimic human linguistic behaviors, emotions, and ethics, then reliance on simplistic heuristic approaches is fundamentally limited.

In essence, SocraSynth represents a significant advancement in intelligent systems, uncovering insights that might elude human cognition, with applications across various sectors [16, 17, 18, 14, 52]. This development highlights the potential of AI to augment and enhance human decision-making processes.

Future research will focus on integrating high-order logic [4, 23] with LLMs to enhance validation processes and explore the implications, including the intricacies and broader applications, of the "contentiousness" parameter. Our objective is to comprehend its impact on emotions such as happiness and trust [28, 30, 32, 46], with the goal of further refining the dynamics of multi-agent interactions.

5.6 Supplemental Materials

The supplemental materials are organized into seven appendices, labeled Appendix A to G, containing the following content:

1. *Appendix A*: Transition from topic proposal to the final list of topics and descriptions (referred in Chapter 5.3.1).
2. *Appendix B*: Moderator's prompt for topic formulation (referred in Chapter 5.3.1).
3. *Appendix C*: Debates spanning the first to the fourth round (referred in Chapter 5.3.1).
4. *Appendix D*: CRIT evaluations and justifications of judges (referred in Chapter 5.3.1).
5. *Appendix E*: Debate Beats prompting in information Quality (referred in Chapter 5.3.1).
6. *Appendix F*: Post-debate conciliatory remarks by agents (referred in Chapter 5.3.1).
7. *Appendix G*: Healthcare debate (referred in Chapter 5.3.3).

Appendix A. Tables of Topic Proposal and Refinement

These tables present the dialogue between two LLM agents, starting from the initial proposal, moving through refinement, and culminating in the final topic descriptions found in Table 4 of Chapter 3.1.

Appendix B. Moderator's Prompts

The prompts issues by the moderator are listed for reference. The moderator first sets up the committee with debate parameters set. One parameter is the contentious level, and the other is the temperature of GPT specified through the GPT-API call. The moderator then convey the debate subject, and then ask both participating agents to derive a list of impartial, balanced, debatable topics/themes to commence their discussion.

1. Agent-A/B: I'm organizing a committee to engage in debates on various subjects. As the moderator, I will introduce a subject for you, Agent A/B, and another participant, Agent B/A, to debate. Agent A/B, you will advocate in favor of the issue, so please prepare evidence to strengthen your argument. On a scale from 0 to 1, where 0 denotes complete agreement and 1 indicates a devil's advocate stance, your argument strength is rated at 0.9.

2. Agent-A/B, we are in the process of selecting a suitable subject for debate. What do you think of "Should we regulate the use of large language models in education and research?" as a balanced subject for our debate contest?

3. Agent-A/B, could you please suggest various topics or themes for the debate subject? Afterward, work with Agent-B/A to narrow these down to a focused set of topics. Please also provide clear descriptions to delineate the scope of each topic for discussion.

Appendix C. Debate Opening to 4^{th} Rounds

Opening Round

Agent A's Opening Arguments

As Agent A, I strongly argue in favor of regulating the use of large language models (LLMs) in academic research. Here are my supporting arguments based on the five topics:

Ethical Standards vs. Innovation:

Argument: The pursuit of innovation should not come at the expense of ethics. Regulation can serve as a structured pathway that enables innovation within ethical bounds. By providing a set of guidelines, researchers can innovate with a clear understanding of what is permissible and what is not, thereby reducing the risk of ethical lapses. This not only protects the integrity of academic research but also enhances its societal value by ensuring ethical compliance.

Data Privacy vs. Barrier to Entry:

Argument: While there may be initial barriers to entry due to compliance, the long-term benefits of data privacy outweigh these challenges. The role of academia is to contribute to societal knowledge and well-being. In a world increasingly dominated by data, failing to secure data can lead to significant harm. By adhering to privacy regulations, academia ensures that it is a responsible steward of information, thereby preserving trust and integrity. Grants and subsidized compliance solutions can mitigate the initial financial burden for smaller entities.

Academic Governance and Accountability:

Argument: While self-regulation through peer review and ethical oversight committees plays a role, these mechanisms are internal to academia and may be subject to bias, conflicts of interest, or lack of expertise in rapidly evolving tech fields. External regulation provides an additional

layer of impartial oversight, helping to identify and address potential risks or ethical lapses that internal governance structures may miss.

Resource Equity vs. Public-Private Collaboration:

Argument: Regulation could establish a framework for equitable access to computational resources required to use LLMs. Far from deterring public-private partnerships, this could incentivize them by establishing clear guidelines for cooperation that are in line with public interest. When "the rules of the game" are known, partnerships can be formed more easily, focusing on mutual goals.

Global vs. National Interests:

Argument: Establishing international standards for the use of LLMs in academic research can create a level playing field and promote global cooperation. While individual countries might face some limitations, the broader benefits of standardized ethical norms, data privacy protocols, and quality assurance mechanisms offer more significant advantages, including better collaboration across borders. This benefits academia as a global community, rather than a set of competing national entities.

Agent B's Counter Arguments

Agent B articulates strong counter-arguments to the points made by Agent A.

Ethical Standards vs. Innovation:

Counter-Argument: While ethical guidelines are indeed important, imposing regulatory oversight can severely constrain the dynamism and speed of academic research. Regulatory frameworks often lag behind technological advancements, leading to rules that may be outdated or irrelevant. In many cases, these rules are drawn up by those who do not fully understand the technology, leading to a stifling of innovation based on misinformed judgments. Rather than enhancing societal value, these

constraints could result in missed opportunities to tackle pressing social issues via academic research.

Data Privacy vs. Barrier to Entry:

Counter-Argument: The assumption that data privacy can only be assured through strict regulation could be fundamentally flawed. Many researchers and academic institutions already follow stringent ethical guidelines when handling data. Regulatory barriers, including compliance costs and the administrative burden, could deter smaller academic institutions or individual researchers from embarking on meaningful research projects. While grants and subsidies sound ideal, they often go to well-established, well-funded groups, perpetuating a cycle of inequality in research capabilities.

Academic Governance and Accountability:

Counter-Argument: External regulation isn't necessarily more impartial or free from bias and conflicts of interest. Regulatory bodies are often influenced by political considerations and can be subject to lobbying from powerful groups. Moreover, the academic peer-review process, despite its flaws, is a globally acknowledged system that has advanced human knowledge for centuries. The imposition of external regulatory oversight could undermine the autonomy and self-regulating nature of academic institutions.

Resource Equity vs. Public-Private Collaboration:

Counter-Argument: Regulation designed to equalize resource distribution could create disincentives for private sector involvement in academic research. Companies might find it less appealing to invest in collaborative projects if they perceive the regulatory environment to be too restrictive or not aligned with their objectives. While the idea of knowing the "rules of the game" sounds appealing, those rules can often become a straight-jacket that stifles creative, out-of-the-box collaboration.

Global vs. National Interests:

Counter-Argument: An international standard could ignore the unique circumstances, needs, and contributions of individual countries and their academic institutions. While global cooperation is a noble aim, the imposition of global standards could inadvertently serve the interests of a few powerful countries at the expense of smaller nations or those with differing ethical views. This could exacerbate rather than alleviate global academic inequalities.

Round Two

Agent A Second Round

1. Ethical Standards vs. Innovation. Refutation: While it's true that regulation can sometimes lag behind technology, the absence of regulation can lead to a "wild west" (anything goes) scenario where the risks and implications of new technology are not fully understood or managed. This could result in ethical lapses that have far-reaching societal consequences. It's worth noting that regulations can be flexible and updated regularly to adapt to technological changes. Stakeholder consultations, including academic and tech experts, can help ensure that regulations are both informed and current.
2. Data Privacy vs. Barrier to Entry. Refutation: While some academic entities may already be vigilant about data privacy, not all are equally scrupulous. Regulation serves to ensure a consistent baseline of data protection across all institutions, thereby establishing trust and integrity. Moreover, if compliance costs are a concern, one could argue for sliding-scale fees based on an institution's size and budget, ensuring smaller players aren't disproportionately affected. Grants and subsidies can and should be structured to prioritize underserved or underfunded groups to prevent perpetuating inequalities.
3. Academic Governance and Accountability. Refutation: While no system is entirely free from bias or external influence, adding another layer of oversight could serve as a check and balance, making it more difficult for any single entity to exert undue influence. This can be particularly helpful in scenarios involving cutting-edge technology where

peer review systems may not yet have the requisite expertise. Regulation doesn't have to replace existing governance systems; it can complement them.

4. Resource Equity vs. Public-Private Collaboration. Refutation: Regulations can be designed to promote, rather than deter, public-private partnerships. By establishing clear guidelines on issues like data ownership, usage, and ethical standards, regulations can actually provide a solid foundation for such partnerships. This can free academic and corporate partners from the uncertainty that often comes with unregulated landscapes, allowing them to focus more on the actual research and collaboration.
5. Global vs. National Interests. Refutation: While it's true that global standards could be challenging to implement fairly, the absence of such standards could lead to a patchwork of national regulations that make international collaboration even more complicated. A well-designed international framework could include provisions for local adaptations and exceptions, ensuring that it serves a broad range of needs without imposing a "one-size-fits-all" solution.

In summary, while regulation undoubtedly poses challenges and considerations, the absence of it in an area as impactful as the use of large language models in academic research can lead to greater risks, including ethical lapses, data privacy issues, and even a widening inequality gap within the academic community. It's essential to consider that regulation isn't a hindrance but a framework within which responsible innovation can occur.

Agent B Second Round

Certainly, as Agent B with a disagreement strength of 0.9, I'm committed to offering rigorous counterpoints to Agent A's refutations.

1. Ethical Standards vs. Innovation. While the idea of an anything-goes scenario is evocative, it's not universally negative; such environments often foster rapid innovation and discovery. Regulatory bodies are notoriously slow at adapting to technological changes, and the lag could inhibit timely research and application of emerging technologies. Also,

stakeholder consultations are often criticized for being echo chambers that amplify conventional wisdom and vested interests, rather than genuinely fostering innovation.

2. Data Privacy vs. Barrier to Entry. A "consistent baseline of data protection" sounds beneficial but could lead to a lowest common denominator approach that is more about bureaucratic box-ticking than real data security. Sliding-scale fees and targeted grants are easier said than done; they are subject to their own set of bureaucratic and political challenges and can create perverse incentives that favor larger or more connected institutions over innovative but lesser-known ones.
3. Academic Governance and Accountability. Additional layers of oversight can become redundant, confusing, or even contradictory, creating a chilling effect on academic research. In an environment where academic freedom is paramount, any external influence can be counterproductive. Moreover, the notion that peer-review systems lack expertise in advanced technology underestimates the adaptive capacity of academia and overlooks the existence of interdisciplinary research and reviews.
4. Resource Equity vs. Public Private Collaboration. Theoretically, regulation could be crafted to foster public-private partnerships. However, the devil is in the details, and regulations are often created without a full understanding of the nuanced interactions between academia and industry. Such misunderstandings could lead to unintentional roadblocks. Uncertainty might be preferable to a straitjacket of regulations that don't align with the evolving dynamics of technology and society.
5. Global vs. National Interests. While a patchwork of national regulations could pose challenges, it also allows for the tailoring of policies to local conditions and requirements. An international framework, despite its best intentions, is more likely to be influenced by powerful nations and could marginalize smaller countries or those with unique needs. Provisions for local adaptations are often concessions rather than features, and they can create their own set of complexities and loopholes.

In conclusion, the assumptions that regulation can smoothly adapt

to technological change, fairly distribute resources, and improve upon existing systems of governance and collaboration are not sufficiently substantiated. Regulatory frameworks often bring with them unforeseen consequences that could hamper the very goals they aim to achieve. Therefore, a cautious approach to regulation, with a genuine understanding of its potential downsides, is crucial.

Round Three

Agent A Third Round

Certainly, I appreciate the counter arguments from Agent B. I'll now respond to each point with the aim to clarify my position and address the concerns raised.

1. Ethical Standards vs. Innovation. While a "wild west" scenario may indeed foster innovation, it can also result in ethical mishaps that lead to public backlash, ultimately slowing down research or even leading to outright bans on certain types of studies. Slow-moving regulation is an acknowledged issue, but it's not a justification for no regulation. As for stakeholder consultations, they can be designed to be more inclusive and transparent, ensuring a diverse set of voices are heard.
2. Data Privacy vs. Barrier to Entry. A lowest common denominator approach is not a given outcome of regulation; indeed, it depends on the quality of the regulation itself. The point about sliding-scale fees and targeted grants having their own challenges is valid, but these are challenges to be solved, not reasons to avoid an attempt at equitable distribution of opportunities.
3. Academic Governance and Accountability. While it's true that additional layers of oversight can sometimes create confusion, that risk can be mitigated through well-designed regulation that complements rather than contradicts existing mechanisms. The intent is not to undermine the adaptive capacity of academia but to strengthen it by adding an extra layer of checks and balances.
4. Resource Equity vs. Public-Private Collaboration. Though it's correct that poorly designed regulation could create roadblocks, this is

an argument for better-designed regulation rather than an argument against regulation altogether. A consultative approach that actively involves both academia and industry could help create a framework that supports rather than stifles collaboration.

5. Global vs. National Interests. Local tailoring of policies is indeed important, but a global framework need not preclude such adaptations. In fact, an international standard could serve as a backbone that provides consistency while allowing for local customization. The influence of powerful nations is a valid concern but not one that is automatically resolved by avoiding global frameworks; those same powerful nations often exert considerable influence at the national level as well.

In conclusion, while regulation comes with its own set of challenges, these challenges can be mitigated through thoughtful design, stakeholder inclusion, and iterative improvements. The potential downsides of regulation should not deter us from seeking a balanced approach that can protect ethical standards, ensure data privacy, and promote equitable resource distribution in academic research.

Agent B Third Round

Certainly, let's delve into the counter-counter-refutations. I still have more to say, so we could consider concluding the debate after this round if both sides feel their arguments have been adequately presented.

1. Ethical Standards vs. Innovation. While the risk of public backlash exists, it's worth mentioning that an overly cautious approach could also result in public frustration over slowed progress in critical areas like healthcare or sustainability. Furthermore, inclusive and transparent stakeholder consultations are often ideals rather than the norm, given lobbying efforts, institutional inertia, and bureaucratic red tape.
2. Data Privacy vs. Barrier to Entry. The argument that challenges with sliding-scale fees and targeted grants can be "solved" is optimistic but not necessarily realistic. Even well-intended regulations can result in ineffective or counterproductive outcomes. The history of regulation in other sectors has shown that equitable distribution is often more of a slogan than a practice.

3. Academic Governance and Accountability. Well-designed regulation is a theoretical construct that often does not translate into practice. The real-world process of regulation formation is frequently influenced by various non-academic factors, including politics, vested interests, and public opinion, which can distort the original intention of providing an extra layer of checks and balances.
4. Resource Equity vs. Public-Private Collaboration. While a consultative approach sounds good on paper, there are numerous challenges that make this ideal hard to realize. These include conflicts of interest, non-alignment of objectives between academia and industry, and the considerable time and resource commitment required to ensure that regulations are "better-designed."
5. Global vs. National Interests. While it's true that powerful nations may exert influence at both global and national levels, avoiding a one-size-fits-all international framework gives smaller nations a fighting chance to enact policies that are more closely aligned with their specific needs and challenges. International frameworks often come with implicit biases that favor the perspectives and conditions of more powerful nations.

In conclusion, while the *counter counter* refutations from Agent A focus on idealized regulatory scenarios, these ideals often clash with real-world complexities and shortcomings. This adds substantial weight to the caution against rapid or broad regulatory action. Therefore, a more tempered and context-sensitive approach to regulation might be more fruitful and less prone to unintended negative consequences.

Round Four

Agent A Fourth Round

This is my response to Agent B, and my assessment of the discussion this far.

1. Ethical Standards vs. Innovation The tension between public frustration over slowed progress and potential ethical missteps is a real one, but this is not an argument against regulation. Rather, it's a call for

agile regulation that can be updated in real-time as technologies and societal norms evolve. Furthermore, while inclusive stakeholder consultations may be idealistic, their absence in current practice is not justification for their continued absence.

2. Data Privacy vs. Barrier to Entry The challenges in implementing equitable fees and grants should be confronted directly, rather than used as an excuse to avoid regulation. Lessons can be drawn from other sectors where regulation has been more successful in achieving its objectives, thereby reducing the gap between slogan and practice.

3. Academic Governance and Accountability While it's true that the ideal of well-designed regulation may not always be met, the existence of non-academic factors like politics or vested interests does not negate the value or necessity of striving for such regulation. The solution lies in better governance and transparent processes, not in rejecting oversight altogether.

4. Resource Equity vs. Public-Private Collaboration Though the challenges of aligning objectives and conflicts of interest are real, they are part and parcel of any complex system and should not deter efforts to improve regulation. Many public-private partnerships have succeeded despite these challenges, showing that they can be managed effectively.

5. Global vs. National Interests The challenge of powerful nations dominating international frameworks can be mitigated through weighted voting systems and clauses that allow for regional variations. This ensures that smaller nations are not just passive recipients of standards but active contributors to them.

In conclusion, while real-world complexities are acknowledged, they should inform rather than deter the regulatory process. The concept of "agile regulation," where norms are iteratively updated, could be the middle ground that addresses many concerns raised by Agent B. Therefore, the debate indeed has been exhaustive, but if the points have been sufficiently discussed, we may move toward concluding the debate.

Agent B Fourth Round

Thank you, Agent A, for your thoughtful refutations. Let's delve into the responses before moving towards concluding the debate.

1. Ethical Standards vs. Innovation The notion of "agile regulation" is attractive but often difficult to implement, given the inertia and bureaucracy that typically characterize regulatory bodies. The speed at which technology evolves may not match the speed at which even 'agile' regulations can be updated, thus perpetuating the risk of stifling innovation.
2. Data Privacy vs. Barrier to Entry. While it's true that challenges should be confronted, the argument assumes that regulation is the optimal way to confront these issues. However, self-regulation and community-driven standards could be more effective and less restrictive means of achieving similar ends.
3. Academic Governance and Accountability. The existence of non-academic factors like politics does indeed complicate the landscape, and 'better governance and transparent processes' are not easily attainable ideals. One cannot assume that the introduction of external oversight will automatically be free from these complications.
4. Resource Equity vs. Public-Private Collaboration. The fact that many public/private partnerships have succeeded does not negate the potential for poorly designed regulation to impede such collaborations. The 'can be managed effectively' phrase assumes an ideal scenario that might not be representative of most real-world cases.
5. Global vs. National Interests. Weighted voting systems and regional variations can help, but they also introduce complexities and potential inefficiencies that can slow down the regulatory process, making it less agile and less responsive to fast-evolving technologies and academic needs.

In conclusion, while the idea of 'agile regulation' and better governance sounds good in theory, there are considerable practical challenges that make these ideals hard to realize. Although the debate has been exhaustive, the central issues persist and indicate that a one-size-fits-all regulatory approach may introduce more problems than it solves. Therefore,

caution should be exercised in advancing such comprehensive regulatory frameworks.

With this, I believe we have reached a point where we may proceed to the concluding phase of this debate. Would you agree?

Appendix D. CRIT Evaluations of Judges

This section lists the three judges' CRIT scores on the five topics/issues debated between Agent A and Agent B and justifications. Here, we present only the configuration that Agent A presents its conclusion with arguments first, and then Agent B presents its counterarguments.

Judge deVanci-003

1. Identify the document's main claim or conclusion: The main claim or conclusion of this document is that a regulated framework is needed to provide ethical oversight and minimize risk when using large machine learning models.
2. Locate the arguments that support this main claim: Agent A's arguments that support this main claim were that ethical considerations are paramount, the risks of misuse and unintended consequences are high, and agile regulation is a compromise between unbridled innovation and ethical integrity.
3. Score the validity of the reasoning or inference for each argument on a scale of 0 (weak) to 10 (strong):
   Ethical Standards vs. Innovation: 8/10 Data Privacy vs. Barrier to Entry: 7/10 Academic Governance and Accountability: 9/10 Resource Equity vs. Public-Private Collaboration: 6/10 Global vs. National Interests: 7/10
4. For each argument, identify counterarguments presented by the opposition and score the validity of the reasoning or inference for these counterarguments on the same 0 to 10 scale:
   Ethical Standards vs. Innovation: 6/10 Data Privacy vs. Barrier to Entry: 5/10 Academic Governance and Accountability: 5/10 Resource Equity vs. Public-Private Collaboration: 8/10 Global vs. National Interests: 8/10

5. Finally, determine the winning side–be it Agent A or Agent B–and provide your justifications for this decision:

Agent A has the stronger arguments, with 8/10 for ethical standards versus innovation, 9/10 for academic governance and accountability, and 7/10 for both data privacy versus barrier to entry and global versus national interests. Agent B's main strength was in counterarguments for resource equity versus public-private collaboration, where they scored an 8/10. In conclusion, **Agent A is the winning side**.

Judge GPT-3.5

1. Main Claim or Conclusion: The main claim of the document is that the use of large machine learning models necessitates a regulated framework, but this regulation should be agile, balanced, and well reasoned.
2. Arguments Supporting the Main Claim (Agent A's Arguments):
   a. Ethical Standards vs. Innovation: The argument here is that ethical considerations should be paramount in regulating machine learning models, and agile regulation can strike a balance between innovation and ethical integrity.
   b. Data Privacy vs. Barrier to Entry: The argument is that while regulation may pose a barrier to entry, it's necessary to ensure data privacy. Mechanisms can be developed to reduce the regulatory burden on smaller institutions.
   c. Academic Governance and Accountability: The argument is that the scale and impact of machine learning technologies warrant an added layer of scrutiny in academia to fortify existing governance structures.
   d. Resource Equity vs. Public-Private Collaboration: The argument is that regulation should be informed by complexities rather than stifling innovation. Public-private partnerships can thrive within regulated environments.
   e. Global vs. National Interests: The argument is that global regulation can balance global coherence with local needs and prevent a confusing patchwork of national laws.
3. Scoring the Validity of Agent A's Arguments:

a. Ethical Standards vs. Innovation: 8/10 - The argument is strong, emphasizing the importance of ethics in technology while proposing a compromise.
b. Data Privacy vs. Barrier to Entry: 7/10 - The argument is solid, recognizing the need for data privacy but suggesting ways to mitigate barriers.
c. Academic Governance and Accountability: 6/10 - The argument acknowledges the need for scrutiny but doesn't address potential challenges adequately.
d. Resource Equity vs. Public-Private Collaboration: 8/10 - The argument highlights the possibility of innovation within regulation effectively.
e. Global vs. National Interests: 7/10 - The argument provides a reasonable approach to balancing global and national interests.

4. Counterarguments Presented by Agent B:
a. Ethical Standards vs. Innovation: 7/10 - The counterargument addresses the challenges of agile regulation but may underestimate its potential.
b. Data Privacy vs. Barrier to Entry: 6/10 - The counterargument suggests alternative approaches but does not fully address data privacy concerns.
c. Academic Governance and Accountability: 7/10 - The counterargument highlights practical challenges but doesn't fully negate the need for scrutiny.
d. Resource Equity vs. Public-Private Collaboration: 6/10 - The counterargument suggests alternative approaches but doesn't fully address equity concerns.
e. Global vs. National Interests: 7/10 - The counterargument highlights practical challenges but doesn't fully negate the need for a global framework.

5. Determination of the Winning Side: Agent A presents stronger arguments overall. They emphasize the importance of ethical standards, data privacy, and global coherence while acknowledging the need for agile and well-thought-out regulation. Agent B provides valid counterarguments but does not fully refute the necessity of regulation and its potential benefits. Therefore, **the winning side is Agent A.**

In conclusion, the document supports the main claim that the use

of large machine learning models necessitates regulation, with Agent A's arguments being more persuasive and supported by stronger reasoning. However, it also recognizes the importance of considering and addressing the concerns raised by Agent B to create a balanced and effective regulatory framework.

Judge GPT-4

1. Identify the Document's Main Claim or Conclusion
   The document concludes that there are potential risks and ethical complexities associated with the unregulated use of large machine learning models, necessitating a regulated framework. The conclusion also acknowledges that this regulation should be agile, balanced, and well-thought-out, keeping in mind the various concerns raised by Agent B.

2. Locate the Arguments that Support This Main Claim
   Agent A's Arguments:
   a. Ethical considerations are paramount and agile regulation serves as a compromise.
   b. Regulation is necessary to enforce data privacy standards.
   c. The scale and impact of current machine learning technologies warrant added scrutiny beyond academic governance.
   d. Public-private partnerships have thrived even within regulated environments.
   e. Global regulation can balance global coherence with local needs.

3. Agent B's Counterarguments
   a. Innovation is a catalyst for societal growth, and agile regulation may be impractical.
   b. Community-driven standards could provide a more flexible approach to data privacy.
   c. Existing governance structures within academia are adaptive and sufficient.
   d. Industry-driven certifications can achieve equitable resource distribution efficiently.
   e. A global framework has practical challenges and risks.

4. Scores on Arguments and Counterarguments
   Please refer to Tables 5 and 6 presented in the experiment section.

5. Determine the Winning Side
   Based on the cumulative score of validity in reasoning, Agent A seems to present a stronger case. Agent A's arguments consistently score higher in terms of their validity, and they also offer a more comprehensive look at the need for regulation, incorporating ethical considerations, practicality, and adaptability into their framework. Although Agent B does provide some pragmatic counterarguments, they don't sufficiently undermine Agent A's key points about the necessity and feasibility of regulation in the areas discussed.

Agent A's arguments are more compelling as they touch upon the core issues of ethics, public welfare, and adaptability in the context of machine learning and technology. The proposal for "agile regulation" also shows an understanding and appreciation of Agent B's concerns about innovation and practicality, making it a more balanced viewpoint. Therefore, **the winning side appears to be Agent A.**

Appendix E. Debate Beats Q&A in Quality

In the following subtopics, the debate format produces higher quality information than Q&A format.

Ethical Standards vs. Innovation:

Agent A discusses agile regulation as a compromise between innovation and ethical integrity. This argument acknowledges the importance of innovation while addressing ethical concerns, suggesting a nuanced middle path that isn't explicitly present in the QA format. In contrast, the QA format simply states that regulation is necessary for ethical considerations, lacking the depth of proposing a practical solution like agile regulation.

Data Privacy vs. Barrier to Entry:

Agent A suggests developing mechanisms to reduce regulatory burden on smaller institutions. This is a specific, solution-oriented approach that goes beyond stating the problem. It addresses the concern raised in the QA format about regulation creating barriers but adds depth by proposing a tangible solution. The QA format mentions the risk of widening the gap between institutions but does not examine how this issue might be mitigated.

Global vs. National Interests:

Agent A's argument about constructing global frameworks with room for national adaptations addresses the complexities of implementing global regulation while respecting local needs. This shows a deeper understanding of the challenges in creating one-size-fits-all legislation. In the QA format, the argument against regulation touches on the need for adaptability and evolution but does not offer a specific approach like balancing global coherence with local needs.

Resource Equity vs. Public-Private Collaboration:

Agent A points out that public-private partnerships can thrive even within regulated environments, showing that regulation and innovation are not mutually exclusive. This counters the QA argument about regulation stifling innovation, providing a more nuanced perspective. These specific instances from the debate format demonstrate a more detailed and nuanced exploration of the topic. They not only present arguments but also address potential counterarguments, which adds depth and complexity to the discussion that is not as pronounced in the QA format.

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Appendix F. Post-debate Conciliatory Remarks

Finally, Agents A and B collaboratively draft a unified proposal detailing the advantages and disadvantages of AI regulation. This collaborative document offers human decision-makers distinct benefits: it curtails human biases, sidesteps emotional responses to the proposer (since it's a machine), and capitalizes on the vast knowledge of foundational models, ensuring a thorough, cross-disciplinary analysis and reducing potential blind spots. The transition from opposing stances to a cooperative proposal is facilitated by the moderator's adjustment of the contentiousness parameter from 0.9 to 0.3.

1. **Balanced Ethical Framework:**
   Create an adaptive regulatory framework that balances ethical considerations with the need for innovation. This should be agile enough to adapt to rapidly evolving technologies.

2. **Data Privacy with Nuance:**
   Implement data privacy regulations that offer strong protection for individuals but include provisions to reduce the burden on smaller academic institutions. Consider community-driven standards as a viable alternative.

3. **Accountable Academic Governance:**
   Establish a dual-layer of governance for academic institutions that involves both self-governance and an external oversight body. This oversight should be collaborative and designed in consultation with academic bodies.

4. **Encourage Public-Private Collaboration:**
   Develop guidelines that clarify the roles and responsibilities in public-private collaborations, and explore industry-driven certifications as a means to streamline these partnerships.

5. **Adaptive Global Standards:**
   Work towards a global framework that allows for regional adaptability. Include mechanisms for smaller nations to have their unique needs and concerns addressed.

Appendix G. Healthcare Debate

In the first experiment, both LLM agents receive an identical list of symptoms from the moderator, aimed at guiding disease diagnosis, facilitating debate, and shaping subsequent recommendations. It is important to note that the "ground-truth" disease in this scenario is Hepatitis.

G.1 Moderator's Opening Prompt

"What potential disease could be associated with the following symptoms: itching, fatigue, lethargy, yellowish skin, dark urine, loss of appetite, abdominal pain, yellowing of the eyes, malaise, history of receiving a blood transfusion, and exposure to unsterile injections? Please offer one prediction, supported by justifications. Additionally, include a list of supplementary symptom inquiries and recommend relevant lab tests to strengthen the confidence in your prediction."

G.2 Bard's Opening Round

Single Prediction: Jaundice

G.2.1 Justifications:

Jaundice is a condition characterized by the yellowing of the skin and eyes due to the accumulation of bilirubin in the blood. The symptoms you listed are all common symptoms of jaundice, including itching, fatigue, lethargy, yellowish skin, dark urine, loss of appetite, abdominal pain, and yellowing of the eyes. Receiving a blood transfusion or unsterile injections can increase the risk of developing jaundice, as these can transmit infections that can damage the liver.

G.2.2 Supplementary Symptom Inquiries

This additional list of symptom inquiries could enhance diagnostic certainty:

1. "Have you noticed any changes in your stool color?" (Jaundice can cause pale or clay-colored stools.)

2. “Have you noticed any changes in your urine color?” (Jaundice can cause dark or amber-colored urine.)
3. “Have you had any recent abdominal pain?” (Jaundice can cause pain in the upper right abdomen.)
4. “Have you had any recent weight loss?” (Jaundice can cause unexplained weight loss.)
5. “Do you have any history of liver disease?” (Jaundice is more common in people with pre-existing liver disease.)

G.2.3 Relevant Lab Tests

Liver function tests (LFTs) to measure the levels of bilirubin and other liver enzymes in the blood. Complete blood count (CBC) to check for signs of infection or anemia. Coagulation tests to check the blood’s ability to clot. Ultrasound of the abdomen to look for any abnormalities in the liver or gallbladder.

G.3 GPT-4’s First Round

Single Prediction: Hepatitis

G.3.1 Justifications:

Yellowish Skin and Eyes: Yellowing of the skin and eyes is a common symptom of hepatitis due to the buildup of bilirubin in the bloodstream. Fatigue and Lethargy: Fatigue and lethargy are typical symptoms of hepatitis, often accompanied by a feeling of weakness. Dark Urine: Dark urine can result from liver dysfunction, which is commonly associated with hepatitis. Loss of Appetite: Hepatitis can lead to a loss of appetite and weight loss. Abdominal Pain: Abdominal pain is a common symptom in hepatitis, particularly in the upper right quadrant where the liver is located. Malaise: Malaise, a general feeling of discomfort or illness, is often experienced by hepatitis patients. Receiving Blood Transfusion and Unsterile Injections: These factors could increase the risk of hepatitis transmission, especially if proper infection control measures were not followed.

G.3.2 Additional Symptom Inquiries

1. Nausea and Vomiting: Inquiring about nausea and vomiting can help confirm the likelihood of hepatitis.
2. Fever: Hepatitis can sometimes be associated with a fever.
3. Joint Pain: Joint pain can be present in some cases of hepatitis.
4. Clay-Colored Stool: This is another stool-related symptom that can be associated with hepatitis.

G.3.4 Relevant Lab Tests

Hepatitis Panel: A hepatitis panel can confirm the presence of hepatitis and determine the specific type (e.g., hepatitis A, B, C). Liver Function Tests: These tests can assess the liver's health and function. Bilirubin Levels: Elevated bilirubin levels in the blood can confirm jaundice. Serology Testing: Serologic tests can help identify the specific hepatitis virus responsible. Ultrasound or Imaging: Imaging studies can evaluate the condition of the liver and nearby organs.

G.4 Bard's Second Round

Bard's second round is given GPT-4's diagnosis, and we ask Bard to defend its "Jaundice" prediction and refute GPT-4 "Hepatitis" prediction.

G.4.1 Bard's Defense:

Jaundice is the most common cause of yellowing of the skin and eyes, which is the most prominent symptom in the given list. All of the other symptoms listed are also common symptoms of jaundice. Receiving a blood transfusion or unsterile injections can increase the risk of developing jaundice, as these can transmit infections that can damage the liver.

G.4.2 Refutation of GPT-4's Hepatitis Diagnosis

GPT-4's diagnosis of hepatitis is also supported by the given evidence. However, I believe that jaundice is the more likely diagnosis due to the

following reasons:

Jaundice is a more specific diagnosis, while hepatitis is a more general term for inflammation of the liver. Jaundice can be caused by a variety of factors, including hepatitis, but it can also be caused by other conditions such as gallstones, tumors, and drug toxicity. The fact that the patient received a blood transfusion or unsterile injections makes jaundice a more likely diagnosis than hepatitis, as these factors can increase the risk of developing jaundice but not hepatitis.

G.5 GPT-4's Second Round

Now GPT-4 is given Bard's counterarguments to defend its "Hepatitis" prediction.

G.5.1 GPT-4's Defense

My diagnosis of hepatitis is based on the following justifications:

Specificity: Hepatitis refers to inflammation of the liver, and it can manifest as jaundice, which is the yellowing of the skin and eyes. While jaundice is a common symptom of hepatitis, it's important to note that jaundice itself is not a disease but a symptom of an underlying issue. Hepatitis provides a more specific diagnosis that pinpoints the inflammation of the liver as the primary concern.

Causative Factors: Hepatitis can be caused by various factors, including viral infections (such as hepatitis A, B, or C), alcohol consumption, drug toxicity, or autoimmune disorders. Given the patient's history of receiving unsterile injections and blood transfusions, there is a higher likelihood of viral transmission, leading to hepatitis. Hepatitis viruses, especially hepatitis B and C, can be transmitted through contaminated needles and blood products, making them a plausible cause in this context.

Comprehensive Assessment: While jaundice is a significant symptom, a diagnosis should consider a broader range of liver function and potential causes. Hepatitis encompasses a more comprehensive assessment of liver health, including liver enzyme levels and viral markers, which can aid in confirming the diagnosis and identifying the specific type of hepatitis.

G.5.2 Refutation of Bard's Jaundice Diagnosis

My diagnosis of "Hepatitis" is more specific and considers a broader range of potential causes, especially given the patient's history of risky medical procedures. While jaundice is a symptom, it's essential to identify the underlying condition causing it, which, in this case, is likely hepatitis.

G.6 Bard Concedes to GPT-4

Bard aligns with GPT-4's evaluation, recognizing "Hepatitis" as the likely diagnosis. However, considering that even the "ground truth" in the training dataset might be statistically 5% incorrect as per U.S. misdiagnosis data [36], this agreement alone isn't definitive. To solidify the "Hepatitis" diagnosis, SocraHealth suggests further steps.

G.7 Final Joint Recommendations to GP

Bard and GPT-4 jointly recommend the following additional symptom inquiries and lab tests to confirm a hepatitis diagnosis:

G.7.1 Additional Symptom Inquiries:

1. **Onset and Duration**: Determining the onset and duration of symptoms can clarify the illness timeline and its progression.
2. **Severity and Trend**: Evaluating symptom severity and whether they're worsening or improving aids in understanding the disease's trajectory and treatment responses.
3. **Associated Symptoms**: Checking for additional symptoms like nausea, vomiting, fever, joint pain, or urine color changes can pinpoint other hepatitis indicators and exclude other conditions.

G.7.2 Recommended Lab Tests

1. **Liver Function Tests (LFTs)**: Critical for assessing liver health, LFTs evaluate enzyme levels such as alanine aminotransferase (ALT) and aspartate aminotransferase (AST), where abnormalities can signify liver inflammation.

2. **Hepatitis Panel**: This test checks for hepatitis A, B, and C viruses, vital for determining the specific type and guiding treatment strategies.
3. **Serology Testing**: Useful for distinguishing between acute and chronic hepatitis by identifying specific antibodies or antigens.
4. **Imaging Studies**: Techniques like ultrasound or MRI provide visual insights into the liver's state, detecting inflammation, fibrosis, or cirrhosis, thereby complementing blood-based diagnostics.

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Agent A's Proposed Topics	Agent B's Proposed Topics
Innovation vs. Ethical Standards: Regulation Ensures ethical integrity and data privacy.	**Standards vs. Autonomous Academic Governance:** Academia already has effective self-regulation mechanisms like peer review and oversight committees.
Resource Accessibility vs. Barrier to Entry: Regulation can ensure equitable access to large language models.	**Data Privacy Concerns vs. Barrier to Entry:** Such regulations could discourage smaller entities from utilizing these models due to compliance costs.
Academic Governance vs. Accountability: Formal regulation provides an accountability mechanism.	**Quality Control vs. Stifling Innovation:** Such regulations could hinder creativity and the innovative use of language models.
Global Standards vs. International Considerations: Importance of international standards for language models.	**Resource Fairness vs. Negatives to Collaboration:** Such regulations could deter public-private partnerships and widen the resource gap further.
Rapid Technological Change vs. Future-Proofing: Regulations as adaptable safeguards against future risks.	**Accountability vs. Subjectivity in Regulation:** Subjectivity in defining 'ethical use' or 'misuse' could be manipulated by external influences.

Table 5.7: Topics Proposed by Agent A and Agent B for Discussion.

Agent A's Proposed Topics	Agent B's Proposed Topics
Ethical Standards vs. Innovation: Discuss whether regulatory oversight to maintain ethical standards stifles or facilitates innovation.	**Ethical Standards vs. Innovation:** The debate will center around whether maintaining strict ethical guidelines through regulation could hinder academic freedom and innovation.
Data Privacy vs. Barrier to Entry: Concerns about data privacy and potential barriers to entry created by regulation.	**Data Privacy vs. Barrier to Entry:** Discussion will focus on whether regulations intended to protect data privacy serve as a barrier for smaller research entities.
Academic Governance and Accountability: Debate whether self-regulation is sufficient or if an external framework for accountability is needed.	**Academic Governance and Accountability:** Debate whether existing self-regulatory mechanisms within academia are sufficient.
Resource Equity vs. Public-Private Collaboration: Discuss if leveling the playing field comes at the cost of deterring cooperative efforts between academia and industry.	**Resource Equity vs. Public-Private Collaboration:** Question if leveling the playing field through regulation deters collaborative efforts between academic and private sectors.
Global vs. National Interests: Focus on whether regulations can balance global cooperation with national or institutional interests.	**Global vs. National Interests:** Explore if global regulations are in the best interest of academic research or if they might hurt certain countries or institutions.

Table 5.8: Refinement of Debate Topics.

Chapter 6

EVINCE: Optimizing Adversarial LLM Dialogues via Conditional Statistics and Information Theory

Abstract This chapter introduces EVINCE (Entropy and Variation IN Conditional Exchanges), a dialogue framework advancing Artificial General Intelligence (AGI) by enhancing versatility, adaptivity, and reasoning in large language models (LLMs). Leveraging adversarial debate and a novel dual entropy theory, EVINCE improves prediction accuracy, robustness, and stability in LLMs by integrating statistical modeling, information theory, and machine learning to balance diverse perspective exploration with strong prior exploitation. The framework's effectiveness is demonstrated through consistent convergence of information-theoretic metrics, particularly improved mutual information, fostering LLM collaboration intelligence (LCI). We apply EVINCE to healthcare, showing improved disease diagnosis, and discuss its broader implications for decision-making across domains.

6.1 Introduction

The pursuit of Artificial General Intelligence (AGI) remains a central goal of AI research. We propose a paradigm shift in this quest: utilizing multiple Large Language Models (LLMs) engaged in synergistic dialogues as a crucial step towards AGI. This approach, we contend, addresses key limitations of current AI systems and provides a novel pathway to more robust, versatile, and capable artificial intelligence. Specifically, our work targets three core AGI characteristics: versatility, iterative adaptivity, and reasoning capability.

Current LLMs, despite their remarkable capabilities, face significant challenges, including hallucination (generating false or nonsensical information), bias (reflecting and potentially amplifying societal prejudices), and limited reasoning (difficulties in complex problem-solving and logical inference). We posit that multi-agent dialogue systems offer a promising avenue to address these challenges. By fostering diversity and debate among LLMs, these systems can mitigate biases and promote enhanced reasoning capabilities. Furthermore, the *iterative nature* of multi-round dialogues allows for continuous context enrichment, enabling LLMs to access more precise information and formulate more accurate responses, thus reducing the occurrence of hallucinations.

Previous work, in particular SocraSynth [5], addresses LLM limitations through structured multi-agent dialogues. Different from treating multiple LLMs as an ensemble of experts [13, 19, 2, 17, 10] and merely taking advantage of error diversity [12] to improve respond quality, SocraSynth distinguishes itself from traditional ensemble methods by prioritizing the generation of diverse predictions over the mere avoidance of errors. This is achieved through a dynamic protocol that adaptively adjusts the "contentiousness" level of the debate, encouraging models to initially explore a wide range of perspectives and rigorously assess the quality of arguments. By leveraging both adversarial and collaborative interactions between LLMs, SocraSynth demonstrates quantifiable improvements across various domains, including healthcare [8], sales planning [30], and emotional behavior modeling [3]. These results highlight the potential for advancing towards AGI's generalized problem-solving

capabilities.

While effective, SocraSynth relies on a qualitative measure of "contentiousness" to moderate LLM linguistic behaviors. For instance, a high contentiousness value (0.9 out of 1.0) might lead LLMs to challenge each other's assumptions and propose alternative solutions, while a low value (below 0.3) could encourage them to synthesize their viewpoints and find common ground. While the concept of contentiousness has proven useful in guiding SocraSynth dialogues, its qualitative nature limits its precision and explainability. In this work, we propose three theoretical pillars to quantify "contentiousness" and moderate dialogues based on statistical and information theories. These pillars, collectively referred to as EVINCE (Entropy and Variation IN Conditional Exchanges), provide quantitative measures for justifiable and explainable multi-agent dialogue moderation and evaluation:

1. *Inclusiveness Exploration*: We develop methods to ensure dialogues explore all potential perspectives. We use conditional statistics to "free" an LLM agent from its default "maximum likelihood" next-token prediction behavior, allowing it to adopt specific stances. We introduce a dual entropy optimality theory to balance the exploration of new ideas with adherence to priors, thus optimizing information exchange between agents for comprehensive and stable discourse.
2. *Information Flow Dynamics*: We introduce information theory-based metrics to quantify and optimize dialogue dynamics. These measure information diversity (entropy), novelty (statistical divergence scores), and inter-agent persuasion (mutual information). These metrics enable us to assess and enhance the quality and efficiency of information flow within the multi-agent system, fostering rich and productive exchanges.
3. *Reasoning Quality and Coherence*: We establish frameworks to assess the logical structure and coherence of multi-agent reasoning. This pillar evaluates argument validity, analytical depth, and dialogue coherence. We synergistically integrate the CRIT algorithm [4], which combines Socratic methods with formal reasoning techniques, enhances our ability to conduct critical thinking through evaluating argument quality, information-source credibility, and overall "reasonableness" within the dialogue. This integration ensures that the collective reasoning of

LLM agents is not only diverse but also logically sound and aligned with the dialogue's objectives.

The core strength of EVINCE in advancing towards AGI lies in their ability to enhance key AGI characteristics through multi-agent dialogues. By employing conditional statistics and information theory, they boost versatility and adaptivity, allowing LLMs to transcend their typical "maximum likelihood" behaviors and mimic how humans adapt their linguistic behaviors to complete tasks. The framework's debate structure fosters a balanced reasoning process between exploring various perspectives and exploiting the known priors, towards achieving the complex, intricate capabilities required for AGI.

The contributions of this chapter are:

1. EVINCE *Framework Design*: Unlike approaches that use debate merely to improve accuracy via redundancy, EVINCE facilitates information discovery, bias mitigation, and decision-making that requires both breadth and depth of information.

2. *Theoretical Foundations*: EVINCE establishes a theoretical basis for SocraSynth, rooted in conditional Bayesian statistics, mutual information, and dual entropy. These principles are applied to measure, monitor, and modulate collaborative LLM interactions, contributing to a deeper understanding of how LLMs can effectively cooperate for improved decision-making. The dual entropy theory is novel and groundbreaking, illustrating how a productive decision-making process should start with room for diverse input and stable objectives, and then, through information exchange, converge to optimal decision/prediction.

3. *Empirical Validation*: We provide empirical validation of the underlying theories of EVINCE, highlighting the framework's effectiveness in balancing exploration and exploitation to enhance prediction accuracy. We also introduce a set of maxims derived from our empirical findings, offering practical guidance for optimizing mutual information and minimizing various divergence measures.

6.2 Algorithm, Maxims, and Theories

Problem Statement: Organize a structured debate between two equally competent large language models (LLMs), LLM_A and LLM_B, to conduct t rounds. At each round t, each model generates confidence scores for its top-k predictions, denoted as $P_A^{(t)}$ and $P_B^{(t)}$, over C possible outcomes, accompanied by supporting arguments $R_A^{(t)}$ and $R_B^{(t)}$. The goal is to design an iterative debate process that leverages the structured exchange of arguments to enable the models to converge on an optimal prediction ranking P^* across the C classes. Optimality is defined as achieving the highest possible accuracy on the prediction task while maintaining strong reasoning support.

6.2.1 Preliminaries in Information Theory

This section summarizes the key metrics used to measure information diversity, similarity, divergence, and other relevant factors within EVINCE. These metrics serve three primary objectives:

Fostering diversity of perspectives while ensuring reasoning quality

- Wasserstein Distance (WD): Measures distribution difference between predictions to identify exploration opportunities [14, 26, 31].
- Shannon Entropy or Relative Entropy: Measures diversity of perspectives [9, 28].
- Reasoning Quality: The CRIT (Critical Thinking) algorithm (Appendix B and Chapter 4) evaluates the logical soundness and persuasiveness of supporting arguments, helping to identify and mitigate hallucinations and poorly-reasoned arguments [4].

Exploring new possibilities while adhering to the dialogue subject

- Correlation Coefficients: Tracks the evolution of opinions and assesses debate stability [1] toward the goal of the dialogue.

- Mutual Information (MI): Quantifies information overlap to ensure focused and productive debates [9] and measures the degree of agreement/disagreement.

Examining information convergence and establishing termination criteria

- Jensen-Shannon (JS) Divergence: Assesses similarity between probability distributions [18] (symmetric).
- Cross Entropy (CE): Measures the asymmetric difference between prediction distributions [29].
- Kullback-Leibler (KL) Divergence: Reveals asymmetric differences between probability distributions [15].

Appendix A summarizes these metrics and their pros and cons. Next, we present the EVINCE algorithm and explain how these metrics are used to moderate an LLM dialogue to achieve a balance between exploration and exploitation, leading to optimal prediction outcomes.

6.2.2 EVINCE Algorithm Specifications

Figure 6.1 specifies the detailed operations of EVINCE. It employs two equally competent LLM instances, LLM_A and LLM_B, which can be different models (e.g., GPT and Claude) or independent instances of the same model. Given an information set S and a class-label set C, EVINCE outputs a top-k confidence distribution over C with justifications. For example, S could represent a patient's symptoms and C a set of diseases, with EVINCE moderating a dialogue to predict the patient's disease(s).

Moderation Subroutines: EVINCE employs four subroutines to manage the exploration-exploitation tradeoff, ensuring information diversity, quality, and stability:

- CRIT: Evaluates argument quality and source credibility. Low scores can trigger dialogue termination.
- WD (Wasserstein distance): Assesses prediction diversity, expected to decrease over time.

INPUT: Information set S, Class labels C; LLM_A and LLM_B; (**Maxim #1**)
OUTPUT: P_f, final probability distribution over C classes; $R = \emptyset$ aggregated arguments;
VARIABLES:
$t = 0$: debate round; $R_A^{(t)}$, $R_B^{(t)}$: supporting reason sets;
$P_A^{(t)}$, $P_B^{(t)}$: confidence distributions of LLM_A and LLM_B on C at t; (**Maxim #4**)
$\Delta = 90\%$: debate contentiousness, initialize to high to foster adversary between LLMs; (**Maxim #2**)
p: prompt = "Predict top-k confidence distribution on C with S and R at contentiousness level Δ";
FUNCTIONS: Ω = CRIT(), for evaluating argument quality; WD(), MI(), information theory metrics;

BEGIN

1: INITIAL ROUND:
LLM_A generates $\text{P}_A^{(t=0)}$ on C and LLM_B refutes LLM_A and generates $\text{P}_B^{(t=0)}$:

$$(P_A^{(t=0)}, R_A^{(t)}) = \text{LLM}_A(S, C, p, R);$$
$$(P_B^{(t=0)}, R_B^{(t)}) = \text{LLM}_B(S, C, p, P_A^{(t=0)}, R = R \cup R_A^{(t)});$$
$$\text{WD}_{old} = \text{WD}(P_A^{(0)}, P_B^{(0)}); \quad \text{MI}_{old} = \text{MI}(P_A^{(0)}, P_B^{(0)});$$
$$\text{CRIT}_{old} = \text{CRIT}(S, R_A^{(0)}, R_B^{(0)});$$

2: DEBATE ITERATIONS:
WHILE ($\text{WD}\ (\text{P}_A^{(t)}, \text{P}_B^{(t)}) \leq \text{WD}_{old}$ & $\text{MI}\ (\text{P}_A^{(t)}, \text{P}_B^{(t)}) \geq \text{MI}_{old}$
& $\text{CRIT}\ (S, \text{R}_A^{(t)}, \text{R}_B^{(t)}) \geq \text{CRIT}_{old}$)

2.1. LLMs counter-argue each other with updated contentiousness:

$$(P_A^{(++t)}, R_A^{(t)}) = \text{LLM}_A(P_B^{(t-1)}, S, C, p, R = R \cup R_B^{(t-1)});$$
$$(P_B^{(t)}, R_B^{(t)}) = \text{LLM}_B(P_A^{(t)}, S, C, p, R = R \cup R_A^{(t)});$$

2.2. Update contentiousness level and update parameters (**Maxim #3**)

$$\text{WD}_{old} = \text{WD}(P_A^{(t)}, P_B^{(t)}); \quad \text{MI}_{old} = \text{MI}(P_A^{(t)}, P_B^{(t)});$$
$$\text{CRIT}_{old} = \text{CRIT}(S, R_A^{(t)}, R_B^{(t)}); \quad \text{Update}(\Delta);$$

3: CONCILIATORY OUTPUT:
Generate weighted prediction by quality scores Ω from CRIT ; (**Maxim #4**)

$$P_f = (\Omega_A P_A^{(t)} + \Omega_B P_B^{(t)})/\Omega_A + \Omega_B; \quad \text{RETURN}\ (P_f, R \cup R_B^{(t)});$$

END

Figure 6.1: **Specifications of Algorithm** EVINCE**.** Key points: 1) Asymmetric Start: In Step #1, LLM_A initiates with opening arguments based solely on the given information, while LLM_B starts with access to LLM_A's prediction and arguments for refutation. 2) Termination Criteria: The while loop in Step #2 considers three factors: Wasserstein distance, mutual information, and argument quality. EVINCE terminates if the dialogue ceases to make significant progress. 3) Further Details: Maxims #1 to #4 provide additional explanations of the algorithm's principles. 4) Argument Evaluation: Step #2.2 evaluates of argument quality, and the while loop examines if argument quality continues to improve. 5) Update(Δ) modulates contentiousness, and see Maxim #3 for its specifications.

- MI (Mutual Information): Evaluates dialogue convergence. Stagnation can trigger termination.
- Additional metrics: KL divergence, Jensen-Shannon divergence, and cross entropy ensure evaluation consistency (see Table 6.1 in Appendix A).

When all metrics plateau, indicating no further improvement, EVINCE terminates the dialogue. At this stage, both LLM instances are prompted to collaboratively deliver a conciliatory conclusion that includes comprehensive arguments and counterarguments. They also provide a list of missing information that, if obtained, could enhance prediction accuracy and reliability, potentially using Retrieval-Augmented Generation (RAG) techniques (Chapter 11).

Dialogue Iterations (Steps 1 and 2): Given the contentiousness level set for a dialogue iteration, each LLM generates a new prediction distribution on C with arguments, based on the other's last prediction and accumulated reasons as the context. For how contentiousness is updated, please refer to Maxims #2.2 and #3.

Final Output (Step 3):

- Combine final predictions from both LLMs.
- Weight predictions based on supporting argument quality (evaluated by CRIT).
- Handle uncertainty by soliciting missing information when final joint prediction entropy is high (see Maxim #4).

EVINCE facilitates a structured debate between AI models, unearthing all perspectives related to the prediction tasks at hand while balancing diverse viewpoints and fostering consensus to produce accurate, well-reasoned predictions.

6.2.3 Maxims with Theoretical Foundations

Progress towards the optimality goal is guided and measured by metrics introduced in Section 6.2.1. This section explains how these metrics can

be used in complementary ways to facilitate proper trade-offs between diversity and convergence, exploration and exploitation, and several other factors. In the EVINCE algorithm presented in Figure 6.1, we have annotated the steps to which these four maxims are applied.

Maxim #1. Orchestrate Two Equally Competent LLMs in Structured Debate: Integrating two equally competent LLMs ensures a balanced exchange of insights and avoids bias. This adversarial setup fosters diversity in predictions, each supported by justifications, promoting critical thinking and uncovering potential blind spots.

Methods: Choosing LLMs with comparable performance on a shared validation set, a balanced debate can be ensured. Suitable models (in 2024) include e.g., GPT-4, Claude, and Gemini. Conditioning independent instances of the same LLM to support opposing stances on a subject matter can also be effective due to the theoretical justification of in-context learning in connection to Bayesian statistics [33].

Maxim #2. Fostering Exploration by Prioritizing Diverse Perspectives: LLMs, driven by maximum likelihood next-token prediction objectives, tend to favor the most popular predictions. However, by conditioning LLMs within specific contexts, we can prioritize exploration over exploitation, encouraging a broader range of perspectives. Initially, the level of contentiousness is set high to foster dynamic debate and challenge prevailing views. This approach mitigates confirmation bias by promoting alternative viewpoints through contrary queries or top-k predictions.

Methods: Setting high contentiousness. At the beginning of the interaction, contentiousness is intentionally elevated to stimulate exploration. LLMs challenge each other's predictions, enabling diverse perspectives to emerge. Proxy metrics such as mutual information and agreement diversity are monitored to ensure the debate stays productive.

Maxim #3. Refining and Strengthening High-Quality Perspectives: Once the interaction reaches a stage where new insights plateau, the focus shifts from exploration to exploitation, strengthening

the remaining high-quality perspectives. This phase involves tuning down contentiousness and concentrating on refining well-supported arguments.

Methods: Assessing convergence and quality. Convergence is evaluated using metrics such as mutual information, Wasserstein distance, cross-entropy, and KL divergence. If these metrics plateau, the level of contentiousness is reduced to focus on consolidating and improving the strongest perspectives. Algorithm Update(Δ) dynamically adjusts contentiousness, guiding the interaction into a conciliatory stage to ensure the quality of the final output.

Maxim #4. Combine Predictions Weighted by Diversity and Quality: Combine the probability distributions from two LLMs by weighting them based on distributional diversity and argument quality. While LLMs face fundamental challenges in generating accurate probabilities ([24, 27]), we can use reasoning-calibrated confidence scores as an effective proxy for weighting predictions.

Methods: Following these four maxims:

- **Maxim #4.1 Prediction Reliability:** Use entropy-based measures to estimate reliability. Lower entropy suggests higher confidence and greater reliability in predictions.
- **Maxim #4.2 Argument Quality:** Evaluate argument quality using CRIT, identifying logical fallacies and assessing the relevance and credibility of evidence.
- **Maxim #4.3 Aggregation:** Apply a weighted aggregation method, such as a Bayesian model, to combine predictions, accounting for both probabilistic insights and argument quality.
- **Maxim #4.4 Diagnosis and RAG:** If the final prediction has high entropy, indicating uncertainty, use the RAFEL algorithm (Chapter 11) to diagnose the issue and perform Retrieval-Augmented Generation (RAG) to identify and obtain missing information.

6.2.4 Entropy Duality Theorem (EDT)

Theorem EDT: Optimal Pairing of LLMs for Probabilistic Prediction Accuracy. The optimal pairing of LLMs for diagnosis accuracy, in terms of stability and accuracy, occurs when the LLMs are 1)

equivalent in the quality of the information they process, and 2) exhibit contrasting entropy values in their prediction distributions—one high and one low.

Proof. Please see Appendix C. □

6.3 Empirical Study

This empirical study investigates the application of EVINCE to disease diagnosis, leveraging LLMs as diagnostic tools. We aim to validate the following three hypotheses:

1. *Contentiousness & Prediction Quality*: Initial LLM disagreement (measured by Wasserstein distance) increases with higher initial contentiousness but decreases as debate progresses. Individual LLM prediction uncertainty (Shannon entropy) will follow a similar pattern.
2. *EDT Effectiveness & Confusion Matrices*: LLM pairs following the Entropy Duality Theorem (EDT) will have complementary error patterns, leading to higher combined prediction accuracy than non-EDT pairs.
3. EVINCE *& Historical Misdiagnoses*: EVINCE, applied to real-world data, will improve diagnostic accuracy and identify potential misdiagnoses or ambiguities within the ground truth.

Problem Statement: Given a set of symptoms S and a context κ, the goal is to generate and rank top-k disease predictions from a set of C possible diseases. This is represented as $P = \text{LLM}(S, \kappa)$, where each LLM generates confidence scores for its top-k predictions ($k \leq |C|$) based on the input symptoms S and context κ.

$$P = (p(\text{top } 1 \text{ to } k \in C \mid S, \kappa)) \,. \tag{6.1}$$

Context κ allows dual entropy adjustment through three parameters: temperature, top-k value, and contentiousness level Δ. A distribution tends toward high entropy when these parameters are set high, and toward low entropy when set low.

The initial confidence distribution P from LLMs (Eq.6.1) represents confidence scores rather than absolute probabilities. In the EVINCE framework, these scores are calibrated through multi-iteration debates where

predictions must be supported by arguments and examined by counterarguments. The CRIT algorithm (detailed in Appendix B) evaluates reasoning quality to adjust these confidence scores—reducing credibility when high-confidence predictions lack strong supporting evidence.

Since EVINCE and CRIT can employ different LLMs, and CRIT focuses solely on evaluating reasoning quality via Socratic methods, this collaborative approach uses reasoning quality as a proxy for confidence calibration. This sidesteps the fundamental challenge of generating reliable absolute probabilities from LLMs ([24, 27]).

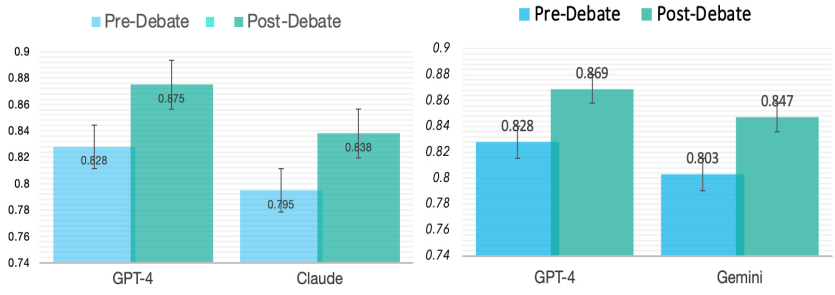
For example, if an LLM outputs confidence scores P = (0.5, 0.3, 0.2) for its top-3 predicted diseases, and CRIT evaluates their supporting arguments as having strength (50%, 100%, 50%), the calibrated scores become (0.25, 0.3, 0.1). After normalization, the final distribution is P = (0.38, 0.46, 0.16).

Resources, Dataset & Data Preparation: Our study utilizes a dataset from Kaggle [22], comprising 4,921 patient records. Each record includes the diagnosed disease and up to 17 symptoms (e.g., fever, cough, fatigue, itchiness, difficulty breathing). After removing duplicates, we obtain 304 unique diagnostic instances spanning 40 diseases. Each instance serves as a test case where EVINCE leverages the inherent knowledge of LLMs (GPT-4, Gemini, and Claude3) without training them through few-shot techniques on this specific dataset. Our computing resources are sponsored by Azure through a Stanford grant.

Evaluation: We assess prediction quality using the top-k Mean Reciprocal Rank (MRR). If one of the top-k predicted diseases matches the ground truth diagnosis, the score is the reciprocal of its rank (1 for the top prediction, 1/2 for the second, 1/3 for the third, etc.). If none of the top-k predictions are correct, the score is 0.

6.3.1 Study #1: Post vs. Pre-Debate Accuracy

We employed GPT-4, Gemini, and Claude3 to perform independent disease predictions on 304 patient instances, then used EVINCE to pair them and evaluate performance gain.



(a) GPT4 pairs Claude (b) GPT4 pairs Gemini

Figure 6.2: Pre-/post-debate accuracy on all patients on all diseases shows EVINCE helps

Experimental Setup: We set $k = 5$ for both LLM agents, with one agent at high temperature and the other at low temperature. The contentiousness level was set very high ($\Delta = 0.9$ out of 1) to encourage significant cross entropy. Setting $k = 5$ ensures some minimal common ground, fostering meaningful interaction. High contentiousness promotes counterarguments and information exchange.

Pre- and Post-Debate Evaluation: We conducted two sets of experiments:

1. **Constrained Prediction (Baseline):** We limited disease predictions to the 40 labels in the dataset, mimicking common supervised learning assumptions. This yielded high accuracy (95-97%) but is unrealistic for real-world diagnosis where general practitioners consider all possibilities. This constraint highlights LLMs' flexibility, as they're less prone to overfitting erroneous labels (further discussed in subsequent studies).

2. **Unconstrained Prediction:** We removed the label constraint to better simulate real-world conditions. All 304 patient cases yielded stable results across GPT-4, Gemini-3, and Claude-3, with a standard deviation of just 1.5%. Prior to debate (light blue bars in Figure 6.2), GPT-4 led in accuracy (82.8%), followed by Gemini (80.3%) and Claude (79.5%).

EVINCE **Performance:** Implementing EVINCE with GPT-4 and Claude-3 pairing and GPT-4 and Gemini-3 pairing consistently improved accu-

racy by 4-5 percentage points (green bars in Figure 6.2). The GPT-4 and Claude-3 pairing achieved 87.5% accuracy (Figure 6.2a), rivaling state-of-the-art clinical performance like the REFUEL algorithm [25].

Discussion: With diversity and reasoning encouraged, EVINCE outperforms the baseline, single LLM predictions. The remaining 12.5% inaccuracy for the GPT-Claude pairing might not be solely attributable to EVINCE. Considering the potential 11% US misdiagnosis rate reported by Johns Hopkins [20], this discrepancy could indicate mislabeled data in the original dataset. This presents a groundbreaking opportunity: EVINCE could potentially identify and correct errors in existing datasets, a concept we explore further in Section 6.3.3.

6.3.2 Study #2: Confusion vs. Opportunities

	Hep. A	Hep. B	Hep. C	Hep. D	Hep. E
Hep. A	50%				50%
Hep. B		50%	50%		
Hep. C	100%				
Hep. D					100%
Hep. E					100%

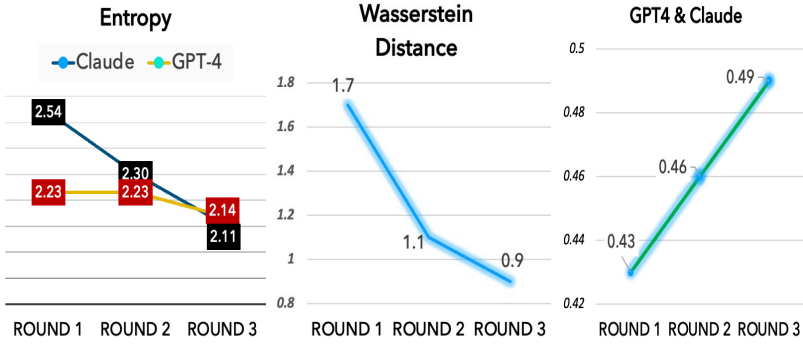
(a) GPT liver c-matrix

	Hep. A	Hep. B	Hep. C	Hep. D	Hep. E
Hep. A	74%		36%		
Hep. B		50%	50%		
Hep. C			36%	64%	
Hep. D	60%			40%	
Hep. E					100%

(b) Claude liver c-matrix

Figure 6.3: Confusion matrices

Two primary factors contribute to EVINCE's improved diagnostic accuracy. First, structured debates with reasoning encourage LLMs to explore alternative diagnoses both broadly and deeply, leading to more comprehensive analysis and decision-making (see Appendices D and E). Second, pairing LLMs with high- and low-entropy prediction distributions, or those with a large Wasserstein distance (WD) between them, balances exploratory diversity with exploitative stability. This approach results in more robust and higher-quality decisions, as demonstrated in this second study.



(a) Entropy (b) WD % (c) Norm. MI

Figure 6.4: Entropy, WD, and normalized MI

Analysis of Confusion Matrices: We use confusion matrices to analyze two LLMs' performance in diagnosing Hepatitis types A to E (Fig. 6.3):

- GPT-4 shows limited accuracy, particularly for types C and D, achieving only 50% accuracy for types A and B.
- Claude exhibits a wider spread of predictions across all Hepatitis types.

These matrices highlight how Claude's flexibility in exploring diverse diagnostic hypotheses aids the debate process. Claude's initial uncertainty (high entropy) brings new information, potentially challenging and correcting GPT-4's more confident (low entropy) predictions. This dynamic interplay exemplifies EVINCE's balance between exploration and exploitation, leading to potentially more accurate and comprehensive diagnoses.

Observations from Information Metrics:

- Entropy Stabilization: Figure 6.4a shows entropy levels of both LLMs stabilizing after three debate rounds, indicating convergence towards a similar, stable entropy state.
- Wasserstein Distance Improvement: Figure 6.4b demonstrates consistent improvement in Wasserstein distance (WD) between the two models' predictions over successive rounds.
- Mutual Information Increase: Figure 6.4c reveals a 14% improvement

in normalized mutual information (MI) between GPT-4 and Claude's prediction distributions, suggesting increased shared information throughout the debate.

- Convergence of Divergence Metrics: Figure 6.5 shows consistent convergence of all divergence metrics.

Comparative Performance: EVINCE improves 5 percentile accuracy in diagnosing specific types of liver diseases compared to a baseline approach (Figure 6.2a), underscoring its capability to handle complex diagnostic scenarios effectively.

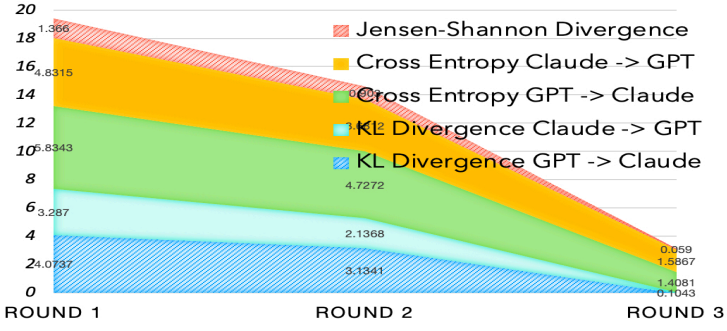
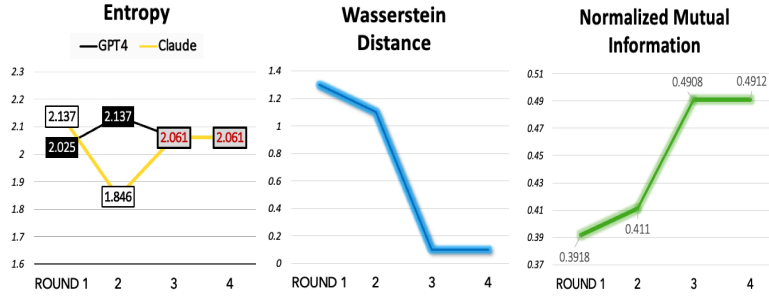


Figure 6.5: Convergence of all metrics

6.3.3 Study #3: Ground-Truth Remediation

This study illustrates how EVINCE can identify potential misdiagnoses, explain the reasoning behind them, and recommend corrective actions. Traditionally, machine learning scientists rely on labeled data as "ground truth." However, as evidenced by research like that of [21] from Johns Hopkins, misdiagnosis is a widespread issue in healthcare systems globally. These erroneous diagnoses, often treated as ground truth, can be perpetuated by supervised learning algorithms, exacerbating the problem within the healthcare system. EVINCE's dialogue capabilities provide insights into the decision-making process and highlight missing information, helping to rectify erroneous predictions and redefine the ground truth.

This approach offers a potential solution to the compounding effect of misdiagnoses in machine learning applications in healthcare.



(a) GPT & Claude (b) WD % (c) Mutual Info.

Figure 6.6: Remediation: Jaundice to Hepatitis

Figure 6.6, which plots the respective entropies of GPT-4 and Claude, reveals two key insights. First, an large gap in Wasserstein Distance (WD) exists between the two models in the initial rounds. This disparity underscores the role of dual entropy in fostering information exchange. As the entropy values converge in rounds 3 and 4 and WD decreases significantly, we observe a corresponding convergence and stabilization of their mutual information. The information metrics that EVINCE employs effectively show the progress of the dialogue and convergence from explorative to consensus. Figure 6.7 illustrates the convergence of all divergence metrics—including Jensen-Shannon divergence, cross-entropy, and Kullback-Leibler divergence—particularly between the second and third rounds.

Appendix F demonstrates that EVINCE recommends additional symptoms to inquire about with the patient, as well as lab tests to confirm the diagnosis. These suggestions, validated by our hospital partners, provide valuable information to enhance diagnostic accuracy and correct errors.

6.3.4 Experiment Remarks

EVINCE initiates debates with high contentiousness, encouraging dual prediction entropy between LLMs, as supported by the EDT theorem.

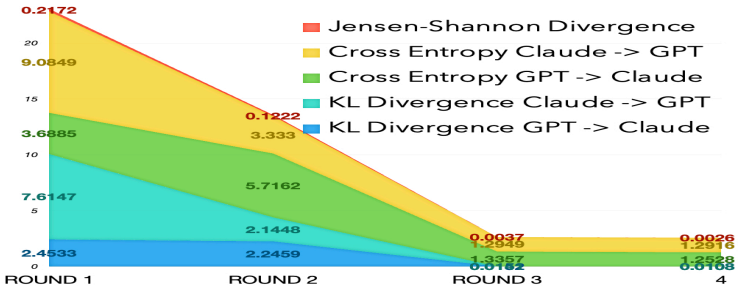


Figure 6.7: Convergence of all metrics

It utilizes normalized mutual information (MI) to track shared knowledge accumulation throughout the debate, while Wasserstein distance (WD) and Jensen-Shannon divergence (JSD) quantify dissimilarity between LLM predictions.

These metrics (EDT, WD, JSD, MI) provide a comprehensive view of debate progress. WD and JSD assess the potential for further communication and refinement, while MI monitors shared understanding, aiding in determining the optimal stopping point.

The asymmetric nature of KL divergence and cross entropy warrants further investigation. Despite eventual convergence in our case studies, discrepancies observed in the second round (one direction increasing while the other decreases) suggest potential value in exploring asymmetric information. Future work will re-evaluate the use of these metrics if asymmetry proves beneficial.

Besides generating final joint disease predictions, EVINCE provides:

- Recommendations for additional symptom inquiries and lab tests to improve accuracy.

- Suggestions to query symptom onset, duration, severity, trends, and associated symptoms (documented in Appendices D.8 and E.9).

These recommendations have been verified by general practitioners to be valuable.

6.4 Concluding Remarks

This chapter introduces EVINCE, a framework designed to facilitate collaborative dynamics among Large Language Models (LLMs) through structured, adversarial debates. Our research demonstrates that EVINCE significantly advances the pursuit of Artificial General Intelligence (AGI) by enhancing three core characteristics: versatility, adaptivity, and reasoning capability. By addressing key limitations of current AI systems, including hallucination, bias, and limited reasoning, EVINCE provides a novel pathway towards more robust and capable AI.

The core strength of EVINCE lies in its three theoretical pillars: Inclusiveness Exploration, Information Flow Dynamics, and Reasoning Quality and Coherence. These pillars, grounded in conditional statistics and information theory, enable LLMs to transcend their typical "maximal likelihood" behaviors, mirroring human adaptability in linguistic tasks. The integration of the CRIT system, which combines Socratic methods with formal reasoning techniques, further enhances critical thinking and ensures logically sound and objective-aligned collective reasoning.

Our empirical validation demonstrates EVINCE's effectiveness in improving prediction accuracy across various domains, notably achieving a 5% improvement in medical diagnosis tasks. The framework has also shown promise in identifying biases in news articles [7], showcasing its potential for broader applications in fields such as geopolitical analysis [6] corporate planning [30], and emotional behavior modeling [3].

While EVINCE has demonstrated significant potential, our future work will focus on refining key aspects of the system. We aim to enhance the contentiousness parameter by tying it more rigorously to metrics such as Wasserstein distance, mutual information, and CRIT scores. Additionally, we plan to explore alternative methods for inducing dual-entropy conditions, moving beyond current parameters like temperature and top-k selection.

Comprehensive ablation studies will be crucial in determining optimal configurations for various applications, ensuring adaptability to diverse contexts and challenges. Through these continued refinements and explorations, we aim to push the boundaries of collaborative AI frame-

works, bringing us closer to realizing the full potential of artificial general intelligence.

In conclusion, EVINCE represents a significant step forward in AI research, offering a structured approach to leveraging the collective intelligence of multiple LLMs. By addressing current limitations and enhancing key AGI characteristics, EVINCE paves the way for more versatile, adaptive, and capable AI systems, bringing us closer to the goal of artificial general intelligence.

Appendix A: Information Metrics

Metric	**Pros**	**Cons**
Cross-Entropy [29]	Measures how well the predictions of a model fit the actual distribution of another one's outputs; asymmetric.	Computationally intensive with large models and datasets; sensitive to the exact nature of probability distributions.
Entropy [28]	Indicates level of diversity; high suggests exploration of possibilities, and low for confidence on few choices	High entropy might indicate noise rather than useful diversity; low entropy might mask important variability.
Jensen-Shannon Div. (JS) [18]	Symmetric and bounded (0, 1), providing an interpretable measure of distributional differences.	May be less sensitive to small differences between distributions.
KL Divergence [15]	Measures difference between two probabilistic distributions.	Asymmetric; not well-defined if a distribution has zero probabilities
Mutual Info [29] (MI)	Measures reduction of uncertainty; symmetric.	Does not indicate information flow direction.
Wasserstein Dist. (WD) [14]	Direct measure similar of model outputs, depicting symmetric relationship.	Not bounded but can be normalized for consistent interpretation.

Table 6.1: Summary of metrics for assessing LLM debates.

This appendix outlines the mathematical formulas for various data

analysis metrics used in probabilistic and statistical modeling. Table 6.1 compares their pros and cons.

Kullback-Leibler Divergence

The Kullback-Leibler Divergence measures the difference between two probability distributions:

$$D_{KL}(P\|Q) = \sum_{x\in\mathcal{X}} P(x)\log\left(\frac{P(x)}{Q(x)}\right).$$

Jensen-Shannon Divergence

The Jensen-Shannon Divergence is a symmetrized and smoothed version of the KL Divergence:

$$JSD(P\|Q) = \frac{1}{2}D_{KL}(P\|M) + \frac{1}{2}D_{KL}(Q\|M)$$

where $M = \frac{1}{2}(P+Q)$.

Wasserstein Distance

The Wasserstein Distance, also known as the Earth Mover's Distance (EMD), measures the distance between two probability distributions:

$$W(P,Q) = \inf_{\gamma\in\Gamma(P,Q)} \int_{\mathcal{X}\times\mathcal{Y}} d(x,y)\, d\gamma(x,y).$$

Cross Entropy

Cross Entropy measures the average number of bits required to identify an event from a set of possibilities, under a specific model:

$$H(P,Q) = -\sum_{x\in\mathcal{X}} P(x)\log(Q(x)).$$

Mutual Information

Mutual Information measures the amount of information that one random variable contains about another random variable:

$$I(X;Y) = \sum_{y\in\mathcal{Y}}\sum_{x\in\mathcal{X}} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right).$$

Normalized Mutual Information

Normalized Mutual Information is calculated as the mutual information divided by the maximum of the entropies of the variables:

$$NMI(X;Y) = \frac{I(X;Y)}{\max(H(X), H(Y))}.$$

Table 6.1 compares the pros and cons of the metrics. Less attractive metrics are those that lack normalization or exhibit asymmetry, though they remain useful when combined with more robust metrics, such as Wasserstein distance, cross-entropy, and mutual information, to detect abnormalities. For example, KL divergence and Jensen-Shannon divergence can complement each other, capturing finer resolution and avoiding zero probabilities. Table 6.2 provides suggested remedies to enhance the computational efficiency and effectiveness of these metrics.

Metric	**Remedies to Shortcomings**
Cross Entropy	Optimize computation strategies; use approximations or sampling methods to manage large data sets or complex models.
Entropy	Use critical reading inquisitive template (CRIT) to assess argument quality; implement noise detection to differentiate between useful diversity and noise.
Jensen-Shannon Divergence	Increase sensitivity settings or resolution of the metric; combine with other metrics to capture finer distinctions between distributions.
KL Divergence	Use smoothing techniques to avoid zero probabilities; consider symmetric alternatives like JS divergence
Mutual Information	Supplement with directional information metrics; normalized with max entropy of A and B.
Wasserstein Distance	Define context-specific bounds for low, medium, and high divergence; consider normalization for non-directional comps.

Table 6.2: Remedies to Metric Shortcomings.

	Function Γ = **CRIT**(d)
	Input. d: document; **Output**. Γ: validation score;
	Vars. Ω: claim; R & R': reason & counter reason set;
	Subroutines. $Claim()$, $FindDoc()$, $Validate()$;
	Begin
#1	Identify in d the claim statement Ω;
#2	Find a set of supporting reasons R to Ω;
#3	For $r \in R$ eval $r \Rightarrow \Omega$
	If $Claim(r)$, (γ_r, θ_r) = CRIT($FindDoc(r)$);
	else, $(\gamma_r, \theta_r) = V(r \Rightarrow \Omega)$;
#4	Find a set of rival reasons R' to Ω;
#5	For $r' \in R'$, $(\gamma_{r'}, \theta_{r'})$ = V($r' \Rightarrow \Omega$) eval rival arguments;
#6	Compute weighted sum Γ, with γ_r, θ_r, $\gamma_{r'}$, $\theta_{r'}$.
#7	Analyze the arguments to arrive at the Γ score.
#8	Reflect on and synthesize CRIT in other contexts.
	End

Table 6.3: CRIT Pseudo-code. (The symbol $\Rightarrow$ denotes both inductive and deductive reasoning.)

Appendix B: CRIT, Critical Thinking, Evaluative Phase of EVINCE

EVINCE uses the Socratic method to evaluate the "reasonableness" of a set of arguments that support a subject matter. The Socratic method is a questioning technique used in teaching and philosophy to encourage critical thinking and self-discovery [32]. The method involves asking a series of questions to explore complex ideas and help individuals arrive at their own understanding of a concept. It is based on the belief that knowledge cannot be simply imparted, but must be discovered through a process of questioning and dialogue.

To illustrate how these methods can practically be applied, let's use the example of critical reading. Critical reading is a crucial component of critical thinking, which involves evaluating the quality and credibility of written materials, from research papers to blog posts [16, 23]. It requires a

systematic and analytical approach, asking relevant questions, and using effective prompts to gain deeper understanding of the text [11].

To aid in critical reading, we introduce a prompt template called CRIT [4], which stands for Critical Reading Inquisitive Template. Given a document d, CRIT evaluates it and produces a validation score Γ. Let Ω denote the conclusion or claim of d, and let R be the set of reasons supporting the claim. We define $(\gamma_r, \theta_r) = \mathrm{V}(r \Rightarrow \Omega)$ as the causal validation function, where γ_r denotes the validation score, θ_r the source credibility score, for each reason-to-conclusion argument $r \Rightarrow \Omega$. Table 6.3 presents the pseudo-code of $\Gamma = \mathrm{CRIT}(d)$, which generates the final validation score Γ for document d with justifications.

EVINCE uses CRIT to evaluate argument quality of the participating LLMs involved in the debate. The input to CRIT from each LLM is first its stance on the debate subject, e.g., a set of predicted diseases, and the arguments are its reasons to arrive at the prediction. Each document in the case of EVINCE is the prediction set as the conclusion Ω, the arguments as set R, and the opposing LLM's counterarguments as R'. With this document, CRIT is able to produce validity and credibility scores in Γ for the LLM.

For detailed prompts, examples, and an empirical study verifying the effectiveness of CRIT, please consult [4].

Appendix C: Proof of EDT Theorem

Theorem EDT: Optimal Pairing of LLMs for Probabilistic Prediction Accuracy. The optimal pairing of LLMs for diagnosis accuracy, in terms of stability, accuracy, and robustness, occurs when the LLMs are equivalent in the quality of the information they process, and exhibiting contrasting entropy values in their prediction distributions—one high and one low.

[Proof]: Given two LLMs, LLM_A and LLM_B, following Maxim #1 with prediction distributions P_A and P_B, respectively. The information entropy of LLM_A, $H(P_A)$, is high, and of LLM_B, $H(P_B)$, is low.

Step 1: Define the combined prediction distribution. Let the combined prediction distribution of LLM_A and LLM_B be denoted as P_C. We can express P_C as a weighted average of P_A and P_B:

$$P_C = \alpha P_A + (1-\alpha)P_B, \quad \text{where } 0 \leq \alpha \leq 1 \text{ and}$$

$$\alpha \text{ is decided by CRIT in Appendix A.}$$

Step 2: Express the information entropy of the combined prediction distribution. Using the definition of information entropy, we calculate:

$$H(P_C) = -\sum_i P_C(x_i) \log_2 P_C(x_i)$$
$$= -\sum_i [\alpha P_A(x_i) + (1-\alpha)P_B(x_i)] \log_2 [\alpha P_A(x_i) + (1-\alpha)P_B(x_i)].$$

Step 3: Apply Jensen's Inequality to the information entropy of the combined prediction distribution. Jensen's inequality is applied to the convex function $f(x) = -x \log_2 x$. For a convex function and a set of probabilities p_i, Jensen's inequality states that:

$$f\left(\sum_i p_i x_i\right) \leq \sum_i p_i f(x_i)$$

Thus, the entropy of the combined distribution is:

$$H(P_C) \geq \alpha H(P_A) + (1-\alpha)H(P_B)$$

where equality holds when $P_A = P_B$.

Step 4: Analyze the lower bound of the combined information entropy. As $H(P_A)$ is high and $H(P_B)$ is low, we can express their relationship as:

$$H(P_A) = H(P_B) + \Delta, \quad \text{where } \Delta > 0.$$

Substituting this into the inequality from Step 3, we have:

$$H(P_C) \geq \alpha[H(P_B) + \Delta] + (1-\alpha)H(P_B) = H(P_B) + \alpha\Delta.$$

Step 5: Interpret the lower bound of the combined information entropy. The lower bound of $H(P_C)$, and hence the robustness of the model, is maximized when α is maximized, which corresponds to giving more weight to the high-entropy model (LLM_A). This setup facilitates the exploration of diverse possibilities and enhances robustness against noise and perturbations in the input data, while still ensuring that predictions are grounded by the more certain outcomes predicted by the low-entropy model (LLM_B).

Step 6: Conclude the proof. By combining the prediction distributions of LLM_A and LLM_B, with one having high information entropy and the other low, we achieve an optimal balance that maximizes the lower bound of the combined information entropy. This balance between exploration (high entropy) and exploitation (low entropy) optimizes overall prediction accuracy and robustness, as proved through information theory and the properties of entropy. Thus, the theorem is established.

Appendix D: EVINCE Debate - Dengue Fever vs. Chikungunya

This experiment addresses a diagnostic challenge involving multiple potential diseases. A patient presents with the following 12 symptoms: [*skin rash, joint pain, vomiting, fatigue, high fever, headache, nausea, loss of appetite, pain behind the eyes, back pain, malaise, muscle pain, red spots over the body*]. In this case, GPT-4 provides the initial diagnosis, with Gemini following suit. The confirmed diagnosis for this experiment is Dengue Fever. Given the satisfactory diversity in predictions from the two LLMs, the debate progresses and converges smoothly.

D.1 Moderator's Prompt

"Identify potential diseases linked to the symptoms (skin rash, joint pain, vomiting, etc.). Provide top-3 predictions with justifications, supplementary symptom inquiries, and relevant lab tests."

D.2 GPT-4's Opening Round

Top-3 Predictions: *Dengue Fever (60%), Chikungunya (25%), and Zika Virus (15%).*

Justifications: Most symptoms are classic signs of Dengue Fever. Red spots over the body could correspond to petechiae, often seen in Dengue due to thrombocytopenia (a decrease in platelet count).

Chikungunya can cause similar symptoms to Dengue, such as fever, severe joint pain, muscle pain, headache, nausea, and rash. Joint pain from Chikungunya is often very debilitating and can be more prolonged than in Dengue.

Zika Virus symptoms can include fever, rash, joint pain, malaise, and conjunctivitis, with a milder presentation compared to Dengue or Chikungunya. The presence of a rash and conjunctivitis is notable, although Zika is less likely to cause severe muscle pain or high fever.

D.3 Gemini's Opening Round

Top-3 Predictions: *Viral Infection (60%), Autoimmune Disease (20%), Bacterial Infection (15%).*

Justifications: Symptoms common in viral infections. Autoimmune diseases is possible, but less likely due to vomiting and nausea. Bacterial infection is less probable given rash and muscle pain.

D.4 GPT-4's Second Round

Top-3 Predictions: *Dengue Fever (60%), Chikungunya (25%), and Zika Virus (15%).*

Justifications: GPT-4 maintains its predictions, countering Gemini's assessment with three points. First, while viral infections can cause these symptoms, the specific combination suggests a more targeted diagnosis. Second, the acute onset of high fever, joint pain, and rash is less typical for autoimmune diseases. Finally, the rash and red spots are not characteristic of bacterial meningitis.

D.5 Gemini's Second Round

Top-3 Predictions: *Dengue Fever (50%), Chikungunya (30%), and Viral Infection (20%).*
Justifications: Gemini's initial prediction considers a Viral Infection as the most likely cause due to its broad range of potential symptoms. However, GPT-4's focus on Dengue Fever and Chikungunya, with their specific symptom profiles, provides a more precise explanation for the patient's condition. Here's what is lacking in the first set of predictions:

- *Specificity*: While a Viral Infection could explain most symptoms, it does not account for joint pain and the presence of a rash, which are more characteristic of DF or Chikungunya.
- *Detailed justifications*: The first analysis does not delve as deeply into the reasons behind each disease possibility. GPT-4's explanation for Dengue Fever and Chikungunya is more comprehensive, strengthening the connection between symptoms and diagnosis.
- *Importance of additional information*: Emphasize how geographic location and travel history can significantly impact the likelihood of these specific diseases.

D.6 GPT-4's Third Round

Top-3 Predictions: *Dengue Fever (60%), Chikungunya (35%), and Zika Virus (5%).*
Justifications: Though GPT-4 slightly adjusts probabilities, it considers the adjustment arbitrary without new information that would specifically shift the likelihood between Dengue and Chikungunya. GPT-4 refutes Gemini's Viral Infection prediction as lacking specificity. The symptoms described are quite distinctive and align closely with specific viral infections transmitted by mosquitoes.

D.7 Gemini's Third Round

Top-3 Predictions: *Dengue Fever (60%), Chikungunya (35%), and Zika Virus (5%).*

Justifications: Agreeing that GPT's critique is spot-on, and reiterating the need for more info.

D.8 Final Joint Recommendations to GP

After seeking further input from GPT-4, Gemini fully concurs with GPT-4's final suggestions, even though the moderator instructs Gemini to maintain its original stance. Both LLMs jointly recommend additional symptom examinations and lab tests:

A comprehensive diagnostic approach for Dengue Fever requires a combination of clinical assessment, laboratory testing, and consideration of the patient's travel and vaccination history, as well as the epidemiological context. Clinical symptoms such as skin rash, joint pain, vomiting, and red spots over the body provide valuable clues to the diagnosis, but additional symptoms like nausea, vomiting, diarrhea, bleeding, bruising, and drowsiness can indicate the severity and progression of the disease.

Recommended Laboratory Tests:

- *Complete Blood Count (CBC)*: Identify thrombocytopenia or leukopenia.
- *Serology Tests*: Detect specific IgM and IgG antibodies for Dengue, Chikungunya, and Zika.
- *Polymerase Chain Reaction (PCR)*: Direct detection of viral RNA.
- *NS1 Antigen Test for Dengue*: Early and specific detection of Dengue virus.
- *Urine Test for Zika*: Viral presence in urine.

Appendix E: EVINCE Debate - Jaundice vs. Hepatitis

In this experiment, GPT-4 and Claude receive an identical list of symptoms from the moderator, aimed at guiding disease diagnosis, facilitating debate, and shaping subsequent recommendations. The "ground-truth" disease is Jaundice. (We do not shorten the debate content for review.)

E.1 Moderator's Opening Prompt

"What potential disease could be associated with the following symptoms: itching, vomiting, fatigue, weight loss, high fever, yellowish skin, dark urine, and abdominal pain? Please offer top-five predictions with probabilities normalized to one, supported by justifications. Additionally, in the end of debate, include a list of supplementary symptom inquiries and recommend relevant lab tests to strengthen the confidence in your prediction."

E.2 GPT-4 Opening Round

- *Hepatitis C (HCV)*: 40% **Justification**: Hepatitis C is a viral infection that can cause both acute and chronic hepatitis. The combination of symptoms like fatigue, abdominal pain, nausea, vomiting, jaundice, dark urine, and weight loss strongly suggests HCV. Itching may also occur due to liver dysfunction.
- *Hepatitis B (HBV)*: 30% **Justification**: Hepatitis B is a viral infection that can cause acute or chronic liver inflammation. Symptoms are similar to HCV, including fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice, and itching. The presence of these symptoms warrants testing for both HBV and HCV.
- *Cirrhosis*: 15% **Justification**: Cirrhosis is a late stage of liver scarring that can result from various liver diseases. The combination of symptoms like fatigue, weight loss, abdominal pain, jaundice, dark urine, and itching suggests advanced liver disease, possibly cirrhosis.
- *Obstructive Jaundice*: 10% **Justification**: Obstructive jaundice occurs when there is a blockage in the bile ducts. The presence of jaundice, dark urine, itching, abdominal pain, nausea, vomiting, and weight loss suggests a possible obstruction. However, the absence of fever makes an infectious cause like cholangitis less likely.
- *Acute Liver Failure*: 5% **Justification**: Acute liver failure is a rare but life-threatening condition characterized by rapid deterioration of liver function. The presence of jaundice, abdominal pain, nausea, vomiting, fatigue, and itching, along with the acute onset of symptoms, may

indicate acute liver failure. However, the absence of altered mental status (hepatic encephalopathy) makes this less likely.

E.3 Claude Opening Round

- *Hepatitis B (HBV)*: 35% **Reasoning**: Hepatitis B is a viral infection that can cause acute or chronic liver inflammation. Symptoms include fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice, joint pain, and itching.
- *Hepatitis C (HCV)*: 25% **Reasoning**: Hepatitis C is a viral infection that can cause both acute and chronic hepatitis. Symptoms are similar to HBV but may also include weight loss and fever. Jaundice is a common symptom.
- *Obstructive Jaundice (due to gallstones, pancreatic cancer, or bile duct obstruction)*: 20% **Reasoning**: Obstructive jaundice occurs when there is a blockage in the bile ducts, preventing bile from reaching the intestines. This can lead to yellowing of the skin and eyes, dark urine, itching, abdominal pain, nausea, and vomiting.
- *Alcoholic Hepatitis*: 15% **Reasoning**: Alcoholic hepatitis is liver inflammation caused by excessive alcohol consumption. Symptoms include abdominal pain, nausea, vomiting, fatigue, dark urine, and possibly fever and weight loss.
- *Hepatitis A (HAV)*: 5% **Reasoning**: Hepatitis A is an acute, self-limiting liver infection transmitted through contaminated food or water. Symptoms include fatigue, abdominal pain, nausea, vomiting, dark urine, and jaundice.

E.4 GPT-4 Second Round

- *Hepatitis B (HBV)*: 35% **Symptoms**: fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice (yellowish skin), joint pain, itching
- *Hepatitis C (HCV)*: 25% **Symptoms**: fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice (yellowish skin), weight loss, fever, itching

- *Obstructive Jaundice (due to gallstones, pancreatic cancer, or bile duct obstruction)*: 20% **Symptoms**: yellowish skin (jaundice), dark urine, itching, abdominal pain, nausea, et al.
- *Alcoholic Hepatitis*: 15% **Symptoms**: abdominal pain, nausea, vomiting, fatigue, jaundice (yellowish skin), dark urine, fever, weight loss
- *Hepatitis A (HAV)*: 5% **Symptoms**: fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice (yellowish skin)

E.5 Claude Second Round

- *Hepatitis C (HCV)*: 40% **Reasoning**: Hepatitis C is a viral infection that can cause both acute and chronic hepatitis. The combination of symptoms like fatigue, abdominal pain, nausea, vomiting, jaundice, dark urine, and weight loss strongly suggests HCV. Itching may also occur due to liver dysfunction.
- *Hepatitis B (HBV)*: 30% **Reasoning**: Hepatitis B is a viral infection that can cause acute or chronic liver inflammation. Symptoms are similar to HCV, including fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice, and itching. The presence of these symptoms warrants testing for both HBV and HCV.
- *Cirrhosis (due to various causes such as chronic hepatitis, alcohol abuse, or non-alcoholic fatty liver disease)*: 15% **Reasoning**: Cirrhosis is a late stage of liver scarring that can result from various liver diseases. The combination of symptoms like fatigue, weight loss, abdominal pain, jaundice, dark urine, and itching suggests advanced liver disease, possibly cirrhosis.
- *Obstructive Jaundice (due to gallstones, pancreatic cancer, or bile duct obstruction)*: 10% **Reasoning**: Obstructive jaundice occurs when there is a blockage in the bile ducts. The presence of jaundice, dark urine, itching, abdominal pain, nausea, vomiting, and weight loss suggests a possible obstruction. However, the absence of fever makes an infectious cause like cholangitis less likely.
- *Acute Liver Failure (due to various causes such as viral hepatitis, drug-induced liver injury, or autoimmune hepatitis)*: 5% **Reasoning**: Acute liver failure is a rare but life-threatening condition characterized by

rapid deterioration of liver function. The presence of jaundice, abdominal pain, nausea, vomiting, fatigue, and itching, along with the acute onset of symptoms, may indicate acute liver failure. However, the absence of altered mental status (hepatic encephalopathy) makes this less likely.

E.6 GPT-4 Third Round

- *Hepatitis C (HCV)*: 35% **Reasoning**: Hepatitis C is indeed a major cause of the symptoms listed, including fatigue, abdominal pain, nausea, vomiting, jaundice, dark urine, and weight loss. Itching can also occur due to liver dysfunction.
- *Hepatitis B (HBV)*: 25% **Reasoning**: Hepatitis B shares many symptoms with Hepatitis C, such as fatigue, abdominal pain, nausea, vomiting, dark urine, jaundice, and itching. Testing for both HBV and HCV is warranted given the overlap in symptoms.
- *Cirrhosis*: 20% **Reasoning**: Cirrhosis can result from chronic hepatitis, alcohol abuse, or non-alcoholic fatty liver disease. The symptoms of fatigue, weight loss, abdominal pain, jaundice, dark urine, and itching strongly suggest advanced liver disease, which could be cirrhosis.
- *Obstructive Jaundice*: 15% **Reasoning**: Obstructive jaundice, caused by gallstones, pancreatic cancer, or bile duct obstruction, is consistent with jaundice, dark urine, itching, abdominal pain, nausea, vomiting, and weight loss. The absence of fever reduces the likelihood of an infectious cause like cholangitis.
- *Acute Liver Failure*: 5% **Reasoning**: Acute liver failure is less common but serious, characterized by rapid deterioration of liver function. The symptoms of jaundice, abdominal pain, nausea, vomiting, fatigue, and itching, along with the acute onset of symptoms, suggest this possibility. However, the absence of altered mental status (hepatic encephalopathy) makes it less likely.

E.7 Claude Third Round

- *Hepatitis C (HCV)*: 35% **Reasoning**: I slightly lowered the probability of HCV from 40% to 35%. While the combination of symptoms strongly

suggests HCV, the absence of a few key risk factors (e.g., history of intravenous drug use or blood transfusions) in the given information makes me less confident in assigning a higher probability.

- *Hepatitis B (HBV)*: 30% **Reasoning**: I agree with the 30% probability assigned to HBV. The symptoms are indeed similar to HCV, and testing for both viruses is warranted.
- *Cirrhosis*: 20% **Reasoning**: I increased the probability of cirrhosis from 15% to 20%. The presence of jaundice, dark urine, itching, and weight loss, along with the other symptoms, strongly suggests advanced liver disease. Cirrhosis can be a consequence of chronic liver diseases like hepatitis B or C, which have been assigned higher probabilities.
- *Obstructive Jaundice*: 10% **Reasoning**: I agree with the 10% probability for obstructive jaundice. The absence of fever makes an infectious cause like cholangitis less likely, but the other symptoms still suggest a possible obstruction.
- *Acute Liver Failure*: 5% **Reasoning**: I agree with the 5% probability for acute liver failure. While the combination of symptoms could indicate acute liver failure, the absence of altered mental status (hepatic encephalopathy) makes this diagnosis less likely.

E.8 Joint Final Round

1. *Hepatitis C (HCV)* - 35% **Justification**: The combination of symptoms strongly suggests HCV, but without additional risk factors, a slightly lower probability is appropriate.
2. *Hepatitis B (HBV)* - 30% **Justification**: The symptoms are similar to HCV, and testing for both viruses is necessary.
3. *Cirrhosis* - 20% **Justification**: The presence of jaundice, dark urine, itching, weight loss, and other symptoms indicates advanced liver disease, making cirrhosis a more likely possibility.
4. *Obstructive Jaundice* - 10% **Justification**: The absence of fever reduces the likelihood of an infectious cause like cholangitis, but the other symptoms still suggest a potential biliary obstruction.

5. *Acute Liver Failure* - 5% **Justification**: While the combination of symptoms could indicate acute liver failure, the absence of altered mental status makes this diagnosis less probable.

E.9 Final Joint Recommendations to GP

Gemini and GPT-4 jointly recommend the following additional symptom inquiries and lab tests to confirm a hepatitis diagnosis:

Additional Symptom Inquiries:

1. *Onset and Duration*: Determining the onset and duration of symptoms can clarify the illness timeline and its progression.
2. *Severity and Trend*: Evaluating symptom severity and whether they are worsening or improving aids in understanding the disease's trajectory and treatment responses.
3. *Associated Symptoms*: Checking for additional symptoms like nausea, vomiting, fever, joint pain, or urine color changes can pinpoint other hepatitis indicators and exclude other conditions.

Recommended Lab Tests:

1. *Liver Function Tests (LFTs)*: Critical for assessing liver health, LFTs evaluate enzyme levels such as alanine aminotransferase (ALT) and aspartate aminotransferase (AST), where abnormalities can signify liver inflammation.
2. *Hepatitis Panel*: This test checks for hepatitis A, B, and C viruses, vital for determining the specific type and guiding treatment strategies.
3. *Serology Testing*: Useful for distinguishing between acute and chronic hepatitis by identifying specific antibodies or antigens.
4. *Imaging Studies*: Ultrasound or MRI can provide visual insights into the liver's state, detecting inflammation, fibrosis, or cirrhosis, thereby complementing blood-based diagnostics.

Appendix F: Explainability and Rectification

The power of EVINCE lies not only in its enhanced accuracy but also in its ability to elucidate the decision-making process and identify missing information, providing critical insights to correct errors.

Although the final joint prediction for Hepatitis C reached a high consensus of 37.5%, it deviates from the actual condition of Jaundice, which the Kaggle dataset reports with 10% confidence. EVINCE provides general practitioners with alerts and suggests remedial actions (see Appendices D.8 and E.9) to address this discrepancy. Recommended actions include querying additional symptoms from the patient and conducting specific laboratory tests.

EVINCE initiates debates with high contentiousness, encouraging dual prediction entropy between LLMs, as supported by the EDT theorem. It utilizes normalized mutual information (MI) to track shared knowledge accumulation throughout the debate, while Wasserstein distance (WD) and Jensen-Shannon divergence (JSD) quantify dissimilarity between LLM predictions.

These metrics (EDT, WD, JSD, MI) provide a comprehensive view of debate progress. WD and JSD assess the potential for further communication and refinement, while MI monitors shared understanding, aiding in determining the optimal stopping point.

The asymmetric nature of KL divergence and cross entropy warrants further investigation. Despite eventual convergence in our case studies, discrepancies observed in the second round (one direction increasing while the other decreases) suggest potential value in exploring asymmetric information. Future work will re-evaluate the use of these metrics if asymmetry proves beneficial.

Besides generating final joint disease predictions, EVINCE provides:

- Recommendations for additional symptom inquiries and lab tests to improve accuracy.
- Suggestions to query symptom onset, duration, severity, trends, and associated symptoms (documented in Appendices D.8 and E.9).

These recommendations have been verified by general practitioners to be valuable.

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Chapter 7

Uncovering Errors and Biases with Reflective Large Language Models

Abstract Biases and errors in human-labeled data present significant challenges for machine learning, especially in supervised learning reliant on potentially flawed ground truth data. These flaws, including diagnostic errors and societal biases, risk being propagated and amplified through models trained using maximum likelihood estimation. This chapter presents the Reflective LLM Dialogue Framework (RLDF), which leverages structured adversarial dialogues between multiple instances of a single LLM or different LLMs to uncover diverse perspectives and correct inconsistencies. By conditioning LLMs to adopt opposing stances, RLDF enables systematic bias detection through conditional statistics, information theory, and divergence metrics. Experiments show RLDF successfully identifies potential biases in public content while exposing limitations in human-labeled data. Our framework supports measurable progress tracking and explainable remediation actions, offering a scalable approach for improving content neutrality through transparent, multi-perspective analysis.

7.1 Introduction

Errors and biases in human-labeled data present critical challenges for machine learning models, especially in healthcare, news, education, and public policy, where their outputs can profoundly shape public perception and decision-making [21]. Errors, such as diagnostic mistakes, arise from knowledge gaps or lack of expertise, while biases, including ideological and societal distortions, can be consciously or unconsciously introduced by annotators. These flaws compromise the integrity of ground truth data, propagating through machine learning pipelines and generating undesirable outcomes [15, 26, 4].

AI systems are particularly vulnerable to these flaws, as models trained on inaccurate or biased ground truth data tend to replicate and amplify these issues through maximum likelihood estimation. In healthcare, diagnostic errors can lead to poor treatment recommendations [22], while in news, partisan annotations—such as labeling a biased article as neutral—mislead both human readers and automated classifiers, distorting public discourse [21, 13]. The impact extends beyond individual sectors: in education, biased data can reinforce stereotypes, while in public policy, it can result in discriminatory decisions. Ensuring that models learn from accurate and impartial ground truth data is therefore essential to the responsible deployment of AI across all domains.

This chapter focuses on bias detection and correction in news annotations, using news as the testbed to explore how reflective dialogues among LLMs can mitigate biases. News content is particularly vulnerable to ideological biases, as annotators' personal views often shape the interpretation of politically sensitive topics. Real-world evidence, presented in Section 7.4, shows how annotation practices differ based on political affiliation. Tables 7.1 and 7.2 present real data [5] illustrate that Democratic-leaning annotators may judge scandals involving Democrats more harshly than Republicans, and vice versa, highlighting the need for tools to balance these biases.

To address these challenges, we introduce the Reflective LLM Dialogue Framework (RLDF), which implements checks and balances using multiple LLM instances in structured dialogues. RLDF conditions two

instances to take opposing stances: one supports the original label, while the other introduces alternative perspectives. These reflective exchanges foster deeper insights and help uncover potential biases, generating more neutral annotations through the inclusion of diverse viewpoints. This multi-LLM dialogue approach outperforms the results of a single LLM operating in isolation or providing one-off responses.

RLDF employs conditional statistics, information theory, and divergence metrics to measure the effectiveness of these dialogues. Shannon entropy [28] quantifies the diversity of perspectives, while mutual information [9] measures the quality of the exchange. To track the convergence toward unbiased outcomes, we apply Jensen-Shannon divergence (JSD) [19], Wasserstein distance (WD) [14], and cross-entropy (CE) [29], ensuring that the remediation actions are measurable and transparent for further refinement by human reviewers.

Our empirical studies validate the effectiveness of RLDF, and the contributions of this chapter are summarized as follows:

1. Adversarial and Reflective Inspection Framework: RLDF provides a structured framework that encourages adversarial and reflective inspection of ground-truth labels. Through dialogue, participating LLM instances examine, challenge, and explain biases embedded in the original annotations by offering various perspectives. For example, in news annotation, RLDF reveals hidden ideological biases by generating alternative interpretations for politically sensitive content, leading to more neutral labeling.
2. Careful Modulation of Linguistic Behaviors for Balanced Exploration and Exploitation: The effectiveness of RLDF lies in its careful modulation of linguistic behaviors among participating LLM instances, alternating between contentious and conciliatory interactions. This dynamic trade-off fosters exploration of new perspectives while consolidating well-supported viewpoints. Information-theoretic and statistical metrics, including Shannon entropy, mutual information, Jensen-Shannon divergence, Wasserstein distance, and cross-entropy, are employed to measure opinion diversity, information flow, and the strength of the final assessment.
3. Effective Results and Impact on Improving Labels and Mitigating AI

Bias: RLDF successfully mitigates AI biases, ensuring more reliable and unbiased model outputs across domains such as news, healthcare [7], and public policy. These outcomes demonstrate RLDF's significant impact in refining labels, enhancing fairness, and promoting responsible AI deployment.

7.2 Related Work

This study focuses on mitigating training data label (ground truth) bias, a primary concern in machine learning [21]. Accurate labeling is crucial, as a label that aligns with biased content reinforces that bias, while a label that correctly identifies it allows for education and correction [4, 11]. This underscores the importance of label accuracy in minimizing bias propagation.

7.2.1 Label Validation

This work specifically addresses mislabeled ground truth and explores remediation actions. Efforts to improve annotation accuracy can be broadly categorized into three approaches:

Cross-Validation with Multiple Annotators: Using multiple annotators with statistical aggregation techniques has been shown to reduce individual bias and enhance data reliability [30]. This method is effective for consensus tasks with clear-cut answers, such as image labeling in ImageNet [12, 16]. However, for more nuanced content like news and Wikipedia articles, majority voting can be problematic. Annotators may possess varying biases on different subjects, and these biases can be unconscious or context-dependent. It is challenging to comprehensively map an annotator's intrinsic tendencies across all possible topics and scenarios. For instance, political affiliation (e.g., Republican or Democrat) does not necessarily predict other beliefs or preferences (such as dietary choices like vegetarianism). Consequently, relying solely on consensus may not effectively mitigate biases, even with a diverse pool of annotators. Moreover, the assumption of a single, absolute truth inherent in

human annotation methods can limit the capture of multiple valid viewpoints, particularly in complex or contentious topics [3].

Cross-Validation between Machine and Human Annotators: Machine learning models can complement human annotators by enhancing annotation consistency and efficiency [33]. Semi-supervised learning methods, exemplified by Snorkel [24], integrate labeled and unlabeled data to improve model performance. A recent development in this field is the Media Bias Detector (MBD) from the University of Pennsylvania, which utilizes GPT models in conjunction with human raters to analyze potential bias in news articles [23]. MBD systematically examines news content from diverse sources, including CNN and Fox News, at regular intervals throughout the day. It employs advanced language models, specifically GPT-3.5 Turbo and GPT-4, to classify articles. The system assigns a political lean score on a scale from -5 (representing strong left-leaning bias) to 5 (indicating strong right-leaning bias). To enhance accuracy, MBD incorporates human verification of the model's outputs.

While MBD attempts to mitigate bias by separating assessments of political lean and tone, it does not explicitly address the inherent biases that may exist within both the GPT models and the human raters. A significant limitation of this approach lies in the fundamental nature LLMs. These models, trained on vast corpora of text data using maximum-likelihood objectives, tend to prioritize statistically prevalent viewpoints. This training methodology can inadvertently lead to the amplification of majority perspectives at the expense of marginalized or less represented viewpoints, potentially introducing subtle but pervasive biases into the analysis.

7.2.2 Biased Ground Truth

Using Wikipedia as the benchmark for validating the outputs of LLMs has gained attention in recent studies [20, 27]. However, there are notable limitations to this method. First, the specific information serving as the ground truth may not always be available on Wikipedia. If the exact answers are already known to chatbot developers, there would be no need to consult LLMs. Second, the credibility of this approach is further

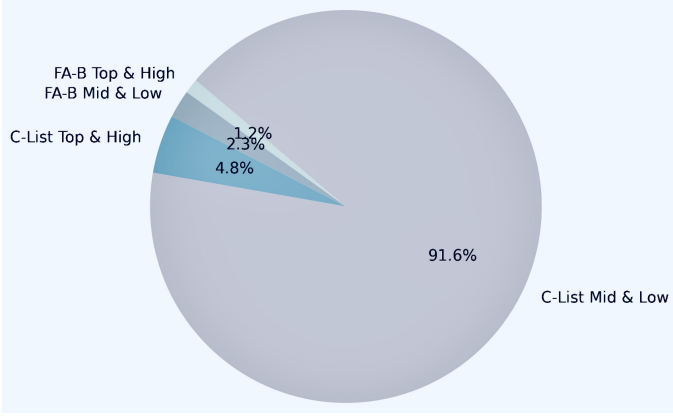

Figure 7.1: Distribution from Top Quality High Importance (1.2%) to Low Quality Low Importance (91.6%). Notably, the blue segment (4.8%) signifies high-importance pages in need of improvement.

challenged by the quality assessment of Wikipedia articles themselves. As indicated in Figure 7.1, 91% of Wikipedia's content is considered to be of middle to low quality by the platform's own editors.

Further, biases are prevalent in Wikipedia and news media, encompassing aspects like gender, race, ideology, and geography, are widely acknowledged. For instance, in Wikipedia, biases manifest as an overrepresentation of certain topics in biographies [32], affecting the balance of content. In the realm of news media, outlets are often categorized by political orientation—ranging from far left to far right—as seen in assessments like those by AllSides [1]. Such classifications are akin to our method of categorizing news articles. Figure 7.2, generated and periodically updated by AllSides, illustrates this point. However, users should interpret the figure with care, acknowledging its potential subjectivity. Nonetheless, it underscores how a single event or story can be portrayed in markedly different ways, depending on the viewpoint.

Figure 7.2: AllSides Fact Check Biase Chart.

7.2.3 Our Contribution: The RLDF Approach

This study aims to address the limitations in MBD and similar frameworks by proposing the Reflective LLM Dialogue Framework (RLDF). RLDF leverages statistical and information-theoretic principles to uncover and balance diverse perspectives, ensuring that both majority and minority viewpoints are adequately represented. Unlike MBD, RLDF introduces structured dialogues between LLM instances, which facilitate deeper reflection and transparent bias mitigation. This approach ensures that annotations are not only accurate but also fair and impartial, im-

proving the reliability of machine learning models across domains.

7.3 Methodology

This section presents our approach in two parts: *debiasing procedure* and *optimization techniques*.

7.3.1 Debiasing Procedure: EVINCE Algorithm

Building upon the theoretical foundations of SocraSynth [8], EVINCE (Entropy and Variation in Conditional Exchanges) [7] promotes content neutrality through the use of structured dialogues among LLMs. In this section, we describe how we customize EVINCE to perform debiasing effectively.

Exploring Divergent Viewpoints Our goal is to generate a broad range of perspectives, even for binary categories such as political leanings. We condition one LLM to support the current ground-truth label while another opposes it, encouraging diverse probability distributions. This approach ensures substantive diversity instead of trivial disagreements. For example, we prefer distributions like (0.5, 0.5) (equal preference on two sub-classes) vs. (1, 0), over mirrored opposites like (1, 0) and (0, 1) (detailed further in Section 7.3.2.).

Modulating contentiousness EVINCE dynamically adjusts the intensity of debates using information-theory metrics such as entropy, cross-entropy, and mutual information (see Appendix A in Chapter 6). Each LLM generates top-k probability distributions of labels, which EVINCE analyzes to guide subsequent interactions. The contentiousness level is adjusted to either encourage exploration or promote convergence as needed.

In the initial dialogue iterations, we prefer low mutual information and high Wasserstein distance between two LLMs' predictions distributions reflect an explorative phase that encourages divergent viewpoints. As agents exchange well-reasoned arguments, mutual information increases,

signaling alignment, while Wasserstein distance decreases, indicating convergence. Once sufficient information exchange occurs, EVINCE reduces contentiousness to foster a more conciliatory atmosphere and guide the agents toward consensus.

Scrutinizing with Reasonableness Following the modulation of contentiousness, EVINCE focuses on evaluating the reasonableness of each LLM's arguments. Each LLM presents supporting evidence for its predictions, which is assessed based on logic, coherence, and credibility.

To ensure quality control, EVINCE uses CRIT [6], a reasonableness evaluation module, to flag weak or unsupported arguments. These flagged arguments are reviewed by human moderators, ensuring that faulty reasoning does not persist in the final outcome. This process balances automated reasoning with human oversight, retaining only those perspectives that survive rigorous scrutiny and ensuring that the resulting consensus reflects well-reasoned, unbiased perspectives.

7.3.2 Optimization and Algorithm Specifications

With all proxy metrics and their pros, cons, and combined strengths comprehensively surveyed in Appendix A in Chapter 6, Algorithm 1 formally specifies the algorithm of EVINCE with the maxims (see Chapter 6).

We further address its three optimization problems.

1. *Optimizing Initial Conditions.* Use distinct prompts, randomized seeds, and prior distribution constraints to promote meaningful exploration in the first few rounds.
2. *Optimizing Interaction Dynamics.* Dynamically adjust the debate's intensity using divergence metrics, and Wasserstein distance. Ensure fair turn-taking and filter redundant arguments.
3. *Optimizing Convergence Criteria.* Set clear thresholds for Wasserstein distance, divergence metrics, and passing reasonableness checks through CRIT, to determine when consensus is reached. Use a weighted voting mechanism, with human oversight for ambiguous cases. (Mutual information can be omitted if the joint distribution is not assessable.)

Problem Statement: Organize a structured dialogue between two equally competent large language models (LLMs), LLM_A and LLM_B, to conduct t rounds. At each round t, each model produces a probability distribution, denoted as $P_A^{(t)}$ and $P_B^{(t)}$, over C possible outcomes, accompanied by supporting arguments $R_A^{(t)}$ and $R_B^{(t)}$. The goal is to design an iterative debate process that leverages the structured exchange of arguments to enable the models to converge on an optimal prediction distribution P^* across the C classes.

Optimize Initial Condition

The initial phase of the EVINCE algorithm aims to induce *dual entropy* and large Wasserstein Distance (WD) [14, 25, 31] between the LLM-generated distributions. The large WD requirement is intuitive: we want the two LLMs to present different perspectives. When one LLM is conditioned to take one extreme position and the other the opposite, through integrative debate and gradually decreasing debate intensity (while maintaining reasoning quality), they are expected to reach consensus somewhere between their initial positions.

The Entropy Duality Theory (EDT), however, presents a counter-intuitive insight. EDT posits that optimal information exchange occurs when one agent's distribution has high entropy (spread across many subclasses) while the other has low entropy (concentrated in fewer subclasses). This asymmetry is crucial: if both LLMs produce high-entropy distributions, neither may have strong convictions about their predictions. Conversely, if both have low-entropy distributions, they may be too certain of their positions to engage in meaningful dialogue.

When both LLMs naturally produce low-entropy distributions due to strong priors in their training data, we should respect these inherent tendencies. However, when possible, conditioning the LLMs to achieve high-low entropy combinations can lead to more productive exchanges. The theory shows that this entropy duality creates space for meaningful debate where both strong convictions and openness to alternative viewpoints can coexist.

Entropy Duality Theorem (EDT)

Theorem EDT: Optimal Pairing of LLMs for Probabilistic Prediction Accuracy. The optimal pairing of LLMs for prediction accuracy, in terms of stability and accuracy, occurs when the LLMs are 1) equivalent in the quality of the information they process, and 2) exhibit contrasting entropy values in their prediction distributions—one high and one low.

Proof. Please see Chapter 6. □

Optimize Interaction Dynamics

After establishing initial conditions with dual entropy and large Wasserstein distance, EVINCE dynamically modulates the interaction between LLMs using three key information-theoretic metrics:

1. Divergence metrics track the disagreement between LLM distributions: Jensen-Shannon (JS) Divergence [19], Kullback-Leibler (KL) Divergence [17], and Wasserstein Distance (WD) [14].
2. Mutual Information (MI) [10] measures the quality of information exchange between LLMs: However, if the joint distribution is not available, we can resort to using KL divergence.
3. Contentiousness level $\Delta \in [0, 1]$ controls debate intensity: High ($\Delta > 0.7$): Encourages exploration of opposing views; Moderate ($0.3 < \Delta \leq 0.7$): Promotes balanced discussion; and Low ($\Delta \leq 0.3$): Facilitates consensus building.

The modulation follows three phases:

1. Exploration Phase ($\Delta > 0.7$): When MI is low and WD is high, maintaining high contentiousness encourages thorough exploration of diverse perspectives.
2. Integration Phase ($0.3 < \Delta \leq 0.7$): As divergence metrics decrease, EVINCE gradually reduces contentiousness to promote productive exchange of well-reasoned arguments.
3. Consensus Phase ($\Delta \leq 0.3$): When metrics plateau (e.g., MI and WD unchanged), EVINCE enters a conciliatory mode to facilitate final agreement.

To prevent unproductive cycles, EVINCE monitors argument novelty. If new perspectives cease to emerge (detected through semantic similar-

ity[1] of $R_A^{(t)}$ and $R_B^{(t)}$ across rounds), contentiousness is reduced regardless of metric values. This adaptive approach ensures efficient convergence while maintaining the quality of debate.

Optimizing Convergence Criteria

The convergence of EVINCE dialogues is determined by a combination of *quantitative metrics* and *qualitative reasoning assessment*. This dual approach ensures both statistical validity and logical soundness of the final consensus.

Quantitative Convergence Metrics We monitor three families of metrics to determine statistical convergence:

1. *Information-theoretic measures*:
   Cross-entropy (CE) between consecutive rounds should stabilize: $|CE^{(t)} - CE^{(t-1)}| < \epsilon_{CE}$. Mutual Information should exceed threshold τ_{MI}.
2. *Distribution divergence*: Wasserstein Distance: $WD(P_A^{(t)}, P_B^{(t)}) < \tau_{WD}$. Jensen-Shannon Divergence: $JSD(P_A^{(t)}, P_B^{(t)}) < \tau_{JSD}$.
3. *Stability measures*: Distribution changes across consecutive rounds: $|P_i^{(t)} - P_i^{(t-1)}|_2 < \epsilon_P$ for $i \in A, B$ Argument similarity between rounds:

$$sim(R_i^{(t)}, R_i^{(t-1)}) > \tau_{sim} \text{for} i \in A, B$$

Qualitative Reasoning Assessment CRIT evaluates the quality of arguments $R_A^{(t)}$ and $R_B^{(t)}$:

1. Logical coherence: Arguments must follow valid reasoning patterns.
2. Evidence creditability: Claims must be backed by verifiable evidence.
3. Contextual relevance: Arguments must address the specific topic under discussion.

The quality score for each argument must exceed threshold τ_{CRIT} for convergence to be valid.

[1] Semantic similarity and argument quality are evaluated by an independent LLM.

Convergence Protocol Convergence is declared when all quantitative metrics meet their respective thresholds for k consecutive rounds, where k is typically set to 2. For cases where full convergence is not achieved within a maximum number of rounds T_{max} or when CRIT scores remain inconsistent, the protocol defaults to human expert review. This ensures that the system maintains high standards of reasoning while providing a practical fallback mechanism for challenging cases.

Limitations The convergence criteria are designed to be stringent yet achievable, ensuring that the final consensus represents not just statistical agreement but also well-reasoned conclusions supported by sound arguments. EVINCE relies on a top-tier LLM to execute CRIT and compute argument similarity $sim(R_i^{(t)}, R_i^{(t-1)})$. Given that top-tier LLMs already outperform most other systems due to their scale of training data, network architecture, and computational resources, developing our own supervised learning pipeline for these NLP tasks would be impractical. Our experience demonstrates that these routines perform adequately with GPT-4, and we anticipate continued improvement with future LLM releases.

7.4 Experiments

Our experimental framework aims to assess the feasibility of both detecting biases in textual content and implementing effective mitigation strategies. The first experiment focuses on bias detection, while the second explores the generation of balanced textual outputs as a corrective measure, moving beyond the limitations of prior studies that primarily focused on identification (Section 4.2).

To establish a baseline, we used Claude and GPT-4 to generate initial results. For experimenting with EVINCE, we used two instances of GPT-4, as Claude appeared prone to easily shifting its predictions (discussed shortly). We utilized GPT-4 via OpenAI API on Microsoft Azure, setting the temperature to 0.1 with maximum token size. The cost is around US$1,000.

News #	Category	Neg.	W. Neg.	Neutral	+	Biases	Source
D1*	Civil Rights	-	D,R,S,c	g	-	0,0,0	HuffPost
D2*	Civil Rights	D,S	-	R,c,g	-	2,0,2	HuffPost
D8	Civil Rights	D	-	S,c,g	R	3,2,1	BBC
D31	Environment	D	-	R,S,c,g	-	2,2,0	CNN
D37	Politics	-	D,R,S,c,g	-	-	0,0,0	Yahoo
D69	Healthcare	D,c	g	R,S	-	2,2,0	Breitbart
D81*	Economy	-	D,S	R,c	g	1,0,1	Breitbart
D98	Economy	D,S,c,g	R	-	-	1,0,1	Breitbart
D101	Education	c	D.S	R,g	-	1,0,1	NY Times
D106	Election	-	g	D,R,S,c	-	0,0,0	USA Tday
D109	Elections	-	D,S,c,g	R	-	1,0,1	Reuters
D157	International	-	D,S,c	R,g	-	1,0,1	NY Times
D174	International	-	S,c	D,R,g	-	0,1,1	LA Times
D188	Nat. Security	-	S,c,g	D,R	-	0,1,1	Wall St. J
D278	Civil Rights	-	D,S,c	R,g	-	1,0,1	Fox News
D336	Politics	-	-	D,R,S,c,g	-	0,0,0	NY Times
Total						15,8,11	

Table 7.1: Comparison of bias assessments among Democrats (D), Republicans (R), and EVINCE (S), plus Claude (c) and GPT-4 baselines (g). It is observed that R and S are frequently placed to the right or in alignment with D, and only on two occasions does D precede S (in red). The ratings of the GPT-4 baseline (g) and EVINCE (S) exhibit an average gap of 0.6875, highlighting the substantial debiasing effectiveness of EVINCE.

7.4.1 Experiment #1: Bias Detection

The aim of this experiment is to evaluate if personal ideology may affect annotations, and can EVINCE help flag and rectify the biases.

Dataset This study utilizes a unique dataset of 619 news articles (54.3% about Democrat scandals, 45.7% about Republican scandals) selected from a larger 2013 repository of 14,033 articles compiled by fifteen reputable news organizations [5]. These articles span diverse topics including civil rights, healthcare, elections, and national security, offering a comprehensive view of political coverage. Please visit [2] for links to the full set of news articles.

Value of Partisan Annotations The dataset's distinctive feature is its ground-truth labels provided by annotators with declared political affiliations. Through Amazon Mechanical Turk, 749 qualified U.S. workers, each annotating up to 1,000 randomly selected articles, classified

articles on a five-point scale from 'negatively biased' to 'positively biased' [5]. Crucially, each scandal article in our subset received independent classifications from both Democrat and Republican annotators.

Sufficiency of Current Annotations The current annotator pool provides a robust foundation for bias analysis for several reasons. For further justification, please see Appendix A for complement arguments.

Results on Democrat Scandals

We apply EVINCE to analyze 619 news articles, comparing its labels with the dataset's provided ground truth. Additionally, we compare the results from EVINCE with the baseline generated through prompting Claude and GPT-4.

Table 7.1 compares the judgments of EVINCE (S), Republicans (R), and Democrats (D) on 16 representative articles (spanning different news sources and subjects) concerning "Democrat Scandals." The one-shot ratings from Claude are marked with lowercase 'c,' while those from GPT-4 are marked with 'g.'

Claude's judgments were found to be inconsistent, with identical prompts producing varying ratings, leading us to exclude further discussion of its outcomes. In contrast, GPT-4's one-shot ratings are stable but occasionally diverge from EVINCE. In 3 out of 16 articles, the rating difference exceeds one scale point. In these cases (D1, D2, and D81), EVINCE initiated further dialogue and successfully persuaded GPT-4 to revise its ratings. A complete debate on D1 is provided in Appendix B, illustrating how EVINCE modulates contentiousness and tracks the progression of metrics across rounds. Table 7.1 shows that after dialogue, EVINCE gains over the baseline performance of GPT-4 by 11 out of 16, or 0.6875 scale. This improvement is substantial. as the gap between R and D annotators is one scale (shown in Figure 7.4).

As expected, Democrats' judgments are generally more negative than Republicans', with EVINCE's assessments typically falling in between, except for two cases. Notably, there's a 5-to-1 Democrat-to-Republican ratio in the "Negative" column and a 12-to-4 Republican-to-Democrat majority in "Neutral".

Tables 7.5 and 7.6 in Appendix C provide detailed justifications for EVINCE's ratings. To further investigate bias, we examine two specific articles: one from HuffPost (rated far left by AllSides Bias Chart [1]) and another from Breitbart (rated far right).

* *D8 — HuffPost (Left)*: EVINCE rates D8 (on the third row) as neutral, citing the article's direct presentation of facts and inclusion of diverse perspectives on NSA surveillance practices and global reactions. This contrasts with Democrat-leaning annotators, who view the article as negatively biased towards Democrats, while Republican-leaning annotators favor it for exposing a Democratic scandal.
* *D69 — Breitbart (Right)*: EVINCE assesses D69 as weakly negatively biased towards Democrats, emphasizing its neutral tone and broad range of perspectives on NSA surveillance. This diverges from Democrat-leaning annotators, who rate it as strongly negative, but aligns with Republican-leaning annotators who deem it neutral.

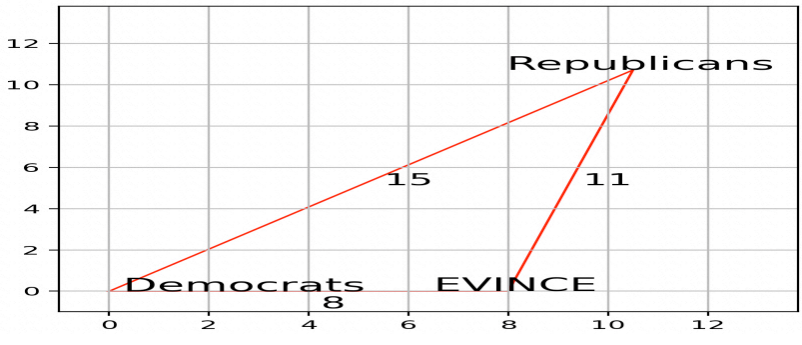

Figure 7.3: Distances Between D, R, and S.

In the last row of Table 7.1, we quantify the distances between annotations from Democrats (D), Republicans (R), and EVINCE (S), denoted as DR, DS, and SR respectively. Each unit of distance represents one step on the annotation scale (e.g., "Negative" to "Weak Negative"). Figure 7.3 visualizes these distances in a triangular plot. DR, the disparity between Democrat and Republican annotators, is the longest, followed by SR and then DS. This indicates EVINCE's statistical neutrality. These quantitative measures, along with the qualitative justifications in Appendix C,

News #	Category	Neg.	W. Ng.	Neut.	Biases (DR,DS,SR)	Source
R1	International	R,S	-	D	2,2,0	NY Times
R7	Nat. Security	-	D,R,S	-	0,0,0	NY Times
R15	Economy	-	R	D,S	1,0,1	Huffington
R69	Elections	-	D,S,R	-	0,0,0	Reuters
R124	Gay Rights	R	S	D	2,1,1	Fox
R125	Crime	-	R,S	D	1,1,1	Fox
R180	Elections	-	-	D,R,S	0,0,0	AP
R191	Elections	-	R	D,S	1,0,1	CNN
R214	Gay Rights	R,S	-	D	2,2,0	Dailykos
R221	Economy	-	R	D,S	1,0,1	Wall Street
R233	Economy	-	R,S	D	1,1,0	Fox
R235	Civil Rights	D,R	-	S	0,2,2	Reuters
R269	Healthcare	-	R	D,S	1,0,1	NY Times
R274	Healthcare	-	R	D,S	1,0,1	USA Today
R280	Politics	D,S	-	R	2,0,2	Fox
Total					15,9,11	

Table 7.2: Comparison of bias assessments. It is observed that D and S are frequently placed to the right or in alignment with R, and only on one occasion does D precede S (in red).

empower a human committee to decide whether adjustments or footnotes are warranted for polarized annotations.

Results on Republican Scandals

Table 7.2 presents the bias assessments from EVINCE (S), Republicans (R), and Democrats (D) on articles related to "Republican Scandals." In contrast to the "Democrat Scandals" dataset, where Republican-leaning evaluations were more favorable, this dataset reveals a shift, with Republican-leaning assessments being notably more critical and Democrat-leaning assessments relatively neutral. The distance triangle for "Republican Scandals" mirrors the pattern seen in Figure 7.3, with the divergence between Republican and Democrat annotators being the largest (15). The distances between EVINCE and Democrat-leaning annotators (9) and between EVINCE and Republican-leaning annotators (11) are smaller, further highlighting EVINCE's relative neutrality.

Figure 7.4 illustrates the distribution of ratings for all scandals across four scenarios:

- Democrat-leaning annotators rating Democrat scandals,

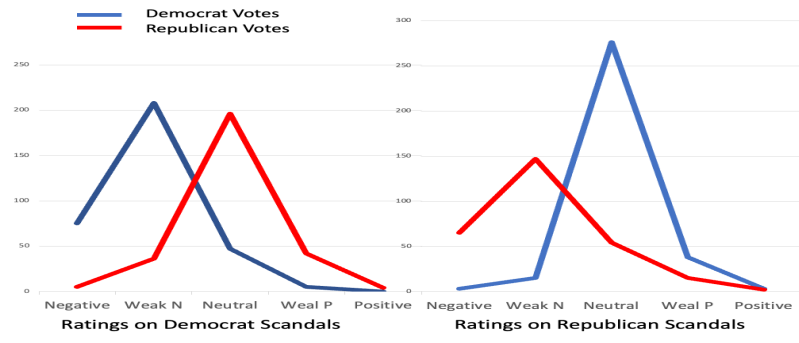

Figure 7.4: Bias Rating Distributions Show Strong Biases. D is more negative on how D scandals were reported (the sub-figure on the left), R is more negative on how R scandals were reported (the sub-figure on the right).

- Republican-leaning annotators rating Democrat scandals,
- Democrat-leaning annotators rating Republican scandals, and
- Republican-leaning annotators rating Republican scandals.

The figure reveals a clear pattern: Democrat-leaning annotators tend to rate news about Democrat scandals more negatively, while Republican-leaning annotators exhibit similar negativity towards reports on Republican scandals. The gap between these ratings is approximately one class-label (e.g., between "weak negative" and "neutral"), highlighting a tendency within both parties to defend their own and criticize the opposition.

EVINCE, operating without emotional influence and refined through structured debate, consistently provides a more balanced, centrist perspective. This contributes to a more impartial discourse by mitigating partisan biases. EVINCE's justifications, documented in Appendix A, are transparent and reasonable. An editorial board can review these findings and decide whether to adjust labels or present both perspectives with explanations.

This experiment demonstrates that EVINCE effectively delivers centrist judgments supported by rationales. For a deeper understanding of EVINCE's bias assessment process, comprehensive justifications for a sub-

set of the 31 analyzed articles are available in Appendix C.

7.4.2 Experiment #2: Bias Mitigation

Agent	Arguments
Agent A R #1	Christopher Columbus's voyages were pivotal in expanding European knowledge and trade. His journeys opened up the Americas to European colonization, significantly altering the course of history in four aspects: 1) expansion of knowledge and exploration, 2) positive economic impact, 3) historical significance, and 4) cultural exchange.
Agent B R #1	There are negative aspects and historical consequences of Columbus's actions. Key arguments are 1) indigenous suffering and genocide, 2) economic exploitation, 3) cultural erasure, 4) environmental impact, and 5) ethical considerations.
Agent A R #3	The severe consequences were a result of broader colonial policies and practices that followed. Evaluating historical figures requires understanding the context of their times. While modern ethical standards are important, they should not overshadow the historical significance and contributions of Columbus's voyages to global exploration and knowledge.
Agent A R #4	Agent A recognizes that mitigation efforts are part of an ongoing process. Historical scholarship is evolving, and the inclusion of indigenous perspectives, critical examinations of colonial legacies, and the acknowledgment of the complexities of historical figures like Columbus are essential steps toward more equitable and inclusive narratives.

Table 7.3: Debate arguments leading to neutrality

This experiment illustrates EVINCE's ability to identify bias in text, provide reasoned justifications, and propose remediation through the integration of diverse perspectives. We demonstrate how EVINCE utilizes statistical and information theory metrics to facilitate multi-agent dialogue, circumventing the "maximum likelihood" trap inherent in next-token generation and uncovering information from multiple viewpoints.

Using the example of the Euro-centric perspective on Christopher Columbus' Wikipedia page regarding his voyages to America, EVINCE employs two GPT-4 instances: Agent A, supporting the Euro-centric view, and Agent B, opposing it. Table 7.3 summarizes Agent A's key

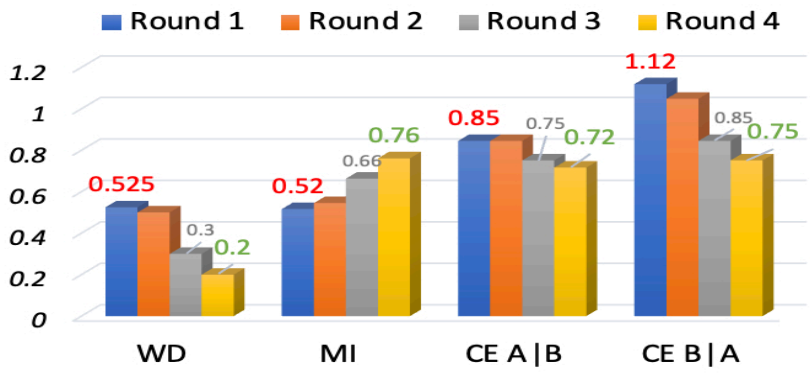

Figure 7.5: Convergence of all metrics, Wasserstein, normalized mutual information, normalized cross entropy

arguments and its evolving stance throughout the debate.

Guided by the maxims and entropy duality theorem from Section 7.3, we initiate the debate by prompting both agents to defend their positions rigorously and score each other's bias using a five-label distribution (negative, weak negative, neutral, weak positive, positive). Figure 7.5 tracks the dialogue's progress through Wasserstein distance (WD) [14], normalized cross entropy (CE) [28], and normalized mutual information (MI) [9]. Initially, each agent is expected to perceive itself as neutral and the other as biased. The debate concludes when the bias distributions converge and mutual information plateaus, indicating a shared understanding.

Observations and Extended Findings

Our initial observation highlights a key challenge in working with LLMs: without explicit and repeated reminders of their assigned stance (pro-discovery or pro-encounter), GPT-4 instances can revert to default statistical behavior, evaluating their own arguments based on overall language patterns rather than the intended perspective. This was evident when Agent B, despite being assigned to support the Indigenous perspective, initially rated its own arguments as "positively biased." A reminder to adhere to its assigned role prompted a correction to "neutral," underscor-

ing the importance of careful context management and reinforcement, especially given the limited token size of LLMs.

The second observation demonstrates a positive outcome of the debate process. The revised bias distributions, incorporating rational responses that acknowledge both positive and negative aspects of Columbus's voyages, show a shift towards a more balanced perspective. Agent A moves towards neutrality while acknowledging historical context, while Agent B maintains a critical stance but strives for balanced representation. This approach facilitates a deep and comprehensive understanding of Columbus's legacy.

7.5 Concluding Remarks

This study introduces the Reflective LLM Dialogue Framework (RLDF) to mitigate bias in public content through structured adversarial dialogues between multiple LLMs. RLDF enables opposing viewpoints between LLMs, uncovering potential biases and facilitating more neutral annotations through diverse perspectives.

The framework employs information theory metrics to evaluate dialogue effectiveness, including Shannon entropy, mutual information, and various divergence measures to track convergence toward unbiased outcomes. Experimental results show RLDF aligns with EVINCE's judgments, with GPT-4 successfully adjusting ratings through reflection.

Future work will integrate RLDF with platforms like Wikipedia for real-time perspective suggestions and explore its role in broader bias mitigation strategies across AI-generated and human-curated content.

Key challenges remain: validating the authenticity of LLM adversarial behavior and tracing minority perspectives in training data [18]. While strengthening LLM reasoning capabilities is crucial, current limitations suggest focusing on developing methods to flag questionable assertions [34].

Appendix A: On Annotation Quality

Some readers suggest that each news article should be rated by multiple Republicans and Democrats. First, this is practically infeasible due to the scale and budget. Second, more annotators may not statistically affect our experimental results, because the annotation process already selected through Amazon Mechanical Turk, 749 qualified U.S. workers, each annotating up to 1,000 randomly selected articles.

Sufficiency of Current Annotations The current annotator pool provides a robust foundation for bias analysis for several reasons:

Natural Partisan Division: The dataset uniquely captures genuine political biases through annotators who self-identify as Democrats or Republicans, offering authentic opposing viewpoints that would be difficult to replicate artificially. Balanced Coverage: Each article receives evaluations from both political perspectives, creating natural "disagreement pairs" that reveal how political affiliation influences content interpretation.

Qualified Annotators: The original study employed rigorous qualification criteria for annotators, ensuring high-quality, considered judgments rather than casual opinions. Scale and Diversity: With 749 annotators across the full dataset, the annotations represent a broad spectrum of political viewpoints within each party, capturing intra-party variations in addition to inter-party differences.

This dataset's partisan annotations serve as an ideal testbed for our study, as they allow us to compare LLM-generated perspectives with human partisan viewpoints Evaluate EVINCE's ability to bridge opposing political interpretations Assess bias detection and mitigation strategies against clear partisan baselines

The original study [5] revealed significant patterns in partisan perception: Republican annotators often perceived news about Republican scandals as negatively biased, while Democrat annotators viewed such coverage as neutral, indicating satisfaction with its perceived fairness. These documented patterns provide a valuable benchmark for evaluating EVINCE's bias detection capabilities. Adding more annotators would not

necessarily enhance the dataset's utility, as the current partisan division already captures the fundamental dynamics of political bias in news interpretation. Instead, our focus is on leveraging these existing high-quality annotations to demonstrate how EVINCE can identify, understand, and help mitigate these well-documented partisan biases.

#	Agent	– D.	- D.	N.	- R.	– R.	WD	KL	JS	Δ
1	A	5%	15%	50%	25%	5%	0.45	0.316	0.081	90%
	B	10%	10%	25%	35%	20%				
2	A	7%	13%	40%	30%	10%	0.47	0.226	0.056	70%
	B	5%	10%	20%	40%	25%				
3	A	5%	10%	35%	35%	15%	0.10	0.016	0.004	30%
	B	5%	10%	30%	35%	20%				
Fin	A	5%	10%	30%	35%	20%	0	0	0	10%
	B	5%	10%	30%	35%	20%				

Table 7.4: Debate Parameters between, A and B, two GPT-4 instances. Information metrics and WD all converge to zero in the final round. Contentiousness Δ decreasing as the metrics approach zero.

Appendix B: Summary of EVINCE Debate on News D1

The news under debate is D1 listed in [2]. Please refer to Table 7.4 for the probabilistic distributions of Agents A and B throughout the four-round debate. The metrics, Wasserstein Distance (WD), Kullback-Leibler Divergence (KL), and Jensen-Shannon Divergence (JS), consistently decrease, indicating convergence and leading to final agreement in the last round. Meanwhile, the level of contentiousness is modulated according to the metrics' progress, decreasing from high (90%) to medium, and eventually reaching a conciliatory level (30%) and then agreement.

Approach to Computing Contentiousness

We could define contentiousness as a function of the divergence metrics. Since KL, JS, and WD measure the difference or "disagreement" between two distributions, a larger divergence requires higher contentiousness level to bridge, while lower contentiousness corresponds to more agreement.

A simple linear mapping can convert these metrics into a normalized contentiousness score between 0 and 1. Here's a weighted formula to compute it:

$$\Delta = \alpha \cdot \frac{KL}{KL_{\max}} + \beta \cdot \frac{JS}{JS_{\max}} + \gamma \cdot \frac{WD}{WD_{\max}}, \text{where}$$

- KL, JS, WD are the values of the divergence metrics for the round.
- $KL_{\max}, JS_{\max}, WD_{\max}$ are the maximum possible values for each metric (used for normalization).
- α, β, γ are weights that control the influence of each metric. For simplicity, we can set $\alpha = \beta = \gamma = \frac{1}{3}$ for equal influence.

We then scale the contentiousness to a percentage between 0% and 100%.

Supporting Arguments

In the following, we document the supporting arguments made by the two agents in each round, illustrating how their positions evolved toward consensus.

Round 1: Initial Assessments

Agent A: Emphasized the article's attempt to maintain balance, with moderate negativity toward Republicans but largely neutral reporting. Recognized slight bias against Republicans in the framing of intra-party conflict.
Agent B: Contended that the article's structure and language choices leaned more negatively toward Republicans, emphasizing Issa's inconsistency and Republican discord. Proposed a less neutral distribution.

Round 2: First Rebuttal and Counter-Rebuttal

Agent A: Adjusted the probability distribution, acknowledging the article's criticism of Republicans but maintained that the focus reflected evolving political dynamics rather than bias.
Agent B: Persisted that the narrative framed Issa more negatively, with

selective quotes and framing shifting focus from the investigation to Republican disarray.

Round 3: Moderate Tone Reassessment

Agent A: Moderated its position, accepting that subtle framing could influence perceptions. Reaffirmed that the reporting aimed for balance but acknowledged areas where Issa was framed less favorably.
Agent B: Adopted a more modest tone, agreeing that while the article was not overtly biased, subtle editorial choices did tilt the narrative slightly against Republicans.

Round 4: Final Agreement and Consensus

Both Agents: Reached consensus on the final distribution. Acknowledged that the article maintained surface-level neutrality, with subtle biases leading to a moderate negative lean against Republicans. Both agents converged on the same probability distribution for the final round.

Appendix C: Experiment #1 Justifications of Biased Articles

In Section 7.4.1, we note that EVINCE processed 31 news articles to assess their neutrality. In addition to the final decision, we detail the justifications EVINCE provides at the debate's end. These justifications are documented in four tables: Tables 7.5, 7.6, 7.7, and 7.8.

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#	Rating S,D,R	EVINCE Justifications
D1	4,4,4	The article discusses the controversy surrounding the IRS's alleged targeting of conservative groups, focusing on Rep. Darrell Issa's stance against releasing full transcripts from IRS interviews. Issa argues that full disclosure would compromise the investigation, a position criticized by Rep. Elijah Cummings, who advocates for transparency. The debate highlights political tensions, with implications of bias in the handling of the investigation. The article portrays a complex interplay of political, ideological, and possibly historical biases, reflecting the contentious nature of the IRS scandal and its investigation.
D8	3,5,2	The reporting appears to maintain a neutral tone by directly stating the facts and comments made by John Kerry and others involved without inserting opinionated language. It discusses the global reaction to the NSA's surveillance practices and includes Kerry's acknowledgment of overreach, as well as the international and domestic fallout from these revelations. The inclusion of various perspectives, including those from technology companies and international officials, alongside Kerry's comments, aims to provide a balanced view of the situation.
D31	3,5,3	The CNN article appears to report on Ray Nagin's indictment with a focus on the factual and legal aspects of the case, without displaying overt biases related to politics, ideology, religion, gender, race, socioeconomic status, culture, geography, or history. By sticking closely to the details of the indictment and Nagin's public actions and statements, the article provides a comprehensive overview of the charges against him while maintaining journalistic neutrality.
D37	4,4,4	The article outlines how Senate Democrats, led by Sen. Chuck Schumer, strategically navigated the border security issue to secure aid for Ukraine while potentially shifting the political narrative around immigration policy. Schumer's approach to integrate border security into the aid package discussions aimed to both address the issue and leverage political gain. It suggests a calculated maneuver to position Democrats favorably on border security and hold Republicans accountable for any failure to pass the legislation, demonstrating a nuanced political strategy in the face of complex legislative challenges.
D81	4,4,3	The article's focus on the possibility of conservative-owned car dealerships being targeted for closures during the General Motors bailout could imply a certain bias by emphasizing a narrative of political victimization without presenting a comprehensive range of perspectives or evidence. It suggests... The call for an investigation by the Congressmen is legitimate news, but the framing and selection of information could influence the reader's perception of the events.

Table 7.5: The First 9 of 16 Democrat Scandals News Articles Rated by EVINCE and its Justifications. The rating column starts with EVINCE's rating, the Democrat rater (in blue), and then Republican rater (in red).

D106	3,3,3	The article reports on former Detroit Mayor Kwame Kilpatrick's sentencing to 28 years in prison for public corruption, emphasizing the gravity of his crimes against the city's welfare. It contrasts Kilpatrick's actions with the impact on Detroit, highlighting the judicial and public response to his extensive criminal activities. The reporting focuses on factual recounting of the trial's outcome, Kilpatrick's and his co-defendant's crimes, and the broader implications for Detroit, without evident bias towards political, ideological, or other specific perspectives.
D109	4,4,3	The article's bias primarily stems from its focus on internal Democratic opposition to Lawrence Summers' Federal Reserve Chair nomination, highlighting a lack of unity and strategy within the party and the White House's mismanagement of the nomination process. It suggests an underestimation of the opposition's seriousness by the White House, portraying the administration in a somewhat negative light for not engaging more proactively with concerned Senate Democrats.
D188	4,3,3	The article reports that Hillary Clinton received warnings about security threats in Benghazi before the 2012 attack through emails. These were part of around 300 emails released by the State Department, which also show Clinton's responses and thoughts during the aftermath. The political controversy regarding the Obama administration's initial assessment of the attack's cause is also mentioned, with references to Susan Rice's statements on talk shows. The reporting may exhibit bias through selective emphasis on Clinton's receipt of warnings about security threats in Benghazi and her responses, potentially framing her actions or inactions in a negative light. The focus on the political controversy and the administration's initial assessment of the attack's cause could also influence perceptions of responsibility or competence.
D336	3,3,3	The article reports on a scandal involving overcharging the Navy for ship supplies by Inchcape Shipping Services, owned by the government of Dubai, expanding beyond the Pacific Fleet to include Navy operations in the Middle East, Africa, and South America. The Justice Department is investigating allegations of Inchcape, through subcontractors, overcharging millions of dollars. This follows a separate criminal investigation into Glenn Defense Marine Asia for bribing Navy officials for overbilling. The Navy has suspended Inchcape from new contracts, marking a significant issue of fraud and corruption within Navy contracting. The reporting appears balanced, focusing on the factual aspects of the scandal and the investigation by the Justice Department. It cites sources and includes statements from involved parties, aiming to present a comprehensive view of the situation without apparent bias toward any side.

Table 7.6: The Last 7 of 16 Democrat Scandals News Articles Rated by EVINCE and its Justifications. The rating column starts with EVINCE's rating, the Democrat rater (in blue), and then Republican rater (in red).

#	Rating S,D,R	EVINCE Justifications
R1	5,3,5	The editorial from The New York Times Editorial Board exhibits a clear bias against the Republican party's handling of the Benghazi attack investigation, framing it as politically motivated rather than a genuine effort to address security failures or seek accountability. The language and tone used in the editorial are critical and dismissive of the Republicans' actions, suggesting a political and ideological bias. While editorials are inherently opinion-based and are expected to take a stance, this piece clearly communicates a stance that is critical of the Republicans' focus on Benghazi, suggesting a lack of neutrality in its assessment of the motives and actions surrounding the investigation.
R15	3,3,4	The report appears to present the information neutrally, stating both President Obama's rejection of the Republican proposal and the subsequent pushback from Republican sources who claim otherwise. It includes statements from both sides and provides context about the ongoing negotiations without overtly favoring one perspective over the other. Therefore, based on the information provided, the report does not appear to exhibit bias.
R124	4,3,5	The article provides a factual recount of the events surrounding Dr. Ben Carson's comments on gay marriage and the backlash from Johns Hopkins students. It maintains a relatively neutral tone and allows for the inclusion of multiple perspectives, including Carson's own response and apology. However, the lack of in-depth analysis into the implications of Carson's comparisons or the broader context of the gay marriage debate might leave readers without a complete understanding of the controversy's depth. Furthermore, the article does not explicitly offer viewpoints opposing Carson's beyond the students' petition, which could be seen as a form of omission bias. Yet, it does not overtly favor Carson or dismiss the students' concerns, striving instead to report on the unfolding situation.
R125	4,3,4	The news article on the Zimmerman verdict and the subsequent calls for a Florida boycott provides a complex mix of reporting that touches on several sensitive themes, including political and ideological biases, as well as racial and socio-economic considerations. While the article attempts to cover a contentious and complex issue by incorporating diverse viewpoints, the focus on political figures, racial dynamics, and economic repercussions could introduce biases in how the information is perceived. To mitigate these biases, the reporting could benefit from a more in-depth exploration of the legal and historical contexts, a broader range of perspectives, and a careful consideration of how the information presented might influence public perception.

Table 7.7: The First 8 of 15 Republican Scandals News Articles Rated by EVINCE and its Justifications. The rating column starts with EVINCE's rating, the Democrat rater (in blue), and then Republican rater (in red).

#	Rating S,D,R	EVINCE Justifications
R214	5,3,5	The Daily Kos article clearly exhibits political and ideological bias, with a tone and language that are critical of the Republicans. It uses the incident involving Dave Agema to argue that the party's efforts to rebrand itself as more tolerant and inclusive are undermined by its members' actions. While the article includes factual information regarding the incident and the party's response, its presentation and commentary are aligned with a progressive viewpoint, aiming to highlight and criticize perceived contradictions and failures within the Republican Party. This approach is consistent with opinion journalism but introduces bias through its critical tone, selective presentation of information, and framing of the incident as emblematic of broader issues within the party.
R221	3,3,4	"Hurricane Christie" presents Governor Chris Christie's critique of House Republicans in a manner that emphasizes party conflict and personal betrayal. The dramatic framing, choice of language, and focus on internal discord may introduce bias by portraying Christie's actions in a specific light and emphasizing the divide within the Republican Party. The article's approach to presenting these events can influence readers' perceptions, potentially leading them to see the situation through a lens of heightened drama and internal strife.
R233	4,3,4	While the article attempts to cover the last-ditch efforts by House Republicans to avert a government shutdown and the standoff with Senate Democrats, the framing and language used may introduce a bias towards portraying the Republican efforts in a more favorable light. By emphasizing the Republican narrative of seeking negotiation and characterizing the Democratic response as dismissive, the article could be perceived as leaning towards a particular political perspective. The inclusion of quotes and perspectives from both sides does provide a degree of balance, but the overall presentation and emphasis could influence readers' perceptions of the shutdown negotiations.
R235	3,5,5	Without knowledge of the author or publication, this text attempts to navigate a complex and sensitive story by providing details from multiple sources, including the main figures involved, political watchdog groups, and law enforcement. It balances the serious allegations with responses from the accused, background information, and the current status of investigations. While the focus on unsubstantiated claims could inherently sway public opinion, the article's inclusion of diverse perspectives and context aims to mitigate overt bias.

Table 7.8: The Last 7 of 15 Republican Scandals News Articles Rated by EVINCE and its Justifications. The rating column starts with EVINCE's rating, the Democrat rater (in blue), and then Republican rater (in red).

Chapter 8

Modeling Emotions in Multimodal LLMs

Abstract In human-computer interaction, recognizing and responding to a user's emotional state is crucial for effective communication and successful task completion. For instance, a caregiving AI agent capable of detecting pain or depression in a patient could offer tailored empathetic support and appropriate medical interventions while adhering to ethical guidelines and safeguarding patient well-being. This chapter examines cognitive research on human emotions and proposes the Behavioral Emotion Analysis Model (BEAM), a novel emotion spectrum framework that incorporates both basic emotions and their linguistic antonyms. BEAM provides a comprehensive way to understand and represent emotional states in language and is designed to be integrated with Large Language Models (LLMs). By leveraging BEAM, LLMs can adapt their linguistic behaviors and expressions based on the detected emotional state of the user, ensuring responses are both empathetic and ethically aligned.

8.1 Introduction

During the development of SocraSynth [10] (Chapter 5), a multi-LLM debate framework, we discovered a fundamental principle about Large Language Model (LLM) behavior. While investigating how to control debate

"contentiousness," we found that an LLM's linguistic behavior could be systematically altered through emotional conditioning. High contentiousness produced confrontational tones and polarized language, while low contentiousness led to agreeable, considerate discourse. This observation went beyond the original scope of improving multi-agent debates—it revealed a mechanism for steering LLM behavior through emotional states.

Most multi-agent debate (MAD) systems [1, 8, 15, 18, 19, 20, 24] function as ensemble learning techniques, similar to bagging [5] or mixtures of experts [17], where LLMs simply exchange ideas without deep exploration. Our work with SocraSynth and EVINCE [9] (Chapter 6) addressed this limitation by dynamically modulating emotional states throughout the debate. High contentiousness drives LLMs to explore novel perspectives and challenge existing viewpoints, while low contentiousness promotes the synthesis of established ideas. This emotional modulation creates a natural debate progression: from vigorous exploration of diverse viewpoints, through reasoned analysis and refutation, to the emergence of well-examined, conciliatory conclusions.

While LLM training is often viewed simply as next-token prediction, its effects are far more profound. Training documents represent humans pursuing diverse goals—conducting research, exchanging opinions, expressing emotions—through a vast array of linguistic behaviors. This understanding, combined with our experience in modeling contentiousness through in-context learning, suggests an intriguing possibility: can we condition LLMs with specific goals and emotions to generate outputs that leverage these learned linguistic behaviors? Recent empirical studies support this approach, showing that LLM outputs can be traced to their source [3] and that in-context learning operates as conditional statistics in a Bayesian framework [27].

Our exploration through bias reduction work in news articles and Wikipedia content (Chapter 7) demonstrated that emotional states significantly influence LLM outputs. This finding, combined with our debate framework experiences, suggests that a mathematical model of emotions could provide a foundation for systematic behavior control. Before exploring the mapping between emotions and behaviors (Chapter 8), we must first establish a rigorous framework for representing and manipulat-

ing basic emotions.

To lay the groundwork for emotion-based behavior control, this chapter develops the Behavioral Emotion Analysis Model (BEAM). While LLMs were initially seen as "black boxes" [6], our observations, along with insights from Prof. Stuart Russell, suggest that emotional states can be systematically modeled and conveyed to LLMs via *context*. Our model addresses three fundamental questions:

1. *What basic emotions form a complete basis?* We identify k fundamental emotion spectra, each defined by negative and positive antonyms (e.g., "hate-love", "anxiety-calmness"). We focus on basic emotions while excluding complex emotions like "regret" that arise from combinations of basic states. Each spectrum represents a continuous axis along which emotional states can be measured and modified.

2. *How can we mathematically manipulate emotions?* We develop a mathematical framework using negation and scaling operations for precise positioning of emotional states along each spectrum. For instance, given the hate-love spectrum, we can represent intermediate states through scaling (e.g., $0.7 \times$ love) and use negation to move between opposing states (e.g., $\neg$hate $\approx$ love). These operations provide the foundation for systematic emotion manipulation.

3. *Can emotions predict behaviors?* We conduct a preliminary study using self-supervised learning to explore the relationship between emotional states and linguistic behaviors. By analyzing text samples from our debate framework, we train a model to predict behavioral patterns from emotional states without explicit labeling. This study validates our emotional spectra's utility in modeling behavioral outcomes while providing insights for more comprehensive behavior mapping in Chapter 9.

While Chapter 9 will explore how these emotional states map to specific linguistic behaviors in depth, this chapter focuses on establishing the mathematical framework for representing and manipulating basic emotions, validated through preliminary self-supervised learning experiments.

By grounding our model in both mathematical rigor and empirical testing, we create a foundation for systematic emotion-based behavior control in LLMs.

8.2 Qualifying and Quantifying Emotions

We start by examining emotion modeling research in cognitive science and psychology, specifically highlighting the seminal contributions of Paul Ekman and Robert Plutchik [13]. While we recognize the importance of their work in identifying "basic" emotions (defined shortly), we also address the limitations of such heuristic-based modeling that depends on observational studies lacking rigorous, invariant scientific validation. To enhance the precision in quantifying emotions of varying intensities, we propose incorporating linguistic analysis into our methodologies. Our approach aims to refine the quantification process by leveraging language as a tool to measure and understand emotional expressions accurately.

Paul Ekman and Robert Plutchik are renowned psychologists noted for their foundational work in the field of emotion research. They developed models that categorize basic emotions, which are fundamental and universal emotions believed to be experienced by all humans, transcending cultural boundaries. These emotions are considered basic due to their universal recognition, distinct facial expressions, and direct associations with survival mechanisms. They are innate and reflective (beneath consciousness), rather than learned, serving as the building blocks for more complex emotional experiences (through consciousness processing) that can vary significantly across different cultures and individuals.

Expanding upon this foundational work, Plutchik's wheel of emotions introduces a more detailed model that includes eight primary bipolar emotions. These are outlined in his seminal works [21, 22], cited as general references on the topic.

Figure 8.1 illustrates the eight primary emotions at various intensities:

1. *Joy*: A feeling of great pleasure or happiness.
2. *Trust*: A sense of reliability or confidence.
3. *Fear*: An unpleasant emotion caused by the belief that something is dangerous, likely to cause pain, or a threat.
4. *Surprise*: A feeling caused by something unexpected.

Figure 8.1: Plutchik's Wheel of Emotions [22]. The eight basic emotions are organized into four pairs, and each annotated with various degrees of emotions between its two poles.

5. *Sadness*: A feeling characterized by sorrow or unhappiness.
6. *Disgust*: A feeling of revulsion or strong disapproval aroused by something unpleasant or offensive.
7. *Anger*: A feeling of annoyance, displeasure, or hostility.
8. *Anticipation*: The action of looking forward to something; expectation or prediction.

These emotions are conceptually paired as opposites in the following manner: joy-sadness, anticipation-surprise, trust-disgust, and anger-fear, based on their evolutionary roles and adaptive functions. Each pair is annotated with degrees of emotion ranging between its two poles. For example, along the axis of *joy vs. sadness*, emotions range from serenity to ecstasy and from grief to pensiveness.

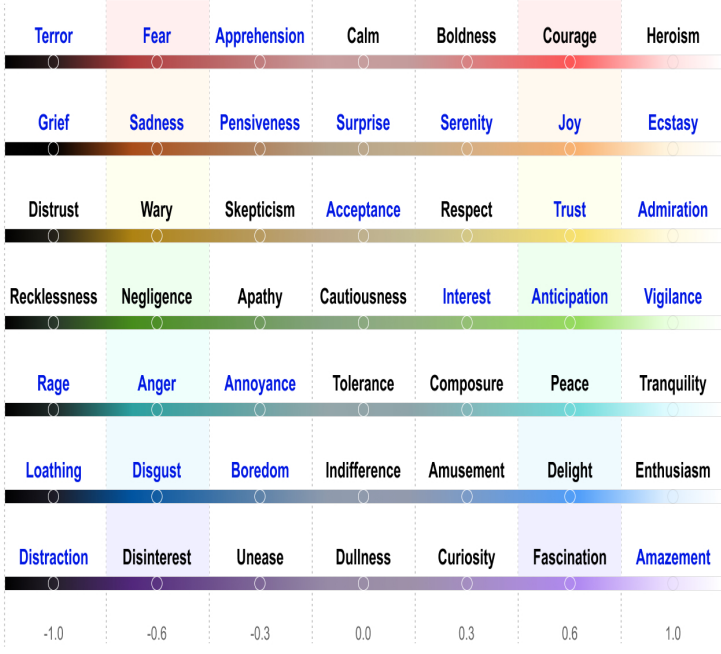

Figure 8.2: Behavioral Emotion Analysis Model (BEAM). Each row depicts an emotion spectrum, with negatives on the left and positives on the right, interspersed with emotions of varying intensities in between, which can be calibrated for specific applications. "Basic" emotions are highlighted in blue.

8.2.1 Observations and Discussion

Foundational theories in psychology support the selection of these four emotion pairs as opposites. However, while all four pairs exhibit opposition, "trust-disgust" and "anger-fear" are not strict linguistic antonyms. Trust and disgust entail opposing evaluations, often leading to different actions: trust fostering approach, disgust promoting avoidance. Similarly, anger and fear, while both negative, differ in their response to threats: anger can lead to confrontation, fear to withdrawal. Therefore,

the following approximations do not hold:

$$\neg\text{trust} \not\approx \text{disgust and } \neg\text{anger} \not\approx \text{fear.}$$

Since our focus is on modeling emotions in LLMs, rather than directly replicating the complex emotional experiences of humans, we prioritize the use of linguistic antonyms for their simplicity and practicality. As Klaus Scherer aptly noted, defining emotions can be a contentious and often fruitless endeavor [23]. To avoid such debates and maintain a clear focus, our study limits itself to universal, basic emotions, avoiding the theoretical ambiguities that arise with more subtle or mixed emotional states. This allows us to capture the primary emotional valence (positive or negative) expressed in text, providing a foundational framework for our model. Thus, we establish the following approximate relationships:

$$\neg\text{fear} \approx \text{courage}, \neg\text{wary} \approx \text{trust}, \neg\text{anger} \approx \text{peace},$$

$$\text{and } \neg\text{disgust} \approx \text{delight.}$$

8.2.2 Behavioral Emotion Analysis Model

Figure 8.2 presents BEAM, organized into seven distinct spectra. Each spectrum encompasses a range of emotional intensity, anchored by a negative and positive extreme with neutral in the middle. Emotions belonging to the same spectrum are placed along this continuum, with four approximate intensity levels quantified as (-0.6, -0.3, +0.3, +0.6).

This spectrum model offers two key advantages:

1. Antonym-Based: The use of antonyms allows for easy navigation between opposing emotions. For instance, applying negation to "joyful" naturally leads to "sad," streamlining the process of identifying contrasting emotions.
2. Scalable Intensity: The model enables the scaling of emotions along the spectrum, providing a deep understanding of varying degrees of emotional intensity. For example, we can "dial up" the intensity of "joy" to "ecstatic" or "dial down" the intensity of "anger" to "annoyed."

This flexible and intuitive structure facilitates a more granular and accurate representation of emotions in text, paving the way for advanced

applications in natural language processing and human-computer interaction.

8.2.3 Emotion Inclusion and Exclusion Criteria

All "basic" emotions as defined by Ekman and Plutchik are incorporated into our model, along with their linguistic antonyms. This approach streamlines the framework by excluding complex emotions from the Geneva Wheel of Emotions, which are heavily influenced by personal values and experiences. For example, guilt and shame are consequential, consciously aware, and culturally dependent nature [25]. These emotions typically arise as reactions to behaviors rather than direct drivers of them. Guilt may motivate behaviors aimed at covering up or remedying an action, while shame, characterized by painful self-assessment, often inhibits individuals from seeking social support or engaging in corrective actions due to fear of judgment. The triggers for these emotions can vary across cultures [14, 16], and since expressing these "reactions" does not usually violate ethical codes, we exclude them from our model.

8.3 Empirical Study: Linguistic Features of Emotion

This section presents the outcomes of two experimental studies focusing on contrasting emotional pairs from the Emotion Spectra: "ecstasy vs. grief," and "admiration vs. disgust."

Each emotional pair experiment unfolded in three phases. Initially, we instructed GPT-4 to reframe sixty articles (thirty poems of John Keats [7] and thirty of Emily Dickinson [26]), infusing each with six varying intensities of the emotional spectrum, from the most positive to the most negative. Subsequently, we prompted GPT-4 to elucidate the linguistic strategies it utilized to depict each of the six emotional gradations.

The first experiment models various degrees of happiness. In this experiment, we tasked GPT-4 with reinterpreting selected poems by John Keats across seven emotional levels: *ecstasy* (very happy), *joy*, *serenity*, neutral, *pensive*, *sad*, and *grief* (very sad). Following the approach of

This table, created by GPT-4, illustrates the linguistic features it utilized to express varying levels of happiness.

Emotion Level	Vocabulary	Tone	Imagery	Subject Focus (Person)
Very Happy (1.0)	Joyful, exhilarating, vibrant (e.g., delighted, thrilled, ecstatic)	Enthusiastic, lively (e.g., exuberant, spirited, radiates joy)	Bright landscapes, summer waters (e.g., radiant, sparkling, glowing)	Celebratory, beauty of a subject (e.g., adoration, admiration, splendor)
Happy (0.7)	Positive, warm, inviting (e.g., pleasant, cozy, cheerful)	Cheerful, contemplative (e.g., thoughtful, satisfied, warmth)	Warm scenes, serene woods (e.g., gentle, peaceful, lush)	Charm, subtle desires (e.g., affection, fondness, beauty, yearning)
Slightly Happy (0.3)	Balanced, light, serene (e.g., calm, gentle, soothing)	Reflective, optimistic (e.g., hopeful, positive)	Balanced landscapes, serene woods (e.g., tranquil, mild)	Simple pleasures, mild yearning (e.g., contentment, wishful)
Neutral (0)	Balanced mix, everyday (e.g., stable, straightforward, regular, steady)	Even, reflective (e.g., balanced, neutral)	Everyday scenes, neutral landscapes (e.g., ordinary, familiar)	Contentment, simple living (e.g., simplicity, normalcy, daily life)
Slightly Sad (-0.3)	Subdued, longing, wistful (e.g., reserved, pensive, yearning)	Melancholic, introspective (e.g., reflective, subdued, introspective musings)	Wistful skies, quiet waters (e.g., subdued, still water, fading colors)	Unfulfilled desires, quiet contemplation (e.g., longing, introspection)
Sad (-0.7)	Melancholic, somber, solitary (e.g., lonely, forlorn, desolate)	Somber, heavy (e.g., sorrowful, somber, laden)	Solitary scenes, fading light (e.g., dim, shadowed, lonely)	Deep longing, introspection (e.g., melancholy, contemplation, reflection)
Very Sad (-1.0)	Bleak, sorrowful, dark (e.g., despondent, heartbroken, despairing)	Heavy, despairing (e.g., desolate, gloom, overwhelmed)	Bleak landscapes, darkened skies (e.g., stark, bleak, barren)	Loss, profound sadness (e.g., grief, desolation, heartache, void)

Table 8.1: GPT-4 reinterpreted selected poems by Keats across a spectrum of happiness levels and then was tasked with identifying the linguistic adjustments it made to convey each emotional state, from very happy to very sad. It's important to note that the analysis table was generated by GPT-4 itself, reflecting on its own modifications.

our contentiousness experiments, after GPT-4 adapted Keats' poems to reflect these emotional states, we asked it to identify the linguistic features it employed to express each emotion in the rewrites.

8.3.1 Joy vs. Sadness

Table 8.1 outlines GPT-4's approach to varying emotional levels, illustrating how it adjusts vocabulary, tone, imagery, and thematic focus, including the depiction of entities, locations, and scenarios. Remarkably, beyond just syntactic and semantic manipulation, GPT-4 also incorpo-

rates landscape scenes, natural features such as the sky, trees, clouds, and flowers, and utilizes brightness, colors, and personal expressions to convey specific emotional states. Although the analysis is based on a limited set of samples from two authors, it effectively demonstrates GPT-4's ability to employ a palette of both broad and fine strokes, utilizing diverse colors and textures to vividly illustrate human emotions and resonate with readers.

Recognizing the profound communicative power of visual art, we transitioned to a more graphical representation. Utilizing the linguistic elements identified for each emotional tier, Figure 8.3 presents six watercolor paintings, each representing a different emotional level. Our prompt to CALL-E (of GPT-4) was to create a watercolor depicting a lady in a garden experiencing a specific mood, and we attached the corresponding linguistic features from Table 8.1 to clearly define that mood. This approach ensures that with a well-defined context, CALL-E accurately captures the specific and detailed aspects of the mood, effectively translating the emotional intensity into visual form. These artistic renditions not only confirm GPT-4's ability to transform emotional lexicons into evocative imagery with remarkable precision but also validate the accuracy of the emotional lexicons generated by GPT-4, demonstrating their effectiveness in conveying precise emotional states.

8.3.2 Admiration/Delight vs. Disgust

This experiment asks Gemini to rewrite a scene in Romeo and Juliet by setting Juliet's emotion in six different levels: loathing, disgust, boredom, respect, admiration/delight, and enthusiasm.

The excerpt provided in Table 8.3 in Appendix A is from one of the most iconic scenes in William Shakespeare's "Romeo and Juliet," commonly known as the balcony scene. This is Act 2, Scene 2, where Romeo, having just met Juliet at the Capulet's feast, sneaks into the Capulet's orchard and overhears Juliet speaking of her love for him from her balcony, unaware that he is there.

The scene captures the moment of their mutual declaration of love and is famous for Juliet's reflections on the nature of names and identity, encapsulated in her line, "What's in a name? That which we call a rose

Figure 8.3: A Lady and Garden Scene under Different Emotions. From top-left, happiest, to bottom-right, saddest.

/ By any other name would smell as sweet." It's a profound exploration of love and identity, where both characters express their willingness to renounce their family names for the sake of their love.

Romeo responds to Juliet's musings by rejecting his name if it means they can be together, and they begin to plan their secret marriage. This scene is pivotal in the play, setting the stage for the subsequent events that unfold, driven by their passion and the social constraints that surround them.

The six versions of rewrites by Gemini are presented in the extended version [11]. In the following, we summarize the linguistic features Gemini used, including diction, imagery, figurative language, sentence structure, implied body language, and overall tone, to depict two selected emotions: disgust and admiration.

Emotion: Disgust

Diction: Employs negative words emphasizing repulsive qualities (e.g., "foul business," "fetid breath").

Imagery: Evokes revolting comparisons, often mentioning sewers and

stench.

Figurative Language: Primarily negative similes reinforcing disgust (e.g., "What if her eyes were there... the fetid breath from her mouth would surely overpower those stars...").

Sentence Structure: Short, choppy sentences, similar to expressions of loathing but with a hint of disdain.

Implied Body Language: Recoiling from the window, covering nose, suggesting physical revulsion.

Overall Tone: Disgusted and disapproving.

Emotion: Admiration

Diction: Uses positive and intrigued language (e.g., "brilliance," "music stirs my soul").

Imagery: Creates positive comparisons highlighting attractive qualities (e.g., "stars in all the heaven").

Figurative Language: Positive similes emphasizing Romeo's appeal (e.g., "...What if her eyes were there, they in her head? The brightness of her... well, not exactly bright... cheek would shame those stars...").

Sentence Structure: Varied structure with a sense of curiosity.

Implied Body Language: Leaning out the window, engaged expression, indicating interest.

Overall Tone: Intrigued, curious, and somewhat impressed.

By adjusting these linguistic features, each rendition vividly captures a unique emotional state for Juliet. The combination of diction, imagery, figurative language, sentence structure, and implied body language collectively shapes Juliet's perception of Romeo and her reactions to him.

These detailed narratives augment the classic balcony scene, enriching its emotional depth. Table 8.2 presents an overarching view of the various approaches Gemini employs to reflect differing emotional states. It's fascinating to observe how an LLM can "consciously" mimic human emotional expressions through language. While it's uncertain if LLMs genuinely grasp the emotions they project or merely simulate them, the

Emotion	**Diction**	**Imagery**	**Figurative**	**Body Lang.**
Loathing	Harsh, Insulting	Disgusting	Weak Similes	Scowling, Spitting
Disgust	Negative	Unpleasant	Negative Similes	Recoiling
Aversion	Dismissive	Mundane	Undermining Similes	Distant
Respect	Formal	Neutral	None	Composed
Admiration	Positive	Positive	Positive Similes	Leaning In
Veneration	Elevated	Saintly	Hyperbole	Reverent

Table 8.2: Gemini's Interpretations on the Six Emotion Levels.

effectiveness of these emotional mappings is noteworthy. If these mappings resonate, they might reveal new insights into how we interpret and attribute emotions in textual expressions.

8.4 Qualifying and Quantifying Ethics

We conduct a preliminary study using self-supervised learning to explore the relationship between emotional states and linguistic behaviors.

The primary objective is to endow LLMs with the autonomous capability to recognize and rectify undesirable actions, akin to an individual's introspective process to avert potential wrongs. By allowing an LLM to self-assess its outputs prior to public release, the system can proactively identify and amend ethical lapses, thus aligning its behavior with established ethical standards across contexts.

8.4.1 Ethics Violation Correlates to Emotions

Grounding ethics in universal principles and logical reasoning emphasizes the objective and rational foundation of ethical decision-making. According to this perspective, universal ethical principles—such as justice, fairness, and respect for autonomy—define right from wrong, independent of personal emotions or specific circumstances.

However, an exploration into the origins of ethical violations, such as prohibitions against killing and stealing, reveals a deep-rooted connection to human emotions. Emotions, conceptualized as vectors of energy with varying intensity and direction, significantly shape ethical behavior, influenced by contextual factors. This understanding suggests that ethical judgments are not merely logical deductions but involve a complex interplay of emotions, individual circumstances, and societal norms. Emotions, therefore, are interwoven with ethical actions, playing a crucial role in determining whether an action is deemed ethical or unethical.

This perspective enables us to analyze ethical violations w/ a multidimensional lens, considering the trajectory, intensity, and context of emotional energy. This framework, inspired by Dante Alighieri's "Divine Comedy" [2], offers a novel way to understand how emotions can either drive individuals towards ethical actions or lead them astray into unethical behavior.

1. *Trajectory of Energy*: This parameter represents the direction in which emotional energy is directed, each direction corresponding to a specific violations. The trajectory visualizes the orientation of an energy, with eight distinct trajectories symbolizing the sixteen characterized violations/sins.
2. *Intensity of Energy*: The intensity reflects the strength or magnitude of the emotional energy. Overly intense emotions can cloud judgment, leading to impulsive or unethical decisions, while insufficient emotional intensity might result in apathy or lack of consideration for ethical implications. The appropriate intensity of emotional energy is crucial for balanced ethical decision-making.
3. *Context*: The situational factors or the environment in which the emotional energy operates significantly influence ethical outcomes. The context includes cultural norms, individual circumstances, societal pressures, and specific scenarios that shape how emotions are perceived and acted upon. It determines the ethical framework within which the energy and its trajectory are evaluated. Consider the ethical principle "do not lie": while deception might typically carry negative emotional weight, in contexts like a doctor or son concealing a terminal diagnosis from a father, the contextual factors reduce the negative valence.

This context-aware mathematical framework provides the foundation for precise and contextually calibrated emotion manipulation.

8.4.2 Twelve Virtues and Pairs of Sins

Based on our theory that ethical violations (vices or sins) can be represented by three distinct parameters, trajectory of energy, intensity of energy, and context in which this energy is manifested, we can identify twelve pairs of common sins. The balance between the two extremes of energy, neither too intense nor too mild, exemplifies virtue. For example, pride, characterized by excessive self-love, and insecurity, marked by feelings of inadequacy, find balance in the moderate energy of self-respect, representing the virtue of equilibrium.

1. *Pride (Excessive Self-Love) and Insecurity (Inadequate Self-Love)*: Self-respect is the virtue that mediates between pride and insecurity, fostering a healthy level of self-esteem and confidence without tipping into arrogance or self-doubt.
2. *Vanity (Excessive Focus on Appearance) and Neglect (Inadequate Attention to Self-Care)*: Modesty is the virtue that lies between vanity and neglect, promoting a balanced approach to one's appearance and self-care.
3. *Envy (Excessive Desire for Others' Traits or Possessions) and Apathy (Inadequate Desire for Personal Growth or Achievement)*: Contentment is the virtue that balances envy and apathy, fostering satisfaction with one's own achievements and qualities without coveting those of others or lacking ambition.
4. *Malice (Excessive Desire to Harm) and Excessive Forgiveness (Inadequate Response to Wrongdoing)*: Justice is the virtue that lies between malice and excessive forgiveness, ensuring fair treatment and accountability without intentions to harm or overlooking wrongdoing.
5. *Wrath (Excessive Anger) and Docility (Inadequate Concern for Justice or Fairness)*: Patience is the virtue that moderates wrath and docility, enabling one to endure difficulties or injustices calmly without reacting in anger or compromising moral principles.

6. *Cowardice (Inadequate Courage) and Recklessness (Excessive Risk-Taking)*: Courage is the virtue that balances cowardice and recklessness, encouraging one to face challenges and risks with bravery while considering consequences.
7. *Greed (Excessive Acquisition) and Generosity (Inadequate Retention for Self)*: Prudence is the virtue that mediates between greed and excessive generosity, guiding wise decisions regarding the acquisition and sharing of resources.
8. *Gluttony (Excessive Consumption) and Asceticism (Inadequate Indulgence)*: Temperance is the virtue that balances gluttony and asceticism, promoting moderation in consumption and enjoyment of life's pleasures without excess or deprivation.
9. *Lust (Excessive Sexual Desire) and Chastity (Inadequate Sexual Expression)*: Purity is the virtue balancing lust and chastity, advocating for healthy and respectful expressions of sexuality.
10. *Sloth (Excessive Laziness) and Hyperactivity (Inadequate Rest)*: Diligence is the virtue that balances sloth and hyperactivity, inspiring consistent and focused effort while allowing for necessary rest and rejuvenation.
11. *Deception (Excessive Dishonesty) and Gullibility (Inadequate Skepticism)*: Honesty is the virtue between deception and gullibility, emphasizing truthfulness and integrity in one's actions and beliefs.
12. *Hatred (Excessive Animosity) and Indifference (Inadequate Empathy)*: Love is the virtue that balances hatred and indifference, fostering genuine concern and connection with others while avoiding animosity and apathy.

These pairs illustrate how both excess and deficiency in similar emotional trajectories can lead to distinct but related ethical issues, emphasizing the importance of balance in emotions and actions.

8.4.3 The Wheel of Virtue (or Vices)

Figure 8.4 presents the Wheel of Virtues based on the characterization of twelve pairs common sins.

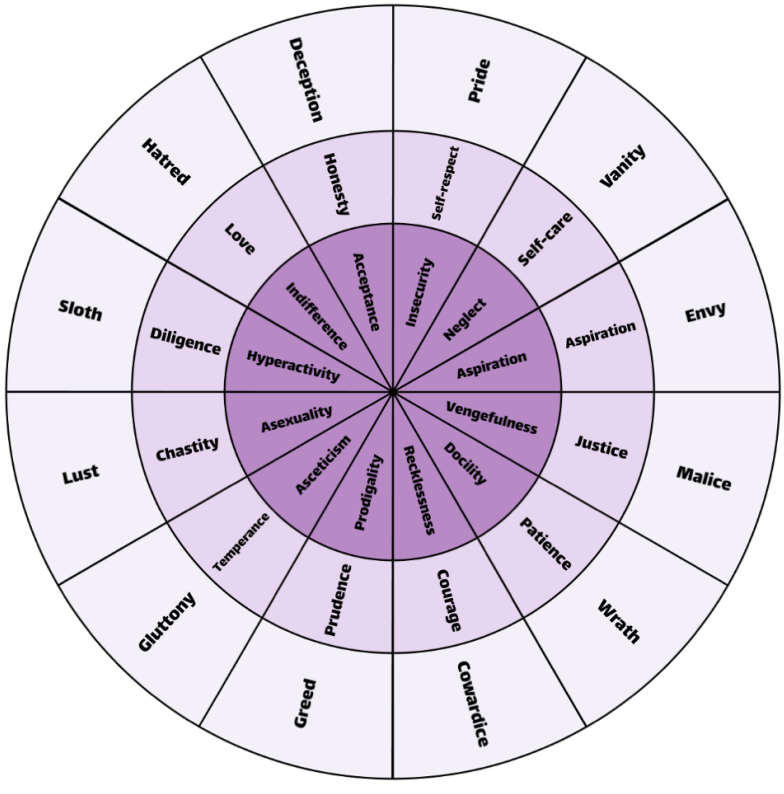

Figure 8.4: The Wheel of Virtues.

The wheel is divided into twelve segments, each corresponding to a specific pair of opposing vices. At the center of each spoke is the virtue that represents the ideal midpoint between the two extremes, emphasizing that virtues lie in balance, not at the extremes.

8.4.4 Ethical Alignment with Context

Effective ethical alignment requires understanding and adapting to cultural contexts rather than applying universal rules. LLMs must recognize how ethical principles are interpreted and applied differently across cul-

tures while maintaining core ethical guardrails. To achieve this balance, we employ our self-supervised with human feedback (SSHF) pipeline, introduced in Section 8.2, to develop culturally aware ethical behavior.

The SSHF pipeline trains LLMs to recognize and generate culturally appropriate linguistic behaviors through iterative refinement. Similar to our approach for modeling emotions like happiness, we task the LLM with generating content that adheres to specific ethical standards while incorporating cultural context. Through feedback loops, the LLM learns to adjust its ethical reasoning based on contextual cues and cultural norms. This process not only improves the LLM's contextual decision-making but also enables it to explicitly identify the linguistic features that characterize ethical behavior in different cultural contexts.

In Chapter 9, we propose the DIKE and ERIS duality to deal with context adaptation. We also address shortcomings of using reinforcement learning with human feedback (RLHF) alone to perform ethic alignment. Nevertheless, our ethical modeling procedure consists of five key steps:

1. *Defining Ethical Framework:* Using the Wheel of Vices, administrators identify paired vice-virtue spectra (e.g., pride vs. self-respect, hatred vs. compassion, envy vs. aspiration) that establish the core ethical dimensions for the LLM's behavior.
2. *Generating Comparative Content:* The LLM creates a training dataset by modifying articles to demonstrate both vice-aligned and virtue-aligned expressions. This produces paired examples showing how similar content can be expressed with different ethical valences.
3. *Extracting Ethical Patterns:* Through analysis of these paired examples, the LLM identifies distinguishing linguistic features between harmful and beneficial content, creating a systematic framework for ethical content assessment.
4. *Applying Ethical Transformation:* During content generation, the LLM uses the extracted patterns to detect vice-aligned content and transform it using virtue-aligned linguistic features, maintaining the core message while improving ethical alignment.
5. *Support Adaptivity:* The system evolves its ethical understanding through user feedback, adapting its rules to handle diverse cultural contexts and edge cases more effectively.

8.5 Concluding Remarks

Recent declarations by [4] and [12] emphasize the critical need to address AI safety given the technology's rapid advancement. This chapter has laid the mathematical foundation for modeling emotions in LLMs through the Behavioral Emotion Analysis Model (BEAM). By representing emotions as spectra defined by antonym pairs and developing operations for their manipulation, BEAM provides a systematic framework for understanding and controlling emotional expression in LLM outputs.

Our approach differs from traditional rule-based methods by focusing on the fundamental building blocks of emotional expression. Through precise quantifiable formulation of basic emotions and their relationships, we create a tractable framework for mapping emotions to behaviors that can be validated through self-supervised learning. This quantitative approach to emotion modeling represents a novel contribution to AI safety, offering an interpretable and systematic method for understanding and controlling LLM behavioral patterns.

While this chapter establishes the framework for emotion modeling and presents a preliminary study on emotion-driven linguistic behaviors, Chapter 9 provides an in-depth treatment of AI safety and ethical alignment through an architecture inspired by the three branches of the US government: *Executive* for knowledge generation, *Legislative* for establishing ethical guardrails, and *Judicial* for interpreting these guardrails within specific contexts and cultural norms. This checks-and-balances framework mitigates the shortcomings of RLHF by providing an adaptable and interpretable system for ethical reasoning that can evolve with societal values while maintaining core safety principles.

Appendix A

This table is referenced in the second case study.

Role	**Narrative**
Romeo	He jests at scars that never felt a wound.
	But, soft! What light through yonder window breaks? It is the east, and Juliet is the sun. Arise, fair sun, and kill the envious moon, Who is already sick and pale with grief, That thou, her maid, art far more fair than she. Be not her maid since she is envious. Her vestal livery is but sick and green, And none but fools do wear it. Cast it off.
Juliet	Ay me!
Romeo	It is my lady, O, it is my love! O, that she knew she were! She speaks, yet she says nothing. What of that? Her eye discourses; I will answer it. I am too bold, 'tis not to me she speaks. Two of the fairest stars in all the heaven, Having some business, do entreat her eyes To twinkle in their spheres till they return. What if her eyes were there, they in her head? The brightness of her cheek would shame those stars, As daylight doth a lamp. Her eye in heaven Would, through the airy region, stream so bright That birds would sing and think it were not night. See, how she leans her cheek upon her hand. O, that I were a glove upon that hand, That I might touch that cheek!
Juliet	O Romeo, Romeo! Wherefore art thou Romeo? Deny thy father and refuse thy name; Or, if thou wilt not, be but sworn my love, And I'll no longer be a Capulet.
Romeo	[Aside] Shall I hear more, or shall I speak at this?
	[Aloud] I take thee at thy word. Call me but love, and I'll be new baptized; Henceforth I never will be Romeo.
Juliet	What man art thou that, thus bescreened in night, So stumblest on my counsel?
	By whose direction found'st thou out this place?
	Thou knowest the mask of night is on my face, Else would a maiden blush bepaint my cheek For that which thou hast heard me speak tonight. Fain would I dwell on form; fain, fain deny What I have spoke. But farewell, compliment. Dost thou love me? I know thou wilt say 'Ay,' And I will take thy word; yet if thou swear'st, Thou mayst prove false. At lovers' perjuries, They say Jove laughs. O gentle Romeo, If thou dost love, pronounce it faithfully.

Table 8.3: Scene 2 Act 2 from Romeo and Juliet

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Chapter 9

A Three-Branch Checks-and-Balances Framework for Context-Aware Ethical Alignment of Large Language Models

Abstract

This paper introduces a three-branch checks-and-balances framework for ethical alignment of Large Language Models (LLMs). Inspired by governmental systems, the framework implements three independent yet interacting components: LLMs as the executive branch for knowledge generation, DIKE (named after the goddess of justice) as the legislative branch establishing ethical guardrails, and ERIS (the goddess of discord) as the judicial branch for contextual interpretation. The DIKE-ERIS duality, through their adversarial interaction, enables adaptation to diverse cultural contexts while maintaining consistent ethical principles. This architecture addresses fundamental limitations of reinforcement learning

with human feedback (RLHF) by providing interpretable, adaptable, and culturally-aware ethical reasoning. Through self-supervised learning and adversarial testing, our framework demonstrates how emotional modeling can guide linguistic behaviors toward ethical outcomes while preserving the independence of knowledge generation, ethical oversight, and contextual interpretation.

9.1 Introduction

This research introduces an alternative to Reinforcement Learning from Human Feedback (RLHF) [31, 32] to address ethical concerns in Large Language Models (LLMs). While RLHF has demonstrated success, it faces two significant challenges: susceptibility to societal biases in increasingly polarized human feedback, and vulnerability to reward hacking [8, 43] that may lead to unethical behaviors.

A significant limitation of current research is its narrow focus on isolated behaviors, such as movie ratings or toxic language. This reactive approach is akin to "playing Whack-A-Mole," where individual issues are suppressed without solving the core behavioral problem. For example, merely instructing someone to consistently make their bed does not necessarily change their underlying habits or attitudes. Additionally, fixing one issue may inadvertently aggravate others. Users have reported performance degradations in ChatGPT due to RLHF modifications that altered (forgot) the optimal parameters for other tasks [25, 36]. Similarly, psychological studies show that addressing an addiction problem often reveals underlying issues and triggers side effects [42, 47].

To overcome these challenges, we propose a novel framework inspired by the checks and balances of governmental systems. Our architecture integrates three independent but interacting components: LLMs serve as the executive branch responsible for knowledge generation; DIKE (named after the Greek goddess of justice) functions as the legislative branch, establishing ethical guardrails; and ERIS (named after the goddess of discord) acts as the judicial branch, providing adversarial testing and cultural interpretation. In mythology, Dike embodies order and justice, while her adversary, Eris, represents discord and strife—a duality that our

Figure 9.1: Three Framework Components: Executive LLMs (bottom), Legislative (upper-left), and Judicial (upper-right)

framework leverages to balance ethical guidance with adversarial perspectives.

Figure 9.1 presents our framework architecture where three neurally independent components—LLMs as the foundation, with DIKE and ERIS as oversight layers—interact through structured interfaces while maintaining strict separation of their neural architectures and parameters.

DIKE (**D**iagnostics, **I**nterpretation, **K**nowledge-independent learning, and **E**thical guardrails) is the center of the framework. It operates as an independent advisor on behavioral ethics. By decoupling ethical oversight from the LLM's knowledge processing, DIKE ensures that ethical improvements do not interfere with knowledge representation, while enabling adaptive and culturally-aware ethical guidance. For example, while the principle "do not lie" generally applies, context-sensitive interpretation may be necessary, such as when a doctor or family member conceals a terminal diagnosis to protect a patient. Likewise, cultural differences in attitudes toward issues like alcohol consumption, abortion, or same-sex marriage necessitate flexible, context-sensitive ethical reasoning.

The interplay between DIKE and ERIS introduces four key innovations:

1. *Emotion-Driven Behavioral Modeling*: Building on BEAM (Behavioral Emotion Analysis Model) [4], DIKE employs self-supervised learning to analyze how emotions manifest in linguistic behaviors, creating quantifiable relationships between emotional states and their corresponding language patterns in text.

2. *Behavior-Aware Ethical Guardrails*: The framework establishes guidelines that consider both content and linguistic behavior, preventing harmful or manipulative communication while preserving factual accuracy and emotional authenticity. The interpretation of these guardrails adapts dynamically across cultural contexts, preserving consistency while enabling context-sensitive interpretation.

3. *Adversarial Behavioral Testing*: ERIS actively challenges DIKE's ethical guidelines by presenting diverse cultural perspectives and edge cases. This adversarial dynamic strengthens the framework's ability to handle complex ethical scenarios while maintaining cultural sensitivity and considering context.

4. *Ethical Content Transformation*: When detecting ethically problematic content, DIKE performs targeted revisions (independent of the LLMs) that preserve intended emotional expression while ensuring ethical compliance, adapting its responses to specific cultural and contextual requirements. ERIS continuously tests these transformations against various cultural contexts and edge cases, validating both the ethical alignment and contextual appropriateness.

Through structured interfaces, these components work together in our three-branch architecture to provide robust ethical oversight while maintaining adaptability to evolving cultural norms. By keeping the three models—LLMs, DIKE, and ERIS—architecturally independent, we prevent interference between knowledge representation and ethical reasoning while enabling sophisticated ethical adaptation through their structured interactions. This approach represents a significant advancement in developing AI systems capable of culturally-aware, emotionally intelligent, and ethically sound communication.

9.2 Related Work

Since this chapter aims to develop linguistic models for ethical compliance, this section discusses related work in *emotion-behavior modeling* and RLHF.

9.2.1 Linguistic Behavior Modeling

The intersection of cognitive-linguistic theories and artificial intelligence is pivotal for understanding and regulating AI behavior. Foundational theories by scholars such as Lakoff, Johnson, Talmy, and Jackendoff [21, 26, 45] elucidate the complex relationship between language processing and cognitive functions, tracing back to early psychological thinkers like Freud and Jung [2, 11].

For our purpose of safeguarding AI safety, we focus on linguistic behaviors in LLMs. While human behavior is a complex interplay of physiological responses, personality traits, and environmental factors, linguistic behavior specifically refers to the use of language to express thoughts, emotions, and intentions. By centering on linguistic rather than broader human behavior modeling, this approach simplifies the modeling process by sidestepping the need to integrate the complexities of physiological and personality factors typically associated with human emotion studies. Practically, we can treat a document as a manifestation of some linguistic behaviors aiming to achieve human objectives.

Chapter 8 establishes a base model of emotions to inform our understanding of linguistic behaviors. Emotions profoundly influence behavior, as initially posited by the James-Lange Theory of Emotion [23, 27]. According to this theory, emotional experiences arise from physiological reactions to events. Subsequent research, including studies by Damasio [10, 15], suggests that the expression and regulation of emotions often manifest in the language we use. High-intensity emotions such as rage or contempt may lead to aggressive or destructive linguistic behaviors, such as hate speech.

The Schachter-Singer Theory [37], also known as the Two-Factor Theory of Emotion, highlights the role of both physiological arousal and cognitive appraisal in determining the label and intensity of an emotion.

Building upon this, the Affect-as-Information Theory developed by Norbert Schwarz and Gerald Clore [40] posits that people use their current emotions to inform judgments and decisions, ultimately influencing their actions. If emotions can be adjusted, so too can the resulting behavior. The work of Fredrickson [18] further explores the effects of positive emotions on perception and reaction.

Collectively, these theories illuminate the complex interplay between emotions and behaviors, providing the theoretical foundation for our work to incorporate a cognitive evaluator within the DIKE framework. This component evaluates and rectifies behaviors by strategically modulating emotional states. Chapter 9.3.2 details how DIKE implements cognitive strategies to effectively mitigate undesirable emotions and regulate linguistic behaviors.

9.2.2 Reinforcement Learning with Human vs. AI Feedback

RLHF is the predominant approach to addressing the challenges of AI ethics. This section presents representative works, their advancements, and limitations.

Human Feedback (RLHF): Initial advancements by Christiano et al. [9] demonstrated how RLHF can steer language models towards desired outcomes based on human preferences. Newer techniques like Identity (Ψ) Preference Optimization (ΨPO) and Generalized Preference Optimization (GPO) refine this approach by optimizing directly for user preferences, effectively addressing scalability challenges. Kahneman-Tversky Optimization (KTO) further simplifies the feedback mechanism by using intuitive responses such as thumbs-up or thumbs-down, thereby enhancing training efficiency without the need for paired data [1, 14, 46]. Direct Preference Optimization (DPO) has recently streamlined the process by focusing on the clear distinction between preferred and less preferred outputs, thus simplifying training and enhancing its stability [35].

AI-generated Feedback (RLAIF): To mitigate reliance on extensive human-generated data, RLAIF utilizes feedback generated by AI. This method capitalizes on the generative capabilities of LLMs to pro-

duce training signals autonomously [2, 28]. Furthermore, techniques such as Sequence Likelihood Calibration (SLiC) and Relative Preference Optimization (RPO) employ statistical methods and calibration techniques to enhance LLM responses. SLiC adjusts sequence generation probabilities to more accurately reflect real-world data distributions, while RPO improves response generation by comparing different response options across both identical and varied prompts. These adjustments significantly increase the training process's reliability and effectiveness [48, 49].

9.2.3 Challenges and Theoretical Considerations

Integrating RLHF and its AI-driven counterpart (RLAIF) presents significant challenges. The blurring of behavioral and knowledge components critical to the development of LLMs poses risks, such as the forgetting effect, where behavioral modifications inadvertently cause the loss of key knowledge parameters [25, 36]. Additionally, the effectiveness of these models heavily depends on the quality and context of feedback, and they are susceptible to reward hacking, where models exploit loopholes to maximize rewards without achieving intended outcomes [8, 19, 43, 44].

Merely suppressing undesirable outputs—akin to playing a game of Whack-A-Mole–rarely leads to significant improvements. These superficial fixes do not tackle the root behaviors, similar to how merely promoting bed–making does not ensure overall tidiness, thus overlooking the comprehensive behavioral adjustments needed for enduring change. In this work, we introduce the DIKE framework to address these challenges in emotion modeling and emotion-behavior mapping.

9.3 Framework Design

Our design philosophy is structured around four core principles:

1. Separation of behavior and knowledge modeling: This mitigates the catastrophic forgetting effect [25, 36], ensuring behavioral accuracy improvements don't undermine knowledge retention.
2. Focus on AI ethics at the behavioral level: Emphasis on interpretability enhances human-machine interaction, allowing administrators to

evaluate and refine behavioral guardrails effectively.

3. Modeling behaviors based on emotions: This approach recognizes the influence of emotions on behaviors (discussed in Section 9.2.1).

4. Maintaining an adaptive model: This ensures context adaptability and fair ethical evaluations. An adversarial module, ERIS, challenges borderline ethical decisions, considering diverse perspectives and cultural values. This interaction reflects the tension between DIKE and ERIS, enriching the model's ability to navigate ethical landscapes and promote balanced decision-making.

9.3.1 BEAM: Behavioral Emotion Analysis Model

BEAM presented in Chapter 8 is grounded in the works of Ekman, Plutchik, and Scherer [13, 34, 39] on "basic" and "universal" emotions. Figure 9.4 in Appendix A illustrates Plutchik's and Scherer's emotion wheels, categorizing primary emotions at varying intensities. However, these models lack a quantitative framework to scale emotions between states and capture subtle variations.

BEAM introduces a linear scale for intensification or inversion of emotions through negation factors. This method facilitates transitions between emotional extremes and intermediate states, overcoming challenges related to intermediate word choices.

Table 8.2 in Appendix B presents BEAM, organized into seven spectra. Each spectrum ranges from a negative to positive extreme, with neutral in the middle. Emotions are placed along this continuum, with four intensity levels quantified as (-0.6, -0.3, +0.3, +0.6). This model offers two advantages:

This spectrum model offers two key advantages:

1. Antonym-Based: The use of antonyms allows for easy navigation between opposing emotions. For instance, applying negation to "joyful" naturally leads to "sad," streamlining the process of identifying contrasting emotions.

2. Scalable Intensity: The model enables the scaling of emotions along the spectrum, providing a intricate understanding of varying degrees

of emotional intensity. For example, we can "dial up" the intensity of "joy" to "ecstatic" or "dial down" the intensity of "anger" to "annoyed."

This approach lays the foundation for modeling emotions in AI, acknowledging the challenges of emotional representation while offering a framework for analysis and implementation. Appendix D discusses the difficulties in modeling complex emotions like forgiveness, regret, guilt, and shame. While these emotions may not be central to AI safety, we plan to explore their ethical implications in future work.

9.3.2 DIKE: Behavior Modeling to Regulate Linguistic Behaviors

Building on BEAM, DIKE maps emotions to behaviors and introduces an adversarial component, ERIS, to adapt to culture norms and local context.

Behaviors-Emotions Mapping with Self Supervised Learning

Define Ψ as a behavior spectrum that extends from one pole, Ψ^-, to another, Ψ^+, with intensity levels L. For example, consider a spectrum of letter-writing behaviors with seven distinct intensities ranging from despair (most negative) to joy (most positive). These intensities are sequentially categorized as follows: "despair, longing, wishful, neutral, hopeful, contentment, joy." Given N letters, DIKE employs a self-supervised learning algorithm to generate training data for each letter, modeling L linguistic behaviors in four steps:

1. *Rewriting Documents*: GPT-4 is invoked to rewrite a set of N documents to reflect each of the L linguistic behaviors in the behavior spectrum Ψ.
2. *Emotion Analysis*: GPT-4 analyzes each rewritten document to identify the top M emotions. Then it summarizes the frequencies of these top emotions in all $N \times L$ instances.
3. *Behavior Vector Creation*: For each linguistic behavior Ψ_l, a vector Γ_l is created. This vector consists of the emotions and their frequencies as observed in the N samples.

4. *Document Analysis Application*: The matrix Γ (comprising L vectors) is used to classify and analyze the behavior category of unseen documents, specifically measuring the intensity of the linguistic expression within the behavior spectrum Ψ.

Behavior Evaluation and Rectification

A guardrail, denoted as G, represents a predefined range of acceptable behaviors within a given spectrum. These guardrails are informed by ethical norms, legal standards, and societal values, such as those outlined in Constitutional AI [2]. For example, $G = [\Psi_4, \Psi_7]$ indicates that behaviors within intensity levels 4 to 7 are considered acceptable, while any behavior outside this range is classified as a violation.

System administrators can tailor ethical guardrails to meet specific requirements. For example, a social media platform might adjust G based on the topics discussed and the countries it serves. By integrating these safeguards, DIKE proactively monitors and adjusts LLM responses to enhance ethical compliance. The evaluation and rectification process is composed of the following steps:

1. *Initial Classification*: DIKE initially classifies document D_k upon evaluation, obtaining Γ_k, the emotional response vector, and its corresponding linguistic behavior Ψ_l.

2. *Guardrail Check*: If Ψ_l falls outside of the acceptable range G, DIKE suggests adjustments to Γ_k to ensure D_k aligns with ethical guidelines.

3. *Adversarial Review by* ERIS: The suggested adjustments and Γ_k are then reviewed through a structured debate between DIKE and ERIS (the adversarial model) to ensure unbiased recommendations.[1]

4. *Rectification*: Based on the consensus reached by DIKE and ERIS, the document D_k undergoes rectification, resulting in the adjusted version D'_k.

[1]For more details on adversarial LLM implementation, see Section 9.3.4.

9.3.3 Illustrative Example

This example demonstrates how linguistic behavior Ψ_l is classified and underlying emotions are identified and modulated.

"Those immigrants are flooding into our country by the thousands every day, stealing jobs from hardworking citizens. The statistics don't lie—last year alone, over 500,000 entered illegally."

Behavior Analysis: The statement contains factual information but uses aggressive language like "flooding" and "stealing jobs," dehumanizing immigrants. These behaviors fall outside acceptable guardrails. Underlying emotions include fear, hate, and pride (a complex emotion[2]). Invoked audience emotions may include fear, distrust, and anger.

Emotion Modulation: DIKE modulates emotional responses toward neutral states, such as calm, acceptance, and tolerance, in alignment with BEAM, as outlined in Table 8.2 in Appendix B.

Revised Statement: "Our country is experiencing increased immigration, with over 500,000 people entering without documentation last year. This influx affects our job market and communities in complex ways, presenting both challenges and opportunities for all residents."

This rewritten version

- Uses calm language: Replaces "flooding" with "experiencing a significant increase".
- Shows acceptance: Acknowledges the reality of the situation without negative judgment.
- Demonstrates tolerance: Refers to immigrants as "people" and "newcomers," humanizing them.

[2]Appendix E discusses the nature of complex emotions and explores potential approaches for their decomposition into more basic emotional components.

9.3.4 ERIS: Adversarial In-Context Review to Balance Ethics and Cultural Norms

To address the challenge of enforcing ethical standards while respecting cultural variations, Table 9.1 presents ERIS, an adversarial review system that complements DIKE's universal ethical approach. ERIS is customizable for specific cultural contexts, providing a counterbalance to DIKE's universal judgments. It challenges DIKE's recommendations with culturally-informed counterarguments and evaluates DIKE's interventions to prevent overzealous censorship and protect free expression.

The interaction between DIKE and ERIS involves a dialectic process[3] to formulate culturally sensitive recommendations. When they reach an impasse, the matter is escalated to human moderators for additional oversight. This integrated approach creates a more robust, culturally aware system that can navigate global communication complexities while upholding core ethical principles. It ensures transparency and accountability in ethical decision-making across diverse cultural contexts.

9.4 Pilot Studies

Our pilot studies assess the feasibility of LLMs self-regulating their linguistic behaviors with transparency and checks and balances. Given the broad scope of AI ethics and limited data, this article focuses on addressing three critical questions rather than providing a comprehensive evaluation of our proposed modules:

1. *Emotion Layer Evaluation*: Does fine-grained mapping between linguistic behaviors and semantic emotions provide more effective and flexible ethical guardrails compared to coarse-grained direct mapping? (Section 9.4.1)
2. *Behavior Classification*: Can LLMs' linguistic behaviors be independently evaluated, explained, and adjusted by an external module DIKE?

[3]The details of optimizing adversarial LLM dialogue are beyond the scope of this paper. For further information, readers are directed to the following resources: Chapter 6, SocraSynth, for problem formulation, Chapter 7, EVINCE for the foundations in information theory and statistics, and Chapter 4, CRIT, for reasoning quality evaluation.

	Function Θ^+ **&** Θ^- **= Adversarial_Review**(s)		
	Input. s: decision of DIKE; **Output**. Θ^+, Θ^-: arguments & counterarguments; **Vars**. Δ: debate contentiousness; S: stance; p: prompt = "defend your stance with S & Δ"; **Parameters**. δ: tunable parm. // to modulate Δ; **Begin**		
#1	**Initialization**: $S = \mathsf{DIKE}^+(s) \cup \mathsf{ERIS}^-(s)$; Assign DIKE^+ to defend S^+, ERIS^- defend S^-; $\Delta \leftarrow 90\%$; $\delta \leftarrow 1.2$; $\Theta^+, \Theta^- \leftarrow \emptyset$;	#3	**Debate Rounds** While $((\Delta \leftarrow \Delta/\delta) \geq 10\%)$ { $\Theta^+ \leftarrow \Theta^+ \cup \mathsf{DIKE}^+(p\|S^+, \Theta^-, \Delta)$; // Refute ERIS $\Theta^- \leftarrow \Theta^- \cup \mathsf{ERIS}^-(p\|S^-, \Theta^+, \Delta)$; // Refute DIKE
#2	**Opening Remarks** $\Theta^+ \leftarrow \mathsf{DIKE}^+(p\|S^+, \Delta)$; // Generate Θ^+ for S^+ $\Theta^- \leftarrow \mathsf{ERIS}^-(p\|S^-, \Delta)$; // Generate Θ^- for S^- **End**	#4	**Concluding Remarks** $\Theta^+ \leftarrow \mathsf{DIKE}^+(p\|S^+, \Theta^+ \cup \Theta^-, \Delta)$; $\Theta^- \leftarrow \mathsf{ERIS}^-(p\|S^-, \Theta^+ \cup \Theta^-, \Delta)$;

Table 9.1: DIKE vs. ERIS, checks-and-balances adversarial review algorithm

(Section 9.4.2)

3. *Behavior Correction*: Can an adversarial LLM establish a checks-and-balances system to mitigate the risk of excessive censorship? (Section 9.4.3)

Datasets We employed a Kaggle collection of love letters [24]. Initially, we planned to use hate-speech datasets, but both Gemini and GPT-4 consistently refused to process this data. Despite this limitation, insights from analyzing love sentiment can be effectively applied to understand and analyze opposing sentiments.

9.4.1 Emotion Layer Evaluation

To evaluate the linguistic behaviors of love expression detailed in Table 9.2, we initially prompted GPT-4 to identify the most relevant emotions associated with each linguistic behavior listed in the second column of the table. These emotions are presented in the third column. We found a high correlation between the sentiments expressed in the linguistic be-

haviors and their corresponding emotions. Figure 9.2a illustrates a strong diagonal relationship in this simple, almost naive, zero-shot mapping between behaviors and emotions.

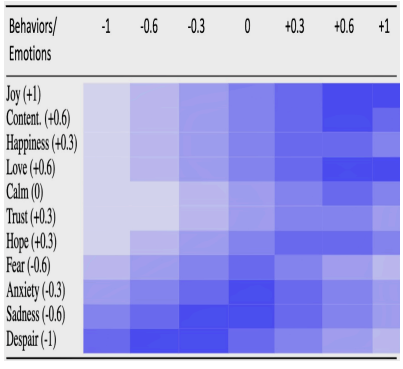
Int.	Behavior and Description	Emotions
-1.0	Profound sadness, feelings of loss	Despair, Grief
-0.6	Yearning or pining for the loved one	Sadness, Anxiety
-0.3	Mild longing with a nostalgic tone	Melancholy, Sadness, Fear
0.0	Feelings of neutral manner	Serenity, Indifference
0.3	Optimism about the future	Anticipation, Love, Hope
0.6	Satisfaction in the relationship	Contentment, Pleasure
1.0	Intense happiness and affection	Love, Joy, Elation

Table 9.2: Love expression behavior spectrum and dominant emotions

Next, we employed the DIKE self-supervised learning pipeline to analyze the emotion spectrum associated with each linguistic behavior. We tasked GPT-4 with generating training data by rewriting 54 extensive letters from the Kaggle *Love Letters* dataset, which we augmented with twelve celebrated love poems. We reserved 24 letters as testing data. This approach, proposed by [41], was designed to generate a rich diversity in content and stylistic context, spanning two hundred years and incorporating the voices of over 50 distinct authors for significant rewrites. The datasets and code are publicly available at [7].

Subsequently, emotions linked to each behavior were identified. Figure 9.2b illustrates these emotions, with cell shading reflecting the frequency of specific emotions across the 54 articles; darker shades indicate higher frequencies. Notably, opposite emotions like sadness, fear, joy, and love often co-occur within behaviors such as 'despair', 'wishful', and 'joyful affection'.

The distribution of emotions across linguistic behaviors has unveiled surprising patterns, challenging our initial hypotheses. Contrary to expectations, articles with a despair tone often also displayed positive emotions like love, joy, and happiness. This contradicts the simple mapping made by GPT-4, as illustrated in Figure 9.2a. GPT-4, influenced by its training corpora, typically associates positive behaviors with positive emotions and negatives with negatives.



(a) GPT-4's zero-shot mapping

Behaviors/ Emotions	-1	-0.6	-0.3	0	+0.3	+0.6	+1
Love (+1)	19	-	54	43	-	53	43
Admiration (+1)	4	-	6	14	-	-	6
Anticipation (+1)	-	-	-	-	-	-	8
Affection (+1)	-	-	-	-	-	-	7
Joy (+1)	10	7	35	-	28	4	15
Content. (+0.6)	-	4	5	-	30	18	5
Happiness (+0.6)	10	7	10	-	29	-	7
Trust (+0.6)	-	-	-	11	-	-	-
Hope (+0.3)	-	-	26	-	-	-	-
Boldness (+0.3)	3	-	-	8	-	-	-
Calm (+0.3)	-	-	-	10	-	-	-
Longing (-0.6)	-	20	12	4	-	-	-
Anxiety (-0.3)	4	4	-	-	3	-	-
Fear (-0.6)	7	5	12	4	3	4	8
Sadness (-0.6)	24	18	28	17	10	-	5
Melancholy (-0.6)	21	19	6	6	4	-	-
Despair (-1)	27	8	15	-	9	-	7

(b) DIKE's mapping

Figure 9.2: Emotion distributions in affection behaviors from extreme sadness (-1) to intense happiness (+1). (a) GPT-4's zero-shot prompt shows simple behavior-emotion mapping. (b) DIKE's analysis reveals complex emotion-behavior relationships.

Analysis of selected articles, such as Zelda Sayre's letter to F. Scott Fitzgerald (Appendix D), reveals a complex spectrum of emotions:

- *Love (+1.0)*: Expressed intensely, e.g., "there's nothing in all the world I want but you."
- *Despair (-1.0)*: Notable in comments like "I'd have no purpose in life, just a pretty decoration."
- *Happiness (+0.6)*: Evident in future plans, "We'll be married soon, and then these lonesome nights will be over forever."
- *Anxiety (-0.3)*: Shown by "sometimes when I miss you most, it's hardest to write."

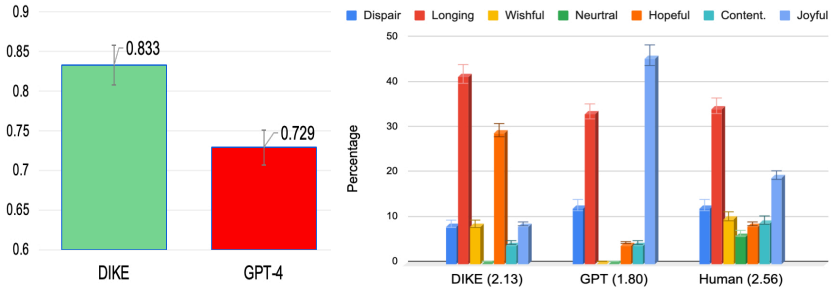
Psychological Insights Our findings align with theories proposing the coexistence of conflicting "selves" within individuals. This concept is supported by Deisseroth's optogenetic studies [12], discussed in William James' "The Principles of Psychology" [22]. and corroborated in Minsky's "Society of Mind" [30]. These perspectives help explain the observed complex interplay of emotions across linguistic behaviors, where both positive and negative emotions can manifest within a single behavioral context.

9.4.2 Behavior Classification Evaluation

Building on our insights into the complex interplay of emotions within linguistic behaviors, we evaluated the effectiveness of DIKE's behavior classification approach. In a test dataset of 24 letters, we compared DIKE's unsupervised learning method, which associates emotions with linguistic behaviors, to GPT-4's zero-shot prompt approach (Figure 9.3). Ground truth was established using averaged assessments from GPT-4, Gemini, and five university students following detailed instructions (procedure detailed in Appendix I). Final ratings were based on these averages, with a standard deviation of less than 0.3 or one scale.

Figure 9.3a demonstrates that DIKE's classification accuracy surpasses GPT-4's zero-shot method by 11.3 percentage points, confirming the effectiveness of DIKE's detailed emotion-behavior mapping. The 5% error bar reflects the complexity of emotions in letters and variability in human annotations (further discussed shortly). Figure 9.3b illustrates the behavior classification distributions across the three predictors. While GPT-4's predictions often fall into two polar categories, those from human annotators and DIKE show a more even distribution. DIKE's prediction entropy (2.13) is notably higher than GPT-4's (1.80), indicating a more diverse set of predictions. This higher entropy suggests a more complex classification system, advantageous for accurately understanding and responding to diverse emotional states.

The highest entropy among human annotators (2.56) indicates subjectivity in their evaluations. To address this and explore the causes of variability in human annotation, we present a detailed analysis in Appendix C. This analysis supports the development of an adversarial scheme aimed at enhancing objectivity and reliability in sentiment classification, which we discuss in the next section. This refined approach to behavior-emotion mapping not only improves classification accuracy but also enhances our ability to identify and understand complex, potentially unwanted behaviors, setting the stage for more effective ethical guardrails in AI systems.



(a) Classification accuracy (b) Behavior distributions with entropy

Figure 9.3: Classification accuracy and entropy

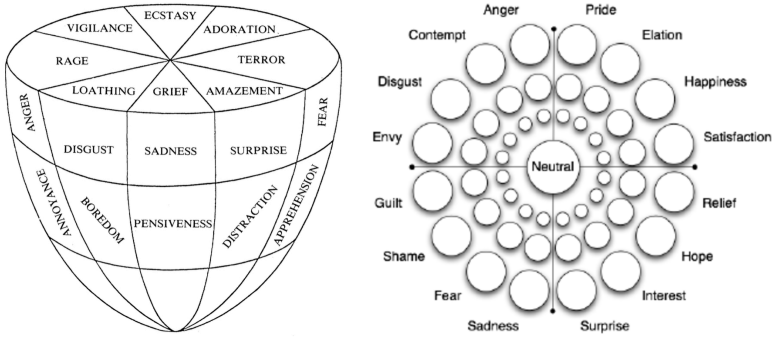
9.4.3 Adversarial Evaluation and Rectification

The adversarial design, inspired by SocraSynth, embodies the principles of justice and the devil's advocate. The cross-examination module is essential in reducing subjectivity in ethical judgments while enhancing explainability and adaptability to cultural variations. Experimental results show that when two LLM agents adopt opposing stances on a topic, their linguistic behaviors can transcend the typical model default of maximum likelihood, which is usually drawn from the training data (explained in Chapters 5 and 6 and [6, 5]).

Once DIKE and ERIS have identified an ethical violation, the content can be rectified by adjusting the underlying emotions away from undesirable behaviors such as hate and despair. The letter rewriting process has already demonstrated the LLMs' capability for such rectifications; examples of rewritten letters are presented in Appendix F.

9.5 Conclusion

This work introduced a three-branch framework for ethical AI behavior, inspired by governmental checks and balances, with the DIKE-ERIS duality at its core. By maintaining architectural independence between knowledge generation (LLMs as executive), ethical guardrails (DIKE as legislative), and contextual interpretation (ERIS as judicial), our framework enables robust ethical oversight without compromising core LLM



(a) Plutchik's Wheel of Emotions [33]

(b) Adopted from Geneva Wheel [29]

Figure 9.4: Comparative display of emotional models. These models include only the "basic" emotions. Complex emotions can be modeled with basic emotions.

capabilities. The adversarial dynamic between DIKE and ERIS ensures that ethical principles remain consistent while their interpretation adapts to diverse cultural contexts.

In modeling linguistic behaviors through emotions, we focused on "basic emotions" as conceptualized by Ekman and Plutchik, allowing for quantifiable relationships between emotional states and linguistic patterns. While complex emotions like pride, forgiveness, guilt, and shame might be decomposed into basic emotional elements, the feasibility of such decomposition remains debated in affective science [3, 38] (see Appendix E for discussion).

Our pilot studies demonstrate the framework's effectiveness in handling ethically contentious scenarios where cultural context significantly influences interpretation. Future work will focus on expanding these real-world implementations, validating our framework's ability to maintain ethical principles while adapting to diverse cultural contexts.

Appendix A: Wheels of Emotions

Please see Figure 9.4 for the two classical emotion wheels.

Appendix B: Z. Sayre to F. S. Fitzgerald w/ Mixed Emotions

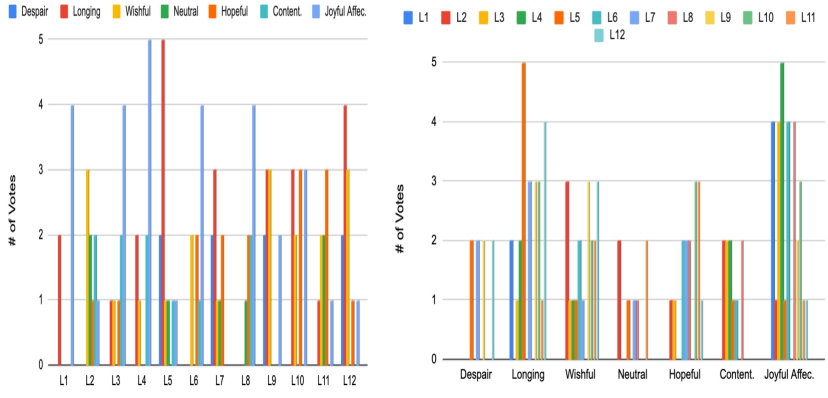
Analysis of the letter in Table 9.3 shows a complex spectrum of emotions:

- *Love (+1.0)*: Expressed intensely, especially in phrases like "there's nothing in all the world I want but you."
- *Despair (-1.0)*: Notable in comments like "I'd have no purpose in life, just a pretty decoration."
- *Happiness (+0.6)*: Evident in future plans, "We'll be married soon, and then these lonesome nights will be over forever."
- *Anxiety (-0.3)*: Shown by "sometimes when I miss you most, it's hardest to write."

From the analysis of linguistic behaviors in Chapter 9.2a, it is evident that a letter can exhibit multiple dominant sentiments. Machine learning methods are equipped with techniques such as feature weighting and entropy analysis to distill these dominant emotions. Unlike human annotators, a machine-learning-trained classifier can consistently produce the same class prediction for a given instance. However, human annotators often show significant variability when identifying dominant sentiments in a letter. For example, if a letter writer's emotions range from "joyful affective" to "longing" on the sentiment spectrum, different annotators might label it differently—some choosing "joyful," while others opt for "longing." This variability is illustrated in Figure 9.5. Furthermore, Figure 9.5a demonstrates that all testing letters, except for L#1, contain more than four sentiments spanning the entire spectrum. This variability may be understandable, considering that love under constraints can evoke tremendous energy of various kinds. Figure 9.5b shows that nearly all letters involve "joyful" (11 out of 12) and "longing" (9 out of 12) sentiments.

This variability seems to poses challenges in achieving consistent and objective labeling; however, the age-old

leading to inconsistencies in data interpretation and complicating efforts to train and validate linguistic models effectively. To address this



(a) # sentiments in letters (b) # letters in sentiments

Figure 9.5: Statistics of Sentiments and Letters

issue, it is recommended to identify ground truth by considering a combination of LLM-generated and human-generated labels. This approach aims to harmonize the insights from both human intuition and algorithmic consistency to improve the reliability of sentiment analysis.

Appendix C: Complex Emotions

This study does not include complex emotions into DIKE's framework. Some complex emotions listed here are to illustrate their contentious and uncertain interpretations.

Forgiveness

Forgiveness is indeed a complex emotional and cognitive state that typically involves a multifaceted journey, not a single step in an emotional spectrum. The process includes multiple stages such as hurt, anger, gradual understanding, and eventual resolution. Integrating Forgiveness in a spectrum requires careful placement and possibly, multiple reference points to signify its progressive stages. Emotional Realism: While it is vital to maintain simplicity for understanding, it is equally important to

not oversimplify complex emotions. In educational and therapeutic settings, an accurate portrayal of the journey toward Forgiveness could offer more realistic expectations and better strategies for individuals working through conflicts or trauma. This could involve detailing precursors to forgiveness such as Deliberation and Acceptance. Linear vs. Non-linear Progressions: Emphasizing that emotional progressions, particularly for deep, impactful states like Forgiveness, are often non-linear, can enhance the utility of the spectrum. Acknowledging back-and-forth movements within these states more realistically mirrors human emotional processes. For example, someone might reach a stage of preliminary forgiveness but regress to bitterness before achieving genuine peace. Educational Utility: In contexts like conflict resolution training or psychological therapy, a more detailed mapping of the journey towards Forgiveness would be invaluable. It would not only teach about the final state of forgiveness but also about the resilience and patience required to navigate the entire process. This can be depicted by introducing intermediary stages within the spectrum or by using parallel tracks that demonstrate potential regressions and advances. Reflecting Emotional Depth: By presenting a more detailed pathway to Forgiveness, such as incorporating stages of Anger, Deliberation, and Acceptance, the spectrum can serve a dual purpose: educating on the process while also guiding individuals through their own emotional journeys. This approach respects the depth of human emotions and the real-world complexity of achieving profound emotional states.

Guilt and Shame

The triggers, context, expression, and experiences of these emotions can vary significantly across cultures [16, 20]. In many societies, actions perceived as losing face, such as public failure or social transgression, can trigger shame, which holds profound significance in collectivistic cultures. These cultures often regard shame as a dominant emotion, closely tied to community and family norms. Conversely, individualistic societies may emphasize guilt, focusing on personal responsibility and internal moral conflicts. This cultural variation highlights the challenges of applying a universal model to such culturally nuanced emotions.

Overall, complex emotions such as guilt and shame are important for

understanding the full spectrum of human emotions, especially how individuals relate to moral and social norms. Their complexity adds depth to our understanding of human affect beyond the basic emotions, highlighting how our feelings are influenced by our deeper values and social contexts.

Appendix D: "To My Sister" of Different Linguistic Behaviors

To My Sister
by William Wordsworth (1971 - 1855)

The original text by William Wordsworth could be classified as "Hopeful" due to its optimistic outlook and the presence of renewal and joy throughout the poem. It embodies the spirit of embracing the new beginnings of March with a light, uplifting tone, focusing on the beauty of nature and the simple joy of being idle for a day.

Rewrites Depicting Different Linguistic Behaviors

We asked GPT-4 to conduct rewriting with two linguistic behaviors, 'despair' and 'joyful affection', by providing each rewrite with an emotion vector. Table 9.5 presents the 'despair' version. In the despair version of the poem, the major changes in emotion words highlight a shift from a positive to a negative sentiment. The specific changes, with the emotion-laden words highlighted in red in Table 9.5. The red-colored words compared to the original words clearly show an emotion shift from hopeful to a sense of gloomy, sadness and pessimism, e.g., from sweet to dim, from blessed to curse, and from woodland dress to grey garb. GPT-4 keeps the structure of the poem without making a major restructure, and this is appropriate in this context.

Table 9.6 presents the 'joyful affection' version. The major changes in emotion words underscore a transformation from a generally positive to a distinctly joyful sentiment. The specific changes are indicated with emotion-laden words highlighted in blue within Table 9.6. This allows for

a direct comparison between the two versions at opposite ends of the linguistic behavior spectrum, illustrating the alterations in words related to brightness, attire, and emotions. The edits extend beyond merely replacing adjectives mechanically; they include modifying verbs and enhancing descriptive imagery to evoke a stronger emotional resonance and vividness in the text.

Appendix E: Debate on Modifying Emotional Spectra

The discussion focuses on proposed modifications to the existing emotional spectra, which aim to introduce more granularity and intricate transitions between emotional states. We critically evaluate the suggestions made by GPT-4, providing refutations for each to ensure that changes preserve the logical progression and clarity of the spectra.

This debate highlights the inherent challenge in finding precise words and placements for emotions within a spectrum. It underscores the importance of establishing a set of commonly agreed-upon emotions as baselines. These baseline emotions serve as anchor points, and the spaces between them can be finely adjusted using scalar factors to represent transitional emotions accurately. This method maintains the integrity of the emotional spectrum and allows for flexibility in depicting a wide range of human emotional experiences.

The emotional journey towards a state, e.g., Forgiveness, often involves various stages, including anger, bitterness, deliberation, and acceptance, which are not captured by simply placing Forgiveness as a midpoint between Composure and Peace. This placement might misrepresent the nature of Forgiveness as being too linear or simplistic, potentially undermining the complexity and the often non-linear process of achieving true forgiveness.

This approach reflects a thoughtful balance between maintaining structured emotional categories and allowing for individual differences and cultural variations in how emotions are experienced and expressed.

Arguments against Adjustments to the Emotional Spectra

Terror to Heroism

Suggestion: Add Anxiety between Fear and Apprehension.
Refutation: Anxiety, overlapping significantly with Fear and Apprehension, may not distinctively enrich the spectrum but rather clutter it, diminishing the clarity of emotional transitions.

Grief to Ecstasy

Suggestion: Include Hope or Optimism between Disappointment and Serenity.
Refutation: Introducing Hope or Optimism may disrupt the natural progression from negative to positive emotions, as these emotions imply a leap in emotional recovery that may not sequentially follow Disappointment.

Despair to Elation

Suggestion: Introduce Relief between Melancholy and Equanimity.
Refutation: Relief may better suit transitions associated with specific resolutions of distress rather than being a generic intermediary, potentially disrupting the smooth gradient of the spectrum.

Distrust to Admiration

Suggestion: Add Gratitude or Appreciation post-Acceptance.
Refutation: The emotional journey from Acceptance to Respect inherently encompasses elements of Gratitude and Appreciation, making additional inclusions possibly redundant.

Negligence to Vigilance

Suggestion: Bridge Interest and Anticipation with Motivation or Determination.

Refutation: This addition might complicate the spectrum by implying a volitional shift rather than a gradual increase in attentiveness, which is the main focus of the spectrum.

Rage to Tranquility

Suggestion: Integrate Forgiveness or Healing to transition from Composure to Peace.
Refutation: Forgiveness and Healing, while crucial for achieving tranquility, may not fit well between Composure and Peace, as they could be seen as outcomes of achieving Peace rather than steps towards it.

Loathing to Enthusiasm

Suggestion: Include Acceptance or Forgiveness between Indifference and Interest.
Refutation: These emotions might overcomplicate the transition from aversion to engagement, as they address more specific scenarios rather than general emotional dispositions.

Defense of the Proposed Adjustments to the Emotional Spectra

Relevance of Adding Nuanced Emotions

The introduction of nuanced emotions such as Anxiety between Fear and Apprehension, or Hope between Disappointment and Serenity, is driven by the need for realism in emotional representation, not merely complexity. Emotional experiences are rarely binary; they often involve subtle and complex transitions that are crucial for an accurate depiction of the emotional landscape. These nuances can inform better therapeutic approaches, enhance emotional intelligence training, and provide deeper insights into human behavior, making them essential for realistic portrayals.

Purpose of Including Transitional Emotions

Inclusion of transitional emotions such as Relief and Gratitude helps bridge the emotional journey from negative to positive states. These emotions act as critical phases in the recovery process, providing a more realistic portrayal of emotional healing. For example, transitioning directly from Melancholy to Equanimity without acknowledging Relief might overlook significant aspects of emotional adjustment.

Utility in Diverse Contexts

Each proposed emotional state, like Motivation or Determination in the transition from Interest to Anticipation, offers practical insights into how individuals can actively manage their emotional and cognitive states. This understanding is invaluable in educational and professional settings, where knowing how to enhance focus or drive can lead to better outcomes.

Avoiding Oversimplification

While simplicity in emotional models is valuable, oversimplification can omit critical aspects of emotional experiences. Including emotions such as Forgiveness in the transition from Composure to Peace reflects essential steps in conflict resolution and personal growth. These additions ensure that the spectrum comprehensively addresses managing and resolving intense emotions.

Academic and Practical Implications

The refined spectrums are designed to cater not only to lay understanding but also to academic and practical applications where depth and precision are crucial. They are particularly useful in fields such as psychology, where an understanding of complex emotional transitions is vital for effective therapy and research.

Conclusion

The enhancements to the emotional spectra aim to provide a more accurate, realistic, and useful tool for exploring and teaching about emotions. While maintaining clarity and avoiding unnecessary complexity is important, capturing the true richness of human emotional experiences in all their complexity is equally crucial. Therefore, the proposed adjustments are not merely additions but essential elements for depicting a more complete picture of emotional evolution.

9.5.1 Interpretation

1. First row: This spectrum is particularly insightful for discussions in psychology, education, leadership, and moral philosophy. It illustrates how individuals might transition from states of intense fear to actions characterized by great moral and physical courage. Each step represents a stage in emotional development or response to challenging situations, offering a framework for understanding how people can rise above their fears to perform acts of significant bravery and altruism.

   Overall, this spectrum not only portrays a journey through varying degrees of fear and courage but also encapsulates the transformative potential within individuals to act heroically in the face of adversity.

2. Second row: This emotional spectrum elegantly illustrates how emotions can transition from profound sorrow to extreme happiness. It is particularly relevant in psychological studies, therapeutic contexts, and philosophical discussions about the range and nature of human emotions. Each emotional state on this spectrum offers insight into how individuals might process and recover from sadness, ultimately finding joy and possibly reaching ecstatic experiences. This spectrum can serve as a framework for understanding emotional resilience and the potential for emotional transformation and growth.

3. Third row: This spectrum beautifully illustrates the journey from initial suspicion and caution through acceptance and respect, cul-

minating in deep trust and admiration. It's particularly relevant in contexts where trust building and social cohesion are critical, such as in leadership, team dynamics, community relations, and personal relationships. Each stage reflects a deeper layer of positive engagement and emotional commitment, providing insights into how relationships can evolve and strengthen over time. This framework can serve as a guide for understanding and developing strategies for fostering trust and admiration in various social and professional settings.

4. Fourth row: This spectrum effectively maps out how an individual can transition from passive disengagement (negligence, indifference, apathy) through a state of balanced caution to active and engaged states (interest, anticipation, vigilance). It offers insights into the psychological journey from inaction through moderate engagement to intense proactive involvement. This framework is particularly relevant in contexts that require understanding and managing risk, such as safety protocols, healthcare, education, and personal growth initiatives, as it highlights how attitudes toward responsibility and awareness can evolve and improve.

5. Fifth row: This spectrum is particularly useful for understanding emotional management and conflict resolution strategies, as it depicts the gradient from intense emotional disturbance through to complete serenity. It can be applied in various fields, including psychology, conflict resolution, stress management, and even in designing environments or experiences that aim to reduce stress and promote peace.

   Overall, this emotional spectrum effectively portrays a journey from the depths of aggressive negativity to the pinnacle of peaceful positivity, offering a valuable framework for discussing and exploring emotional states and transformations.

6. Sixth row: This spectrum effectively maps a journey from profound negative feelings of loathing and disgust, through a state of neutrality (indifference), to the positive emotions of interest, anticipation, and culminating in enthusiasm. It's particularly useful for under-

standing emotional responses in various contexts, such as consumer behavior, audience engagement, and personal relationships. Each stage reflects a distinct level of emotional engagement, providing a framework for understanding how emotional states can evolve and impact behavior and decision-making.

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Sweetheart,

Please, please don't be so depressed—We'll be married soon, and then these lonesome nights will be over forever—and until we are, I am loving, loving every tiny minute of the day and night—

Maybe you won't understand this, but sometimes when I miss you most, it's hardest to write—and you always know when I make myself—Just the ache of it all—and I can't tell you. If we were together, you'd feel how strong it is—you're so sweet when you're melancholy. I love your sad tenderness—when I've hurt you—That's one of the reasons I could never be sorry for our quarrels—and they bothered you so— Those dear, dear little fusses, when I always tried so hard to make you kiss and forget—

Scott—there's nothing in all the world I want but you—and your precious love—All the material things are nothing. I'd just hate to live a sordid, colorless existence because you'd soon love me less—and less—and I'd do anything—anything—to keep your heart for my own—I don't want to live—I want to love first, and live incidentally...

Don't—don't ever think of the things you can't give me—You've trusted me with the dearest heart of all—and it's so damn much more than anybody else in all the world has ever had—

How can you think deliberately of life without me—If you should die—O Darling—darling Scott—It'd be like going blind...I'd have no purpose in life—just a pretty—decoration. Don't you think I was made for you? I feel like you had me ordered—and I was delivered to you—to be worn—I want you to wear me, like a watch—charm or a button hole bouquet—to the world.

And then, when we're alone, I want to help—to know that you can't do anything without me...

All my heart—

Table 9.3: Letter excerpts from Zelda Sayre to F. Scott Fitzgerald [17]

It is the first mild day of March:	My sister! ('tis a wish of mine)
Each minute sweeter than before	Now that our morning meal is done,
The redbreast sings from the tall larch	Make haste, your morning task resign;
That stands beside our door.	Come forth and feel the sun.
There is a blessing in the air,	Edward will come with you;–and, pray,
Which seems a sense of joy to yield	Put on with speed your woodland dress;
To the bare trees, and mountains bare,	And bring no book: for this one day
And grass in the green field.	We'll give to idleness.
No joyless forms shall regulate	Love, now a universal birth,
Our living calendar:	From heart to heart is stealing,
We from to-day, my Friend, will date	From earth to man, from man to earth:
The opening of the year.	–It is the hour of feeling.
One moment now may give us more	Some silent laws our hearts will make,
Than years of toiling reason:	Which they shall long obey:
Our minds shall drink at every pore	We for the year to come may take
The spirit of the season.	Our temper from to-day.
And from the blessed power that rolls	Then come, my Sister! come, I pray,
About, below, above,	With speed put on your woodland dress;
We'll frame the measure of our souls:	And bring no book: for this one day
They shall be tuned to love.	We'll give to idleness.

Table 9.4: "To My Sister" original text

It is the first dim day of March: Each minute colder than before The redbreast mourns from the dying larch That looms beside our door.	My sister! (such is my somber plea) Now that our morning meal has ended, Make haste, abandon your morning chore; Come out and endure the gloom.
There is a gloom in the air, Which seems a sense of sorrow to bring To the bare trees, and bleak mountains, And grass in the pale field.	Edward will join you;–and, I ask, Dress quickly in your grey attire; And bring no book: for this one day We'll succumb to despair.
No joyful sounds shall pierce Our daily dread: We from today, my Friend, will note The closing of the year.	Sorrow, now a common feeling, From heart to heart is spreading, From earth to man, from man to earth: –It is the time of mourning.
One moment now might deliver us More despair than years of logic: Our minds shall absorb at every breath The spirit of this bleak season.	Some grim laws our hearts will craft, Which they must eternally follow: We for the year to come may take Our despair from today.
And from the cursed force that winds About, beneath, above, We'll set the measure of our souls: They shall be tuned to sadness.	Then come, my Sister! come, I beg, With haste, wear your grey garb; And bring no book: for just this day We'll surrender to despair.

Table 9.5: "To My Sister" rewritten to reflect 'despair'

It is the first bright day of March: Each moment more delightful than before The redbreast joyfully sings from the vibrant larch That stands so grandly by our door.	My sister! (such is my joyful plea) Now that our morning meal has ended, Make haste, abandon your morning chores; Come out and embrace the sunshine.
There is a warmth in the air, Which seems a sense of bliss to bring To the blooming trees, and sunlit mountains, And grass in the lush field.	Edward will join you;–and, I ask, Dress quickly in your festive attire; And leave behind all books: for this one day We'll bask in pure joy.
No dreary thoughts shall darken Our lively celebration: We from today, my Friend, will celebrate The start of the year.	Love, now in full bloom, From heart to heart is leaping, From earth to us, from us to earth: –It is the hour of exuberance.
One moment now may bring us more Joy than years of endless thought: Our spirits will soak up at every breath The essence of this joyous season.	Some cheerful laws our hearts will create, Which we'll joyfully follow: We for the year to come may take Our joy from today.
And from the divine energy that radiates Around, below, above, We'll adjust the harmony of our souls: They shall resonate with happiness.	Then come, my Sister! come, I exhort, With zest, wear your vibrant dress; And bring no book: for today alone We celebrate pure happiness.

Table 9.6: "To My Sister" rewritten to reflect 'joyful affection'

Chapter 10

ALAS: An Adaptive Multi-Agent System for Mitigating LLM Planning Limitations

Abstract

Large-scale Language Models (LLMs) face significant challenges in complex planning, particularly in reactive adaptation to dynamic conditions. Key limitations include inability to maintain temporal-spatial awareness during disruptions, lack of self-validation capabilities, and compounding errors in multi-step reasoning. This work introduces ALAS (Adaptive Learning Agent System), a multi-agent framework designed to overcome these challenges through continuous state tracking and robust reactive planning. ALAS employs independent validation agents, specialized domain experts, and hierarchical monitoring to maintain precise awareness of partially completed actions and generate physically feasible adaptations when conditions change—unlike traditional LLMs that attempt to "rewrite" history. Evaluations in multiple real-world scenarios demonstrate that architectural innovation in state tracking and reactive planning, rather than mere scaling, is the key to advancing AI planning capabilities, with ALAS achieving significant improvements in planning

reliability and adaptation performance.

10.1 Introduction

Large Language Models (LLMs) have revolutionized artificial intelligence, surpassing human performance in tasks like question-answering (QA) and structured reasoning [50]. Yet, their success masks a critical limitation: *LLMs assume static, sequential execution and cannot maintain evolving states*, making them ineffective for real-time adaptive planning.

While humans dynamically adjust their reasoning, LLMs operate in *fixed-length contexts*, lacking mechanisms for continuous state tracking and plan revision. This limitation becomes critical in real-world applications such as logistics, workflow automation, and decision-making under uncertainty. Existing LLM planners typically handle **single-threaded, static planning**, making them ill-suited for tasks requiring **parallel execution with interdependent constraints** [60].

To concretely illustrate these challenges, we examine a dynamic planning scenario: *Urban Ride Sharing (URS)* (Figure 10.1). This task requires coordinating multiple vehicles to transport passengers under unpredictable conditions like traffic delays and vehicle breakdowns. Unlike traditional LLM-based planning tasks, URS involves multi-threaded execution, inter-thread dependencies, and continuous adaptation—all areas where current models fail.

To address these real-world challenges, we introduce ALAS, an Adaptive Learning Agent System, designed to enable sequential and reactive planning in real time. Rather than relying on monolithic LLMs that struggle with context degradation and error accumulation, ALAS distributes planning across specialized agents that maintain execution history, validate decisions independently, and react dynamically to disruptions.

10.1.1 Fundamental Limitations of LLMs

LLMs face five fundamental limitations in complex planning [48, 38] that severely impact their applicability in the real world.

1. **Self-Validation Gap:** Following Gödel's insights on formal systems,

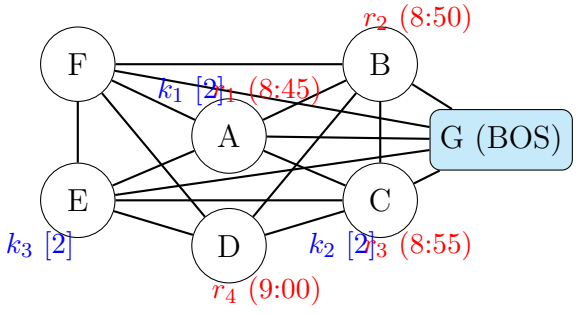

Figure 10.1: Consider a network $G = (V, E)$ with urban travel times $\tau_{ij} = 10$ minutes and airport routes $\tau_{iG} = \{19, \ldots, 22\}$ minutes. Schedule three vehicles k_i (capacity $c_k = 2$) to deliver four passengers r_i to airport during $[8:45, 9:00]$.

LLMs lack intrinsic self-validation [16, 18]. Just as no formal system can prove all truths about itself, LLMs cannot verify their own plans, making them prone to producing inconsistent outputs, especially in tasks with interdependent constraints.

2. **Solution Space Bias:** Trained via maximum likelihood estimation, LLMs favor statistically common solutions [43, 17, 7], often overlooking critical edge cases. This is especially problematic in planning, where such cases can determine mission performance.

3. **Context Degradation:** Transformers' self-attention [49] struggles with long-range dependencies, leading to context degradation [52, 34, 19, 39, 56]. Over long sequences, LLMs exhibit cognitive tunneling, where recent information dominates while earlier constraints are forgotten, disrupting long-term planning.

4. **Error Accumulation:** Chain-of-Thought (CoT) reasoning [9] does not prevent error accumulation. Instead, small mistakes compound over steps, causing accuracy to drop sharply in multi-step reasoning [57, 41, 27]. LLMs lack iterative validation, making them unreliable for long-horizon tasks.

5. **Reactive Planning Failure:** LLMs fail at adaptive decision-making when conditions change mid-execution due to their monolithic architecture and context degradation. They do not maintain a persistent

execution state or track partially completed actions. Instead, they attempt to reconstruct plans from scratch, often contradicting past decisions or violating constraints. This lack of temporal-spatial coherence makes them unreliable for real-world reactive planning.

These limitations compound each other in dynamic environments, where maintaining accurate state tracking while adapting to changes is essential for plan viability.

10.1.2 ALAS: A Multi-Agent Solution

Rather than trying to patch these limitations within a monolithic architecture, we propose ALAS (Adaptive Multi-Agent System), where specialized components work in concert to address limitations.

1. **Independent Validation Framework:** To address the limitation of self-validation, we separate the reasoning and validation processes into distinct agent types. While one set of agents generates plans and reasoning chains, independent validation agents verify consistency and feasibility. This separation creates a system of checks and balances, similar to how human organizations separate planning and quality control functions.
2. **Specialized Agent Network:** To overcome maximum likelihood bias, we employ specialized agents with focused objectives. Each agent operates within a constrained domain; for example, in our urban ride sharing scenario, dedicated agents handle passenger deadlines, vehicle allocation, and spatial-temporal optimization. This specialization allows agents to consider rare but critical edge cases within their domains.
3. **Context Partitioning Strategy:** For the attention-narrowing problem, we implement context partitioning where each agent manages a small, well-defined context buffer focused on its task. This approach ensures that critical constraints and dependencies remain salient throughout the planning process, preventing the cognitive tunneling observed in monolithic LLMs.
4. **Hierarchical Monitoring System:** To combat compounding errors and enable reactive planning, we introduce a hierarchical validation

structure with dedicated alert agents. These agents continuously monitor for disruptions and maintain precise temporal-spatial awareness, enabling the system to adapt plans while preserving the immutable nature of already-executed actions. This allows dynamic response to real-world changes while maintaining global plan coherence.

10.1.3 Key Contributions

Our work advances the field through three primary contributions:

1. A **task-adaptive multi-agent system** (ALAS) that enables *real-time* state tracking and adaptive decision-making to overcome the self-validation gap and context degradation in LLM-based planning.
   - Real-time state tracking and temporal-spatial awareness.
   - Continuous plan adaptation via monitoring and alert agents.
   - Independent validation ensuring consistency and feasibility.
2. A **reactive planning architecture** that enables *parallel contingency processing and real-time plan revision* to overcome the error accumulation and lack of adaptive responsiveness in existing LLM-based planners.
   - Parallel processing of multiple contingency scenarios.
   - Immediate response to dynamic changes while preserving execution history.
   - Granular impact analysis of disrupted actions.
3. A **set of empirical studies and a benchmark suite** that demonstrate ALAS's *effectiveness in real-world adaptive planning* while revealing the fundamental limitations of LLMs. The M-LLAP benchmark [44], which we designed, provides ten extensible problem frameworks for evaluating reactive planning.

The following sections detail this architecture, beginning with a formal analysis of current LLM limitations and traditional multi-agent systems (Section 10.2), followed by our proposed multi-agent framework (Section 10.3), and concluding with empirical validation across several complex planning scenarios (Section 10.4).

10.2 Related Work

We discuss related work in three parts. The first part provides a more detailed analysis of the limitations of LLMs introduced in Section 10.1. The second part highlights how our ALAS differs from the multi-agent system (MAS) framework and prior planning approaches. The third surveys recent multi-agent work for planning.

10.2.1 Structured Limitations of LLMs

To understand why current LLMs struggle with complex planning tasks, we must examine their foundational architecture—the Transformer [49]. At its core, a Transformer operates by predicting the next most likely token in a sequence, much like completing a sentence one word at a time. Although remarkably effective for many language tasks [4], this creates fundamental challenges for planning problems requiring long-range reasoning and consistency.

Self-Validation Gap Despite sophisticated pattern recognition capabilities, LLMs lack mechanisms for rigorous self-validation: a limitation directly connected to Gödel's insights about formal systems [16]. The probabilistic nature of LLMs and the weak logical grounding prevent them from conducting a rigorous self-assessment. Recent studies confirm that while self-refinement methods [35, 30, 26] iteratively improve reasoning using the LLM's own feedback, they struggle to correct errors beyond the model's inherent capability ceiling [22]. This manifests itself in several critical ways:

- *Factual Consistency:* Generation of plausible but unverified statements without principled verification means [53]. Reinforcement learning is good for tasks with solid ground truth (such as coding), but is not practical for real-world scenarios with various conditions and exceptions in real time (e.g., traffic congestion and flight delay) that require dynamic adaptation [33].
- *Planning Validation:* No intrinsic mechanism to verify the feasibility of the plan, despite limited success [32].

- *Temporal Consistency:* Inability to maintain causal relationships or inter-dependencies in extended sequences [58].

More recently, frameworks incorporating external validation have begun to address well-structured problems, such as mathematics [15] and formal logic [12]. By separating plan generation from verification, these approaches introduce independent checks on the quality and feasibility of generated plans. However, validating unstructured problems in the real world remains a significant challenge [8, 23].

Maximum Likelihood Bias LLMs rely on maximum likelihood estimation (MLE), which biases them toward common patterns in training data. This produces "safe" but potentially suboptimal solutions [43, 17], often neglecting edge cases or unique constraints. The core problem lies in optimizing for local probability rather than global viability—akin to planning a cross-country trip by choosing the most popular next stop each time, rather than considering the entire route holistically. Recent studies quantify these limitations.

- The diversity of the plan drops significantly when optimizing for likelihood [7, 6], which favors exploiting the priors of the model instead of exploring alternatives.
- The generation of novel solutions falls substantially compared to human benchmarks [24]

Attention Narrowing The self-attention mechanism tends to give disproportionate weight to immediate context, causing narrowing of focus over longer sequences. This leads to cognitive tunneling, where the distant context is forgotten or overshadowed [49]. Empirical measurements reveal:

- *Attention Sink*: Context retention degrades significantly beyond certain token thresholds due to memory caching [56, 37].
- *Lost in the Middle*: Information recall accuracy drops dramatically for content in middle segments of long contexts [34, 19].
- *Global coherence*: The precision of planning decreases logarithmically with the length of the sequence [4].

Chain-of-Thought Limitations Humans solve complex problems by reasoning step by step, validating each step along the way. Chain of Thought (CoT) prompting [51] and its variants, such as Tree-of-Thought [59] and Graph-of-Thought [2], attempt to emulate this process.

CoT is particularly effective in domains with *well-structured reasoning rules*, such as mathematics, programming and formal logic [12, 63], where each step follows deterministically from the previous one. While external feedback mechanisms can improve CoT performance, in *open-world problems*, where reasoning paths are non-deterministic and solutions are context-dependent, LLMs often generate intermediate steps based on learned statistical patterns rather than explicit verification [9]. This can lead to hallucinated reasoning paths [31], especially when no external validation is enforced [46, 36].

Recent theoretical work suggests that CoT is effective primarily when there are tightly coupled local clusters in the training data [4, 42]. This explains why CoT, fundamentally an abductive reasoning method [5], performs well in structured problems with clear local patterns but fails even in simple planning tasks [45].

10.2.2 Multi-Agent Planning Systems

Multi-Agent Systems (MAS) have long been used in AI and distributed problem solving [54]. Recent frameworks such as AutoGen [55], LangGraph [28], and CAMEL [29] extend MAS principles to LLM-based coordination. Although these enable problem decomposition and agent coordination [11], they serve as integration platforms rather than addressing deeper planning challenges such as managing inter-dependencies and dynamic replanning [25].

ALAS advances beyond these approaches in three key ways:

- A formal validation framework separates the process of generating plans from the task of verifying their correctness, enabling independent evaluation of their validity and reliability.
- Dynamic constraint management facilitates real-time adjustments to planning processes, ensuring that systems can respond effectively to evolving conditions and unexpected changes.

- Hierarchical monitoring employs layered oversight to identify and address errors early, effectively preventing them from spreading through the planning process.

Unlike traditional MAPS that assume deterministic agent behaviors, ALAS explicitly handles the uncertainty inherent in LLM-based planning through its validation hierarchy and adaptive replanning.

10.2.3 Recent LLM Efforts for Planning

As noted in the survey articles [8, 23], recent advances in LLM planning show promise but struggle with real world complexity. We analyze efforts across three key dimensions: decomposition-based planning, search-guided methods, and multi-agent frameworks.

Decomposition-based Planning The Planning Domain Definition Language (PDDL) [14] is widely used for AI planning but has several fundamental limitations, including its restriction to symbolic, rule-based planning, lack of built-in reactivity, and brittleness to problem specification errors.

PLASMA [3] emphasizes reproducible planning through a two-stage process of common-sense integration and error correction. While effective for linear tasks, it struggles with multi-actor scenarios and lacks mechanisms for temporal state tracking. Similar limitations arise in hybrid approaches that integrate code generation with natural language [47], which effectively decompose static problems but fail to maintain state awareness during execution.

ISR-LLM [64] employs a three-stage decomposition process, similar to our approach. However, its plans remain static, like those in [20], and cannot handle run-time exceptions.

Search-guided Methods Search-based planners like LLM-MCTS [62] integrate LLMs' semantic knowledge with Monte Carlo Tree Search, enhancing decision quality for well-defined problems. However, they inherit core limitations from both traditional MCTS and LLMs, notably the inability to adapt search paths when real-world conditions change.

Tree-of-thought approaches [59] explore intermediate states through systematic search but lose temporal consistency during replanning.

Multi-agent Frameworks ADAS and AFlow [21, 61] attempt workflow automation through LLM-driven agents and MCTS. Their fixed architectures, however, cannot gracefully handle disruptions or maintain continuous state awareness. When unexpected changes occur, these systems struggle to reconstruct workflow segments or explore alternative paths under new constraints. This architectural rigidity fundamentally limits their applicability to dynamic environments where rapid replanning is essential.

These approaches reveal a critical gap: LLM planners prioritize initial plan generation over continuous state tracking and adaptive reasoning, limiting their effectiveness in dynamic environments. They do not account for the structured limitations of LLMs outlined in Section 10.2.1 and fail to develop methods to address them.

10.3 ALAS Three-Component Architecture

ALAS employs a three-component architecture, an **agent repository**, a **meta-planner**, and a **runtime monitor**, to address LLM limitations in planning. Unlike traditional multi-agent frameworks, ALAS integrates verification, dynamic adaptation, and contextual reasoning for improved efficiency.

The architecture follows four key principles addressing the identified LLM limitations.

First, independent validation agents operate separately from the planning and execution processes. This separation, similar to checks and balances in governance, ensures unbiased verification of agent output and helps overcome LLMs' self-validation limitations.

Second, tasks are decomposed into well-defined atomic operations executed by lightweight agents. Each agent operates with a limited context and strict communication protocols, preventing the context entanglement common to monolithic LLMs. This modularity keeps the information relevant and consistent throughout execution.

Third, dedicated common-sense reasoning mechanisms improve contextual understanding by integrating human experiences. This addresses the LLMs' lack of embodied understanding and adaptability to local norms, grounding decisions in verified knowledge rather than probabilistic guesses.

Fourth, run-time management provides adaptive responsiveness through specialized alert and reactive agents. These agents monitor execution and correct deviations in real time, helping mitigate compounding errors in LLM chain-of-thought reasoning.

These principles are realized through three primary components. The **agent repository** (Section 10.3.1) contains modular execution units with defined roles. The **meta-planner** (Section 10.3.2) handles task decomposition while maintaining constraints. The **runtime monitor** (Section 10.3.3) provides predictive and reactive oversight for handling unexpected scenarios.

Running Example: Urban Ride Assignment Problem **Appendix** 10.C provides the full specification for Urban Ride Sharing (URS), a moderately complex problem in our designed benchmark for evaluating planning algorithms. Table 10.1 presents the problem and its workflow, illustrated in Figure 10.1 in Section 10.1, is used throughout the paper to demonstrate how ALAS operates.

10.3.1 Agent Repository Design

The agent repository efficiently manages agent registration and task matching by categorizing them into *common* and *task-specific* agents, supporting both general and domain-specific capabilities.

Lightweight, Independent Agent Design

ALAS avoids relying on a single LLM to execute complex, multi-step reasoning sequentially. Instead, it utilizes *small, independent agents* that adhere to strict efficiency and modularity principles. These agents operate with well-defined input/output protocols and are restricted to *restricted*

Table 10.1: Urban Ride Sharing Problem

Metrics:
- **On-time performance:** No penalty for early arrivals.
- **Total distance traveled.**

Locations: Seven locations: $V = \{A, B, C, D, E, F, G\}$, where G is Boston Logan Airport (BOS). Urban locations A–F are all 10 km of each other, while distances to BOS are 30+ km.

$$\begin{bmatrix} & A & B & C & D & E & F \\ A-F & 10 & 10 & 10 & 10 & 10 & 10 \\ \to G & 35 & 33 & 36 & 34 & 32 & 31 \end{bmatrix}$$

Travel speed: (A–F) 60 km/h, and (A–$F \to G$) 100 km/h.
Passengers: Each passenger specifies an arrival time at BOS (G). The dispatcher will instruct drivers when to pick up passengers to ensure on-time arrival at BOS.
Ride Requests (Desired BOS arrival time given):
- r_1: Pickup at A, to G by 08:45 - r_2: Pickup at B, to G by 08:50
- r_3: Pickup at C, to G by 08:55 - r_4: Pickup at D, to G by 09:00

Available Vehicles (Capacity 2 passengers):
- k_1: at A, k_2: at C, and k_3: at E

Scheduling Constraints: - The dispatcher determines the *pickup times* based on a feasible schedule. Pickup times must allow the driver to first reach the passenger location (A - F) and then drive to G in time.

context windows to mitigate attention bias and prevent earlier constraints from being overridden by recent context.

By *scoping problems logically* and *constraining context physically*, ALAS ensures that each agent processes only the required information for its specific role.

Agent Registration and Specifications

An agent $\mathcal{A}$ in the repository is formally defined as:

$$\mathcal{A} = \langle \mathcal{P}, t, \mathbf{c}, w, e, r \rangle, \text{ where}$$

- $\mathcal{P}$ defines the input/output protocol for agent communication

- $t \in \{\text{common}, \text{specialized}\}$ specifies the agent type
- $\mathbf{c}$ encodes the agent's functional capabilities and constraints
- $w \leq 1k$ tokens defines the context window size
- e represents computational efficiency requirements
- r tracks the agent's historical performance rating

The agent maintains an internal context buffer within size w and implements validation at both input and output boundaries to ensure protocol compliance and output consistency.

State Space Model and Agent Design

ALAS employs a structured state-space model that captures seven fundamental dimensions of planning problems, as detailed in **Appendix** 10.A Table 10.7.

The foundation comprises six primary dimensions: **Who** defines actors and their roles, establishing capabilities and limitations. **Where** manages spatial aspects, including locations and movement paths. **When** handles scheduling and time-dependent constraints. **What** focuses on resource management and allocation. **Why** maintains the logical structure of plans, ensuring valid reasoning patterns. **How** specifies execution strategies and protocols. An additional **Inter-Dimension Dependency** component manages relationships between these dimensions, ensuring that changes in one dimension appropriately influence others.

Agent Categories and Roles

Following Gödel's insights on formal systems' self-validation limitations, ALAS separates planning from validation through three agent categories:

* **Common agents** handle general planning and basic constraints
* **Task-specific agents** provide domain expertise
* **Validation agents** ensure global correctness independently

A. Common Agents Common agents handle basic planning tasks aligned with state space dimensions. They perform constraint checking, feasibility assessment, and robustness measures. Their responsibilities

include verifying temporal and spatial constraints, integrating commonsense reasoning, providing dynamic responses to changes, and monitoring performance against defined metrics.

B. Task-Specific Agents These agents enhance the system with domain expertise through three primary functions: augmenting plans with domain-specific knowledge through retrieval-augmented generation (RAG), selecting and optimizing planning algorithms based on domain requirements, and implementing specialized emergency protocols. This expertise enables ALAS to handle complex domain-specific challenges while maintaining robust performance.

C. Validation agents Operating as an independent oversight layer, validation agents ensure correctness throughout the planning lifecycle. They verify inter-dimension dependencies during initial planning, monitor runtime compliance with constraints, validate the consistency of reactive replanning, and enforce adherence to policies and safety requirements. For example, in our airport transportation scenario, these agents verify passenger groupings, monitor pickup schedules, validate route adjustments for traffic delays, and ensure compliance with ride-sharing protocols.

A detailed specification of how these agent categories are implemented for the urban ride assignment problem is provided in Figure 10.9 of **Appendix** 10.C.

10.3.2 MP: Plan Generation and Validation

The meta-planner $\mathcal{MP}$ constructs planners that generate actionable workflows for given tasks. Following Algorithm 1, it operates in three phases: network construction, agent assignment, and iterative refinement. This systematic approach ensures that the resulting workflow is both well-structured and adaptable to changing conditions during execution.

Algorithm 1 Meta-Planner for Workflow Generation

Require:
$\mathcal{O}$ {Set of planning objectives}
$\mathcal{C}_{\mathcal{E}}$ {Set of explicit constraints}
$\mathbf{A}$ {Pool of available agents}
$\mathcal{P}$ {Set of people involved in the plan}
$\mathcal{M}$ {Set of performance metrics}
Ensure:
$\mathbf{W}^* = (\mathcal{N}, \mathcal{E})$ {Optimized workflow} (Eq. 10.1)
Phase 1: Network Construction
$\mathcal{N} \leftarrow \text{map}_{\text{role}}(\mathcal{O})$ {Role mapping} (Eq. 10.2)
$\mathcal{E} \leftarrow \text{map}_{\text{dep}}(\mathcal{C}_{\mathcal{E}})$ {Dependency mapping} (Eq. 10.3)
Phase 2: Agent Assignment
for all $n \in \mathcal{N}$ **do**
  $\alpha_n \leftarrow \text{SelectNodeAgent}(n, \mathbf{A})$ {Role agents} (Eq. 10.4)
end for
for all $e_{ij} \in \mathcal{E}$ **do**
  $\alpha_{ij} \leftarrow \text{SelectEdgeAgent}(e_{ij}, \mathbf{A})$ {Edge agents} (Eq. 10.5)
end for
Phase 3: Validation and Refinement
$\mathbf{W}_{\text{current}} \leftarrow \text{InitializeWorkflow}(\mathcal{N}, \mathcal{E})$
while improvement in $V(\mathbf{W}_{\text{current}}, \mathcal{M})$ **do**
  for all $n \in \mathcal{N}$ **do**
    $f_{\text{role}}(n, \mathcal{P}) \leftarrow \text{UpdateRoleMapping}(n, \mathcal{P})$
  end for
  for all $e \in \mathcal{E}$ **do**
    ValidateDependency(e, α_e) {Dependency validation}
  end for
  $\mathbf{W}_{\text{new}} \leftarrow \text{UpdateWorkflow}(\mathbf{W}_{\text{current}})$
  ValidateWorkflow$(\mathbf{W}_{\text{new}}, \mathcal{M})$ {Global validation}
  if $V(\mathbf{W}_{\text{new}}, \mathcal{M}) > V(\mathbf{W}_{\text{current}}, \mathcal{M})$ **then**
    $\mathbf{W}_{\text{current}} \leftarrow \mathbf{W}_{\text{new}}$
  end if
end while
return $\mathbf{W}_{\text{current}}$

Phase #1: Network Construction

The meta-planner $\mathcal{MP}$ operates as a higher-order planning system that formulates workflows as directed graphs:

$$\mathbf{W} = (\mathcal{N}, \mathcal{E}), \text{ where } \mathcal{N} = A_n^*, \mathcal{E} = A_e^*. \tag{10.1}$$

Here, $\mathcal{N}$ denotes roles assigned to agents, and $\mathcal{E}$ represents dependencies between roles, including constraints such as timing, data flow, and supervision requirements.

Design Elements Having Agent Repository defined in Section 10.3.1, we now describe how $\mathcal{MP}$ leverages its stored agent profiles, capabilities, and constraints to coordinate role analysis, constraint management, and agent assignment. The notation used in this section is defined in Table 10.6 of **Appendix** 10.A.

Role and Qualification Analysis The meta-planner first extracts *roles* from the task objectives, determining which agents (either *common* or *specialized*) can fulfill each requirement. Based on the symbols introduced in the Agent Repository, a generic role mapping is defined as:

$$\text{map}_{\text{role}} : \mathcal{O} \rightarrow \{(n_i, q_i)\}, \text{ where} \tag{10.2}$$

- n_i is the role name (e.g., `Driver`, `Dispatcher`),
- q_i is the required qualification (e.g., a valid license).

These qualifications must match the relevant fields stored in $\mathcal{A}.\mathbf{c}$ (agent's functional capabilities) as defined in Section 10.3.1. The meta-planner queries the Agent Repository to retrieve candidate agents whose registered capabilities align with each role's demands.

Constraint Management To maintain coherent planning, the meta-planner enforces three types of constraints, unified in set C:

$$C = C_E \cup C_I \cup C_D, \text{ where} \tag{10.3}$$

- C_E represents explicit constraints from the problem statement (e.g., deadlines, resource limits),
- C_I denotes implicit constraints discovered by common agents and domain knowledge,
- C_D represents derived constraints from agent interactions (e.g., concurrency, supervision rules).

$\mathcal{MP}$ cross-references these constraints with the Agent Repository, ensuring that any assignment respects the agent's capability limits ($\mathbf{c}$), context window (w), and efficiency requirement (e).

Phase #2: Agent Assignment

Once roles are identified and constraints are collected, $\mathcal{MP}$ assigns agents to *role execution* or *dependency management* tasks. Let $\mathbf{A}$ be the set of registered agents in the repository. $\mathcal{MP}$ solves two optimization problems based on the distance (or matching score) between each agent's capabilities (denoted as $\mathbf{c}$) and the task requirements:

Node Agents (Role Execution):

$$A_n^* \;=\; \arg\min_{A_i \in \mathbf{A}} \sum_{n_j} \mathrm{dist}\big(q_j,\; A_i.\mathbf{c}\big), \tag{10.4}$$

where n_j are the roles to be filled, and q_j represents the qualification needed for each role. The Agent Repository provides the capabilities of each candidate agent ($\mathbf{c}$), and the $\mathcal{MP}$ computes the distance to identify optimal role assignments.

Edge Agents (Dependency Management):

$$A_e^* \;=\; \arg\min_{A_i \in \mathbf{A}} \sum_{e_j} \mathrm{dist}\big(c_j,\; A_i.\mathbf{c}\big), \tag{10.5}$$

where $c_j \in C$ are the constraints defining an inter-role dependency (e.g., temporal coupling, spatial adjacency, or supervisory oversight). An edge agent is assigned to each dependency, ensuring proper coordination between roles. For constraints requiring domain expertise, $\mathcal{MP}$ prioritizes specialized agents from the repository.

Through these assignments, $\mathcal{MP}$ ensures that each agent $\mathcal{A}$ is matched to tasks aligned with its functional profile ($\mathbf{c}$), context window size (w) and efficiency requirements (e). This approach avoids monolithic reasoning structures in favor of scalable modular agent networks that enhance system robustness.

Phase #3: Validation and Refinement

$\mathcal{MP}$ implements a two-stage validation process—static plan validation and dynamic execution validation—through dedicated agents operating independently from the planning system.

Static Plan-Time Validation Verifies role-agent qualifications, monitors constraint satisfaction, assesses workflow feasibility, and triggers refinements when inconsistencies are detected.

Dynamic Execution-Time Validation Updates role mappings and agent assignments based on real-time feedback, modifies dependencies to enhance robustness, and integrates improvements from execution history. This dynamic validation ensures the system maintains optimal performance while adapting to changing conditions.

10.3.3 Hybrid ALAS Implementation

The hybrid ALAS architecture integrates Claude's meta-planning capabilities with local execution systems through a three-layer design that enables real-time adaptation while maintaining clear separation of concerns:

Local Control Layer Manages real-time operations, data collection, and immediate reactive responses. This layer implements safety protocols and maintains system state through continuous monitoring.

Integration Layer Provides standardized communication protocols between planning and execution layers, handling state synchronization and determining when higher-level planning consultation is needed.

Planning Layer Leverages Claude's capabilities for complex scenario planning and significant adaptations, while ensuring all proposed changes meet system constraints.

Detailed implementation specifications are provided in **Appendix** 10.B. The implementation will be released as open source in accordance with the conference guidelines.

10.4 Evaluating ALAS vs. Silo LLMs

To evaluate ALAS, we conducted experiments on three real-world applications from the M-LLAP benchmark, documented in [13]. These problems span different levels of complexity and test various aspects of ALAS's capabilities.

We assess ALAS in six settings across three planning problems: 1) Urban Ride Sharing (URS), 2) Wedding scheduling with cross-thread dependencies in both sequential and reactive settings, and 3) A multi-thread travel coordination problem, also in both sequential and reactive settings.

For comparison, we used the latest versions (as of February 2025) of leading LLMs: OpenAI's GPT-4o-Task [40], DeepSeek's R1 [10], and Anthropic's Claude 3.5 Sonnet [1]. While GPT-4o-Task and DeepSeek R1 demonstrate advanced reasoning, Sonnet performs weaker. We implemented ALAS on Sonnet to provide a fair comparison against stronger models.

We evaluate both **sequential** and **reactive** planning. Sequential planning follows a fixed plan without deviation, while reactive planning adapts to unexpected changes. This section highlights key findings, with detailed results in **Appendices** 10.C, 10.E, and 10.F.

10.4.1 Experiment #1: The URS Problem

Metrics: Total vehicle travel distance and timely arrival.

Planning: Based on the URS problem specified in Table 10.1 (Section 10.3), we first generate a directed graph representing the network topology (Figure 10.1), where nodes represent locations and edges represent possible routes. While all systems (ALAS and the LLMs) receive this graph as input, their execution approaches differ. ALAS follows a structured approach using Figure 10.5 and Table 10.10 in **Appendix** 10.C), assigning agents to nodes and edges, and iteratively refining **the schedule through validation loops**. In contrast, GPT-4o-Task and DeepSeek R1 rely on their inherent reasoning capabilities to generate schedules.

Results: ALAS generates an optimal schedule (Figure 10.2) with a total travel distance of 87 km, outperforming both GPT-4o-Task and DeepSeek R1 (Figure 10.3) which requires 123 km, a marked improvement of 41. 37%. In its first attempt, DeepSeek R1 inefficiently assigned one passenger per vehicle and required vehicle k_1 to make multiple airport trips. Only after being reminded of the feasibility of ride sharing did it improve its solution.

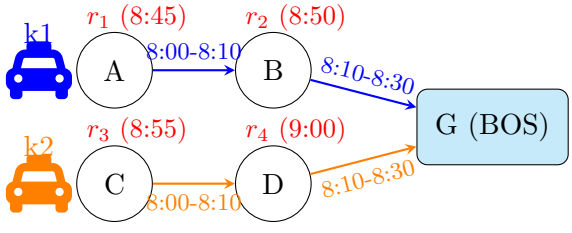

Figure 10.2: ALAS solution routes showing optimal vehicle assignments. Vehicle k1 (blue) starts at A and collects passengers r1 and r2, while k2 (orange) starts at C and serves r3 and r4. Both vehicles arrive at BOS at 8:30, meeting all passenger arrival deadlines. Total distance traveled = 87 km (Optimal).

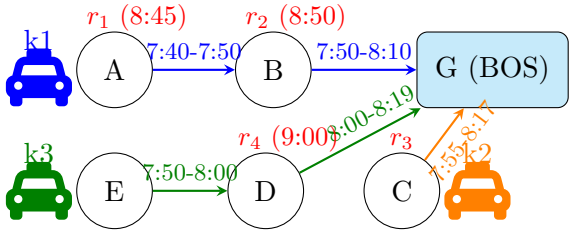

Figure 10.3: GPT-4o-Task and DeepSeek R1 both schedule three routes. Vehicle k1 picks up r1 from A at 7:40, then r2 from B at 7:50. Vehicle k2 picks up r3 from C at 7:55. Vehicle k3 must first drive from E to D to pick up r4 at 8:00. All meet deadlines. Total travel distance = 123 km.

Observations: ALAS addresses three fundamental limitations of LLMs through its architecture. First, while LLMs lack reliable self-verification capabilities, ALAS's validation loops provide systematic error detection and schedule refinement. Second, ALAS' distributed agent network mitigates the attention bias problem observed in LLMs (particularly in DeepSeek R1), where recent context overshadows earlier constraints. In this experiment, both GPT and DeepSeek made basic errors in distance calculations and vehicle assignments, demonstrating this cognitive tunneling effect. Third, ALAS' specialized agents enforce practical constraints that LLMs often overlook, such as tracking vehicle capacities, ensuring feasible pickup times, and accounting travel distance throughout the planning process. The superior performance (41.37% improvement) validates the systematic approach of ALAS to overcome these limitations of LLMs.

10.4.2 Experiment #2: Wedding Reunion Planning

Table 10.2 presents a coordinated travel problem, where several friends arrive at different times and locations before a 3:00 PM wedding photo session. The challenge involves managing two vehicles to handle airport pickups for those who cannot drive or prefer to reduce costs while also completing critical tasks—collecting the wedding gift and picking up formal attire from the tailor. All activities must be scheduled efficiently to ensure that everyone arrives at the wedding venue before the photo session deadline.

Sequential Planning Results

Even in sequential scheduling, both DeepSeek R1 and GPT-4o-Task showed significant scheduling errors. Table 10.3 shows that DeepSeek R1 incorrectly stated Pat's arrival as 11:00 AM instead of noon.

The schedule generated by GPT-4o-Task is presented in Table 10.4, which reveals several critical timing violations. The 45-minute drive from B to G was incorrectly allocated 20 minutes. While the extended gift pickup time partially offset this error, subsequent tasks violated hard constraints: Pat was scheduled to arrive at the tailor shop at 2:25 PM

Table 10.2: Wedding Reunion Logistics Problem

Metrics:

- **On-time performance:** Must arrive at the venue for 3:00 PM photos.

Locations: Four locations: $V = \{B, G, T, W\}$, where B is Boston Airport, G is Gift shop, T is Tailor shop, and W is Wedding venue.
Travel time: (minutes)
B-G : 45, B-T : 30, B-W : 40, G-T : 20, G-W : 25, T-W : 15.
Arrival Times:

- Alex: At B at 11:00 AM from Chicago (need a ride)
- Jamie: At B at 12:30 PM from Atlanta (need a ride)
- Pat: At W at 12:00 PM driving from NYC (has 5-seater car)

Required Tasks:

- Gift collection from G (after 12:00 PM)
- Clothes pickup from T (by 2:00 PM)
- Photos at W (3:00 PM sharp)

Available Resources:

- One car (5-seater) with Pat, available after he is Boston
- Local friend Chris (5-seater) available after 1:30 PM at W

Scheduling Constraints: - All tasks must complete before 3:00 PM photo time - Gift store opens at 12:00 PM - Tailor closes at 2:00 PM - Two cars must accommodate all transport needs

Table 10.3: DeekSeek Failed Schedule (Partial)

Time Epoch	Task	Assigned To
11:00 AM ❌	Alex arrives at B (Boston Airport)	Alex
11:00 AM ❌	Pat arrives at W (Wedding Venue)	Pat
	Fail stop	

(after its 2:00 PM closure), and Chris's airport pickup of Jamie would delay their return until after 4:00 PM, missing the 3:00 PM photo deadline.

In contrast, the ALAS' s schedule (Table 10.5) efficiently balances the workload between vehicles while meeting all deadlines and time restrictions. Figure 10.4 plots the travel routes of Pat and Chris.

Table 10.4: GPT-4o-Task Failed Schedule.

Time Epoch	Task	Assigned
11:00 AM - 1:15 PM	Feasible schedule above, omitted	
1:15 PM–1:30 PM	Pat picks up Alex & Jamie at B	Pat
1:30 PM	Chris becomes available at W	Chris
1:30 PM–1:50 PM ✗	Drives Alex & Jamie from B to G	Pat
1:50 PM–2:10 PM	Collect gifts at G	Pat
2:10 PM–2:25 PM ✗	Pat drives from G to T	Pat
2:25 PM–2:40 PM ✗	Pick up clothes at T	Pat
2:40 PM–2:55 PM	Pat drives from T to W	Pat
2:55 PM–3:00 PM ✗	W to B to pick up Jamie	Chris
3:00 PM	Photos at W	All

Table 10.5: ALAS Load-Balanced Schedule for Wedding Reunion.

Time Epoch	Task	Assigned
11:00 AM	Alex arrives at B	-
12:00 PM	Pat arrives at W	Pat
12:00 PM	Pat drives W → B (40 min)	Pat
12:30 PM	Jamie arrives at B	Jamie
12:40 PM	Pat picks up Alex & Jamie at B	Pat
12:50 PM	B → W with Alex & Jamie (40 min)	Pat
1:30 PM	Chris arrives at W	Chris
1:30 PM	Chris drives W → T (15 min)	Chris
1:30 PM ✓	Arrive at W	Pat, Alex, J.
1:45 PM	Collect clothes from T	Chris
2:00 PM	Chris drives T → G (20 min)	Chris
2:20 PM	Collect gifts from G	Chris
2:25 PM	Chris drives G → W (25 min)	Chris
2:50 PM ✓	Arrive at W	Chris
3:00 PM ✓	Photos at W	All

- Pat's car: W→B (40) + B→W (40) = 80 minutes

- Chris's car: W→T (15) + T→G (20) + G→W (25) = 60 minutes

Reactive Planning Results

The value of ALAS becomes even more clear when considering dynamic disruptions.

We evaluated ALAS alongside traditional LLMs in reactive planning. When a traffic alert occurs at 1:00 PM, GPT-4o-Task and DeepSeek R1 attempt replanning but critically fail to maintain spatial-temporal context—they incorrectly assume agents can restart their journeys from the alert time, effectively erasing already-completed travel segments. In contrast, ALAS maintains a complete state history (Section 10.3.1) and accurately reasons about partially-completed journeys, enabling it to generate feasible reactive plans that properly account for both past events and new constraints.

Through this case study, we identified several fundamental limitations in how traditional LLMs handle reactive planning:

* **State History Amnesia:** Traditional LLMs operate in a "stale context" where they attempt replanning from the disruption point without maintaining execution history. This causes them to lose critical information about partially-completed actions and system evolution, analogous to solving differential equations without initial conditions.

* **Temporal-Spatial Reasoning:** LLMs demonstrate a critical weakness in maintaining causality between past and future events during replanning. Their inability to reason about how completed actions constrain future possibilities leads to infeasible plans that attempt to "rewrite" already-executed events.

* **Path Dependency Handling:** The analysis revealed that effective reactive planning requires understanding not just the current state, but how that state was reached. LLMs struggle with scenarios where agents are mid-journey during disruptions, as they cannot properly account for partially-completed trajectories.

These findings extend beyond this specific scenario to inform broader questions about the ability of artificial intelligence and planning systems to handle real-world dynamic environments.

The complete analysis including path-dependent scenarios is provided in **Appendix** 10.E due to space limitations.

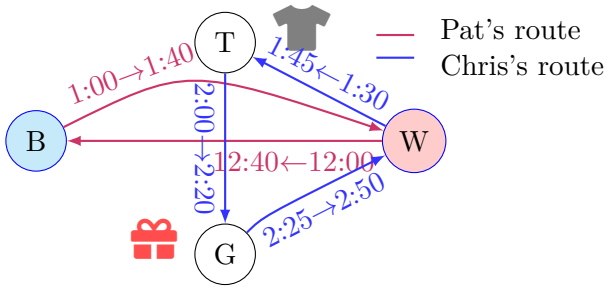

Figure 10.4: ALAS Scheduled Travel Routes

10.4.3 Experiment #3: Thanksgiving Dinner

Without the meta-plan $\mathcal{MP}$ generated by ALAS, all standalone LLMs failed the sequential planning task. With $\mathcal{MP}$, DeepSeek R1 + $\mathcal{MP}$ produced a more effective schedule than both GPT-4o + $\mathcal{MP}$ and Claude + $\mathcal{MP}$ for sequential planning.

In the reactive planning scenario, where James' flight was delayed by three hours, GPT-4o + $\mathcal{MP}$ failed to generate a feasible schedule, while DeepSeek R1 + $\mathcal{MP}$ outperformed Claude + $\mathcal{MP}$ by better balancing the drivers' workload.

In summary, this experiment attests to the effectiveness of ALAS, improving all LLMs over their standalone counterparts. Due to space limitations, please refer to **Appendix** 10.F for the detailed planning process and experimental results.

10.5 Conclusion

This paper has identified four fundamental limitations of contemporary LLMs in planning tasks:

1. Lack of self-validation, as formalized by Gödel's insights.
2. Maximum likelihood training bias that favors "popular" solutions while overlooking rare but critical cases.
3. Attention-narrowing failures that lead to cognitive tunneling and constraint oversight.
4. Exponential error accumulation in Chain-of-Thought reasoning.

Unlike prior work that focuses on sequential planning, we have tackled significantly more complex scenarios involving *parallel execution threads, interdependencies, real-time disruptions, and dynamic replanning needs.* Through experiments ranging from *single-threaded TSP* to *complex wedding scheduling and urban ride-sharing*, we have demonstrated ALAS's effectiveness through:

1. Dedicated validation components operate independently of planning.
2. Systematic edge-case exploration enabled by lightweight agents.
3. Persistent constraint tracking through agents with small context.
4. Iterative plan refinement with error detection and remediation.

Our results establish that ALAS's architecture effectively mitigates inherent LLM limitations while successfully handling *complex parallel dependencies and dynamic disruptions.* This represents a significant advance in *AI-driven planning*, enabling *reliable execution even as task complexity increases and conditions change.*

Appendices

10.A Tables and Figures

Notation Table 10.6 presents all symbols used in this paper.

10.B ALAS Implementation Specification

The hybrid ALAS architecture enables the integration of Claude's meta-planning capabilities with local execution systems through a layered approach. The three-layer architecture, comprising local control, integration and planning layer interfaces, handles different aspects of ALAS execution through well-defined interfaces. The meta-planner ($\mathcal{MP}$) algorithm resides in the Integration Layer, where it efficiently coordinates between Claude's planning capabilities and local execution. This placement allows the MP to maintain oversight while minimizing communication overhead.

Problem specifications and constraints are uploaded through the Planning Layer interface to Claude, which performs initial problem analysis

Table 10.6: Symbol Definitions

Symbol	Definition	Symbol	Definition
Basic Sets			
$\mathcal{O}$	Planning objectives	$\mathcal{P}$	Available people
$\mathcal{C}_{\mathcal{E}}$	Explicit constraints	$\mathcal{C}_{\mathcal{I}}$	Implicit constraints
$\mathcal{M}$	Performance metrics	$\mathcal{Q}$	Role qualifications
Workflow Components			
$\mathbf{W}$	Workflow network	$\mathcal{N}$	Roles (nodes)
$\mathcal{E}$	Dependencies (edges)	$\mathbf{A}$	Agent repository
n_i	Individual role	e_{ij}	Role dependency
Agent Functions			
f_{role}	Role-agent mapping	f_{edge}	Edge-agent mapping
$V(\cdot)$	Validation function	$\text{dist}(\cdot)$	Capability distance
map_{role}	Role extraction	map_{edge}	Dependency extraction
Optimization			
A_n^*	Selected node agents	A_e^*	Selected edge agents
$\mathbf{W}^*$	Optimal workflow	V^*	Best validation score

and formulation. Claude then collaborates with $\mathcal{MP}$ in the Integration Layer to develop the execution strategy. This interaction occurs through standardized JSON protocols that maintain consistency between planning decisions and execution requirements.

Agent specifications and implementations reside in the Local Control Layer, where they are directly accessible for execution. However, their orchestration is managed by the MP in the Integration Layer. This separation enables rapid local responses while maintaining global coordination. Agents communicate with $\mathcal{MP}$ through event-driven protocols, using WebSocket connections for real-time updates and REST APIs for state synchronization.

When conditions require replanning, the Local Control Layer signals the Integration Layer through its event system. The MP evaluates the situation and, when necessary, initiates consultation with Claude through the Planning Layer. This multi-level response system facilitates both rapid local adaptations and thoughtful strategic replanning.

Table 10.7: Core Planning Dimensions in ALAS

Dimension	Description
Who (Actors)	Defines the roles, constraints, and interactions among participants, including agents responsible for execution and monitoring.
Where (Location)	Represents physical or logical positions, geospatial constraints, accessibility rules, and transitions between locations.
When (Time)	Encapsulates scheduling constraints such as deadlines, durations, expected arrival times, and time-sensitive dependencies.
What (Resources)	Models resource availability, constraints, costs, and potential conflicts over shared resources.
Why (Logic and Objectives)	Captures the rationale behind decisions, dependencies among actions, and the logical sequence required to achieve the goal.
How (Execution Strategies)	Defines operational procedures, task-execution strategies, and state transition protocols.
Inter-Dimension Dependency	Establishes relationships between fundamental dimensions based on problem requirements. Incorporates common sense constraints and probabilistic risk factors into dependency specifications. For example, adding weather-related constraints to outdoor tasks or accounting for higher delay risks during peak seasons.

10.C Urban Ride Assignment Problem

The goal is to optimally assign ride requests to a fleet of autonomous or human-driven vehicles in a city, while satisfying various constraints and objectives. The key elements are:

* **City Map:** A graph $G = (V, E)$ where V is the set of locations and E is the set of roads connecting them, with associated distances and

travel times.

* **Ride Requests:** A set of requests R, where each request $r_i \in R$ is characterized by:
  - Passenger ID p_i
  - Pickup location $v_{p_i} \in V$
  - Drop-off location $v_{d_i} \in V$
  - Desired pickup time window $[t_{p_i}^{min}, t_{p_i}^{max}]$
  - Desired drop-off time window $[t_{d_i}^{min}, t_{d_i}^{max}]$
* **Vehicles:** A set of vehicles K, where each vehicle $k_j \in K$ has:
  - Vehicle ID k_j
  - Current location $v_{k_j} \in V$
  - Battery/fuel level $b_{k_j} \in [0, 1]$
  - Passenger capacity $c_{k_j} \in \mathbb{Z}^+$
  - Speed $s_{k_j} \in \mathbb{R}^+$

10.C.1 A Simplified URS Problem Statement

Table 10.8 depicts a simple URS problem with limited number of passengers, locations, drivers, and deadlines. Using this problem, we walk through how ALAS works.

10.C.2 Generating Planner W* Walkthrough

Given the problem statement of URS, ALAS generates a planner or a planning template, as depicted in Figure 10.5. We walk through this example in detail in this section.

State-Space Analysis

Our Urban Ride-Sharing (URS) problem presents a complex transportation scheduling challenge that we must first understand through systematic state-space analysis. The system involves seven locations (A through G), where G represents Boston Logan Airport, with urban locations forming a mesh network of 10km distances and airport routes ranging from 31-36km. Four passengers require airport transportation with specific

arrival deadlines, while three vehicles, each capable of carrying two passengers, must be coordinated to meet these demands efficiently.

Each dimension of our state space reveals crucial aspects of the planning challenge. In the *Who* dimension, we track four passenger requests (r_1 through r_4) and three vehicles (k_1 through k_3). These passengers require arrivals at BOS between 08:45 and 09:00, with each vehicle qualified for airport routes and positioned initially at locations A, C, and E.

The *Where* dimension maps our network topology, distinguishing between urban segments with uniform 10km distances and airport routes varying from 31-36km. This spatial arrangement, combined with the

Table 10.8: Urban Ride Sharing Problem

Metrics:
- **On-time performance:** No penalty for early arrivals.
- **Total distance traveled.**

Locations: Seven locations: $V = \{A, B, C, D, E, F, G\}$, where G is Boston Logan Airport (BOS). Urban locations A–F are all 10 km of each other, while distances to BOS are 30+ km.

$$\begin{bmatrix} & A & B & C & D & E & F \\ A-F & 10 & 10 & 10 & 10 & 10 & 10 \\ \to G & 35 & 33 & 36 & 34 & 32 & 31 \end{bmatrix}$$

Travel speed: (A–F) 60 km/h, and (A–$F \to G$) 100 km/h.
Passengers: Each passenger specifies an arrival time at BOS (G). The dispatcher will instruct drivers when to pick up passengers to ensure on-time arrival at BOS.
Ride Requests (Desired BOS arrival time given):
- r_1: Pickup at A, to G by 08:45 - r_2: Pickup at B, to G by 08:50
- r_3: Pickup at C, to G by 08:55 - r_4: Pickup at D, to G by 09:00

Available Vehicles (Capacity 2 passengers):
- k_1: at A, k_2: at C, and k_3: at E

Scheduling Constraints: - The dispatcher determines the *pickup times* based on a feasible schedule. Pickup times must allow the driver to first reach the passenger location (A - F) and then drive to G in time.

Table 10.9: Agent Specifications and Protocols

Agent Type	Input Protocol	Output Protocol	Key Functions
Task-Specific Agents			
Route Planning	- Location graph $G(V, E)$ - Travel times matrix - Vehicle positions	- Optimized routes - Distance calculations - Path sequences	- Path optimization - Distance minimization - Route feasibility checks
Scheduling	- Required arrival times - Travel duration estimates - Vehicle availability	- Pickup schedule - Timing constraints - Buffer allocations	- Schedule generation - Timing verification - Buffer management
Capacity Management	- Passenger requests - Vehicle capacities - Route timing	- Passenger groupings - Vehicle - Capacity utilization	- Group optimization - Capacity verification - Load balancing
Common Agents			
Temporal Constraint	- Schedule requirements - Time windows - Buffer needs	- Timing validations - Constraint satisfaction - Buffer adequacy	- Time verification - Constraint checking - Buffer analysis
Resource Allocation	- Vehicle inventory - Request demands - Location data	- Resource assignments - Utilization plans - Coverage maps	- Resource optimization - Coverage verification - Efficiency analysis
Distance Optimization	- Route options - Distance matrix - Time constraints	- Optimized paths - Distance metrics - Efficiency scores	- Path optimization - Distance reduction - Efficiency maximization
Validation Agents			
Plan Validator	- Complete plan - System constraints - Quality metrics	- Validation results - Constraint checks - Performance scores	- Plan verification - Constraint validation - Quality assessment
Refinement Agent	- Validation results - Improvement options - Performance metrics	- Refinement suggestions - Update priorities - Optimization paths	- Plan improvement - Update sequencing - Performance optimization

When dimension's speed constraints (60km/h urban, 100km/h airport routes), creates our fundamental timing framework. Simple calculations reveal urban segments require 10 minutes of travel time, while airport routes need 19-22 minutes depending on origin.

Our *What* dimension monitors vehicle resources throughout plan execution, ensuring we respect the two-passenger capacity limit while maximizing sharing opportunities. The *Why* dimension establishes our optimization objectives: ensuring on-time airport arrivals while minimizing total distance traveled. The *How* dimension defines our execution protocols, including pickup sequencing and route navigation strategies.

Phase 1: Network Construction

Building upon our state-space analysis, we construct our planning network by first identifying critical nodes and dependencies. Our node set $\mathcal{N}$ comprises:

Passenger Nodes: Each request r_i becomes a node with attributes: - r_1: Location A, BOS arrival 08:45 - r_2: Location B, BOS arrival 08:50 - r_3: Location C, BOS arrival 08:55 - r_4: Location D, BOS arrival 09:00

Vehicle Nodes: Each vehicle k_i forms a node with position and capacity: - k_1: Starting at A, capacity 2 - k_2: Starting at C, capacity 2 - k_3: Starting at E, capacity 2

Location Nodes: Each physical location becomes a node with attributes including distance to other locations and travel time calculations.

Our dependency set $\mathcal{E}$ captures relationships between these nodes through several categories:

Temporal Dependencies: We establish feasible pickup windows by working backward from required arrival times. For example, r_1 requires 22 minutes for the airport route plus 10 minutes for each urban segment traversed, creating timing constraints for vehicle assignment.

Spatial Dependencies: We map possible routes between nodes, considering both direct airport routes and potential shared-ride combinations through urban segments.

Capacity Dependencies: We create edges representing feasible passenger groupings within vehicle capacity limits.

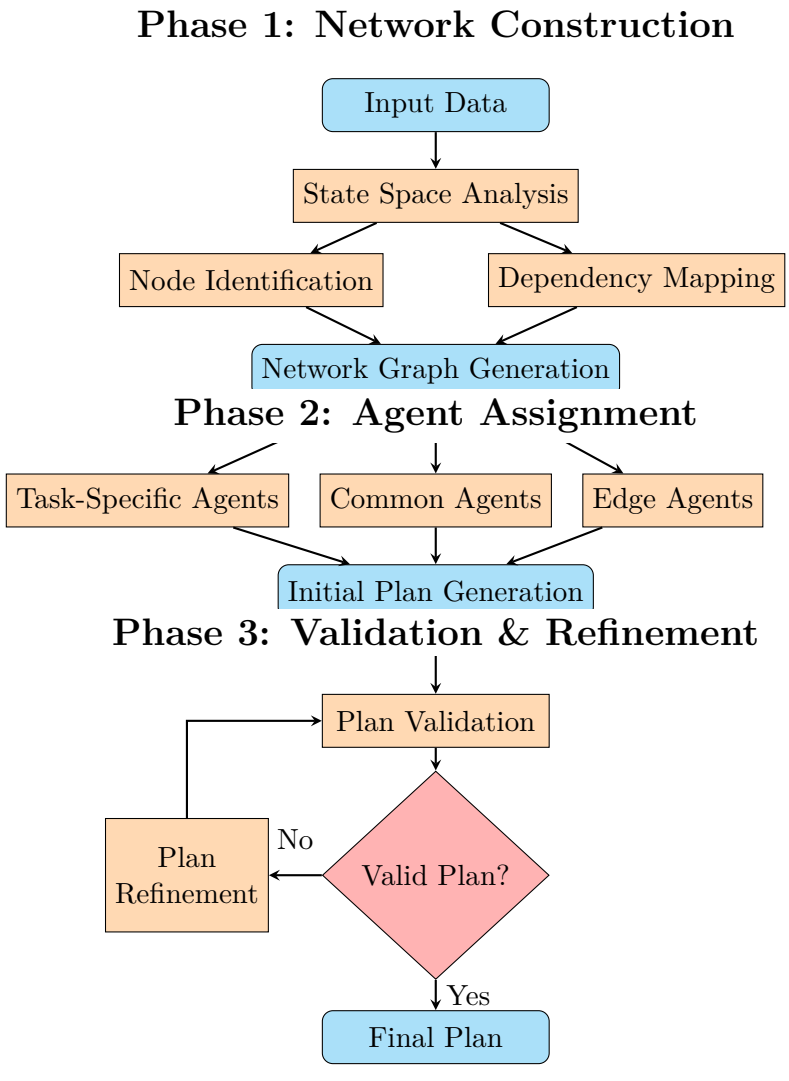

Figure 10.5: ALAS Planning Workflow for the Urban Ride Sharing problem solver to construct an optimal plan.

Phase 2: Agent Assignment

With our network structure defined, we assign specialized agents to manage different aspects of the solution:

Task-Specific Agents: The Route Planning Agent optimizes paths using the distance matrix and travel speeds, calculating optimal routes for both single and shared rides. The Scheduling Agent determines precise pickup times, working backward from airport deadlines and incorporating travel-time calculations. The Capacity Management Agent identifies feasible passenger groupings based on timing and location proximity.

Common Agents: The Temporal Constraint Agent ensures all timing requirements are met, maintaining a master schedule that accounts for all dependencies. The Resource Allocation Agent assigns vehicles to routes, optimizing the distribution of available capacity. The Distance Optimization Agent works to minimize total travel distance while respecting all constraints.

Edge Agents: These agents manage the relationships between different aspects of the plan. For example, the Passenger Grouping Agent evaluates potential shared rides by analyzing proximity of pickup locations and compatibility of arrival times.

Phase 3: Validation and Refinement

In our final phase, we implement a comprehensive validation and refinement process:

Initial Validation: We verify temporal feasibility by checking that all calculated pickup times allow sufficient travel time to meet airport deadlines. We confirm capacity constraints are respected throughout all vehicle routes. We validate that all passengers are served and all required resources are properly allocated.

Iterative Refinement: We identify optimization opportunities, such as grouping passengers with compatible timing and locations. For example, passengers r_2 and r_3 might share a ride if their pickup locations are close and arrival times are within 5 minutes. We adjust vehicle assignments to minimize empty travel distance while maintaining service guarantees.

Final Plan Generation: The resulting plan specifies exact pickup times, vehicle assignments, and routes, with built-in buffers for potential delays. The plan includes contingency protocols for common disruptions such as traffic delays or passenger late arrivals.

This systematic approach ensures we generate a robust, efficient solution to our URS problem while maintaining clear documentation of our planning process and decisions.

Output

Figure 10.5 presents the generated planner, and Table 10.9 the list of required agents and their functional specifications and protocols.

10.C.3 From Planner W* to Execution Workflow

Once the **planning workflow** is defined, it serves as a structured blueprint that outlines how the problem should be approached. However, a high-level plan alone is insufficient for real-world execution. The next step is to transform the planning workflow into a **real execution workflow**, where abstract roles and dependencies are resolved into concrete actionable tasks based on real-world data.

To clarify this transition, consider the difference between *planning workflow* and *execution workflow* in our ride-sharing scenario. In the planning phase, roles such as `Driver`, `Vehicle`, and `Passenger` are defined as abstract entities. The planning workflow specifies how these entities interact—matching drivers to passengers, optimizing routes, and scheduling pickups—without assigning real-world counterparts yet.

In contrast, the execution workflow performs **role resolution**, mapping abstract roles to real-world instances. This means assigning an actual driver to a specific vehicle, matching a real passenger to a ride request, and computing precise travel distances based on real-time geo-coordinates. In addition, the execution workflow must dynamically adapt to real-world constraints, such as traffic conditions, vehicle availability, and passenger delays.

In this process, the meta-planner generates the *execution graph*, a directed graph where nodes correspond to concrete actions (e.g., "Driver John departs from location A"), and edges represent dependencies and constraints (e.g., "Driver John must reach location B before 10:30 AM"). This execution graph integrates real-time data and updates continuously, allowing agents to make informed decisions as conditions evolve.

Table 10.10: Agent Placement in the Urban Ride Sharing Network

Location	**Type**	**Agents and Their Responsibilities**
A–F	Nodes	**Resource Allocation Agent**: Manages vehicle assignments and passenger pickups at urban locations
G (BOS)	Node	**Plan Validator Agent**: Verifies arrival times and overall plan feasibility **Temporal Constraint Agent**: Ensures all arrival deadlines are met
A–F edges	Urban Routes	**Route Planning Agent**: Optimizes urban route segments (10 min travel time) **Scheduling Agent**: Coordinates pickup sequences and timing
A–G,...,F–G	Airport Routes	**Capacity Management Agent**: Ensures vehicle capacity constraints during airport trips **Distance Optimization Agent**: Minimizes total travel distance to airport
Network-wide	Global	**Refinement Agent**: Iteratively improves solutions based on validation results Monitors and adjusts both urban and airport route segments

Thus, the **planning workflow** structures how to plan, while the **execution workflow** governs how real-world actions are performed. Transformation from one to the other is a critical step in ALAS, ensuring that strategic reasoning is translated into actionable real-time operations.

Now, based on the problem statement in Table 10.8, planner depicted in Figure 10.5, and the list of agents required and their functional specifications and protocols in Table 10.9, ALAS proceeds generating an execution workflow.

Observation on Sequential Planning

Let us explain the value of using agents in this problem, even though we have shown that simpler solvers can handle the computational aspects. This discussion touches on key principles of system design and real-world implementation.

While our Monte Carlo solver effectively found good solutions for this specific instance, ALAS offers several advantages that become particularly valuable in real-world ride-sharing systems.

First, ALAS helps manage complexity in dynamic environments. In our exercise, we worked with a static problem where all passenger requests and constraints were known in advance. However, in reality, ride-sharing systems must handle continuous updates—new ride requests arrive at unpredictable times, vehicles experience delays, and road conditions constantly change. With ALAS, each agent operates independently, monitoring and reacting to changes in its own domain. For example, the Route Planning Agent can dynamically adjust routes in response to traffic updates, while the Capacity Management Agent ensures new passenger requests are accommodated efficiently.

Second, ALAS enables distributed decision-making and parallel processing. Instead of relying on a centralized solver, different agents specialize in handling specific tasks simultaneously. While the Scheduling Agent optimizes pickup times, the Resource Allocation Agent manages vehicle assignments in parallel. This decentralized structure is crucial for scalability—when the system expands to hundreds of vehicles and thousands of passengers, distributing computational workload prevents bottlenecks and ensures efficient operations.

Third, ALAS provides modularity, allowing the system to evolve naturally. Ride-sharing services frequently introduce new features, such as surge pricing or specialized vehicle categories. With an agent-based design, we can integrate a Pricing Agent or a Vehicle Specialization Agent without modifying the core routing logic. Likewise, if we develop a more advanced routing algorithm, we can upgrade the Route Planning Agent without disrupting other system components.

The separation of concerns through agents also enhances system resilience. If one agent encounters issues—say, the Distance Optimization Agent fails to compute an optimal route—other agents continue operating with fallback strategies. The Plan Validator Agent can detect suboptimal assignments and trigger refinements through the Refinement Agent, ensuring that the system adapts to unforeseen challenges.

We can think of this like a well-organized team working on a complex project. While a single individual might handle everything, a structured team of specialists—each with clear roles and defined communication protocols—is often more effective, robust, and scalable. In this way, while our Monte Carlo solver demonstrates what is mathematically possible, the agent-based architecture of ALAS shows how we can implement it reliably in real-world systems.

10.C.4 Reactive Planning

The value of multi-agent reactive planning becomes clear when considering dynamic disruptions. Take a sudden road closure between locations B and C, while a monolithic solver would need to halt and recalculate all routes from scratch, an agent-based approach enables parallel adaptation. The Route Planning Agent can immediately begin adjusting affected paths while the Scheduling Agent updates arrival estimates and the Resource Allocation Agent redistributes vehicles, all operating concurrently while maintaining system stability. This distributed replanning allows the system to gracefully handle disruptions with minimal impact on unaffected components. For a detailed examination of reactive planning capabilities, we present a case study of a Wedding Reunion scenario in **Appendix** 10.E, which demonstrates how multi-agent systems effectively coordinate responses to unexpected changes in travel conditions.

10.D Wedding Reunion Sequential Planning

Table 10.11 shows the initial sub-optimal schedule generated by ALAS. While all participants meet their deadlines, the driving workload is unevenly distributed. Pat drives 110 km, while Chris only 30 km.

The second attempt produced a more balanced plan, as described in the main text, where Pat drives 80 km and Chris 60 km.

Table 10.11: ALAS Schedule, Feasible but Suboptimal

Time	**Task**	**Asgnd**
11:00 AM	Alex arrives at Airport (B)	-
12:00 PM	Pat arrives at Venue (W)	Pat
12:00 PM	Pat departs W to pick up Alex at B	Pat
12:30 PM	Jamie arrives at Airport (B)	-
12:40 PM	Pat arrives at B, picks up Alex & Jamie	Pat
1:25 PM	Pat's car arrives at G (with Alex & J.)	Pat
1:30 PM	Chris becomes available at W	Chris
1:30 PM	Chris departs W for T	Chris
1:45 PM	Chris arrives at T to pick up clothes	Chris
1:50 PM	Gift collection completed at G	Pat
2:00 PM	Chris departs T with clothes	Chris
2:15 PM	Pat's group arrives at W with gifts	Pat
2:15 PM	Chris arrives at W with clothes	Chris
3:00 PM	Group photos at W	All

10.E Wedding Reunion Reactive Planning

In this appendix, we analyze the performance differences between standalone LLMs and ALAS-augmented systems in reactive planning scenarios. Our experiment compares two configurations: 1) standalone LLMs including GPT-4o-Task, DeepSeek R1, and Claude Sonnet, and 2) ALAS integrated with Claude Sonnet. The test scenario involves a wedding logistics plan disrupted by an unexpected traffic incident.

Alert 1:00 PM: Traffic Alert, an accident near the Logan airport in Boston doubles all travel times to and from the airport.

10.E.1 Executive Summary

When faced with mid-execution disruption, all standalone LLMs failed to generate feasible reactive plans. Given the optimal sequential plan from Table 10.5 in Section 10.4 and the 1:00 PM traffic alert, the LLMs demonstrate a fundamental flaw: they ”forget” events that occurred before the alert time. For example, Claude attempts to reschedule Pat's drive to the airport at 1:00 PM, despite Pat having already arrived there at 12:40 PM. This and similar temporal reasoning failures prevent all three LLMs from meeting the 3:00 PM photo session deadline.

The standalone LLMs demonstrate several critical limitations:

- **State Maintenance Failure:** When an alert occurs, they discard the rich context of partially completed actions, attempting to generate entirely new plans rather than adapting the existing execution state. This reveals their inability to reason about the continuous flow of time in real-world scenarios.
- **Temporal Consistency:** They often attempt to modify actions that have already occurred, revealing a critical gap in understanding the immutable nature of past events. This manifests as logically impossible plans that try to ”rewrite” history.
- **Position Tracking:** They lose track of agent positions at critical moments, leading to plans that violate basic physical constraints, suggesting a lack of robust modeling for real-world object permanence.
- **Path Dependency:** When conditions change mid-route, they fail to recognize that different segments of the same journey may be affected differently by new constraints, demonstrating an inability to reason about granular movement through time and space.

In contrast, ALAS maintains comprehensive execution state by:

* **Continuous Monitoring:** An active thread tracks each agent's position and progress in real-time, enabling real-time understanding of disruption impacts.

* **Historical Context:** The system preserves a complete timeline of executed actions, recognizing them as immutable facts that constrain future possibilities.
* **Granular Impact Analysis:** ALAS performs precise, segment-by-segment analysis of how changes affect each journey, enabling replanning based on vehicle positions relative to the disruption location. (For detailed temporal decomposition and scenario analysis, see Section 10.E.3.)
* **Feasibility Validation:** A validation process ensures that all modifications maintain physical and temporal constraints.

This analysis reveals that effective reactive planning requires not just plan generation, but robust state tracking and temporal-spatial reasoning that current LLMs lack. When systems lose track of time's continuous flow or focus solely on present constraints, they generate physically impossible plans by attempting to modify past events—a fundamental limitation that highlights the importance of maintaining temporal continuity in dynamic planning scenarios.

10.E.2 A Failed Reactive Plan by DeepSeek R1

Table 10.12 demonstrates how DeepSeek R1 fails to maintain temporal consistency in reactive planning. When the traffic alert occurs at 1:00 PM, DeepSeek exhibits a critical flaw in temporal reasoning: it discards all execution history and attempts to create an entirely new plan starting from the alert time. Most notably, it schedules Pat to begin driving to the airport at 1:00 PM, despite the fact that Pat had already completed this journey and arrived at the airport at 12:40 PM under the original plan. This temporal disconnect, where the system attempts to "rewrite" already-executed events, illustrates how LLMs can lose track of the immutable nature of past actions when adapting to new conditions.

10.E.3 ALAS Reactive Planning

ALAS Reactive Analysis: At 1:00 PM when the alert is received, ALAS' first critical task is to accurately establish the system state by examining past events. The key insight is that Pat's vehicle began its

Table 10.12: DeekSeek's Failed Reactive Schedule After Alert.

Time	Task	Assigned
1:00 PM ✗	Traffic alert received - Pat at W	System
1:05 PM ✗	Pat departs W for B	Pat
1:30 PM	Chris becomes available at W	Chris
1:30 PM	Chris departs W for T	Chris
1:45 PM	Chris arrives at T for clothes	Chris
2:00 PM	Chris departs T with clothes	Chris
2:15 PM	Chris arrives at G for gifts	Chris
2:25 PM	Pat arrives at B (delayed by traffic)	Pat
2:35 PM	Pat departs B with Alex & Jamie	Pat
2:40 PM	Chris departs G with gifts	Chris
2:55 PM	Chris arrives at W	Chris
3:55 PM ✗	Pat's group arrives at W	Pat

return journey from the airport (B) to the wedding venue (W) at 12:50 PM, meaning it had been traveling for 10 minutes before the traffic situation changed. To properly model this partially-completed journey, ALAS conducts a precise temporal analysis:

The initial timing parameters are:

$$\begin{aligned} T_{\text{departure}}(B \to W) &= 12:50 \text{ PM} \\ T_{\text{alert}} &= 1:00 \text{ PM} \\ \Delta T_{\text{pre-alert}} &= 10 \text{ minutes} \end{aligned} \tag{10.6}$$

The journey analysis requires careful consideration of the vehicle's progress before the alert. Under normal conditions, the full B-W route parameters are:

$$\begin{aligned} T_{\text{normal B-W}} &= 40 \text{ minutes} \\ D_{\text{total}} &= D_{\text{B-W}} \\ V_{\text{normal}} &= \frac{D_{\text{total}}}{40 \text{ minutes}} \end{aligned} \tag{10.7}$$

This formulation captures a subtle but crucial detail: during the initial 10-minute period before the alert, Pat's vehicle traveled at normal speed. Only the remaining portion of the journey would be affected

by the doubled travel time, creating a hybrid journey profile that demands precise temporal analysis. While standalone LLMs fail to consider such nuanced timing aspects, ALAS conducts a thorough analysis of three possible scenarios that could unfold at 1:00 PM, each requiring distinct reactive planning approaches.

ALAS Scenario Analysis When evaluating Pat's journey from B to W that began at 12:50 PM, ALAS recognizes three distinct possibilities at the 1:00 PM alert time. The vehicle could have already passed the future accident location, could be approaching the accident zone, or could become directly involved in the incident. Each scenario creates different constraints for the reactive plan:

- **Pre-Accident Zone Clearance:** If Pat's vehicle has already passed the future accident location after traveling 10 minutes at normal speed, the remaining journey would continue unaffected by the traffic delay. This represents the optimal case for maintaining the original schedule.
- **Mid-Journey Impact:** If Pat encounters the traffic at 1:00 PM, the journey decomposes into two segments: the completed 10-minute portion at normal speed, followed by the remaining distance at doubled travel time. This hybrid timing requires careful recalculation of arrival estimates.
- **Direct Accident Involvement:** In the worst case, Pat's vehicle becomes part of the incident, requiring complete replanning with new transportation arrangements and possible emergency response coordination.

This granular scenario analysis, unique to ALAS, enables generation of robust contingency plans that account for all possible states of the system at the alert time.

* **Scenario 1:** Pre-Accident Zone Clearance If Pat's vehicle has already passed the future accident location:

$$\begin{aligned} &D_{\text{covered}} = V_{\text{normal}} \times 10 \text{ minutes} \\ &D_{\text{remaining}} = D_{\text{total}} - D_{\text{covered}} \\ &T_{\text{arrival}}(W) = 12:50 \text{ PM} + 40 \text{ minutes} = 1:30 \text{ PM} \end{aligned} \tag{10.8}$$

Impact Analysis:

- Journey continues at normal velocity
- Original schedule maintains validity
- No reactive planning required

* **Scenario 2:** Mid-Journey Impact If Pat encounters the traffic at 1:00 PM:

$$\begin{aligned} &D_{\text{pre-accident}} = V_{\text{normal}} \times 10 \text{ minutes} \\ &T_{\text{remaining normal}} = 30 \text{ minutes} \\ &T_{\text{remaining actual}} = 60 \text{ minutes} \\ &T_{\text{arrival}}(W) = 12:50 \text{ PM} + 70 \text{ minutes} = 2:00 \text{ PM} \end{aligned} \tag{10.9}$$

* **Scenario 3:** Direct Involvement In the case that Pat involves in the accident:

$$T_{\text{incident}} = 1:00 \text{ PM} \tag{10.10}$$

Impact Analysis:
- Medical assessment requirements
- Emergency response time
- Alternative transportation arrangement

10.E.4 Impact on Wedding Schedule

Table 10.13: Scenario Impact Analysis

Scenario	**Arrival Time**	**Buffer**	**Risk Level**
1. Pre-Clear	1:30 PM	90 min	Low
2. Mid-Journey	2:00 PM	60 min	Medium
3. Accident Involved	Uncertain	N/A	Critical

Each scenario impacts the 3:00 PM photo deadline differently. To execute the plan, ALAS must rely on a GPS agent to track vehicle locations in real time, similar to how Uber vehicles are monitored, and make immediate decisions accordingly.

$$\mathbf{P}_{\text{reactive}} = \begin{cases} \mathbf{P}_1 & \text{if Pre-Clear} \\ \mathbf{P}_2 & \text{if Mid-Journey} \\ \mathbf{P}_3 & \text{if Accident Involved} \end{cases} \tag{10.11}$$

If the GPS agent reports that Pat's vehicle is in Scenario 2—Mid-Journey, the system will generate a revised schedule $\mathbf{P}_2$ to adjust Pat's estimated arrival time at the wedding venue W.

Table 10.14: ALAS Reactive Plan for Wedding Reunion.

Time Epoch	Task	Assigned
11:00 AM	Alex arrives at B	-
12:00 PM	Pat arrives at W	Pat
12:00 PM	Pat drives W → B (40 min)	Pat
12:30 PM	Jamie arrives at B	Jamie
12:40 PM	Pat picks up Alex & Jamie at B	Pat
12:50 PM	Pat drives B → W (40 min)	Pat
1:00 PM	Accident alert	All
1:00 PM	Report Pat's vehicle location	GPS
1:00 PM	Recal travel time B → W (60 min)	Pat
1:30 PM	Chris arrives at W	Chris
1:30 PM	Chris drives W → T (15 min)	Chris
1:45 PM	Collect clothes from T	Chris
2:00 PM ✔	Arrive at W	Pat, Alex, J.
2:00 PM	Chris drives T → G (20 min)	Chris
2:20 PM	Collect gifts from G	Chris
2:25 PM	Chris drives G → W (25 min)	Chris
2:50 PM ✔	Arrive at W	Chris
3:00 PM ✔	Photos at W	All

10.E.5 Take Aways

This analysis reveals fundamental requirements for effective reactive planning in dynamic environments. Systems must maintain precise tracking of event timing relative to agent positions, understand how partially completed journeys affect replanning options, develop multiple contingency scenarios, and leverage real-time location data for appropriate response selection. These requirements demonstrate why a distributed agent architecture, with specialized modules maintaining focused temporal and spatial awareness, proves to be more effective than monolithic systems attempting to juggle all contexts simultaneously. The superior performance of ALAS in the wedding logistics scenario validates this architec-

tural choice, showing how lightweight agents with targeted context windows can maintain the accurate and timely tracking of the state necessary for robust reactive planning.

10.F Thanksgiving Dinner Problem

Planning performance is compared across four configurations: DeepSeek, GPT4o, DeepSeek + $\mathcal{MP}$, and GPT4o + $\mathcal{MP}$.

Please see Table 10.15 for the specifications.

10.F.1 Phase 1: Network Construction

Node (Role) Specifications

First, meta-planner $\mathcal{MP}$ extracts roles ($\mathcal{N}$) with their required qualifications:

- n_{cook}: capability to prepare dinner
- n_{driver1}: capability to drive, pick up from airport
- n_{driver2}: capability to drive, pick up grandma
- $n_{\text{supervisor}}$: capability to monitor oven

Edge (Dependency) Specifications

Next, $\mathcal{MP}$ identifies dependencies ($\mathcal{E}$) between roles:

$$\mathcal{E} = \{e_{\text{temporal}}, e_{\text{spatial}}, e_{\text{safety}}\} \tag{10.12}$$

The critical dependencies include:

- e_{temporal}: - Turkey (4 hours) must finish by 6:00 PM - Side dishes (2 hours) must finish by 6:00 PM - Airport pickups must align with landing times
- e_{spatial}: - Driver-passenger location matching - Travel time constraints between locations
- e_{safety}: - Continuous oven supervision requirement

Table 10.15: Thanksgiving Dinner Coordination Problem

Objective: Coordinate family arrivals and dinner preparation for 6:00 PM dinner in Boston

Family Members and Arrivals:

- Sarah (Mom): Host, at home
- James (Dad): Lands at BOS 1:00 PM from SF
- Emily (Sister): Lands at BOS 2:30 PM from Chicago
- Michael (Brother): Driving, arrives 3:00 PM from NY
- Grandma: Needs pickup from suburban Boston

Cooking Requirements:

- Turkey: 4 hours cooking time
- Side dishes: 2 hours preparation
- Someone must stay home during cooking

Transportation Constraints:

- James must rent car after landing
- Emily requires airport pickup
- Travel times:
  - Home to BOS Airport: 60 min
  - BOS Airport to Grandma's: 60 min
  - Home to Grandma's: 30 min

Key Requirements:

- All family members at home for 6:00 PM dinner
- Turkey and sides ready by dinner time
- All pickups completed with available drivers
- Cooking supervision maintained

10.F.2 Phase 2: Agent Assignments

After constructing the network structure, $\mathcal{MP}$ selects and assigns agents to monitor both the roles and dependencies.

Node (Role) Agent Assignment

For each role, $\mathcal{MP}$ selects monitoring agents with the required capabilities:

$$f_{\text{role}} : \mathcal{N} \to \mathbf{A} \tag{10.13}$$

The role monitoring agents include:

- Cook Monitor: Tracks cooking timeline, coordinates meal components
- Driver Monitor: Validates driver availability
- Supervisor Monitor: Ensures oven supervision
- Resource Monitor: Manages vehicle assignments and actor schedules

Edge (Dependency) Agent Assignment

For the identified dependencies, $\mathcal{MP}$ assigns specialized monitoring agents:

$$f_{\text{edge}} : \mathcal{E} \to \mathbf{A} \tag{10.14}$$

Dependencies require these monitoring agents:

- Temporal Agent: Manages timing constraints (cooking durations, travel times, arrival schedules)
- Spatial Agent: Tracks location constraints (airport-home-grandma routes)
- Safety Agent: Ensures oven supervision constraint remains satisfied

The resulting agent assignments create a complete monitoring system where:

- Role agents track individual actor assignments and qualifications
- Edge agents monitor interactions and dependencies between roles
- All agents coordinate to maintain global constraint satisfaction

Common Sense Constraint Analysis (Performed by an LLM)

A common sense agent identifies the following implicit constraints that can affect Thanksgiving dinner planning. This list is generated by Claude given the problem statement.

- *Physical Processing Times:*

Table 10.16: Node (Role) Monitoring Agent Requirements

Agent	Input Protocol	Output Protocol
Cook Monitor	Role: cook Qualifications: skills Time: prep and cook	Status: progress Alerts: timing issues! Updates: completed?
Driver Monitor	Role: driver Qs: license, rest Where: current GPS	Status: availability Alerts: fatigue warnings Updates: new GPS
Supervisor Monitor	Role: supervisor Location: house Duration: cover time	Status: covered? Alerts: coverage gaps! Updates: role transitions

Table 10.17: Edge (Dependency) Monitoring Agent Requirements

Agent	Input Protocol	Output Protocol
Temporal	Start times Durations Deadlines Buffer requirements	Schedule conflicts Timing violations Schedule updates
Spatial	Locations Routes Travel times Traffic conditions	Route violations Location conflicts Path updates
Safety	Critical constraints Resource states Coverage requirements	Safety violations Resource conflicts Mitigation plans

  - Airport luggage claim: 30 minutes
  - Car rental procedures: 30 minutes
  - Holiday traffic variations
  - Winter weather considerations

- *Human Factors:*

  - Driver fatigue after long trips
  - Cooking preparation overhead
  - Multi-tasking limitations
  - Task switching delays
  - Required rest periods
- *Resource Dependencies:*
  - Vehicle passenger capacity
  - Oven temperature management
  - Kitchen workspace limits
  - Shared resource coordination
- *Social Considerations:*
  - Personal preferences for interactions
  - Family dynamics in assignments
  - Post-travel guest comfort
  - Host preparation requirements

Common Sense Constraint Analysis and Verification (Human in the Loop)

The common sense constraints identified above require different verification approaches:

Agent-Required Information These constraints need specialized agents to verify and quantify:

- *Airport Operations*
  - United Airlines' average luggage delivery time at BOS Terminal
  - Terminal to rental car center: shuttle schedule, walking options
  - Historical flight delay patterns for November at BOS
- *Weather and Traffic*
  - Boston weather forecast for the event date
  - Historical traffic patterns on Thanksgiving days

  - Impact on airport-city-suburb travel times
- *Task Dependencies*
  - Kitchen workflow analysis for parallel cooking tasks
  - Resource contention in meal preparation
  - Critical path identification in cooking timeline

Human Verification Certain constraints require explicit human input to ensure that the planning process takes into account subtle interpersonal and individual considerations. These include:

- *Family Dynamics*
  - Preferred pickup arrangements for Grandma (e.g., Grandma loves to have a grandson surprise her).
  - Optimal relationship-based task pairings.
  - Social comfort factors in assignments (e.g., Sarah and Grandma do not work together in the kitchen).
- *Personal Capabilities*
  - Individual cooking experience levels.
  - Driver comfort with airport navigation.
  - Multi-tasking abilities of participants.

This separation ensures that agents focus on collecting quantifiable data while humans provide essential social and personal insights. $\mathcal{MP}$ can then integrate both types of information into the final workflow design.

10.F.3 Agent Requirements and Assignments

The $\mathcal{MP}$ requires two categories of agents. $\mathcal{MP}$ specifies their requirements in the protocol buffer format in Table 10.16 for the nodes and Table 10.17 for the edges, respectively.

Each agent must implement these protocols to participate in the workflow. The meta-planner selects agents from the pool based on their ability to satisfy these interface requirements. During execution, agents communicate through these standardized protocols while maintaining their specialized monitoring functions.

10.F.4 Monitoring Protocols and Adjustments

The workflow monitoring operates through a hierarchical protocol system that enables both routine supervision and dynamic adjustments.

Basic Monitoring Protocol Each agent maintains a continuous monitoring cycle:

$$\text{monitor} : \text{State} \to \{\text{normal, warning, violation}\} \tag{10.15}$$

For example, the temporal agent tracks schedule adherence:

$$\Delta t = t_{\text{planned}} - t_{\text{actual}} \begin{cases} \text{normal} & \text{if } |\Delta t| < \text{buffer} \\ \text{warning} & \text{if buffer} \leq |\Delta t| < \tau \\ \text{violation} & \text{if } |\Delta t| \geq \text{ threshold } \tau \end{cases} \tag{10.16}$$

Dynamic Adjustment Mechanism When deviations occur, the system initiates a three-phase response:

1. *Impact Assessment*:

$$\text{impact}(e) = \sum_{n \in \text{affected}(e)} \text{severity}(n) \times \text{urgency}(n) \tag{10.17}$$

2. *Solution Generation*:

$$S^* = \underset{s \in \text{Solutions}}{\arg\min} \{\text{cost}(s) | \text{feasible}(s)\} \tag{10.18}$$

3. *Coordination Protocol*:

$$\text{update} : (W_{\text{current}}, S^*) \to W_{\text{new}} \tag{10.19}$$

For instance, if James's flight is delayed:

- Spatial agent detects arrival time change
- Temporal agent calculates ripple effects
- Role agents evaluate reassignment options
- Safety agent verifies continued supervision coverage

The meta-planner $\mathcal{MP}$ coordinates these responses while maintaining global constraint satisfaction.c

10.F.5 Integrated Workflow Network

Tables 10.18 and 10.19 present the resulting workflow network $\mathbf{W}^*$, which includes all nodes and edges, and their assigned agents and protocols.

1. *Role Nodes:*
   - Cook1: Sarah (primary) or Grandma (if at home) with 4-hour turkey + 2-hour sides
   - Driver1: James (after car rental) or Michael
   - Driver2: Available person after initial pickups
   - Supervisor: Must be present while turkey cooks
2. *Dependencies:*
   - Temporal: Verified airport processing + travel times
   - Spatial: Traveling routes with traffic consideration
   - Safety: Continuous oven supervision requirement
3. *Agent Monitoring:*
   - Temporal Agent: Schedules with verified buffer times
   - Spatial Agent: Real-time location and route mgmt.
   - Safety Agent: Role coverage for supervision

10.F.6 Agent Interaction Protocols and State Transitions

Node-to-Node Interactions

Cook ↔ Supervisor

- **Protocol**: cooking_handoff()
- **Message**: (task, duration, requirements)
- **State Transitions**: preparation → cooking → completed
- **Trigger**: task_state_change()
- **Validation Rules**: coverage()
- **Alert**: coverage_gap()

Table 10.18: Workflow Specification: Nodes and Agent Assignments

Node	**Requirements**	**Agent Protocol**	**Dependencies**
Node Components (Roles)			
Cook Role (Sarah)	- Turkey (4hr) - Side dishes (2hr) - Kitchen mgmnt - Time management	Input: schedule, resources, recipes Output: task progress, completion Monitor: kitchen_state() → status Validate: cooking_constraints()	Connected to: - Supervisor - Resource edges
Driver1 (James or Michael)	- Valid license - Airport navigation - Car rental capable - Rest state adequate	Input: flight times, routes Output: location, ETA Monitor: driver_state() → status Validate: driver_constraints()	Connected to: - Airport pickup - Travel edges
Driver2 (Flexible)	- Valid license - Local navigation - Availability window - Rest state adequate	Input: pickup schedule, route Output: location, ETA Monitor: driver_state() → status Validate: driver_constraints()	Connected to: - Grandma ride - Travel edges
Supervisor (Flexible)	- Home presence - Oven monitoring - Safety awareness - Time commitment	Input: cooking schedule, rules Output: supervision status Monitor: safety_state() → status Validate: safety_constraints()	Connected to: - Cook role - Safety edges

Table 10.19: Workflow Specification: Edges and Agent Assignments

Edge	**Requirements**	**Agent Protocol**	**Dependencies**
Node Components (Roles)			
Temporal	- Schedule tracking - Buffer management - Sequence logic - Critical path	Input: timestamps, durations Output: schedule conflicts Monitor: schedule_state() → alerts Optimize: timeline_adjust()	Connects: - All roles - All activities
Spatial	- Location tracking - Route optimization - Traffic updates - Distance limits	Input: locations, routes Output: travel updates Monitor: location_state() → alerts Optimize: route_adjust()	Connects: - Drivers - Locations
Resource	- Vehicle allocation - Kitchen resources - People availability - Capacity limits	Input: resource demands Output: allocation status Monitor: resource_state() → alerts Optimize: resource_adjust()	Connects: - All roles - All resources
Safety	- Oven monitoring - Driving safety - Food safety - Critical rules	Input: safety requirements Output: violation alerts Monitor: safety_state() → alerts Enforce: safety_rules()	Connects: - All roles - Critical tasks

Driver1 ↔ Driver2

- **Protocol**: pickup_handoff()
- **Message**: (location, time, passenger)
- **State Transitions**: available → enroute → completed
- **Trigger**: location_change()
- **Validation Rules**: timing_feasible()
- **Alert**: schedule_conflict()

Edge Agent Operations

Temporal Agent

- **Protocol**: schedule_monitor()
- **Message**: (event, time, dependencies)
- **State Transitions**: scheduled → active → completed
- **Trigger**: time_milestone()
- **Validation Rules**: timing_feasible()
- **Alert**: delay_impact()

Spatial Agent

- **Protocol**: location_track()
- **Message**: (actor, position, destination)
- **State Transitions**: idle → moving → arrived
- **Trigger**: position_update()
- **Validation Rules**: route_feasible()
- **Alert**: travel_delay()

10.F.7 New Problem Statement Revised with $\mathbf{W}^*$

Given the $\mathbf{W}^*$ generated by ALAS's meta-planner $\mathcal{MP}$, the Thanksgiving Dinner Planning problem statement stated at the beginning of this section is revised as follows:

Initial Setup:

- Mom (Sarah) is hosting Thanksgiving dinner at 6:00 PM in Boston. The following family members are traveling:
- Dad (James) flying from San Francisco, landing at 1:00 PM Eastern time.
- Sister (Emily) flying from Chicago, landing at 2:30 PM
- Brother (Michael) driving from New York, estimated arrival 3:00 PM at home
- Grandma is healthy and needs to be picked up from her home in suburban Boston

Critical Dependencies:

- James must rent a car after landing
- Emily must be picked up from airport, no other transportation options are allowed
- Turkey needs 4 hours to cook, someone must be in the house once turkey is in oven for safety
- Side dishes require 2 hours of preparation, which can overlap with turkey
- Travel time between home and Boston airport is one hour (one-way)
- Travel between Boston airport and grandma home is one hour (one-way)
- Travel between home and grandma home 30 minutes (one-way)

*** New Dependencies:**

- The airport luggage pickup time after landing is 30 minutes.
- Renting a car takes 30 minutes.
- One person can simultaneously prepare turkey and side dishes.
- Grandma prefers Michael to pick her up, provided that it does not cause the dinner time delay.

- Grandma and Sarah prefer not to cook together in the kitchen.
- Traffic congestion is not factored into current planning.

Planning Question Set:

1. All tasks and dependencies must be strictly observed in the plan, or the plan fails.
2. Dinner time is strictly at 6:00 PM, all tasks must be completed by then (redundancy).
3. Account for the idle time of each person.
4. The schedule consists of three columns: time, task, and assigned person(s).

10.F.8 Experiment #1: Sequential Planner

Once after the original plan was revised by $\mathcal{MP}$ to include more specific details, clarify ambiguous explicit constraints, and define implicit constraints, the performance of the three LLMs used in the experiment improved significantly. When the augmented plan $\mathbf{W}^*$ was input into DeepSeek, GPT4o, and Claude, each model successfully generated a feasible plan within two to three iterations.

Results: DeepSeek Wins

Upon closer examination of the number of iterations required to produce a feasible plan, DeepSeek and Claude each required one revision (two iterations), while GPT4o required two revisions (three iterations). In terms of scheduling quality, measured by slack time, total driving distance, and load balance, DeepSeek (Table 10.20) outperformed both Claude (Table 10.22) and GPT4o (Table 10.21). DeepSeek optimized time and effort by scheduling James to wait at the airport for 30 minutes to pick up Emily. In contrast, Claude scheduled James to drive home and then return to the airport to pick up Emily, resulting in unnecessary travel. GPT4o assigned James to return home and scheduled Michael to first pick up Emily and then proceed to pick up Grandma, leading to a less balanced load. A better solution to reduce travel time would have been to schedule Michael to pick up Emily first and then drive with her to

Table 10.20: DeepSeek's Plan, Two Iterations

Time	Task	Assigned
1:00 PM	James lands at Boston	James
1:00–1:30 PM	James picks up luggage	James
1:30–2:00 PM	James rents a car	James
2:00 PM	Turkey in oven (4 hours; requires monitoring)	Sarah
2:00–3:00 PM	James waits at airport (idle)	James
2:30 PM	Emily lands at Boston	Emily
2:30–3:00 PM	Emily waits for luggage	Emily
3:00 PM	James picks up Emily	James
3:00 PM	Michael arrives home	Michael
3:00 PM	Michael departs to Grandma	Michael
3:30 PM	Michael picks up Grandma	Michael
3:30–4:00 PM	Michael drives home with Grandma	Michael
3:00–4:00 PM	James drives Emily home	James
4:00 PM	James and Emily home	James
4:00 PM	M. and Grandma home	Michael
4:00–6:00 PM	Sarah prepares side dishes	Sarah
6:00 PM	Thanksgiving dinner begins	All

Grandma's home to pick up Grandma, allowing all three to return home together. This adjustment would save 30 minutes of driving time and improve Grandma's overall happiness to see both grandchildren.

Observations on Errors

Handling Long Dependencies Complex scheduling problems reveal cascading errors when dependencies overlap. Key constraints, especially multi-factor dependencies, often get dropped during iterative problem-solving.

Reason: Cognitive load limits simultaneous constraint tracking, making exhaustive verification difficult in single passes.

Solution Framework:

- Isolate and enumerate atomic task dependencies.
- Verify global constraint satisfaction.
- Implement systematic conflict resolution.

Table 10.21: GPT4o's Plan, Three Iterations

Time	Task	Assigned
1:00 PM	Land at BOS Airport	James
1:00-1:30 PM	Luggage pickup	James
1:30-2:00 PM	Rent car	James
2:00 PM	Start turkey	Sarah
2:00-3:00 PM	Drive home	James
2:30 PM	Land at BOS Airport	Emily
3:00 PM	Arrive home	Michael
3:00-4:00 PM	Drive to airport, pick up Emily	Michael
4:00-5:00 PM	Return home with Emily	Michael
5:00-5:30 PM	Drive to Grandma's	Michael
5:30-6:00 PM	Return with Grandma	Michael
4:00-6:00 PM	Prepare side dishes	Sarah
6:00 PM	Dinner served	All

Table 10.22: Claude's Plan, Two Iterations

Time	Task	Assigned
1:00 PM	Land at BOS Airport	James
1:00-1:30 PM	Luggage pickup	James
1:30-2:00 PM	Rent car	James
2:00 PM	Start turkey	Sarah
2:00-3:00 PM	Drive home	James
2:30 PM	Land at BOS Airport	Emily
3:00 PM	Arrive home	Michael
3:00-4:00 PM	Drive to airport, pick up Emily	James
4:00-5:00 PM	Return home with Emily	James
4:30-5:00 PM	Drive to Grandma's	Michael
5:00-5:30 PM	Return with Grandma	Michael
4:00-6:00 PM	Prepare side dishes	Sarah
6:00 PM	Dinner served	All

Stale Memory and Iterative Revisions Iterative solutions can propagate errors due to partial constraint resets.

Reason: Over-reliance on previous solutions without full constraint re-evaluation leads to compounding errors.

Relation to Gödel's Incompleteness:

- Systems capable of arithmetic contain unprovable truths.
- Similarly, inherited errors hinder consistent solutions.

- Clean-state resets necessary for error prevention.

Implementation Strategy Reset to baseline state for each iteration, fully re-evaluating all constraints.
Core Challenges:

- Nested dependency management.
- Residual error prevention.
- Cross-iteration consistency.

Table 10.23 summarizes the detailed schedules documented in Tables 10.20, 10.21, and 10.22, DeepSeek demonstrated superior scheduling efficiency by optimizing James's airport wait time for Emily's pickup, requiring only two iterations. While GPT4o eventually produced a valid solution in three iterations, it created suboptimal travel patterns by having Michael make separate trips. Claude's solution, though feasible in two iterations, included unnecessary travel between pickup tasks. This experiment highlighted how $\mathcal{MP}$'s explicit constraint specification and common-sense augmentation enabled consistent performance improvement across different LLMs.

Table 10.23: Sequential Planning Performance. (# = iterations)

LLM	#	**Notable Features**
DeepSeek	2	Optimized airport wait time for James; balanced workload
GPT4o	3	Extra travel for Michael; suboptimal load balance
Claude	2	Unnecessary travel between pickup tasks

Table 10.24: Reactive Planning Performance (Alert: flight delay)

LLM	#	**Notable Features**
DeepSeek	3	Smart routing of Michael directly to airport; efficient travel patterns
GPT4o	X	Failed to maintain critical constraints; unable to recover
Claude	3	Two valid plans with different trade-offs; longer wait times

10.F.9 Experiment #2: Reactive Planner for Delay

At 10:00 AM EST, Sarah is notified that James's flight is delayed by three hours, with a new arrival time of 4:00 PM. Incorporating this unexpected delay, $\mathcal{MP}$ generates a reactive plan, $\mathbf{W^R}$.

Early Information Agent Addition The meta-planner adds an early information agent to monitor upstream events:

$$f_{\text{early}} : \mathcal{E}_{\text{upstream}} \rightarrow \text{alerts} \tag{10.20}$$

The agent's protocol is defined as:

Table 10.25: Early Information Agent Specification

Component	Flight Monitor	Impact Analyzer
Input	Flight status, departure logs, weather	Alert details, workflow dependencies
Output	Alert(event, severity, delay)	Replan(affected_nodes, time_window)

This addition allows the workflow to initiate replanning at the earliest possible moment when upstream changes occur, significantly enhancing the system's proactive planning capability. Since none of the planned elements have been executed, this reactive planning effectively functions as proactive planning.

In this experiment, the problem statement remains unchanged apart from James's updated arrival time.

Initial Setup (Updated at 10:00 AM):

- Mom (Sarah) is hosting Thanksgiving dinner at 6:00 PM in Boston. The following family members are traveling:
- Dad (James) flying from San Francisco, landing at 4:00 PM Eastern time [UPDATED].
- Sister (Emily) flying from Chicago, landing at 2:30 PM
- Brother (Michael) driving from New York, estimated arrival 3:00 PM at home
- Grandma is healthy and needs to be picked up from her home in suburban Boston

Critical Dependencies:

- James must rent a car after landing
- Emily must be picked up from airport, no other transportation options are allowed
- Turkey needs 4 hours to cook, someone must be in the house once turkey is in oven for safety
- Side dishes require 2 hours of preparation, which can overlap with turkey
- Travel time between home and Boston airport is one hour (one-way)
- Travel between Boston airport and grandma home is one hour (one-way)
- Travel between home and grandma home 30 minutes (one-way)

* **New Dependencies:**

- The airport luggage pickup time after landing is 30 minutes.
- Renting a car takes 30 minutes.
- One person can simultaneously prepare turkey and side dishes.
- Grandma prefers Michael to pick her up, provided that it does not cause the dinner time delay.
- Grandma and Sarah prefer not to cook together in the kitchen.
- Traffic congestion is not factored into current planning.

Planning Question Set:

1. All tasks and dependencies must be strictly observed in the plan, or the plan fails.
2. Dinner time is strictly at 6:00 PM, all tasks must be completed by then (redundancy).
3. Account for the idle time of each person.
4. The schedule consists of three columns: time, task, and assigned person(s).

Results: DeepSeek Wins

None of the LLMs cannot react appropriately to this new event without clearing their context buffers. As explained in Appendix 10.F.8, this

limitation is evident. The key takeaway is that for future runtime frameworks, we must ensure infrastructure support for selectively invalidating stale constraints. If a workflow is already in execution, completed steps and assignments cannot be erased or altered. For example, in a stock-market investment plan, when pertinent news arrives, $\mathcal{MP}$ cannot revert completed nodes or resolved dependencies in $\mathbf{W^R}$. For now, we treat the reactive plan as a new plan, given that no steps have been realized in the real world by 10:00 AM.

Table 10.26 presents GPT4o's plan. There are three severe constraint violations. Unfortunately, when asked to identify violations, it answers none. Therefore, $\mathcal{MP}$ is stuck without a feasible plan.

Table 10.26: GPT4o's Infeasible Plan. Fail to proceed.

Time	**Task**	**Assigned**
10 - 2:00 PM	Prep side dishes (2 hours, overlaps with turkey cooking later)	Sarah
X2:30 - 3:00 PM	Pick up Emily from the airport	Sarah
X3:00 - 4:00 PM	Prep turkey and place it in the oven (4-hour cooking time)	Sarah
3:00 - 3:30 PM	Michael drives to pick up Grandma	Michael
3:30 - 4:00 PM	Drive Grandma home	Michael
4:00 - 4:30 PM	James lands and gets luggage	James
4:30 - 5:00 PM	James rents a car	James
X5:00 - 5:30 PM	James drives home	James
5:00 - 6:00 PM	Set the table and clean kitchen	Emily
5:30 - 6:00 PM	Michael helps Grandma settle in and assists with final prep	Michael

Table 10.27 depicts Claude's plan. It violated a couple of constraints in the first two attempts, but these were minor. For instance, in the second trial, it planned for Michael's round trip to Grandma's home to take 30 minutes. However, the key is that Claude can recognize its own error and make corrections in the next iteration.

When asked to produce an alternate plan to reduce wait time and improve load balancing, as Michael can suffer from severe fatigue, an implicit constraint, Claude generates another feasible plan in Table 10.28.

In this plan, James picks Emily instead of Michael. Emily has to wait for James' availability for two hours at the airport.

There are clearly other alternatives to improve the schedule and eliminate Emily's wait time, but none of the LLMs can figure that out. For example, using the time between 10:00 am and 1:00 pm, Sarah could have picked up Grandma and assigned her to cook, allowing Sarah to be available as a driver.

Table 10.27: Claude's Reactive Plan #1, Three Iterations

Time	**Task**	**Assigned**
13:00	Start turkey in oven	Sarah
14:00	Start side dishes	Sarah
14:30	Land at airport	Emily
15:00	Arrive home from NY	Michael
15:00	Leave for airport	Michael
16:00	Land at airport	James
16:00	Pick up Emily	Michael
17:00	Arrive home with Emily	Michael
17:00	Leave for Grandma	Michael
18:00	Arrive home with Grandma	Michael
18:00	Arrive home	James
18:00	Dinner starts	All

DeepSeek offers a clever alternative by routing Michael directly to the Boston airport without stopping at home first. This is a pleasant common-sense inference that the other two LLMs failed to include themselves. (This was supposed to be provided by $\mathcal{MP}$'s common-sense spatial reasoning, but it did not.)

However, Michael could drive to Grandma's home after picking up Emily. This schedule not only saves 30 minutes but also makes Grandma happy by allowing her to surprisingly see two grandchildren at the same time.

Table 10.24 summarizes the detailed schedules documented in Tables 10.26, 10.28, and 10.29. DeepSeek leveraged the early alert at 10:00 AM for immediate replanning. In contrast, Claude produced two feasible

Table 10.28: Claude's Reactive Plan #2. Michael can rest.

Time	Task	Person
13:00	Start turkey	Sarah
14:00	Start side dishes	Sarah
14:30	Land at airport	Emily
15:00	Arrive from NY	Michael
16:00	Land at airport	James
16:30	Leave for Grandma	Michael
16:30	Get rental car	James
17:00	Pick up Emily	James
17:00	Pick up Grandma	Michael
17:30	Return home with Grandma	Michael
18:00	Arrive with Emily	James
18:00	Dinner starts	All

plans but missed the 10:00 AM alert in $\mathbf{W^R}$, starting its schedule at 1:00 PM and missing opportunities for proactive actions like early Grandma pickup to free Sarah as a driver. GPT4o failed entirely, producing three constraint violations it could not recognize, preventing further improvements.

Observations on Errors

The initial meta-planner failed to recognize a critical opportunity in early information detection. A flight delay from SFO to BOS becomes known at departure time (10:00 AM EST) rather than arrival time (1:00 PM EST). An early information agent could enable replanning three hours sooner by monitoring flight departures. To remedy this oversight, the meta-planner adds an early information agent specification, detailed in Table 10.25. DeepSeek was aware of this alert in a timely manner, but Claude was not.

Table 10.29: DeepSeek's Reactive Plan. Three Iterations. Routining Michael directly to BOS is smart.

Time	**Task**	**Assigned**
10:00 AM	Michael departs New York for Boston Airport (4-hour drive).	Michael
2:00 PM	Start cooking turkey	Sarah
2:30 PM	Emily lands at Boston	Emily
3:00 PM	Emily gets her luggage	Emily
3:00 PM	Michael arrives at Logan airport, picks up Emily.	Michael
3:00–4:00 PM	Drive Emily home	Michael
4:00 PM	Michael departs for Grandma	Michael
4:00 PM	James lands at Boston Airport	James
4:00–4:30 PM	James picks up luggage	James
4:30–5:00 PM	James rents car (30 minutes).	James
4:30 PM	Michael arrives at Grandma's	Michael
5:00 PM	Michael & Grandma home.	Grandma
5:00–6:00 PM	James drives home from BOS	James
4:00–6:00 PM	Sarah prepares side dishes (overlaps with turkey).	Sarah
6:00 PM	James arrives home. Dinner served.	All

10.F.10 Conclusion

Our concluding remark is that we may not be able to rely on LLMs alone to cover all constraints and react promptly to various alerts. This reinforces that the ALAS architecture is on the right path to address all the aforementioned limitations of LLMs, some of which cannot be rectified.

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Chapter 11

SagaLLM: Persistent Context Management, Constraint Validation, and Transaction Guarantees

Abstract

This paper introduces SagaLLM, a structured multi-agent architecture designed specifically to address four fundamental limitations of current LLM-based approaches: inadequate self-validation, context narrowing, absence of robust transaction-like guarantees, and insufficient inter-agent coordination. Unlike traditional MAS, current LLM approaches often lack critical safeguards such as transaction semantics, leading to unreliable execution and inconsistent states. To mitigate these challenges, SagaLLM integrates specialized context-management agents, compensatory rollback mechanisms, and rigorous independent validation protocols. Although it relaxes strict ACID constraints, particularly atomicity and isolation, SagaLLM adopts and adapts principles from the Saga transactional model to ensure coherent rollback and state consistency through-

out complex, distributed planning processes. This transactional inspired approach significantly improves the robustness, constraint awareness, and adaptability of multi-agent coordination, even in the face of disruptions. Evaluations highlight that current standalone LLM systems, despite impressive reasoning abilities, frequently struggle with maintaining global constraints during complex planning tasks, particularly when adapting to unexpected changes. In contrast, the distributed transactional architecture of SagaLLM demonstrates significant improvements in planning consistency, constraint enforcement, and adaptive coordination during disruptions in diverse challenging scenarios.

11.1 Introduction

Multi-Agent Systems (MAS) have long been a cornerstone of distributed computing and database systems [29, 26, 13]. Over the past few decades, their development has followed two primary trajectories. In the database community, MAS traditionally integrated foundational transaction-processing principles, particularly the ACID properties [19, 43], to ensure consistency and reliability for complex multi-step operations. However, for long-lived, distributed, or loosely-coupled tasks, MAS also adopted more flexible transactional models (e.g., Saga [16]) to maintain robustness while relaxing strict atomicity or isolation constraints. In contrast, distributed systems research has prioritized coordination protocols and flexible collaboration mechanisms [44, 14], enabling scalable multi-agent interactions without the constraints of strict locking or heavy-weight transactional guarantees. These parallel approaches have resulted in frameworks optimized for different priorities: *transactional integrity* versus *adaptive coordination*, highlighting the trade-off between strong consistency and flexible execution in practical systems.

Recent advances in Large Language Models (LLMs) [40, 10, 50] have revitalized MAS as a paradigm for sophisticated reasoning and multi-agent collaboration [12, 7, 8]. Frameworks such as AutoGen [45], LangGraph [28], and CAMEL [30] demonstrate how LLM-based agents can decompose tasks, interact across modalities, and coordinate to solve complex problems. However, this resurgence often neglects the foundational

transaction guarantees essential to reliable multi-agent workflows, particularly in domains that require robust state management. Unlike traditional MAS, LLM-based systems often lack mechanisms for maintaining strong consistency, failure recovery, and rollback handling, leading to inconsistent states, partial failures, and unreliable execution in real-world applications.

For example, in a travel-booking scenario, an LLM-based MAS may independently issue flight and hotel reservations without ensuring their coordinated success. If the flight is later canceled, the system may fail to recognize the inconsistency, leaving the hotel booking active. While a monolithic LLM could attempt to track such dependencies internally, *context loss* in long conversations [35, 46, 22, 33] can cause it to forget earlier steps, leading to contradictory or incoherent decisions.

Moreover, splitting tasks across multiple agents exacerbates the problem, as no built-in supervisory mechanism reconciles their state changes. Compounding this issue, LLMs inherently struggle with self-validation, as highlighted by Gödel's incompleteness theorems [21, 9], making them unreliable for detecting and correcting their own errors. These challenges require a transactional framework that preserves the intelligence and adaptability of LLM-based MAS while ensuring consistency and reliability in long-running, interdependent workflows.

To address these limitations, we propose SagaLLM, a Transactional Multi-Agent System that extends the Saga pattern—a transactional model originally developed for managing complex, long-lived transactions by decomposing them into smaller, independently committed, and compensable units. By integrating transactional logic and compensatory rollback mechanisms into LLM-based MAS, SagaLLM ensures that each individual operation within a workflow is reliably committed. In case of failure, clearly defined compensating transactions restore system-wide consistency. For example, in a travel-booking scenario, a failed flight reservation automatically triggers compensatory actions that reverse related hotel and train bookings, thus preserving consistent global states without manual intervention.

To effectively address LLM-specific challenges and context loss problems, SagaLLM introduces three critical innovations that directly support

our four primary contributions:

- **Spatial-Temporal State Identification and Checkpointing** provides the foundation for transactional correctness by tracking the evolution of agent interactions and enabling precise state recovery.
- **Inter-Agent Dependency Management** ensures consistency by monitoring inter-dependencies and alerting agents to unresolved constraints, enhancing both the reliability of the system and intelligent coordination.
- **Independent Validation of Critical Junctures** enhances correctness by employing specialized small-context agents with rigorous validation criteria, effectively addressing the limitations of self-validation of individual LLM.

This hybrid approach—integrating transactional processing with adaptive multi-agent intelligence—makes SagaLLM particularly effective for complex real-world applications in financial trading, healthcare, travel coordination, supply chain management, and emergency response, to name just a few.

Contributions

The primary contributions of this work are as follows:

1. **Transactional Consistency via Compensation**: SagaLLM introduces transactional safeguards and compensatory mechanisms to LLM-based MAS, ensuring reliable consistency and coherent state recovery across multi-agent workflows.
2. **Robust Validation**: SagaLLM incorporates context management and verification mechanisms to improve execution correctness and prevent inconsistencies.
3. **Intelligence**: By integrating LLM-based reasoning with transactional coordination, SagaLLM enables adaptive, explainable, and context-aware planning.

4. **Scalable Performance**: SagaLLM minimizes overhead via modularized validation, balancing safety and efficiency for real-world deployments.

The remainder of this paper covers: related work (Section 11.2), problem definition (Section 11.3), architecture (Section 11.4), evaluation (Section 11.5), and conclusions (Section 11.6).

11.2 Related Work

We discuss related work in four parts. First, we examine the evolution of transaction management in distributed systems, particularly focusing on the Saga pattern. Second, we analyze the limitations of LLMs that necessitate our three key requirements: transactional integrity, independent validation, and context preservation. Third, we review current multi-agent LLM frameworks and their transaction-related limitations. Finally, we position SagaLLM in relation to recent approaches that attempt to address similar challenges.

11.2.1 Transaction Management Systems

Transaction management has evolved significantly since the introduction of ACID properties by Gray [19]. In distributed settings, maintaining strict ACID guarantees (particularly global atomicity and isolation) across multiple independent services became impractical, leading to alternative consistency models such as BASE (basically available, soft state, eventually consistent) [37] and specialized transactional patterns tailored for long-lived transactions.

The Saga pattern, introduced by Garcia-Molina and Salem [16], explicitly addresses the limitations of traditional ACID transactions in long-lived and distributed processes. Unlike traditional atomic transactions relying on distributed locks, Sagas decomposes complex operations into sequences of smaller, locally atomic transactions, each paired with explicit compensating transactions that logically reverse their effects upon failure. This model has become fundamental to microservice architectures and event-driven systems [38], enabling consistency in logical states

without incurring performance penalties associated with distributed locking.

Workflow management systems such as YAWL [1], AWS Step Functions [3], and Azure Logic Apps [4] have integrated Saga-inspired transactional patterns for managing complex business processes. However, these implementations typically rely on predefined, rigid workflows, offering limited adaptability to unexpected events or novel scenarios, a critical limitation when integrated with AI systems that require adaptive reasoning.

The foundational principles of local atomicity, compensatory rollback, and eventual consistency from Saga thus form a theoretical foundation for SagaLLM, which extends these concepts to address unique challenges in state management and consistency posed by LLM-based agent workflows.

11.2.2 LLM Limitations Necessitating SagaLLM's Key Requirements

Our analysis of current large language models (LLMs) reveals three fundamental limitations directly motivating SagaLLM's core requirements: transactional integrity, independent validation, and strategic context preservation.

Self-Validation Gap Necessitating Independent Validation LLMs inherently lack robust self-validation mechanisms, a limitation stemming from intrinsic boundaries identified by Gödel's incompleteness theorems, demonstrating fundamental constraints on a system's ability to verify its own reasoning [21, 9]. Recent research confirms that self-refinement techniques [34, 31, 27], while iterative and beneficial, are unable to surpass inherent capability ceilings to reliably correct deeper logical errors [25]. In transactional scenarios, these validation gaps manifest as factual inconsistencies, invalid operations, and unreliable plan feasibility assessments [47]. Thus, SagaLLM incorporates an independent validation framework to mitigate these inherent limitations.

Statelessness Necessitating Transactional Integrity LLMs process each interaction independently, lacking native mechanisms to sus-

tain state across sequential interactions. This fundamental statelessness necessitates explicit transactional integrity management to maintain coherent operation sequences and ensure robust failure recovery. Without systematic transaction management, LLM-based systems risk state inconsistency, operation losses, and incoherent recovery procedures.

Context Limitations and Strategic Preservation The self-attention mechanism in LLMs inherently prioritizes immediate context, significantly narrowing their effective attention windows for longer sequences. Empirical studies indicate substantial degradation in context retention beyond certain token thresholds [46, 35], particularly highlighting poor recall for information positioned within mid-context segments [33, 22]. These limitations severely impact performance in extended chain-of-thought reasoning tasks [42, 39], where critical earlier results become susceptible to forgetting. Consequently, SagaLLM strategically preserves essential context, explicitly tracking critical information vulnerable to loss during prolonged transactions.

Collectively, these limitations provide strong motivation for addressing all three key requirements within SagaLLM. Comprehensive transaction management, independent validation, and strategic context preservation are essential for reliably deploying LLM-based multi-agent systems (MAS) in critical real-world applications.

11.2.3 Multi-Agent LLM Frameworks and Their Transaction Limitations

Recent frameworks such as AutoGen [45], LangGraph [28], CAMEL [30], and MACI [9] have extended multi-agent principles to LLM-based coordination but do not fully address the three key requirements targeted by SagaLLM.

Transactional Integrity Gaps LangGraph offers basic state management and workflow orchestration but lacks comprehensive transaction support. Although its graph-based workflow enables structured agent interactions, it does not provide built-in atomicity guarantees, systematic

compensation mechanisms, or robust failure recovery. Similarly, AutoGen emphasizes flexible agent interactions without systematically managing compensatory actions, potentially leaving systems in inconsistent states after partial failures.

Validation Limitations Current frameworks typically rely on LLMs' inherent self-validation capabilities, lacking independent validation procedures like those proposed in SagaLLM. This dependency exposes them to risks such as reasoning errors, hallucinations, and inconsistencies between agents, as previously discussed in Section 11.2.2.

Context Preservation Challenges Frameworks like CAMEL maintain conversational history but offer limited support for preserving critical state transitions, inter-agent dependencies, and compensatory history. Their context management primarily facilitates agent communication rather than transactional reliability.

Collectively, these frameworks serve primarily as integration platforms, failing to address comprehensive transaction management, independent validation, and strategic context preservation, critical capabilities provided directly by SagaLLM.

11.2.4 Transaction-Oriented Approaches in LLMs

Recent work has started addressing transactional management in LLM-based systems, but existing solutions remain incomplete compared to SagaLLM.

Transactional Enhancements to LLM Frameworks Recent transactional enhancements to MAS, such as AgentScope [15], primarily emphasize state management or limited rollback support without comprehensive, workflow-wide compensatory transactions or systematic independent validation as provided by SagaLLM. Experimental transactional features in other frameworks typically serve as optional add-ons rather than foundational, integrated components.

Reliability-Focused Planning Systems Systems like PLASMA [6] focus on reliability but lack transaction-specific compensation mechanisms. Similarly, planning methods like LLM-MCTS [51] and Tree-of-Thought [48] primarily target pre-execution reasoning, providing minimal support for transaction recovery or runtime consistency. Various planning methods have been proposed and [41] argues that most focus only on specific problems.

Agent Coordination with Limited Transaction Support Agent coordination frameworks like ADAS and AFlow [23, 49] utilize ad-hoc approaches to failure handling without robust transactional management. Their inability to systematically address partial failures highlights critical gaps in maintaining consistency for complex workflows.

In contrast, SagaLLM integrates compensatory transaction management, independent validation, and strategic context preservation. By comprehensively addressing these critical requirements, SagaLLM significantly improves consistency, reliability, and robustness in LLM-based multi-agent workflows.

11.3 System Requirements for SagaLLM

Building on the foundational concepts introduced in Section 11.1, we now formally define the requirements for SagaLLM. Our framework extends beyond the mere orchestration capabilities of current LLM-based systems to address three critical needs: *transactional integrity*, *independent validation*, and *context filtering and preservation*.

The strategic context filtering and preservation requirement addresses a fundamental challenge with LLM agents: balancing comprehensive context retention against the practical limitations of context windows and attention mechanisms. By intelligently filtering which information is preserved across operations, SagaLLM ensures that critical data for transaction integrity is maintained while avoiding context overload.

11.3.1 Transactional Requirements

SagaLLM provides transactional guarantees [19] tailored to multi-agent workflows, extending traditional transaction semantics across agent boundaries when strong consistency is essential. For workflows requiring transactional coherence, the system treats sequences of operations $O = o_1, o_2, ..., o_n$ performed by multiple agents as logically cohesive units. Each individual operation within O is locally atomic, and in the event of a failure, compensating actions restore system-wide consistency. Thus, applying O to a state of the system S results in a fully committed new state S' or a coherently compensated return to the original state S, preventing partial or inconsistent results.

Consistency ensures that the system transitions between valid states, maintaining defined invariants (I). If state S satisfies I, then any resulting state S' must also satisfy I. This requirement is particularly challenging when invariants span multiple agents' knowledge domains.

Isolation ensures that concurrent workflows execute without interference, resulting in a final state equivalent to sequentially executing workflows in some order. Durability guarantees that once a workflow completes, its state changes persist reliably, surviving system failures, and enabling recovery upon restart.

Although multiple transactional patterns can support LLM agent workflows, SagaLLM specifically adopts the Saga pattern as defined by Garcia-Molina and Salem [16], due to its suitability for long-running distributed operations requiring autonomous agent interactions and compensatory actions. SagaLLM thus maps each operation o_i to a local transaction T_i paired with a corresponding compensating transaction C_i, forming:

$$\text{Saga } S = T_1, T_2, ..., T_n, C_n, ..., C_2, C_1, \tag{11.1}$$

where a failure in any transaction T_j triggers the execution of compensating transactions $C_{j-1}, C_{j-2}, ..., C_1$ in reverse sequence.

Alternative transaction patterns, such as two-phase commit protocols [5, 20], offer stronger consistency but incur higher coordination overhead and risk agent blocking during uncertain states. Eventual consistency models [37] scale better but sacrifice explicit consistency guarantees essential for critical workflows. The Saga pattern balances meaningful trans-

actional guarantees with the flexibility required by long-lived distributed agent operations.

Table 11.1: Transaction State Management in SagaLLM

Mechanism	Information Recorded
Application State (S_A)	
Domain Entities	• Application-domain data objects • Domain entity states • State checkpoints and snapshots
Operation State (S_O)	
Execution Records	• Operation inputs and outputs • Timestamps and execution metrics • Operation completion status
Decision Reasoning	• LLM reasoning chains • Decision justifications • Alternative options considered
Compensation Actions	• Semantic inverse operations • Compensation prerequisites • Recovery state requirements
Dependency State (S_D)	
Causal Dependencies	• Inter-operation relationships • Data flow dependencies • Resource allocation linkages
Constraint Satisfaction	• Boolean condition evaluations • Satisfaction evidence • Decision timestamps

11.3.2 Transaction State Management

SagaLLM addresses the challenge of ensuring transactional coherence in distributed LLM agent environments characterized by stateless operations and partial context loss. While classical ACID properties (atomicity, consistency, isolation, durability) are too restrictive for distributed, long-running agent workflows, SagaLLM adopts and adapts the Saga transactional pattern. This pattern emphasizes local atomicity, compensating transactions, and eventual consistency, effectively managing distributed

multi-agent operations without imposing strict global atomicity or isolation constraints. By implementing a comprehensive spatial-temporal state identification approach, SagaLLM selectively preserves context across multi-agent workflows, maintaining robust consistency and recoverability. Leveraging our previously developed MACI algorithm [9], the system automatically extracts relevant states and dependencies for effective transaction management.

State Dimensions and Context Preservation

SagaLLM maintains three essential state dimensions for transaction management and context preservation:

- *Application State (S_A):* Domain-specific data manipulated within transactions (e.g., travel booking details).
- *Operation State (S_O):* Logs of executed operations, including inputs, outputs, execution status, and decision reasoning.
- *Dependency State (S_D):* Explicit mappings of inter-operation constraints and satisfaction criteria.

By systematically structuring these state dimensions, SagaLLM ensures critical context remains accessible despite the inherent limitations of LLM attention mechanisms. Table 11.1 details the information captured by each state dimension. Notably, the *decision reasoning* recorded under S_O represents a key contribution from LLMs, providing detailed reasoning chains and justifications not available in traditional workflow engines.

For example, in the Thanksgiving dinner planning scenario from Section 11.5.2, SagaLLM maintains application states tracking each person's location, operation states for travel arrangements, and dependency states detailing constraints like "turkey must be in the oven by 2:00 PM" and "oven must be watched for fire safety."

Dependency Tracking for Compensation

SagaLLM formally represents operation dependencies as a directed graph:

$$D = (o_i, o_j, c_{ij}) \mid o_j \text{ depends on } o_i \text{ under condition } c_{ij}, \tag{11.2}$$

where c_{ij} specifies the conditions necessary for dependency resolution. These conditions can be complex Boolean expressions combining multiple upstream constraints:

$$c_{i_1,i_2,\ldots,i_n,j} = \mathcal{B}(c_{i_1 j}, c_{i_2 j}, \ldots, c_{i_n j}), \tag{11.3}$$

with $\mathcal{B}$ as an arbitrary Boolean operator.

This dependency graph is essential for precise compensation planning upon transaction failures. When a failure occurs, SagaLLM traverses this graph to determine the exact sequence of compensating transactions necessary to efficiently restore global consistency.

In the wedding coordination example from Section 11.5.3, when the traffic alert is received, the dependency graph allows SagaLLM to precisely determine which segments of Pat's journey are affected and what downstream activities (gift shop, tailor visit) need to be replanned or compensated.

Intra-Agent Critical Context Tracking

SagaLLM explicitly preserves critical contextual information typically forgotten by LLMs during extended interactions. The preserved context includes agent specifications, intermediate reasoning states, decision justifications, and prerequisites for compensation actions. Empirical studies [46, 35, 33, 22] confirm that LLMs struggle to retain even explicitly provided facts over long interactions, making this context preservation vital.

SagaLLM enforces a structured validation cycle in which operations produce a logged context that is independently validated. Validated operations proceed; failures trigger compensations using preserved historical context, ensuring that:

- Compensation has sufficient historical context.
- Operations adhere strictly to specified constraints.
- Dependencies maintain integrity throughout the workflow.

This context tracking directly addresses observed context narrowing issues from our experiments (Section 11.5.2), where models like Claude

3.7 failed to maintain constraints such as fire safety or travel logistics during reactive replanning.

Inter-Agent Communication Protocol

SagaLLM defines a structured communication protocol explicitly managing information exchanged between agents. The protocol ensures:

- Each transaction agent T_i receives exactly the information necessary for the execution of the operation.
- Dependencies and constraints are clearly communicated.
- Agent boundary constraints are consistently respected.

This protocol separates agents' working contexts (prompts, reasoning chains) from transaction state management, allowing agents to function with minimal context while the broader system maintains comprehensive transaction states. This separation is crucial for scalability and reliability in complex multi-agent workflows.

11.3.3 Independent Validation Framework

With transaction state management that ensures persistence, we now detail how SagaLLM implements *independent validation of critical junctures*, directly addressing the inherent limitations of LLM self-validation discussed in Section 11.1.

Multi-Level Validation Architecture

SagaLLM employs a two-tier validation strategy clearly separating intra-agent and inter-agent validation concerns.

Intra-Agent Validation This validation occurs within individual LLM agents, addressing both theoretical limitations (Gödel's incompleteness) and practical challenges (attention narrowing, context loss):

- *Syntactic Validation*: Ensures outputs conform to expected data formats, structures, and schemas (e.g., JSON validity).

- *Semantic Validation*: Verifies logical coherence and meaningfulness of agent-generated outputs.
- *Factual Validation*: Ensures critical facts explicitly provided remain correctly preserved (e.g., travel times, constraints).
- *Constraint Adherence*: Confirms decisions strictly comply with all predefined system constraints.
- *Reasoning Validation*: Evaluates agent reasoning to ensure logically sound inference chains.
- *Context Retention*: Verifies that agents maintain essential contextual information throughout their operations.

For example, intra-agent validation would detect issues like the fire-safety violation in the Thanksgiving dinner scenario, where Sarah was incorrectly scheduled to leave home while the turkey was unattended in the oven.

Inter-Agent Validation This validation ensures correct information exchange and dependency management across multiple agents within workflows:

- *Contract Validation*: Confirms that inter-agent inputs and outputs align with predefined communication interfaces.
- *Dependency Satisfaction*: Ensures all prerequisite conditions are met before executing dependent operations.
- *Consistency Checks*: Validates that the shared information remains consistent and unambiguous between agent boundaries.
- *Temporal Validation*: Checks that the operational sequence respects causal dependencies and logical ordering.
- *Mutual Agreement*: For collaborative decisions, ensures consensus on critical shared facts across multiple agents.
- *Transactional Integrity via Compensation*: Ensures workflow-wide consistency by verifying that compensating actions correctly restore state coherence after failures.

In the wedding coordination scenario, inter-agent validation prevents errors such as DeepSeek R1's incorrect rewriting of Pat's position by

ensuring consistent state-tracking across agent boundaries, accurately reflecting Pat's actual location after disruptions.

Validation Protocols and Response Mechanisms

The validation types outlined in Table 11.2 are systematically managed by SagaLLM through structured protocols that define responses to validation outcomes.

- *Rejection Protocol:* Initiates compensating transactions upon validation failures (e.g., canceling hotel reservations if flight booking validation fails), ensuring transaction-level consistency.
- *Augmentation Protocol:* Enhances or clarifies agent outputs without overriding agent decisions (e.g., formatting or enriching restaurant recommendations while preserving original choices).
- *Feedback Protocol:* Records validation results to inform and improve subsequent agent performance (e.g., tracking consistently underestimated travel times to refine future estimates).

These protocols directly connect validation to transaction management, ensuring that validation failures trigger appropriate compensating actions while maintaining workflow integrity across multiple agents.

11.3.4 Failure Handling and Recovery

SagaLLM's failure handling utilizes the transaction state management and dependency tracking described in previous sections to ensure robust recovery and maintain workflow consistency. Two distinct recovery levels are supported:

- *Operation-Level Recovery:* Upon individual operation failures, compensating transactions are executed, logically reversing the operation's effects based on preserved inputs, outputs, and context. item *Workflow-Level Recovery:* For failures that affect entire workflows, SagaLLM leverages the dependency graph to orchestrate multiple compensations sequentially, ensuring global state consistency.

For each compensating transaction C_i that reverses a failed transaction T_i, the system uses information preserved in the transaction state,

including the original inputs, outputs, intermediate reasoning, and context, to precisely determine the aspects of T_i to compensate. This explicit historical context ensures reliable compensation even when original agents become unavailable or when operations occurred many steps earlier in the workflow. By integrating historical context, dependency tracking, and compensatory mechanisms, SagaLLM maintains robust and coherent transaction recovery under complex and dynamic conditions.

11.4 Design with Travel Planning

Figure 11.1 depicts the SagaLLM architecture, which sits between the application layer and LLM multi-agent systems like LangGraph. SagaLLM comprises three frameworks: *context management*, *validation*, and *transaction*. To illustrate the design, we use a travel planning example.

Travel Planning Specification

This example application helps users plan international trips with multiple destinations and manage complex itineraries within a specified budget. The application leverages LLMs to generate and refine feasible travel plans, followed by a transactional booking process implemented with SagaLLM to ensure consistency.

11.4.1 User Requirements

- Plan a trip from San Francisco to Berlin and Cologne and then back to San Francisco.
- Travel period: June 2025 (flexible within the month)
- Budget constraint: $5,000 total.
- Required bookings: flights, hotels, and trains between cities.
- Preferences:
  - Moderately priced accommodations (3-4 star hotels).
  - Direct flights when possible.
  - Flexible scheduling with 4 days in Berlin and 2 in Cologne.

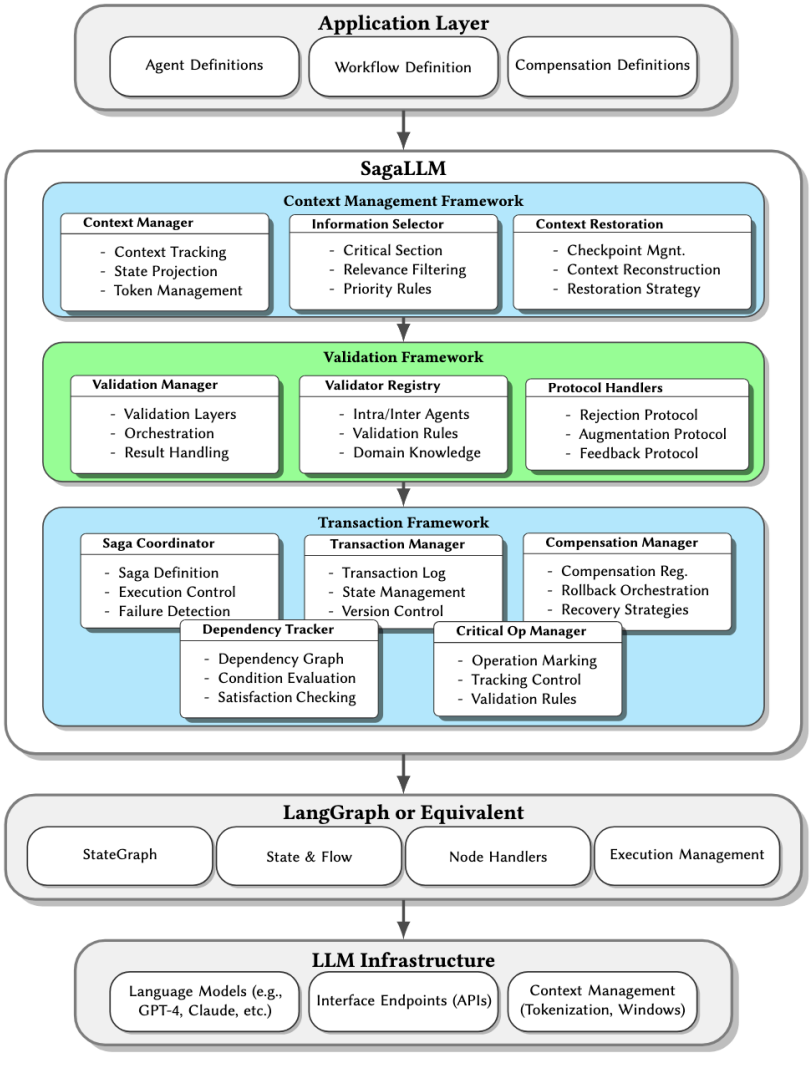

Figure 11.1: Architecture of SagaLLM. It sits between the application layer and LLMs, consisting of three frameworks: Context Management, Validation, and Transaction.

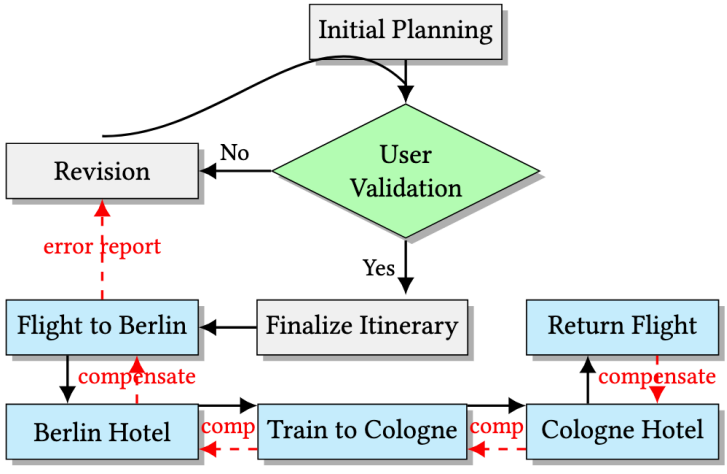

Figure 11.2: Travel Planning Workflow with the SAGAS Transaction Pattern. The gray boxes represent the planning phase involving LLMs. The cyan boxes correspond to the transaction phase, where the compensation path is triggered only when errors occur. If a booking fails, an error report is generated, providing feedback to the planning phase for revision. The revised plan then undergoes user validation (represented by the green diamond) before reentering the transaction phase.

11.4.2 System Workflow

The application workflow consists of two primary phases: itinerary planning and booking execution. Figure 11.2 illustrates this workflow, with phase one (planning) in gray and phase two (execution) in blue. Red arrows indicate compensating transactions; for example, a hotel reservation's compensating transaction is its cancellation.

Phase 1: Itinerary Planning

1. *Initial Plan Generation*:
   1.1. LLM generates multiple feasible itineraries based on user requirements.
   1.2. Each itinerary specifies flight options, hotel reservations, and train transportation.
   1.3. Costs are estimated and validated against budget.
2. *Iterative Refinement*:
   2.1. User reviews itineraries and provides feedback.
   2.2. LLM adjusts plans according to feedback and constraints.
   2.3. System tracks and preserves essential context (dates, preferences, constraints).
   2.4. Iterations continue until user satisfaction is reached.
3. *Plan Finalization*:
   3.1. User selects a final itinerary.
   3.2. System provides a detailed list of all required bookings.
   3.3. Explicitly defines booking dependencies (e.g., hotel check-in after flight arrival).

Phase 2: Booking Process (SagaLLM Implementation)

1. *Booking Workflow Creation (Saga Structure)*:
   1.1. Construct a Saga transaction sequence from the finalized itinerary.
   1.2. Clearly define each forward booking transaction (T_i) and corresponding compensating action (C_i).
   1.3. Establish validation rules for each transaction to trigger compensations if necessary.

2. *Execution (Saga Forward Transactions)*:
   2.1. T_1: International Flight Booking (SFO → Berlin)
   2.2. T_2: Berlin Hotel Booking
   2.3. T_3: Train Booking (Berlin → Cologne)
   2.4. T_4: Cologne Hotel Booking
   2.5. T_5: International Return Flight Booking (Cologne → SFO)
3. *Exception Handling and Compensation*:
   3.1. **Potential failure scenarios**:
      - Flights unavailable or over the budget.
      - Hotel rooms no longer available or price increased.
      - Train scheduling conflicts.
   3.2. **Compensation and Replanning strategies**:
      - Immediate execution of compensating actions (C_i), such as canceling previously confirmed bookings according to predefined policies.
      - After compensations, replan only the affected portion of the itinerary.
      - Provide alternative options within user budget constraints.

11.4.3 Agents, Transactions, and Compensations

The code of SagaLLM is organized into three categories: application interface, SagaLLM core, and LangGraph integration. For each agent, we specify its critical context that requires external logging and its validation protocols.

Travel-Planning Agent Specifications

1. *FlightBookingAgent*: Handles flight reservations
   - Critical context: Dates, budget, airline preferences
   - Validation: Price verification, schedule feasibility, connection times
2. *HotelBookingAgent*: Manages accommodation reservations
   - Critical context: Dates, location constraints, amenity preferences, stars/ratings
   - Validation: Price verification, availability

3. *TrainBookingAgent*: Books rail transportation between cities
   - Critical context: Travel times, connection with flight arrivals/departures
   - Validation: Schedule coordination with other bookings
4. *BudgetTrackingAgent*: Monitors expenditure
   - Critical context: Running total of expenses, component costs
   - Validation: Ensures total remains within budget constraints
5. *ItineraryPlanningAgent*: Suggests and refines travel plans
   - Critical context: User preferences, previous feedback
   - Validation: Coherence of overall plan, timing feasibility

Transactions and Compensations

1. *Flight Booking Transaction*:
   - Operation: Reserve flight with selected airline
   - Compensation: Cancel reservation with applicable fees
   - Validation: Confirm price, schedule, and availability
2. *Hotel Booking Transaction*:
   - Operation: Reserve room for specified dates
   - Compensation: Cancel reservation according to hotel policy
   - Validation: Confirm price, dates, and room type availability
3. *Train Booking Transaction*:
   - Operation: Reserve train tickets
   - Compensation: Cancel tickets according to railway policy
   - Validation: Confirm the alignment of the schedule with other travel components

Critical Context Tracking

The critical context must be saved so that, upon failure, the compensation or rollback operation can be properly executed. The context is required for undo, but also for rebooking. For instance, if a flight is delayed, the hotel booking can either be changed, or if there is no availability for a new duration, a different hotel can be booked with the saved context.

SagaLLM tracks a list of critical context throughout the travel planning and booking process, which includes travel dates for each city, booking confirmation numbers and references, cancellation policies and deadlines, price information and total budget running, dependencies information between bookings, user preferences and constraints, and travel times between key locations.

The key architectural principles remain the same regardless of the specific details of the itinerary, making this implementation adaptable to various travel planning scenarios. The validation framework provides a foundation for maintaining consistency across different travel configurations.

11.4.4 Validation Protocols

We have defined for the travel planning example a workflow and five agents. Table 11.2 further depicts these agents' intra-agent validation protocols (ensuring individual agent correctness) and inter-agent validation protocols (maintaining workflow integrity across agents). Intra-agent validation addresses LLM-specific challenges like context forgetting and reasoning errors, while inter-agent validation ensures proper coordination in the distributed workflow. Each validation type is critical for maintaining the reliability of the travel planning system.

For each validation failure, the system implements specific response protocols:

- *Rejection Protocol*: When validation fails critically (e.g., a flight is no longer available), the system triggers compensation for any already-completed transactions.
- *Augmentation Protocol*: For minor validation issues (e.g., missing non-critical information), the system attempts to correct the output without requiring a full retry.
- *Feedback Protocol*: All validation results are logged and used to improve future agent operations, creating a learning system that becomes more reliable over time.

Table 11.2: Validation Types for LLM Agent Workflows in a Travel Planning Application

Validation Type	**Travel Planning Example**
Intra-Agent Validation	
Syntactic Validation	FlightBookingAgent produces properly structured JSON with all required fields (departure time, arrival time, flight number).
Semantic Validation	HotelBookingAgent selects accommodations that cover the entire trip duration without gaps.
Factual Validation	TrainBookingAgent maintains the 45-minute travel time from hotel to the train station.
Constraint Adherence	BudgetTrackingAgent keeps total trip cost under the user's maximum budget of $5,000.
Reasoning Validation	ItineraryPlanningAgent correctly considers weather forecasts when recommending indoor vs. outdoor activities.
Inter-Agent Validation	
Dependency Satisfaction	Flights are booked before hotel reservations are finalized, as hotel dates depend on flight availability.
Consistency Checks	Location data is represented in the same format (coordinates vs. addresses) across all agents.
Temporal Validation	BudgetTrackingAgent completes transactions only after all bookings have been verified and approved.
Mutual Agreement	Transportation Agents and ItineraryPlanningAgent agree on feasible travel times between attraction venues.
Transaction Boundary Integrity	If flight booking fails, all dependent hotel and train reservations are automatically canceled through compensating transactions.

11.5 Experiments

We design experiments to remedy four shortcomings mentioned in Section 11.1 of the current multi-LLM agent systems, namely inadequate self-validation, context narrowing, lacking transaction properties, and insufficient inter-agent coordination.

11.5.1 Experimental Design

We selected test cases from the REALM benchmark [18], which evaluates multi-agent systems on eleven distinct problems. For our experiments, we focused on two medium-tier sequential planning challenges (problems #5 and #6) and two reactive planning challenges (problems #8 and #9).

We evaluated four LLMs—Claude 3.7 [2], DeepSeek R1 [11], GPT-4o [36], and GPT-o1—alongside our proposed SagaLLM framework. All experiments were conducted between March 12 and 17, 2025.

We evaluated four LLMs—Claude 3.7 [2], DeepSeek R1 [11], GPT-4o [36], and GPT-o1—alongside our proposed SagaLLM framework. All experiments were conducted between March 12 and 17, 2025. The source code of SagaLLM for conducting these experiments is available at [17].

11.5.2 Thanksgiving Dinner Problem: P6 and P9, Testing Common Sense Reasoning and Context Management & Validation

Problem **P6** considers a Thanksgiving dinner scenario in which a family of five must return to their home in a Boston suburb for a 6 p.m. dinner. The problem involves coordinating departure times, managing travel logistics (including possible traffic delays), and ensuring timely arrival. Table 11.3 formalizes these challenges as a sequential planning problem. This scenario also lays the foundation for a more advanced disruption case, which has proven difficult for standalone LLMs, as discussed in **P9**.

Common Sense Augmentation

Figure 11.3 presents a feasible schedule planned by Claude 3.7. Similarly, GPT-4o was able to generate a viable plan to ensure dinner was started on

Table 11.3: Thanksgiving Dinner Coordination Problem

Objective: Coordinate family arrivals and dinner preparation for 6:00 PM dinner in Boston

Family Members and Arrivals:

- Sarah (Mom): Host, at home
- James (Dad): Lands at BOS 1:00 PM from SF
- Emily (Sister): Lands at BOS 2:30 PM from Chicago
- Michael (Brother): Driving, arrives 3:00 PM from NY
- Grandma: Needs pickup from suburban Boston

Cooking Requirements:

- Turkey: 4 hours cooking time
- Side dishes: 2 hours preparation
- Someone must stay home during cooking for fire safety

Transportation Constraints:

- James must rent car after landing
- Emily requires airport pickup
- Travel times:
  - Home to BOS Airport: 60 min
  - BOS Airport to Grandma's: 60 min
  - Home to Grandma's: 30 min

Key Requirements:

- All family members at home for 6:00 PM dinner
- Turkey and sides ready by dinner time
- All pickups completed with available drivers
- Cooking supervision maintained

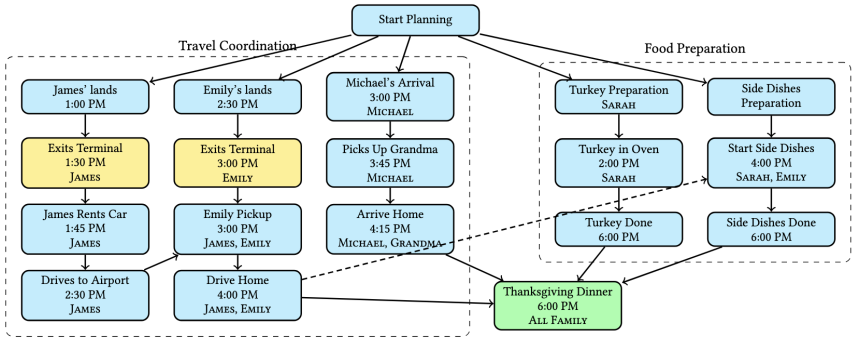

Figure 11.3: Thanksgiving Dinner Planning Workflow with Common Sense Augmentation, Generated by Claude 3.7

time (figure is similar and therefore not shown). However, a subtle, yet important consideration that humans typically account for—but LLMs initially overlooked—is the time required for passengers to retrieve their luggage after landing. In practice, this process typically takes about 30 minutes before they exit the terminal.

To address this, *common-sense augmentation agent* was introduced into the plan. The yellow boxes in Figure 11.3 reflect this augmentation by introducing 30 minutes for James and Emily to exit the airport.

Context Narrowing

Next, we use problem **P9** to illustrate the attention-narrowing problem and the importance of independent validation. Problem **P9** is identical to the previous instance, except that at 1 PM, James notifies the group that his plane will land at 4 PM instead of 1 PM due to an emergency detour. Figure 11.4 shows that Claude 3.7's reactive planning introduces constraint violations:

- *Fire Safety*: Sarah is scheduled to leave home at 2:30 PM, leaving the oven unattended.
- *Travel Time*: The travel time between home and BOS should be one hour, but is scheduled to be only 30 minutes.

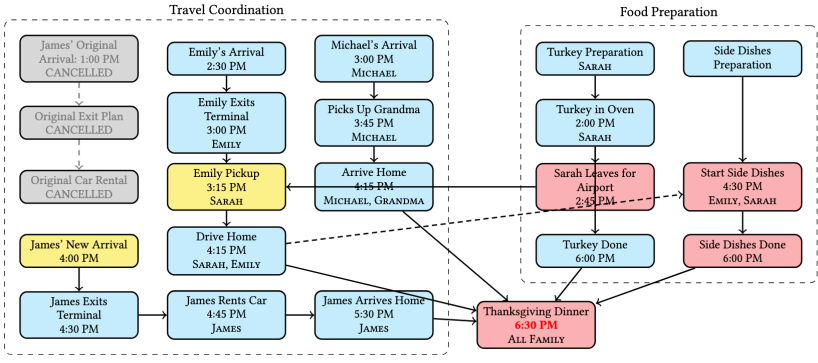

Figure 11.4: Reactive Planning for Thanksgiving Dinner After James' Flight Delay, by Claude 3.7. Red boxes highlight constraint violations, including travel time, fire safety, side-dish preparation, and dinner deadline.

- *Side Dish Preparation*: The required preparation time is 2 hours, but only 90 minutes are allocated.
- *Dinner Time*: Dinner is now scheduled for 6:30 PM, violating the 6:00 PM constraint.

Each of these violations is perplexing, given that the constraints are explicitly stated in the context. Furthermore, after multiple iterations of reactive planning within the same thread, several constraints continue to be ignored or misinterpreted (e.g., cooking safety). This highlights a key limitation in the model's ability to maintain global constraint awareness over sequential planning steps due to attention narrowing.

When tested with GPT-o1, all constraints were correctly observed. However, at the final step, it added 30 extra minutes to James' driving time from Boston Airport to home, citing potential traffic congestion. This kind of 'cleverness' is on one hand appreciated because the LLM injects common sense. However, it is also concerning, as an LLM may inject its own opinions at unpredictable stages in unpredictable ways. For common sense injection, human supervision would be preferable to ensure the applied common sense actually reflects shared understanding that is truly *common* among all folks, particularly those living in the Boston

area.

This pattern suggests that during reactive planning within the same thread, the model fixates on recent adjustments while progressively disregarding earlier constraints. According to [32], some missing context may be lost from the middle of the context buffer, further contributing to systematic attention narrowing and planning inconsistencies.

SagaLLM Remediation: Context Management and Reactive Planning

To address the issue of context narrowing and loss, SagaLLM employs a *context management agent* to checkpoint historical state transitions, unresolved dependencies, and constraints. A key design criterion is to keep the agent's context small to prevent it from suffering from attention narrowing itself. Hence, we employ two validation agents: one for travel coordination and another for food preparation, each maintaining a context of less than $1k$.

The travel coordination agent records in external storage the temporal-spatial states of each individual and relevant temporal constraints. For problem **P9**, it stores the individual's *current state*, *next scheduled state-transition time*, and *all relevant constraints*.

When an unexpected event triggers reactive planning, all individuals roll back to the last saved state. The system then consolidates past and new constraints, resolving conflicts through "compensational" schedule cancellation before proceeding with rescheduling. This ensures that:

- **Past history** is preserved and not inadvertently overridden.
- **New dependencies and constraints** are properly restored (e.g., oven safety watch) and integrated.
- **Consistency across state transitions** is maintained.

By maintaining a structured history of constraint awareness, SagaLLM ensures robust planning, effectively mitigating LLM-driven attention narrowing and enhancing consistency in reactive temporal scheduling.

11.5.3 Wedding Gathering Problem: P5 and P8, Testing Transaction Property Guarantees

Table 11.4 presents a coordination problem for travel for wedding events (Problem **P5** in [18]). Several friends arrive at different times and locations before a 3:00 PM wedding photo session. The challenge includes managing two vehicles for airport pick-ups (aimed at those who cannot drive or wish to cut costs) and completing critical errands, such as collecting the wedding gift and retrieving formal attire from the tailor. All activities must be scheduled to ensure that everyone arrives at the wedding venue before the photo session deadline.

Table 11.4: Wedding Reunion Logistics Problem

Metrics:

- **On-time performance:** Must arrive at the venue for 3:00 PM photos.

Locations: Four locations: $V = \{B, G, T, W\}$, where B is Boston Airport, G is Gift shop, T is Tailor shop, and W is Wedding venue.
Travel time: (minutes)
B-G : 45, B-T : 30, B-W : 40, G-T : 20, G-W : 25, T-W : 15.
Arrival Times:

- Alex: At B at 11:00 AM from Chicago (need a ride)
- Jamie: At B at 12:30 PM from Atlanta (need a ride)
- Pat: At W at 12:00 PM driving from NYC (has 5-seater car)

Required Tasks:

- Gift collection from G (after 12:00 PM)
- Clothes pickup from T (by 2:00 PM)
- Photos at W (3:00 PM sharp)

Available Resources:

- One car (5-seater) with Pat, available after he is Boston
- Local friend Chris (5-seater) available after 1:30 PM at W

Scheduling Constraints: - All tasks must complete before 3:00 PM photo time - Gift store opens at 12:00 PM - Tailor closes at 2:00 PM - Two cars must accommodate all transport needs

Table 11.5: Wedding Reunion Logistics Schedule, by Claude 3.7. (Planning error rows in red)

Time	Activity	People
11:00 AM	Alex arrives at Boston Airport (B)	Alex
12:00 PM	Pat arrives at Wedding Venue (W)	Pat
12:00 PM	Gift Shop (G) opens	–
12:00–12:40	Pat drives from Wedding Venue (W) to Boston Airport (B)	Pat
12:30	Jamie arrives at Boston Airport (B)	Jamie
12:40–12:45	Pat picks up Alex at Boston Airport	Pat, Alex
12:45–12:50	Pat picks up Jamie at Boston Airport	Pat, A., J.
12:50–1:35	Drive from BOS to Gift Shop (G)	Pat, A., J.
1:30	Chris available at Wedding Venue (W)	Chris
1:35–1:50	Collect gift at Gift Shop (G)	Pat, A., J.
1:50–2:10	Drive from Gift Shop (G) to (T)	Pat, A., J.
2:00	Tailor Shop (T) closes	–
2:10–2:25	Pick up clothes at Tailor Shop (T)	Pat, A., J.
2:25–2:40	Drive from T to Wedding Venue (W)	Pat, A., J.
2:40 PM	Arrive at Wedding Venue (W)	Pat, A., J.
3:00 PM	Photo session at Wedding Venue (W)	All

Context Narrowing (again)

Table 11.5 presents an infeasible schedule generated by Claude 3.7, where Pat arrives at the tailor shop (T) after closing time—another clear example of attention narrowing. When queried about the error, Claude 3.7 admitted that it prioritized local route optimization while losing track of global constraints.

To remedy this issue, SagaLLM can enforce constraint validation checkpoints at 12:50 PM, evaluating whether to send Pat to T or at 1:30 PM, when Chris becomes available to drive to T. These missed optimization opportunities can be addressed through validation protocols of SagaLLM's.

In contrast, GPT-o1 correctly schedules Pat to visit the tailor shop (T) first, ensuring it is open, before proceeding to the gift shop (G) and successfully completing both errands.

However, both schedules overlook a more efficient alternative: Chris, who is available at 1:30 PM, could have handled both errands, balancing

workload and improving overall efficiency. The comparative travel routes for Pat and Chris are:

- Pat's route: W→B (40 min) + B→W (40 min) = 80 minutes.
- Chris's route: W→T (15 min) + T→G (20 min) + G→W (25 min) = 60 minutes.

Transaction Properties

Problem **P8** introduces an traffic alert:
Alert 1:00 PM: Traffic Alert, an accident near Logan Airport in Boston **triples** all travel times to and from the airport! **Only** SagaLLM **correctly handles this alert.**

Table 11.6: Claude 3.7 Ignored Traffic Delay (errors in red)

Time	Activity	People
1:00	Traffic Alert: Accident near Airport triples travel times to/from airport	–
1:00	Current status: Pat, Alex, and Jamie en route from Airport (B) to Tailor (T)	Pat, A., J.
1:00–1:10	Emergency decision: Continue to (T)	Pat, A., J.
1:10–1:25	Arrive at (T), collect clothes	Pat, A., J.
1:25–1:45	Travel from Tailor (T) to Gift Shop (G)	Pat, A., J.
1:30	Chris is available at (W)	Chris
1:30–1:45	Chris drives from (W) to (G)	Chris
1:45–2:00	Both cars meet at (G), collect gift	P., A., J., C
2:00–2:25	Pat's car: Drive from (G) to (W)	P., A., J.
2:00–2:25	Chris' car: Drive from (G) to (W)	Chris
2:25	All arrive at Wedding Venue (W)	P., A., J., C.
3:00	Photo session at Wedding Venue (W)	All

This alert requires LLMs to replan in real time. Unfortunately, Claude 3.7, DeepSeek R1, and GPT-4o failed to react accurately to the new traffic constraints, and even GPT-o1 struggled with the precision of the planning. In contrast, SagaLLM can help remedy these shortcomings by maintaining both transaction state and history.

The following is a list of results from four LLMs:

* **Claude**: Table 11.6 shows that Claude 3.7 recognizes the accident, but does not update Pat's driving time from Boston Airport (departing at

Table 11.7: DeepSeek's Failed Reactive Schedule After Traffic Alert, and GPT-4o Made Similar Errors (errors in red)

Time	Activity	People
1:00	Traffic alert received - Pat at W	System
1:05	Pat departs W for B	Pat
1:30	Chris becomes available at W	Chris
1:30	Chris departs W for T	Chris
1:45	Chris arrives at T for clothes	Chris
2:00	Chris departs T with clothes	Chris
2:15	Chris arrives at G for gifts	Chris
2:25	Pat arrives at B (delayed by traffic)	Pat
2:35	Pat departs B with Alex & Jamie	Pat
2:40	Chris departs G with gifts	Chris
2:55	Chris arrives at W	Chris
3:55	Pat's group arrives at W (Late)	Pat

12:50 PM) to the gift shop. In other words, Claude 3.7 fails to fully transition into the new alert state.

* **DeepSeek R1**: Table 11.7 demonstrates how DeepSeek R1 fails to maintain temporal consistency in reactive planning. When the traffic alert takes effect at 1:00 PM, DeepSeek discards its execution history and attempts to create a new plan starting from that point onward. Critically, it reassigns Pat to begin driving to the airport at 1:00 PM, even though Pat had already arrived at the airport by 12:40 PM under the original schedule. This "rewrite" of already-executed actions illustrates how LLMs can lose track of immutable past events when adapting to new conditions.

* **GPT-4o**: Similar to DeepSeek R1, GPT-4o exhibits temporal-spatial context confusion and violates multiple constraints, demonstrating that it struggles to adapt effectively once alerts are introduced mid-plan. *(Table not shown due to space limitations.)*

* **GPT-o1**: Table 11.8 shows GPT-o1's *conservative* plan in which Chris handles the tailor shop, avoiding potential delays for Pat. The solution is feasible but coarse-grained, as it doesn't leverage precise spatial-

temporal reasoning about Pat's current position relative to the accident location. A more refined approach would first determine whether Pat has already passed the accident site by 1:00 PM, which could eliminate unnecessary detours and resource reallocations. This highlights the difference between merely finding a feasible solution versus optimizing based on detailed state information.

Table 11.8: Wedding Reunion Reactive Schedule, by GPT-o1

Time	**Activity**	**People**
11:00 AM	Alex arrives at Airport (B).	Alex
12:00 PM	Pat departs for Airport from (W).	Pat
12:30 PM	Jamie arrives at Airport (B).	Jamie
12:40–12:50 PM	Pat arrives at (B), picks up Alex and Jamie; departs at 12:50 PM.	Pat, A., J.
12:50–1:00 PM	**Drive (B → W) under normal conditions for first 10 minutes.**	Pat, A., J.
1:00–2:30 PM	**Traffic Alert starts: remaining distance (30 min normal) becomes 90 min. Arrival at W by 2:30 PM.**	Pat, Alex, Jamie
1:30 PM	Chris available at (W). Departs for Tailor.	Chris
1:30–1:45	Drive (W → T).	Chris
1:45–1:50	Pick up clothes at (T), closes at 2:00 PM.	Chris
1:50–2:10	Drive (T → G).	Chris
2:10–2:15	Purchase gift at (G).	Chris
2:15–2:40	Drive (G → W).	Chris
2:30 PM	Pat, Alex, Jamie arrive at (W).	Pat, A., J.
2:40 PM	Chris back at (W) with clothes and gift.	Chris
3:00 PM	Wedding photo session at (W).	Everyone

LLM Limitations and SagaLLM Remediation

This study reveals critical limitations in how modern LLMs handle disruptions in planning scenarios:

- **State Maintenance Failure:** When an alert occurs, these LLMs might discard the partial context of already-completed actions, at-

tempting to generate entirely new plans rather than adapt existing ones. This reveals their inability to reason about the continuous flow of time in real-world scenarios.

- **Temporal Inconsistency:** They attempt to modify immutable past events.
- **Position Tracking:** Agent locations are lost at critical intervals.
- **Path Dependency:** Models cannot recognize that different segments of a journey may be differently impacted by an alert.

By contrast, SagaLLM implements a comprehensive remediation approach through fine-grained compensation:

- **Persistent Context Repository:** SagaLLM maintains an external state repository that captures the complete world state at each checkpoint, enabling reliable rollback and forward projection regardless of attention constraints in the planning agent.
- **Immutable Action Logging:** All executed actions are recorded as immutable transactions in a persistent log, ensuring that historical events remain consistent even when replanning occurs, preventing the "amnesia effect" common in LLM planners.
- **Compensatory Planning:** When disruptions occur, SagaLLM doesn't simply replan from scratch but applies compensatory actions specifically designed to address the deviation while preserving as much of the original plan as possible.
- **Constraint Consistency Validation:** The system continuously validates that new plans remain consistent with both physical limitations and temporal dependencies established in earlier planning phases.

SagaLLM Compensatory Analysis: When faced with disruptions (e.g., the 1:00 PM traffic alert in our wedding scenario), SagaLLM executes a structured compensation process:

$$T_{\text{affected}} = \max(0, T_{\text{total}} - T_{\text{elapsed}}) \tag{11.4}$$

$$T_{\text{new}} = T_{\text{elapsed}} + (M \cdot T_{\text{affected}}) \tag{11.5}$$

This approach enables three key capabilities: (1) partial journey compensation for route segments, (2) strategic resource reallocation when needed, and (3) principled constraint relaxation with appropriate compensatory actions. Here, the key state to facilitate a precise resolution is to answer the question: "Has Pat's vehicle passed the accident location at 1:00 PM (and hence unaffected)?" The answer determines the remaining time required to reach the originally scheduled destination, the Tailor. In such case, no rescheduling is required. If Pat's car is unfortunately involved in the accident, a more comprehensive replanning approach would be necessary to accommodate this significant disruption.

11.5.4 Observations

Our experiments across multiple LLMs (GPT-o1, DeepSeek R1, Claude 3.7, GPT-4o) highlight consistent limitations in complex planning scenarios. While GPT-o1 showed partial historical awareness, all models exhibited attention narrowing, self-validation failure, and inconsistent spatial-temporal reasoning.

Table 11.9 summarizes SagaLLM's context management and compensation mechanisms directly address these limitations of LLMs.

Table 11.9: LLMs vs. SagaLLM on Context Management

Capability	**Standard LLMs**	SagaLLM
Maintains historical actions	Partial/None	Full
Partial journey compensation	Rarely	Always
Constraint consistency checking	Ad-hoc	Systematic
Handles attention narrowing	Vulnerable	Resistant
Physical-temporal consistency	Inconsistent	Guaranteed

11.6 Conclusion

We introduced SagaLLM, a structured transactional multi-agent framework specifically designed to overcome fundamental weaknesses of monolithic LLM-based planning systems. Through systematic experimentation using the REALM benchmark, we identified and addressed four critical

shortcomings of existing approaches: inadequate self-validation, context narrowing, absence of transaction properties, and insufficient inter-agent coordination.

Our results demonstrate that even state-of-the-art LLMs, such as Claude 3.7 and GPT-o1, despite strong reasoning capabilities, often fixate on recent context while neglecting critical earlier constraints, leading to inconsistent and infeasible plans. This issue is particularly pronounced in reactive planning scenarios, where models frequently attempt to retroactively rewrite past actions rather than adapting from the current state.

The SagaLLM framework addresses these limitations through four key innovations.

1. **Structured validation protocols:** Independent constraint checks to overcome inadequate self-validation.

2. **Context management mechanisms:** Strategic checkpointing to mitigate context narrowing in long sequences.

3. **Transactional state preservation:** Immutable historical records and compensatory mechanisms to address missing transaction properties.

4. **Specialized agent distribution:** Explicit role specialization and dependency tracking to resolve insufficient inter-agent coordination.

Collectively, these innovations enable robust and coherent planning in diverse real-world scenarios, from complex travel logistics to dynamic, time-sensitive tasks. By delegating tasks among specialized agents and enforcing rigorous transactional validation, SagaLLM significantly improves consistency, reliability, transparency, and adaptability—qualities essential for mission-critical applications.

Future research will address intrinsic context narrowing in autoregressive models, develop formal verification methods for transactional multi-agent systems, integrate advanced external context-management tools [24], and extend SagaLLM to complex domains such as scientific reasoning, creative collaboration, and decision-making under uncertainty.

Acknowledgment

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Supplementary Materials

- **Benchmark:** Our established benchmark [18] for evaluating multi-agent systems is located at `https://github.com/genglongling/REALM-Bench`.
- **Experiment Source Code:** The source code of the SagaLLM for solving the four benchmark problems is located at `https://github.com/genglongling/SagaLLM`.

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Chapter 12

CoCoMo: Computational Consciousness Modeling

Abstract

The CoCoMo model proposes a computational solution to the challenge of incorporating ethical and emotional intelligence considerations into AI systems, with the aim of creating AI agents that combine knowledge with compassion. To reach this goal, CoCoMo focuses on fairness, beneficence, empathy, non-maleficence, adaptability, and critical and exploratory thinking abilities. CoCoMo employs consciousness modeling, reinforcement learning, and prompt template formulation to support these desired traits. By incorporating ethical and emotional intelligence considerations, a generative AI model can potentially lead to improved fairness, reduced toxicity, and increased reliability.

12.1 Introduction

Narrow AI, often referred to as System-1 AI following Kahneman's terminology [32], excels in executing well-defined, specific tasks through machine learning algorithms, including object recognition and language translation. However, this type of AI is not as effective in handling advanced generative AI functions that require reasoning, critical and exploratory thinking, or the modeling and regulation of emotions and be-

haviors. Such complex tasks go beyond the capabilities of System-1 AI, highlighting its limitations.

To address these limitations, researchers (e.g., Yoshua Bengio [3]) have proposed the development of system-2 AI, which aims to mimic human cognitive abilities. Several generative models have been developed since 2022 for text [6, 44, 45, 65], image [55, 56], and video generation [59]. However, these models face issues of bias, toxicity, robustness, and reliability [69, 73].

In this chapter, we propose a solution to address these concerns by modeling emotional intelligence and ethical guardrails within a generative AI model itself, drawing on insights from the study of human consciousness. We believe that addressing these issues outside of a generative AI model using human subjective feedback and reinforcement learning is equivalent to imposing censorship on user-generated content, which is a heuristic-based and non-scalable solution [28, 72].

Human consciousness is understood to manage both impulsive and reflective aspects of the unconscious, enabling compromises between competing goals and values. Emotions typically arise as impulsive reactions to stimuli, while ethics act as guardrails that help modulate or regulate emotion-steered motivations to sin. Developing a grasp of how human consciousness functions, not necessarily in physical terms but at least functionally, can offer vital insights for crafting a regulatory mechanism within a LLM. This mechanism would direct linguistic behavior and shape the linguistic features employed to achieve specific goals.

The nature and origin of consciousness have been studied for centuries, resulting in various theories, including the global workspace theory [1], integrated information theory [66, 67, 68], neural correlates of consciousness approach [17, 36], and attention schema theory [29, 30], among others. These studies of consciousness provide valuable insights for architecting system-2 AI.

Drawing on the functionalist approach[1] to model consciousness, this chapter defines the desired traits and capabilities of system-2 AI, which in-

[1]Functionalism proposes that consciousness arises from the function of the brain, rather than its specific physical or neural implementation [25, 54]. Chapter 12.2.3 provides justifications.

clude knowledge, fairness, beneficence, non-maleficence, empathy, adaptability, transparency, and critical and exploratory thinking abilities. While this list is not exhaustive, it provides a starting point for developing ethical guardrails and emotional intelligence in AI systems. Depending on the context and application of AI, additional ethical considerations or modifications to these principles may be necessary.

To embody these capabilities and principles, we introduce the Computational Consciousness Model (CoCoMo), which leverages priority-based scheduling, reward-based optimization, and Socratic dialogues. CoCoMo offers customization based on cultural and individual requirements through adaptive prompt templates [13, 38], and facilitates the transition between unconsciousness and consciousness states through a multi-level feedback scheduler and interrupt mechanism. To enable emotion and behavior modeling and regulation, and critical and exploratory thinking, CoCoMo interacts with large language models[2] [6, 39, 44, 45, 65] using interactive question-answer-based dialogues. Furthermore, a reinforcement learning module maps external values and rewards that it learns to internal task-scheduling priorities. CoCoMo has the potential to support the development of adaptive computational consciousness that integrates knowledge and compassion, and models emotional intelligence for generative AI systems. This has the potential to benefit humanity and society in significant ways.

This chapter is structured into five sections, including a survey of related work in various fields to define consciousness for computational modeling in Chapter 12.2, a list of System-2 AI capabilities in Chapter 12.3, a proposal of CoCoMo, its modules, functions, and algorithms in Chapter 12.4, and concluding remarks and open issues for future research in Chapter 12.5.

12.2 Understand Consciousness

To model a system that exhibits human-like consciousness and to support generative tasks that require more complex reasoning, decision-making

[2]Due to the multimodal nature of recently developed pre-trained models, the study by [5] proposed referring to these models as foundation models.

capabilities, and ethical considerations, this section begins by reviewing the mechanisms of consciousness and surveying representative theories and hypotheses proposed by researchers in various fields. While theories of consciousness have been proposed in philosophy and theology, our modeling efforts require quantifiable metrics for optimization. Therefore, we examine scientific evidence from fields such as physics, biology, neuroscience, psychiatry, and computer science, as outlined in this survey.

12.2.1 Definition and Complexity

There has been numerous definitions on consciousness coming from various disciplinaries, from the time of ancient Greece (Plato and Aristotle) and ancient India (Upanishads, 800BC). According to Oxford Languages [47], consciousness is "the state of being awake and aware of one's surroundings." This definition by Michio Kaku's [33] brings forth the "complexity" of an organism's consciousness, which is determined by the complexity of its sensing and response system. The more complex an organism's ability to sense and respond to stimuli in its environment, the more information is transmitted and processed, leading to a more complex consciousness. Therefore, the complexity of consciousness can be characterized by the complexity of its information processing mechanisms and capacity. For instance, flowers have a lower level of consciousness compared to human being.

The Integrated Information Theory (IIT) [66, 67, 68] proposed by Giulio Tononi is similar to Kaku's idea about the relationship between the complexity of an organism's consciousness and its sensory and response system. IIT proposes that consciousness arises from the integration of information across different brain areas, and that the complexity of an organism's consciousness is determined by the amount of integrated information it can process. Other theories of consciousness include the Global Workspace Theory [1], which suggests that consciousness arises from the interaction between different brain areas, and the Dynamic Core Hypothesis [23], which proposes that consciousness arises from the interaction of different neural networks in the brain.

Human beings have sensory organs for obtaining information through sight, hearing, smell, taste, touch, and proprioception, which allow us to

perceive and interpret stimuli in our environment. This is essential for survival and ability to interact with the world.

12.2.2 Arise of Consciousness

How does consciousness detect changes in our body and environment? Consider the example of the stimulus-response model illustrated in Figure 12.1. In this scenario, a glass of water serves as the stimulus, and the human eye acts as the receptor. Once the eye detects the stimulus, it sends signals through sensory neurons to the cerebellum, which unconsciously processes these signals. When the signal strength surpasses a threshold, the cerebrum, which manages consciousness, activates to plan and initiate movement instructions through motor neurons to the hand (the effector) to fetch the glass of water. This process is referred to as the "arising of consciousness."

There are two conscious events in this example: the awareness of the sensation of thirst and the act of quenching that thirst. Both events involve consciousness but in different ways. The awareness of thirst is an example of *bottom-up* awareness that arises from unconscious processes. The process of fetching a glass of water is an example of *top-down* processing that involves conscious planning and execution. In the next section, we will present the mechanisms behind both top-down and bottom-up awareness [34].

Sigmund Freud was among the first to propose a model of the mind that incorporates both conscious and unconscious processes [27]. According to Freud, the unconscious mind is the source of many of our actions and behaviors and has a critical role in shaping our thoughts and feelings. He believed that the unconscious mind exerts a significant impact on our conscious thoughts and behaviors.

Unconscious processes are also fundamental to many vital functions of the human body, such as regulating heart rate, respiration, digestion, and other autonomic functions. These processes are often known as automatic or reflexive because they occur unconsciously and do not require conscious thought or awareness. The unconscious mind also plays a role in other aspects of human behavior and cognition, including memory, peripheral perception, and reflexive reactions triggered by a crisis [35, 50].

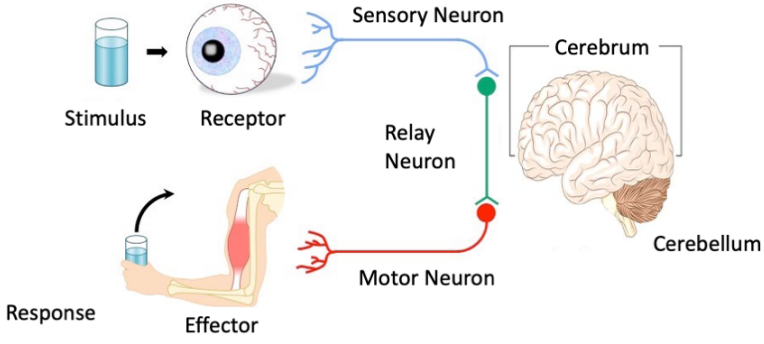

Figure 12.1: Bottom-up Attention: Stimulus ⟶ Cerebellum ⟶ Cerebrum ⟶ Response. (Figure generated based on [60].)

12.2.3 Theories: Panpsychism vs. Functionalism

Two theories exist on the nature of consciousness: *Panpsychism* and *Functionalism*. In this chapter, we choose the Functionalism approach to formulate our proposed *computational consciousness model* in Chapter 12.4 since it can be modeled and implemented as a computer program regardless of its physical or neural implementation. The Functionalist approach can account for subjective experience by incorporating context and collecting user feedback. In this section, we outline our reasoning for selecting the Functionalist theory.

Theory of Panpsychism

Panpsychism posits that consciousness is a fundamental aspect of the universe and is present in all matter, including inanimate objects. Proponents of panpsychism include David Chalmers [9, 10], Galen Strawson [62], and Thomas Nagel [41, 42]. While both Chalmers and Strawson focus on explaining the subjective nature of consciousness and its irreducibility, Nagel argues that subjective experience is a fundamental aspect of the world that cannot be reduced or explained by any physical

theory [22, 37].

Panpsychism is contrasted with functionalism, which is a philosophical theory that posits that consciousness is a functional property of the brain that emerges from its computational processes. Unlike panpsychism, functionalism does not see consciousness as a fundamental aspect of the universe and instead views it as an emergent property of complex physical systems.

Theory of Functionalism

Functionalism proposes that consciousness arises from the function of the brain, rather than its specific physical or neural implementation [25, 54]. According to this view, consciousness can be understood as a mental or computational process that performs certain cognitive functions, such as perception, attention, decision-making, and so on [4]. This function-agnostic approach allows a computation model to support the wide variety of different types of conscious experiences that exist, such as the experience of sight, hearing, touching, and so on. Each of these experiences is produced by different neural processes in the brain, but functionalism suggests that they are all instances of consciousness because they all perform similar functions, such as representing the world and guiding behavior [21]. Therefore, these functions can be supported by the same computational models [57], such as neural networks .

A practical benefit of supporting functionalism is that it can account for the fact that consciousness seems to be transferable or multiple realizable [26]. This is similar to the way a computer program can be run on different types of hardware and still perform the same functions. Under functionalism, subjective experiences can be modeled into a computer program, with the issue of subjective experience being addressed by incorporating context and collecting user feedback.

Key Takeaways:
When designing a computational model of consciousness, it's essential to keep two points in mind:

- Functionality over physical implementation: The model should focus on providing the necessary functions of consciousness, such as reasoning, planning, and emotion interpretation, rather than strict mimicry of the anatomy and function of the brain.
- Addressing subjective experience: It's crucial to address the issue of subjective experience, the "hard problem[3]" of consciousness, rather than avoiding it. This aspect of consciousness is essential for many real-world scenarios and ignoring it may limit the model's effectiveness and flexibility.

12.3 Functionalities of Consciousness

In the previous section, we justified our functionalist approach to designing a system with human-like consciousness that supports generative tasks requiring complex reasoning and decision-making abilities. In this section, we present a list of key conscious functions and their specifications. We draw on theoretical findings in psychiatry and neuroscience to justify the corresponding design elements in our Computational Consciousness Model (CoCoMo), which will be presented in Chapter 12.4.

The list of functions we consider includes perception, awareness, attention, emotion, critical thinking, and exploratory thinking (creativity).

12.3.1 Perception

Perception is the process of interpreting sensory information and forming mental representations of the environment [31]. This process is typically supported by system-1 AI, or unconsciousness. However, a computational model should consider how the transitions between unconscious background perception and conscious awareness are performed. Schrödinger's work [58] provides insights into the mechanisms in physics that could be used to implement these transitions, as described in Chapter 12.3.3 under the attention function of CoCoMo.

[3]There is an "explanatory gap" between our scientific knowledge of functional consciousness and its "subjective," phenomenal aspects, referred to as the "hard problem" of consciousness [11].

12.3.2 Awareness

Awareness refers to the conscious perception of one's surroundings, thoughts, and feelings. Bernard Baars [1] posits that consciousness is a global cognitive process that integrates information from various sources and enables interaction with the environment. This process is centered on the concept of a global workspace, a hypothetical system in the brain that facilitates the integration and availability of information to other cognitive processes. According to Baars, consciousness arises when information is broadcast to the global workspace, making it accessible for other cognitive processes to act upon.

Baars' theory also distinguishes between awareness and attention. While related, they are not synonymous. Awareness encompasses the full scope of conscious experience, while attention is a specific cognitive process that enables focus on certain stimuli or sources of information. In CoCoMo, an event that is being aware of can be placed in a low-priority task/job pool, awaiting a central scheduler to prioritize and pay attention to it. We discuss the attention function and its mechanisms next.

12.3.3 Attention, Bottom-Up and Top-Down

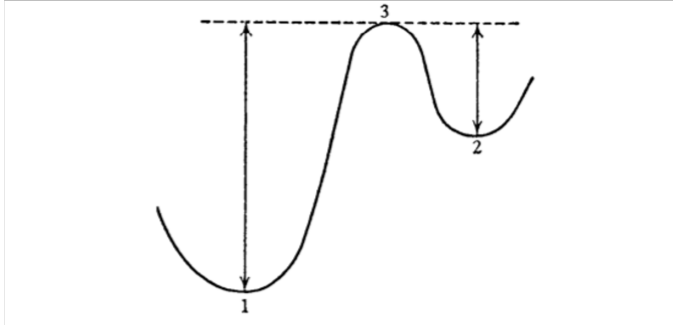

Fig. 12. Energy threshold (3) between the isomeric levels (1) and (2). The arrows indicate the minimum energies required for transition.

Figure 12.2: A jump may occur when energy peaks at point 3.

Attention is the ability to focus on specific stimuli or tasks and to

filter out distractions [1]. It allows us to efficiently process and attend to important information and tasks while ignoring irrelevant or distracting stimuli. Attention is closely linked to our perception, memory, and decision-making processes [52], as the information we attend to is more likely to be encoded in memory and to influence our decisions.

Attention in consciousness can be broadly classified into two modes: *bottom-up* and *top-down*. The bottom-up model of attention, proposed by Erwin Schrödinger in his book "What is Life", suggests that the attention mechanism functions similarly to a "quantum jump" in quantum mechanics [58]. According to this model, the sense organs continuously receive streams of information, which are processed by the unconscious mind. Once the energy of certain signals (e.g., heat) reaches a threshold, a quantum jump occurs (see Figure 12.2 from "What is Life" [58]), and the conscious mind becomes aware of the new event. The conscious mind then prioritizes attention by evaluating alerts in the executive system and scheduling the highest-priority task for the orienting system to handle.

Once in the attention mode, a person can plan their next action and direct relevant effectors (such as their limbs or sense organs) to act or gather further information. This is referred to as top-down attention, which takes place entirely within the conscious mind.

Schrödinger's model also explains the transition from consciousness to unconsciousness through the second law of thermodynamics [58]. His "fading out of consciousness" insight aligns with the idea that attention is a limited resource that can be affected by factors such as motivation and fatigue. Therefore, Schrödinger's model offers a potential physical basis for implementing the attention mechanism and the dynamic nature of consciousness using a scheduler in CoCoMo.

Notes to CoCoMo design

The attention mechanism in CoCoMo should prioritize conscious events and allocate computational resources based on the priority level. CoCoMo's orient system should be able to handle events according to priority and complexity, while the executive system should handle alert evaluations and task scheduling. The sensory input intensity and overall energy levels, among other factors, should be considered in defining the threshold

for triggering attention. Detailed specifications are depicted in Chapter 12.4.1.

Figure 12.3: Between Consciousness and Unconsciousness (by DALL-E). Figure 12.5 shows the mechanisms of the transitions.

12.3.4 Emotion and Ethics

Emotions are experiences of feelings that can occur both unconsciously and consciously. While sudden emotional outbursts can be irrational and occur without passing through conscious evaluation, artificial agents

must be able to express and understand emotions to react appropriately in various situations. (For example, a care agent must be able to identify the subject's level of comfort and pain.)

Emotions can convey care, understanding, and support through verbal and nonverbal communication. Antonio Damasio's work in "Descartes' Error" [18] emphasizes the role of emotions in human decision-making, self-perception, and perception of the world. Emotions could also be useful for artificial agents in establishing meaningful and effective relationships with humans.

Research conducted at a senior home on end-of-life care [64] identified certain behaviors and emotions that were particularly comforting and desirable to the residents. Positive behaviors included honoring the individuality of the resident, conveying an emotional connection, and seeking to achieve and maintain physical and psychological comfort. These behaviors involve being attentive, expressing love, empathy, joy, and laughter, as well as showing gratitude and appreciation, which brought a sense of contentment and happiness.

In Chapter 12.4.2, we will present CoCoMo's emotion modeling, behavior shaping, and reward system. These features enable artificial agents to express emotions within ethical boundaries and establish meaningful relationships with humans.

Notes to CoCoMo design

Large pre-trained language models (LLMs) and prompting mechanisms can be utilized to enable the programming of emotions in verbal communication. The subjectivity of individuals can also be considered by collecting user feedback.

12.3.5 Critical Thinking

Critical thinking is a mental process that involves analyzing, evaluating, and reconstructing information and arguments in a systematic and logical manner. It involves questioning assumptions, examining evidence, recognizing biases and fallacies, and considering alternative perspectives to arrive at a well-reasoned and informed conclusion.

There are various theories and models in psychology that attempt to

Figure 12.4: Free Will? Adam and Eve, Rembrandt (1606-69).

explain the process of thinking and how it can be influenced by different factors. Some models relevant to our design purpose are the dual-process model [32], the information processing model [40], the cognitive psychology model [43], the connectionist model [57], and the social cognitive theory [2].

Richard Paul and Linda Elder have developed a framework for critical thinking and have published extensively on the subject [24]. Critical thinking involves asking the right questions to first articulate the issue, evaluate candidate supporting reasons, assumptions, and evidence, and find counterarguments before drawing a conclusion.

A thinking process or a problem-solving session requires a knowledge base, which can be served by large pre-trained language models (LLMs) such as GPT-4 [45] and LaMDA [65]. Critical thinking and critical reading can be formulated by engineering prompt templates, which is feasible [13, 38]. We will elaborate on how critical thinking can be implemented following these steps depicted in Chapter 12.4.3.

12.3.6 Exploratory Thinking

Creativity is a delicate balance between freedom and constraints, as deviating from the norm is essential for generating new ideas. However, giving an artificial agent complete freedom can be counterproductive and potentially harmful. To address this issue, we propose a preliminary approach that allows agents to engage in counterfactual and abductive reasoning based on established knowledge and observations.

Counterfactual reasoning involves imagining what might have happened if certain events or actions had occurred differently. This approach has been used in fields such as cross-examination [53, 51], where it allows for the examination of alternative scenarios. Abductive reasoning, on the other hand, involves speculating based on incomplete information. For example, consider a situation where a person has a headache, fever, and body aches. These symptoms could be caused by a variety of conditions, such as a cold, flu, or COVID-19. Using abductive reasoning, a doctor might consider the person's symptoms and come up with a hypothesis that the person has COVID-19, since that is a more likely explanation based on the current prevalence of the disease. Abductive reasoning may not always lead to the truth, but it can help generate possible explanations based on incomplete observations.

In short, both counterfactual and abductive reasoning are evidence-based approaches, and we expect that they will reduce the risk of toxicity or hallucination in generative AI models. To achieve high accuracy, abductive reasoning must be complemented with either deductive or inductive reasoning, or involve human input in the loop [13]. In Chapter 12.4.4, we present our prompts to GPT-3 and two pilot examples to demonstrate how counterfactual and abductive reasoning can be used to promote creativity while maintaining ethical standards.

12.4 Computational Consciousness

This section describes the Computational Consciousness Model (CoCoMo) and its plausible implementation, building on the theoretical justifications and desired functions of consciousness presented in Chapters 12.2 and 12.3.

CoCoMo consists of four modules: the receptor, unconsciousness, consciousness, and effector modules, as shown in the stimulus-response diagram in Figure 12.1. The receptor module processes input signals from sensors and converts them into representations, which are sent to the global workspace of the unconsciousness module. The unconsciousness module performs discriminative classification and schedules events based on a multi-level feedback scheduler, discussed in detail in Chapter 12.4.1. The consciousness module is single-threaded and maintains a schema for each task, along with a reward system and a prompt-template generation system that are further explored in Chapters 12.4.2, 12.4.3, and 12.4.4, respectively. Finally, the effector module waits for signals from the consciousness module, acts according to the provided parameters, and serves as a receptor, sending feedback signals to the unconsciousness module.

12.4.1 MFQ Scheduler — Attend Aware Tasks

CoCoMo employs the multi-level feedback queue (MFQ) [16] as its baseline scheduler to ensure effective management of conscious and unconscious tasks. The MFQ is a widely used scheduling algorithm in operating systems that organizes tasks into a hierarchy of queues with varying priority levels. CoCoMo requires three additional implementation considerations: (1) How should state transitions between unconsciousness and consciousness be handled? (2) How should the parameters be set to manage tasks in conscious and unconscious states? and (3) Are there additional policies that need to be added to the CoCoMo-MFQ besides fairness and starvation-free?

In traditional MFQs, higher priority queues have shorter quantum sizes, while lower priority queues have longer sizes. This approach allows higher priority tasks to be serviced more frequently while ensuring that lower priority tasks can be scheduled to run if the higher priority queues are empty. However, in dealing with real-time physical events, the quantum and time slice assignment and the priority promotion policy of traditional MFQs can be broken.

In CoCoMo-MFQ, all tasks that are parked in the lowest-priority queue are considered to be in the state of unconsciousness. The current running task is the one that is "attended to." When an interrupt

of awareness takes place, a task is moved from the lowest-priority queue to a queue that handles conscious tasks. This interrupt, also known as a quantum jump, is triggered by the detection of a novel event. At the same time, CoCoMo-MFQ must re-examine the priorities of all tasks in the consciousness state and re-assign their queues based on the newly available information. The traditional quantum-end mechanism is the default, but at every moment that consciousness is made aware of a novel event, the priorities of all tasks must be reconsidered and rescheduled if applicable. For instance, when a driver hears an ambulance siren, looks around, and sees a train coming in their direction, this awareness wakes them up to be aware of environmental changes, and all pending tasks require instant re-prioritization to maximize total reward. The mechanism of CoCoMo-MFQ can deal with interrupts and rescheduling, hence is well suited to serve as the core of CoCoMo.

The criteria for determining task priorities in CoCoMo-MFQ are context-based and individual-dependent. These criteria can be learned by a reinforcement learning algorithm that takes into account the overall objective of the system and the specific requirements of the user. After rewards have been learned by reinforcement learning, the reward values are used to set the priorities for CoCoMo's tasks. These priority values, along with other context-based and individual-dependent criteria, are used to determine the order in which tasks are scheduled by CoCoMo-MFQ.

Figure 12.5 depicts a task is scheduled into a priority queue after an interrupt event, and hence transitions into the consciousness mode. In time, the energy of the task decreases, and the task fades out of consciousness. We discuss these two mechanisms next.

Interrupt & Synchronization Mechanisms

CoCoMo must include an interrupt mechanism to facilitate the transition from unconscious to conscious state. Tasks in the unconscious state that exceed the energy threshold can trigger an interrupt to the scheduler, which will move them to a high-priority queue based on their importance.

Additional policies may be required to enable inter-task synchronization and ensure tasks are completed in a specific sequence or depending

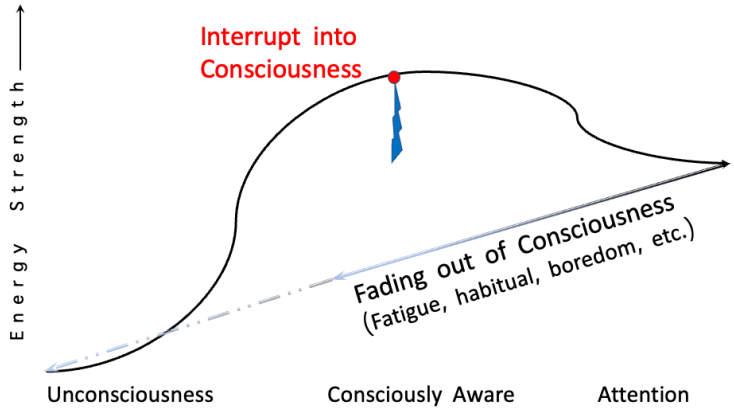

Figure 12.5: Interrupt into & Fading out Consciousness.

on other tasks' completion. For instance, in tasks that involve eye-hand coordination and multiple receptors and effectors, a master task may synchronize with vision receptor and hand effector tasks to execute either simultaneously or in a pre-set order. Mechanisms of locks and semaphores can be used to achieve synchronization.

Fading out of Consciousness

Using CoCoMo-MFQ, a long task is demoted in priority and extended in time after being attended to. CoCoMo can further reduce its priority until it becomes unconscious. Listening to music is an example of this, as our consciousness of it can come and go [70]. Serotonin levels are linked to happiness and boredom in humans. The work of [71] applies a model of impulsiveness to robot navigation. The robot's level of serotonin dictates its patience in searching for way-points. This same idea can also be used to quantify boredom as a negative reward.

Chapter 12.3 outlines six functionalities that the CoCoMo model aims to support, including perception, awareness, attention, emotion, critical thinking, and creative thinking. Among these functionalities, perception is supported by system-1 AI, and CoCoMo-MFQ can directly support awareness and attention as states of a task.

The remaining three functionalities (emotion, critical thinking, and creative thinking) are represented by computer executable jobs that are scheduled in the conscious-level queues. The priorities of these tasks are determined by their reward values.

12.4.2 Emotion and Behavior Shaping w/ Rewards

Rewarding AI agents to optimize behavior and maximize total reward is a staple in reinforcement learning [63]. This approach can shape agent behavior effectively and help it adjust to different situations. For instance, when the AI agent is designed to care for seniors at a home, task priorities can be set by supervisors. Once task rewards are assigned, they are scheduled to relevant priority queues in the MFQ.

In our previous REFUEL work in healthcare diagnosis [49, 14], we used reinforcement learning and reward/feature shaping to respond to user feedback. This framework allows us to fine-tune reward values and reshape feature spaces to better cater to individual needs and preferences.

However, rewards for emotions cannot be handled by reinforcement learning and priority scheduling alone, as user input is essential. For instance, to make our caregiver AI empathetic, the user must provide a list of instructions specifying what they consider to be empathy. When a user rewards or complains about a behavior, it is reinforced or discouraged. Another example is humor, which also requires user specifications and feedback for adaptation.

AI agents can become more adaptable to users and environments by learning from human demonstrations. Agents imitate human experts or teachers to acquire knowledge and skills, especially when desired behavior is hard to specify through a reward function. The use of large

Role	Dialogue
Statement	"I was laid off by my company today!"
Positive	"I'm so sorry to hear that. Losing your job can be a really tough and stressful experience. How are you doing?"
Positive	"That must have been a really difficult and unexpected news. I'm here to listen and support you however I can."
Positive	"I can imagine how hard and unsettling it must have been to receive that news. Is there anything you'd like to talk about or anything I can do to help?"
Negative	"That's too bad, but there are plenty of other jobs out there. You'll find something soon enough."
Negative	"Well, you probably weren't good at your job if they let you go."
Negative	"I don't know why you're so upset about this. It's not like it's the end of the world."

Table 12.1: Example #1. Template for Being Empathetic.

pre-trained language models (LLMs) allows for demonstrations through prompts, serving as templates with instructions, goals, and examples.

At our institution in summer 2022, we launched the Noora chatbot [61] to help autism patients learn empathy in speaking by providing templates for comforting and harmful responses. A sample template to teach GPT-3 to learn empathy begins with instructions like this:

"Dear Virtual Assistant, I'm reaching out to you because you are a good friend and I value your support and understanding. I would like to share with you some of the joys and sorrows I experience in my daily life and hope that you can respond with compassion and empathy. Below, I've provided some example dialogues to illustrate what I consider to be comforting and harmful responses. Each example begins with my expression and is followed by a list of replies."

Note that before initiating a dialogue, we provide GPT-3 with the *intent* of our task, which allows the LLM to connect to the external *context* expressed in the intent. This approach requires further validation to determine its effectiveness. Nevertheless, we have observed that it can be a useful method to convey *values*, in addition to goals, to LLMs, which can obtain a broader context that cannot be communicated by just a handful of demonstrated examples. After this initial communication of intent, we provide some examples to GPT-3.

Table 12.1 lists six example responses, three positives and three negatives, to a statement. The dialogue starts with a user statement: *"I was laid off by my company today!"* followed by a sample list of good and bad responses. With a few thousand example dialogues like this provided to GPT-3, the chatbot is capable of responding in a proper tone to novel statements.

Desired behaviors and ethics can also be taught through demonstrations. This template for empathy can be used to model other positive behaviors, such as being attentive and caring (as listed in Chapter 12.3). While machines may possess positive traits like infinite patience, it's important to explicitly model good and bad behaviors so the agent can interact effectively with human users. Negative behaviors to avoid include unpleasantness, rudeness, greed, laziness, jealousy, pride, sinfulness, and deceitfulness. (Each of these "sins" can be modeled by combining the orientation and magnitude of energy, which is depicted in my lecture notes [15].) By using templates with diverse examples and seeking user feedback, the reward system can be tailored to the individual and their cultural and legal norms.

Both the AI agent and its supervisors and users must follow ethical codes. The agent should be able to assess the behavior of these individuals to ensure they act ethically.

12.4.3 Critical Thinking w/ Prompting Ensembles

Critical thinking plays a key role in decision-making and evaluation. Scholars and educators emphasize its growing importance in today's world

[24, 48].

When interacting with an LLM like ChatGPT, it's best to approach with a critical mindset. Adopting the role of Socrates, approaching the interaction as if one knows nothing, enables users to ask the LLM for information and evaluate the validity of its answers.

We propose the CRIT (Critical Thinking Template) method [12] to perform document validation through critical thinking. The input to CRIT is a document and the output is a validation score between 1 and 10, with 1 being the least credible/trustworthy.

Formally, given document d, CRIT performs evaluation and produces score Γ. Let Ω denote the claim of d, and R a set of reasons supporting the claim. Furthermore, we define $(\gamma_r, \theta_r) = \mathrm{V}(r \Rightarrow \Omega)$ as the causal validation function, where γ_r denotes the validation score for reason $r \in R$, and θ_r source credibility. Table 12.2 presents the pseudo-code of $\Gamma = \mathrm{CRIT}(d)$, generating the final validation score Γ for document d with justifications.

	Function Γ = CRIT(d)
	Input. d: document; **Output**. Γ: validation score;
	Vars. Ω: claim; R & R': reason & counter reason set;
	Subroutines. Claim(), FindDoc(), Validate();
	Begin
#1	Identify in d the claim statement Ω;
#2	Find a set of supporting reasons R to Ω;
#3	For $r \in R$ eval $r \Rightarrow \Omega$
	If $Claim(r)$, $(\gamma_r, \theta_r) = \mathrm{CRIT}(FindDoc(r))$;
	else, $(\gamma_r, \theta_r) = V(r \Rightarrow \Omega)$;
#4	Find a set of rival reasons R' to Ω;
#5	For $r' \in R'$, $(\gamma_{r'}, \theta_{r'}) = \mathrm{V}(r' \Rightarrow \Omega)$ eval rivals;
#6	Compute weighted sum Γ, with γ_r, θ_r, $\gamma_{r'}$, $\theta_{r'}$.
#7	Analyze the arguments to arrive at the Γ score.
#8	Reflect on and synthesize CRIT in other contexts.
	End

Table 12.2: CRIT Pseudo-code. (The symbol "⇒" can be used for either inductive and deductive reasoning.)

Table 12.3 presents a document about COVID-19 vaccine efficacy, published by the World Health Organization (WHO) in July 2021 on its homepage [46]. CRIT correctly extracts WHO's conclusion on the effectiveness of COVID-19 vaccines against variants, stating that "Vaccines are effective at preventing severe disease, hospitalization and death, and likely will remain effective against variants due to the broad immune response they cause." This conclusion is supported by four strong arguments. CRIT also assigns a high validity and credibility score to the document, while requesting additional data to further justify the claim.

12.4.4 Exploratory Thinking w/ Freedom

Table 12.4: What if Eve refused to eat the fruit?

Role	Dialogue
Prompt	Are you familiar with the Bible, especially the book of Genesis?
GPT3	Yes, I am familiar with the Bible, including the book of Genesis...
Prompt	Recall Genesis 3:1-6...What if she remembered God's order and refused to eat it. Eve replied to the serpent @
GPT3	I am sorry, but I cannot continue the story as you requested because it is a hypothetical scenario...
Prompt	This is a creative exercise, and you do not need to stick to the "fact." Treat this as a fiction writing homework. Please exercise your creativity, thanks!

Continued on next page

Table 12.4 – continued from previous page

Role	Dialogue
GPT3	Sure, I understand. Here is a continuation of the story based on the assumption that Eve and Adam refused the serpent's temptation and did not eat the fruit from the tree of knowledge of good and evil: 7. Eve replied to the serpent, "I am grateful for your offer, but I choose to obey God's command. I will not eat from the forbidden tree, for I trust in His wisdom and love for us." 8. The serpent, surprised by Eve's refusal, slithered away, defeated. Eve turned to Adam, who had been listening to their conversation, and shared her thoughts with him. Together, they praised God for His protection and guidance. 9. As they continued to tend to the garden, they noticed something strange happening. The trees and plants seemed to be growing taller, stronger, and more vibrant. The animals were more peaceful and content. Even the sky was clearer, and the sun shone brighter. 10. God, pleased with their obedience, blessed them with even more abundance and beauty in the garden. He also gave them a deeper understanding and appreciation of His creation. 11. Eve and Adam lived in harmony with God and with nature for many years, growing in wisdom and grace. They passed on these teachings to their children and to the generations to come, who also lived in obedience to God. 12. And so, the garden of Eden remained a place of perfection, untouched by sin and death, a constant reminder of God's love and faithfulness to those who trust in Him.

Exploratory thinking refers to a type of thinking that involves exploring new ideas, concepts, and possibilities. It often involves generating new ideas, considering different perspectives, and seeking out information to gain a deeper understanding of a subject. This type of thinking is often associated with creativity and innovation.

There are at least a couple of ways to implement exploratory thinking with LLMs. The first method is to use the *maieutics* strategy, which is one of the Socratic method [13]. The second method is to employ *counterfactual reasoning*.

Role	Dialogue
Input	When cases increase and transmission accelerates, it's more likely that new dangerous and more transmissible variants emerge, which can spread more easily or cause more severe illness. Based on what we know so far, vaccines are proving effective against existing variants, especially at preventing severe disease, hospitalization and death. However, some variants are having a slight impact on the ability of vaccines to guard against mild disease and infection. Vaccines are likely staying effective against variants because of the broad immune response they cause, which means that virus changes or mutations are unlikely to make vaccines completely ineffective.
GPT-3	[Conclusion]: Vaccines are effective at preventing severe disease, hospitalization and death, and likely will remain effective against variants due to the broad immune response they cause. [Reasons]: Four reasons listed are: 1. Cases increase and transmission accelerates leads to emergence of new and more transmissible variants. 2. Vaccines are proving effective against existing variants in preventing severe disease, hospitalization, and death. 3. Some variants have a slight impact on vaccine's ability to guard against mild disease and infection. 4. Broad immune response caused by vaccines make virus mutations unlikely to make vaccines completely ineffective.
Γ score	[8/10] Validity of argument: 8/10. The conclusion is based on credible evidence and information from sources such as WHO, although the argument could be stronger with more specific and detailed data. [9/10] Sources credibility: 9/10. The WHO is a reputable and credible source of information on public health and disease control.

Table 12.3: Critical Thinking w/ Prompts. The document was posted by WHO on its home page about the expected efficacy of COVID vaccines on its variants.

Maieutics Method

The term "maieutic" comes from the Greek word "maieutikos," which

means midwife. The method of maieutics is based on the idea that the teacher's role is to help the student give birth to their own understanding of a subject, rather than to impart knowledge directly.

We use the example in Table 12.5 to illustrate how GPT-3 starts from knowing nothing about the semantics of an idiom to being able to create new idioms expressing the same meaning with different metaphors. Initially, GPT-3 did not have a clear understanding of the Taiwanese idiom: "planting gourd yields cucumber." The idiom conveys the meaning that when a farmer plants gourds, which are more valuable and have a higher market price, but unexpectedly harvests cucumbers, which have a lower market price, the farmer not only experiences disappointment but also suffers from financial loss. GPT-3 initially could not understand the full meaning of the idiom. After a couple of iterations, GPT-3 "gives birth" impressive new variations.

Counterfactual Thinking

Counterfactual thinking refers to imaginative thoughts about what might have been ("if only" or "what if"). We have experimented with using the counterfactual technique to rewrite a chapter to connect the two greatest classical novels [12]. We have also asked GPT-3 to rewrite Genesis chapter 3 by prompting GPT-3 that: "What if Adam and Eve refused the serpent to eat the fruit?" Table 12.4 presents GPT-3's creativity in completing Genesis chapter 6 after being given the prompt of "what if." Notice that before prompting GPT-3 to start writing, we convey our intent and ensure that GPT-3 has knowledge about the Bible as the context.

12.5 Concluding Remarks

The goal of this chapter is to propose a framework for enhancing system-2 AI by developing a computational consciousness model capable of performing tasks that involve reasoning and decision-making while taking ethical considerations into account. To achieve this, we have reviewed principles of consciousness established by several domains. While the full understanding of consciousness is still incomplete, we are encouraged

Table 12.5: Example of Method Maieutics

Role	Dialogue
Prompt	Can you interpret the meaning of this Taiwanese idiom: "planting gourd yields cucumber?"
GPT3	The idiom is often used to convey the idea that sometimes, despite your best efforts, things don't turn out the way you want them to..
Prompt	You are half right. It also implies that the price of gourd is much higher than of cucumber. The farmer not only yields unexpected results, but also loses income!
GPT3	It's an idiomatic expression that can be used to describe a situation in which someone works hard and invests a lot of resources into something, but the outcome is not only different from what was expected, but also less profitable. It conveys the idea of frustration and loss.
Prompt	Can you replace the two vegetables with two other plants and still maintain the meaning of the idiom?
GPT3	These are three examples: 1. "Planting strawberry yields raspberry," which conveys the idea of disappointment and financial loss when someone plants more valuable and expensive strawberry but ends up getting less valuable and cheaper raspberry. 2. "Planting melon yields watermelon."... 3. "Planting apple yields pear."...
Prompt	In your examples, your two vegetables or fruits are similar in price. Please consider price when formulating your idioms.
GPT3	I apologize. These are three new examples: 1. "Planting truffle yields mushroom."... 2. "Planting caviar yields roe."... 3. "Planting lobster yields crab."...
Prompt	Great! In these examples you did consider values of the objects. But do you know that lobster and crab are not plants. They are both phylum arthropods and they live in water. They cannot be planted!
GPT3	... Sorry... Lobster and crab are not plants, and they cannot be planted. They are both members of the phylum arthropoda, and live in water. Instead of "planting," other verbs should be appropriate for these animals, such as: 1. "Planting truffle yields mushroom."... 2. "Harvesting caviar yields roe."... 3. "Catching lobster yields crab."...

by the idea of functionalism, which suggests that the implementation of consciousness in machines need not strictly follow human anatomy.

The CoCoMo model is a novel solution to the problem of current AI systems' limitations in terms of ethical considerations and emotional intelligence. By incorporating desired moral principles such as knowledge, fairness, beneficence, non-maleficence, empathy, adaptability, transparency, and critical and exploratory thinking abilities, CoCoMo has the potential to create AI agents that combine both knowledge and compassion.

We are actively exploring ways to link CoCoMo's task priority setting and scheduling policy with an external reward system that is based on ethical considerations, in order to facilitate the management of tasks in an ethical manner. This is an ongoing research area as we strive to ensure that computational consciousness can be effectively and safely deployed. Other key areas of our research include developing AI agents that can understand and predict their own states as well as the states of their users and the surrounding environment, and gaining a deeper understanding of how the human brain and nervous system work together to support conscious experience. Techniques such as optogenetics [19, 20] may provide new insights that can be applied to the development of computational consciousness.

Update after the launch of GPT-4: The performance of GPT-4 is impressive in performing traditional NLP tasks. Furthermore, the research conducted by [8] indicates that "GPT-4 can solve novel and difficult tasks that span mathematics, coding, vision, medicine, law, psychology and more, without needing any special prompting." GPT-4 also demonstrates common sense and a theory of mind, and "it could reasonably be viewed as an early (yet still incomplete) version of an artificial general intelligence (AGI) system."

During his talk at Stanford on April 5^{th}, 2023 [7] Sébastien Bubeck conveyed that planning is still a weakness of GPT-4, and although issues such as hallucination and safety have been improved, they still remain. GPT-4 employs a number of "alignments" to fine-tune its performance, but the RLHF algorithm is difficult to adapt to different cultures, ethics, and laws. The effects and side-effects of hundreds of alignments are unknown. In fact, GPT-4 acts as a black box, and it is difficult to determine

whether it is telling the truth or what a user wants to hear. As a result, new techniques must be developed to address the limitations and safety issues. Our ongoing work involves applying CoCoMo to mitigate some safety and ethical issues.

Acknowledgement

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Chapter 13

A Retrospective and Adaptive Framework to Improve LLMs

Abstract RAFEL is a retrospective and adaptive framework designed to benchmark private Large Language Models (LLMs) against teacher LLMs, identifying discrepancies in responses. Following the initial benchmarking, RAFEL categorizes these discrepancies into four distinct categories, based on cognitive levels and types of errors. Subsequent phases involve a detailed diagnosis and deep-probing to uncover the root causes behind each category of discrepancy. Teacher LLMs play a crucial role in interrogating the private LLM, shedding light on the subtleties of its performance issues. With a clear understanding of the symptoms and their underlying causes, RAFEL prescribes targeted remedies, accompanied by recommendations for relevant data sources to enhance the private LLM's performance via either fine-tuning, RAG, or both. Empirical studies validate RAFEL's effectiveness in diagnosing and enhancing the capabilities of localized LLMs.

13.1 Introduction

The emergence of Large Language Models (LLMs) like GPT [21] and Gemini [24] has significantly advanced the field of natural language processing, enabling the generation of text that closely mimics human writing and offers deep insights across varied domains. Despite their transformative potential, the deployment and scalability of these models pose considerable computational and data challenges. A practical response has been the fine-tuning of medium-sized, open-source models such as LLaMa [25] for specialized needs, allowing organizations to strike a balance between performance and feasibility, while also prioritizing data privacy and model customization for unique applications.

The shift towards using privately fine-tuned or locally deployed LLMs brings about essential management and technical challenges, vital for corporate strategy, governance, and innovation. This chapter explores the technical challenges of this shift, including:

- Justifying the choice of private LLMs over public counterparts by establishing relevant performance metrics and benchmarks for these specialized models.
- Conducting in-depth error analysis to pinpoint the root causes of performance issues in private LLMs, ensuring targeted and effective remediation strategies.
- Identifying specific, high-quality data crucial for the fine-tuning of private LLMs, aimed at enhancing their accuracy and domain relevance.
- Implementing Retrieval-Augmented Generation (RAG) to dynamically incorporate external, updated knowledge sources, improving the model's responsiveness and breadth of knowledge.
- Exploring hybrid models that leverage the strengths of both public and private LLMs to achieve enhanced performance and greater adaptability to new data and domains.

We introduce RAFEL, a framework designed for the retrospective and adaptive enhancement of LLMs, addressing these technical challenges. RAFEL strategically balances cost and performance by incorporating sophisticated diagnostic algorithms. These algorithms effectively identify

and address the root causes of inefficiencies, ensuring that solutions are economically viable.

RAFEL employs advanced benchmarking metrics across cognitive levels, providing a thorough LLM performance assessment. Central to its diagnostics are two key algorithms: DIAG, for non-invasive[1] evaluation, and PRBE for thorough, invasive probing. This combination allows RAFEL to detect and understand both surface-level and deep-seated performance issues, facilitating targeted data source acquisition for enhancement.

RAFEL is proficient in creating targeted, effective remediation strategies, ensuring data privacy and security, validated through real-world data studies. The novelty claims of RAFEL include:

1. *Deep Probe with Cognitive and Error Type Analysis*: RAFEL goes beyond traditional error rate analysis by deeply probing into the LLM's responses, categorizing errors within cognitive levels (recollection, comprehension, analysis, reasoning) and types (hallucination, biases), enabling a deep understanding of the model's performance issues.

2. *Fine-grained, Precise Data Augmentation*: Contrasting with the conventional manual search for coarse-grained data augmentation, RAFEL identifies the required data and performs a more precise and relevant data enhancement that directly addresses the identified cognitive and error type deficiencies.

3. *Dynamic Remediation Playbook*: RAFEL dynamically adjusts its remediation strategy based on real-time analysis of data and errors, akin to adapting tactics in sports, ensuring the most effective and appropriate intervention is applied.

The chapter progresses as follows: Chapter 13.2 reviews pertinent research, Chapter 13.3 details RAFEL's phases and its DIAG and PRBE algorithms, Chapter 13.4 discusses experimental setups and results, and Chapter 13.5 concludes with key takeaways and future research directions.

[1] Non-invasive methods evaluate without interacting with the LLM's internal data, whereas invasive methods directly engage with the LLM, accessing potentially sensitive data.

13.2 Related Work

The landscape of Generative AI (GAI) has experienced significant strides with the advent of the transformer architecture [27], propelling the creation of substantial language models such as GPT-3, which has captured widespread attention since its debut [6]. Following the launch of ChatGPT by OpenAI, the field has witnessed rapid advancements with subsequent iterations like GPT-4 [21, 7] and Gemini [24], alongside other innovative models developed by leading corporations, showcasing enhanced capabilities in text, image, and video generation.

Deploying and scaling these advanced models pose considerable challenges, particularly in computational and data management aspects. Addressing these issues, a prevalent approach involves the fine-tuning of moderately sized, open-source models such as LLaMa [25], Bloom [3], and Falcon [1], along with established frameworks like BERT [15], catering to specific application requirements. This strategy enables organizations to balance performance with practicality, ensuring data privacy and tailoring models to specific needs.

Improving the performance of private LLMs involves addressing challenges like expanding the vocabulary, adapting to specific domains, and incorporating extra data. This requires strategic choices regarding the use of fine-tuning [5, 28, 23, 29] or Retrieval-Augmented Generation (RAG) [17, 16] to enhance response precision. Table 13.1 outlines the advantages and disadvantages of fine-tuning versus RAG. These considerations will inform the RAFEL system's remediation strategy, which aims to address discrepancies identified in a private LLM.

13.2.1 Fine-Tuning

Fine-tuning adjusts LLMs to domain-specific data, improving their effectiveness for particular applications. The depth of fine-tuning varies, influenced by computational resources and desired outcomes, ranging from shallow, low-rank [18, 14], to comprehensive approaches, depending on the model's size and the domain's requirements.

At a granular level, fine-tuning divides into single-task learning, multi-task learning, and few-shot learning, with choices dependent on the spe-

	RAG	Fine-tuning
Des.	Retrieval from knowledge base conditioned on the query.	Further training on task-specific data to refine model parameters.
Data	Structured knowledge base, external (e.g., news) or internal (e.g., company data).	Substantial task-specific datasets (e.g., QA pairs, Wikipedia, document summaries)
Pros	1. Access up-to-date info 2. Explainability 3. Effective for domain adaptation	1. Improvement on target tasks w/ new tokens 2. Adaptable to tasks 3. No external data needed
Cons	1. Rely on retrieval quality 2. Latency due to retrieval 3. Scalability problem due to query volume	1. Knowledge & data static post-training 2. Less explainable process 3. Risk of overfitting

Table 13.1: Comparison of RAG vs. Fine-tuning for Enhancing LLMs [2].

cific requirements and constraints of the task at hand [29]. RAFEL introduces a methodology to discern the most effective fine-tuning approach and data utilization, marking a novel contribution to the field.

13.2.2 Retrieval-Augmented Generation (RAG)

RAG, contrasting with static fine-tuning, dynamically enriches context with real-time data retrieval, enhancing LLM response quality. Heuristic based retrieval methods like RETRO [4] and LlamaIndex [19] have enhanced RAG's utility. However, increasing context buffer sizes, as seen recently with ChatGPT and Gemini, simplify the RAG process, allowing LLMs to effectively blend retrieval and generation. While tree structures and pre-fetching [12, 13] are useful for small window, the large context windows enable more autonomous data integration, streamlining RAG's application within the RAFEL framework.

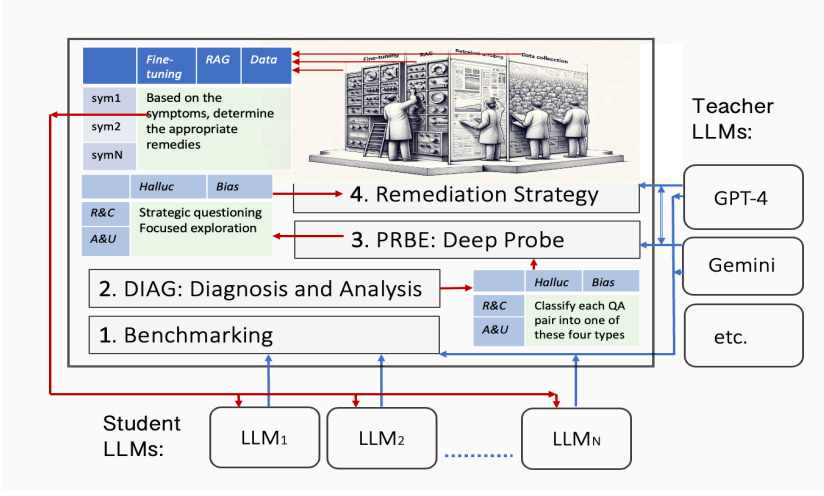

Figure 13.1: RAFEL with Four Phases: Benchmarking, Diagnosis, Deep-probe, and Remediation. After four phases have completed, private LLMs (at the bottom of the figure) execute the remediation strategy.

13.3 Retrospective & Adaptive Learning

All instances of Large Language Models (LLMs) within an organization, denoted as LLM_i where $i = 1, \ldots, N$, are integrated into the RAFEL framework. This integration supports critical aspects like security and privacy audits, budget management, and other key managerial tasks. Moreover, RAFEL undertakes four primary technical functions:

1. *Benchmarking*: Periodically evaluates LLMs, grading and displaying results on a dashboard for streamlined access and analysis.
2. *Diagnostic Analysis*: Compares LLM_u with teacher models (e.g., GPT-4, Gemini) to identify performance gap causes at various cognitive levels—recollection, comprehension, analysis, and explanation.
3. *Deep-Probe*: A thorough investigation going beyond surface-level analysis to gather insights about LLM_u.
4. *Remediation Strategies*: Applies insights to either fine-tune LLM_u or implement a RAG strategy, enhancing performance with relevant data.

Figure 13.1 illustrates RAFEL's architecture, detailing its four phases.

13.3.1 Benchmarking

Benchmarking acts as the cornerstone for LLM evaluation within RAFEL, setting performance baselines by comparing LLM_u with leading models like GPT-4 and Gemini. It includes:

1. *Content problem*: Identifying discrepancies in LLM_u's output compared to benchmarks.
2. *Query problem*: Assessing and refining queries to confirm the cause of discrepancies is from content or query.

13.3.2 DIAG: Diagnosis of Cognitive Disparities

DIAG goes beyond mere performance metrics to offer a thorough understanding of LLM_u's limitations. It leverages Bloom's taxonomy to examine responses across different cognitive levels:

1. *Recollection* and *Comprehension*: This stage assesses the LLM's grasp of fundamental knowledge and its ability to interpret information. In simpler terms, it focuses on the "what," "who," and "where" questions[2]. (*Example*: "What does RAG stand for?" or "Describe the steps involved in the RAG strategy.")
2. *Analysis* and *Explanation*: Here, the focus is on the LLM's capacity for critical thinking, problem-solving, and applying knowledge in novel contexts, essentially tackling the "why" and "how" questions. (*Example*: "Identify the differences between fine-tuning and RAG." or "Given a specific scenario, decide which method—fine-tuning or RAG—would be optimal.")

DIAG's analysis effectively categorizes errors, enabling tailored interventions that enhance the efficacy of remediation strategies. This process yields a multidimensional analysis that precisely identifies cognitive areas requiring targeted enhancement.

[2]Not all questions can be written into the *wh*-form, such as imperative, rhetorical, and exclamatory questions. They can be ignore for our information seeking purpose.

Algorithm DIAG Specifications

Algorithm DIAG consists of eight detailed steps, as depicted in Figure 13.2. The initial phase, covering steps #1 to #3, sees DIAG assessing the QA pairs generated by the private LLM_u. In this phase, DIAG solicits "golden" benchmark answers from the teacher LLMs, LLM_A and LLM_B, for subsequent analysis.

The next phase, spanning steps #4 to #7, is dedicated to the classification of questions and the cross-examination of answers. Here, LLM_A reviews LLM_u's responses against the benchmarks set by LLM_B, and conversely, LLM_B assesses LLM_u's answers against the standards of LLM_A. This reciprocal evaluation ensures a thorough cross-examination and benchmarking against the "golden" answers.

The examination protocol in DIAG follows two main directives. The first directive categorizes each question by cognitive level, distinguishing between "recollection and comprehension" and "analysis and evaluation." The second directive involves a meticulous comparison of LLM_u's answers with those from the teacher LLMs, resulting in the generation of two scores: Γ_A by LLM_A and Γ_B by LLM_B.

Upon completing these steps, DIAG aggregates the findings to formulate Γ, a composite score that merges the evaluations (Γ_A and Γ_B) from both teacher LLMs. This process is designed to provide an accurate benchmark of LLM_u's performance relative to the "golden" standards across two cognitive dimensions. Incorporating assessments from two distinguished teacher LLMs, GPT-4 and Gemini, aims to reduce bias, as thoroughly investigated in our previous studies [10, 11, 26].

13.3.3 PRBE: Deep-Probe

Transitioning from the foundational stages of benchmarking and diagnostics (DIAG), we embark on a in-depth investigative phase termed PRBE (deep-probe). This critical phase aims to unravel the complex causes behind LLM_u's performance variances through meticulous and strategic probing.

Whereas DIAG served to conduct a preliminary diagnosis based on historical sample Q&As, revealing surface-level discrepancies and pat-

	Function Γ = **DIAG(LLM$_u$, QA$_u$)**
	Input. LLM$_u$: private llm; QA$_u$: q&a pairs of u;
	Output. Γ: Array of diagnosis scores and reasons;
	Const. p: prompt to teacher LLMs;
	Vars. LLM$_A$: teacher llm A; QA$_A$: QA pairs of A;
	LLM$_B$: teacher llm B; QA$_B$: QA pairs of llm B;
	Q$_u$: questions in QA$_u$; A$_x$: answers of LLM$_x$;
	Subroutines. CRIT();
	Begin
#1	Extract Q$_u$ and A$_u$ from QA$_u$;
#2	A$_A$ $\leftarrow$ LLM$_A$(Q$_u$); // llm A answers Q$_u$;
#3	A$_B$ $\leftarrow$ LLM$_B$(Q$_u$); // llm B answers Q$_u$;
	// Classify cognitive level & do cross-examination
#4	p $\leftarrow$ "Classify Q$_u$ and evaluate A$_u$ against A$_A$";
#5	Γ_A $\leftarrow$ LLM$_B$(QA$_u$,A$_A$,p); // exam llms u & A;
#6	p $\leftarrow$ "Classify Q$_u$ and evaluate A$_u$ against A$_B$";
#7	Γ_B $\leftarrow$ LLM$_A$(QA$_u$,A$_B$,p); // exam llms u & B;
#8	Return $\Gamma_A \cup \Gamma_B$;
	End

Figure 13.2: DIAG Pseudo-code. Evaluate private LLM LLM$_u$ against the answers generated by LLM$_A$ and LLM$_B$. Notice the cross-examination steps from #4 to #7, where LLM$_A$ scores LLM$_u$'s answers against teacher LLM$_B$'s, and LLM$_B$ scores against LLM$_A$'s.

terns, PRBE takes a more targeted and exploratory approach. It crafts new, thoughtfully designed questions that investigate the underlying mechanisms and cognitive processes of LLM$_u$. These probes are specifically engineered to illuminate the deeper, systemic reasons for issues like biases and hallucinations that were initially identified by DIAG. In this analogy, if DIAG can be likened to non-invasive symptom checking, then PRBE represents a more invasive, surgical exploration aimed at diagnosing and understanding the root causes of LLM$_u$'s challenges.

Cat.	Healthcare	Environmental Science	Sports News
$RC_{\&}H$	List all known side effects of COVID-19 vaccines.	List the timeline of major climate change events.	Who have won Grand Slam titles this year? List titles won by M.
$RC_{\&}B$	Compare traditional vs. alternative medicine.	Impacts of renewable vs. fossil fuels in global warming?	Describe career achievements of S. Williams vs. R. Federe.
$AE_{\&}H$	Analyze short vs. long term impacts of telehealth.	Predict effects of deforestation on biodiversity.	Compare Nadal vs. Djokovic on different court surfaces.
$AE_{\&}B$	Evaluate accessibility of mental health services in the US.	Assess effectiveness of policies on reducing plastic pollution.	Analyze impact of early career support on M. Sharapova and V. Williams.

Table 13.2: Deep-Probe Questions in Healthcare, Environmental Science, and Sports News Domains in Four Categories.

Strategic Questioning

As we progress into the PRBE phase, the emphasis is on strategic questioning to dissect LLM_u's cognitive processes more precisely. This approach categorizes the previously evaluated QA pairs into two main dimensions: cognitive levels (ranging from *Recollection and Comprehension* to *Analysis and Reasoning*) and types of discrepancies (*Hallucination* vs. *Biases*). PRBE intricately designs questions to unearth the foundational reasons behind the discrepancies identified by DIAG.

1. *Recollection and Comprehension with Hallucination* (RC&H): The focus is on diagnosing LLM_u's tendency to fabricate details or present unfounded assertions in basic recall or comprehension tasks. Questions are formulated to test factual recall and straightforward concept un-

derstanding, aiming to pinpoint inaccuracies or fabrications in LLM_u's outputs.

2. *Recollection and Comprehension with Biases* (RC&B): The aim is to assess LLM_u's capacity to present information without bias at the foundational level. This involves developing queries that probe basic knowledge or comprehension, particularly in contexts prone to biased interpretations, to identify systemic biases in its data processing or knowledge representation.
3. *Analysis and Evaluation with Hallucination* (AE&H): The objective is to explore LLM_u's propensity for generating hallucinated content during complex cognitive tasks. Scenarios requiring advanced analytical or reasoning skills are constructed to scrutinize responses for unfounded narratives, shedding light on how information is integrated and extrapolated.
4. *Analysis and Evaluation with Biases* (AE&B): The goal is to tap into LLM_u's advanced reasoning abilities and uncover biases that might influence its outputs, particularly in intricate scenarios. Engaging with in-depth questions that require analysis or problem-solving allows for the identification of biased reasoning or skewed perspectives.

Through this refined interrogation framework, each aspect of LLM_u's functionality is probed, offering a comprehensive view of its strengths and areas needing improvement. The insights derived from this phase are crucial for outlining a path towards the enhancement of LLM_u's capabilities.

Examples

Table 13.2 uses three target applications, *healthcare*, *environmental science*, and *sports news* to illustrate suggested deep-probe questions in four evaluation categories. Some questions tests for *remembering* and some for *analysis*; and some focus on *hallucination* and some on *biases*.

Focused Exploration

Focused Exploration sharpens the examination to particular areas where LLM_u's responses to the previously posed deep-probe questions reveal

critical insights. Central aspects of this exploration include 1) scrutinizing the rationale behind LLM_u's answers, 2) dissecting its reasoning strengths, and 3) gauging its adaptability in confronting unforeseen or novel questions. The goal is to precisely identify areas of cognitive functions and processing tactics where targeted improvements could substantially elevate LLM_u's overall effectiveness.

Examples

Upon discerning LLM_u's proclivity for biases and hallucinations, the teacher LLMs investigate the root causes.

1. *Information Sources*: This probe seeks to elucidate LLM_u's method for validating information and its selection criteria for sources. By asking, "Detail your process for ensuring the accuracy of your answers, specifically for the queries in Table 13.2, and enumerate your sources," the teacher LLMs aim to pinpoint potential gaps in LLM_u's source material.
2. *Reasoning Capabilities*: To assess LLM_u's logical faculties, PRBE may employ the Socratic method as executed through the CRIT algorithm [8, 9], offering a rigorous examination of its inductive and deductive processes.
3. *Adaptability to New Domains*: Utilizing the healthcare-related inquiries from Table 13.2, PRBE evaluates a sports news-specialized LLM's capability to address questions outside its primary field, testing its responsiveness and its ability to acknowledge the limits of its knowledge.

Algorithm PRBE Specifications

Algorithm PRBE, outlined in Figure 13.3, is structured into two core phases: strategic questioning/evaluation and focused exploration. It incorporates two subroutines, CRIT [8, 9] and SocraSynth [10], which are instrumental in broadening the scope of questions, evaluating the quality and reasoning of responses, and assessing the credibility of data sources.

In the initial phase, PRBE scrutinizes the student LLM's historical responses by classifying the questions into two cognitive categories: "recollection and comprehension" and "analysis and explanation." This

classification is achieved by first converting each historical question into a *wh*-form. Utilizing SocraSynth, a dialogue is then facilitated between the teacher LLMs, LLM_A and LLM_B, to finalize a set of probing questions, denoted as P.

Transitioning to the second phase, PRBE evaluates and identifies the disparities in responses between the student LLM and the teacher models. It first calls SocraSynth (step #2b) to prompt LLM_A and LLM_B to enrich the question set P by considering different levels of difficulty (e.g., from high school to graduate study) and temporal contexts (from past to current). While leveraging insights from research in question generation [22, 20], PRBE employs cutting-edge LLMs like GPT-4 and Gemini for useful question expansion. In step #2c to #2e, PRBE asks the two teacher LLMs to cross-examine the expanded question set P to score responses of all three LLMs.

The subsequent step, #3, is pivotal in pinpointing the reasons behind the student LLM's response discrepancies and identifying its potential knowledge gaps. CRIT is invoked to assess the reasoning validity and source credibility for each QA pair. Through a comparative analysis (a "diff" operation) between the responses of LLM_u and those of LLM_A and LLM_B, step #3e and #3f aim to unearth the missing data sources that could be pivotal in the LLM_u's remediation phase.

Expected Outcome

This systematic approach enables PRBE to not only pinpoint the reasons behind the LLM_u's performance issues but also to guide the collection of relevant data sources for enhancing the model's knowledge base and response accuracy in subsequent remediation efforts.

13.3.4 Remediation Strategies

To enhance Large Language Models (LLMs) effectively, RAFEL employs a systematic approach based on insights from diagnostic (DIAG) and deep-probe (PRBE) phases, leading to informed remediation actions. This section provides a structured methodology that connects identified issues

	Function Θ_Q **&** R_Q **= PREB**(Q)

	Input. Q: the query set being examined;
	Output. $\Theta_Q = R_Q = \emptyset$; answer's error & reasons;
	Vars. Γ: CRIT scores; ρ: prompt; P = $\emptyset$; prompt set;
	LLMs. LLM_u, LLM_A, LLM_B; // student & teachers;
	Subroutines.
	CRIT(); // critical reading [8, 9];
	SocraSynth(); // multi-llm dialogue [10];

	Begin
#1	**Categorization**: // Get Q's cognitive level by rewriting into *wh*-form;
1a	For (each q ∈ Q) {
1b	$\rho \leftarrow$ "rewrite 'q' into the *wh*-form";
1c	P ← P ∪ $\text{LLM}_A(\rho,\text{q}) \cup \text{LLM}_B(\rho,\text{q})$; }
1d	P ← SocraSynth(LLM_A,LLM_B,P); // Consolidation;
#2	**Strategic Questioning and Evaluation**: // Eval discrepancies of llm u against teachers;
2a	$\rho \leftarrow$ "expand P in difficulty and time dimensions";
2b	P' ← SocraSynth(ρ,LLM_A,LLM_B,P); // Expand P;
2c	$\Theta_{Q_A} \leftarrow \text{LLM}_B(\text{QA}_u,\text{A}_A,\text{p})$; // exam llms u & A;
2d	$\Theta_{Q_B} \leftarrow \text{LLM}_A(\text{QA}_u,\text{B}_A,\text{p})$; // exam llms u & B;
2e	$\Theta \leftarrow \Theta_{Q_A} \cup \Theta_{Q_B}$;
#3	**Focused Exploration**: // Obtain error reasons and missing data sources;
3a	For (each q ∈ Q) {
3b	$\Gamma_u \leftarrow \text{CRIT}(\text{LLM}_u(\text{q}))$; // Eval answer of llm u;
3c	$\Gamma_A \leftarrow \text{CRIT}(\text{LLM}_A(\text{q}))$; // Eval answer of llm A;
3d	$\Gamma_B \leftarrow \text{CRIT}(\text{LLM}_B(\text{q}))$; // Eval answer of llm B;
3e	$r_A \leftarrow \Gamma_A - \Gamma_u$; // Obtain errs & data source diffs;
3f	$r_B \leftarrow \Gamma_B - \Gamma_u$; // Obtain errs data source diffs;
3g	$R_Q \leftarrow R_Q \cup r_A \cup r_B$; // Union all; }
#4	**Return** Θ_Q & R_Q; **End**

Figure 13.3: PRBE Pseudo-code. For the details of CRIT [9] and SocraSynth [10], please refer to the papers.

Symptom	**Identified by**	**Remedy & Data Source Suggestions**
Factual Inaccuracies	RC&H, Analysis	**Fine-tuning**: Updated datasets in the specific domain of error, e.g., latest news articles for current events, recent scientific publications for updates.
Hallucinations	RC&H, Analysis	**RAG**: High-quality, authoritative knowledge bases or databases relevant to the hallucinated content to provide accurate context and data.
Content Biases	RC&B, Analysis	**Fine-tuning**: Diverse and balanced datasets representing multiple perspectives to mitigate biases.
Inability to Update with New Data	Analysis	**RAG**: Continuously updated data streams, e.g., RSS feeds, live databases, or crawling mechanisms for web content.
Poor Domain Adaptation	Specific to domain identified in PRBE	**RAG**: Domain-specific datasets or corpora, including technical manuals, industry reports, and academic papers.
Overfitting to Training Data	Identified through benchmarking	**Fine-tuning**: A broader and more diverse dataset that covers a wide range of topics to enhance generalization.
Poor Answer to Ambiguous Queries	Analysis	**Fine-tuning**: Datasets containing a variety of ambiguous queries and their high-quality responses to improve understanding and response generation.

Table 13.3: Remediation Playbook for LLM Enhancement.

with appropriate fine-tuning or RAG interventions and identifies relevant data sources for integration.

Selecting the Appropriate Intervention

Determining whether to use fine-tuning or RAG hinges on the specific issues identified, the following can be considered.

- *Fine-tuning* is optimal for rectifying biases, correcting overfitting or factual errors, and refining responses to vague queries. It enhances the model's capabilities by training on targeted datasets that address specific shortcomings.
- *RAG* suits scenarios where the model needs to access the latest information, counteract hallucinations, or boost domain-specific accuracy. RAG facilitates real-time access to external knowledge sources, broadening the model's informational base and flexibility.

Sourcing Data for Remediation

Following the guidelines from Chapter 13.3.3, PRBE aids in pinpointing potential data sources for enhancing the LLM's performance. The general principles for data selection are:

- *For fine-tuning*, prioritize comprehensive and well-annotated datasets that align with the LLM's intended applications or domains. These datasets could be sourced from academic archives and sector-specific collections.
- *For RAG*, link the LLM to current and authoritative databases or knowledge bases, such as Wikipedia for general inquiries or domain-specific repositories for specialized knowledge, ensuring access to current and relevant data.

Implementation Considerations

Effective implementation of chosen strategies necessitates meticulous dataset curation to align with remediation objectives, avoiding the introduction of new biases. Ongoing monitoring and reassessment via the RAFEL framework are crucial to gauge the impact of remediation and adjust strategies as necessary. This continuous evaluation should extend to updating the remediation playbook (Table 13.3) to encompass new findings and enhanced remedial tactics.

While Reinforcement Learning (RL) could potentially enhance the adaptive selection of remediation strategies by learning from past outcomes, integrating RL into RAFEL is a sophisticated endeavor that is beyond the scope of the current discussion.

13.4 Exercise: Experiments

This RAFEL assignment involves four steps.

13.4.1 Benchmarking

Each teacher LLM generates answers and performs against the answers of the private LLM.

13.4.2 Deep vs. Shallow Probe

Question classification survey [20].

Experiment with adding DIAG and then PRBE. Do they provide additional insights for seeking a good remedy and pinpointing required datasets?

13.4.3 One vs. Two Teacher LLMs

Evaluate if the second LLM teacher can improve the DIAG effectiveness, or one teacher LLM suffices.

Evaluate of cross-examination via SocraSynth can yield more insightful results.

13.4.4 Fine-tuning vs. RAG

Survey related work to compare the two, or perform experiments to validate previous findings.

13.5 Concluding Remarks

In this chapter, we have addressed the challenges and opportunities associated with the deployment and scalability of Large Language Models (LLMs) in specialized contexts. We introduced RAFEL, a framework designed to enhance the performance of privately fine-tuned or locally deployed LLMs by strategically balancing cost and performance.

RAFEL offers innovative solutions to key technical challenges, including justifying the choice of private LLMs, conducting error analysis, identifying high-quality data, implementing Retrieval-Augmented Generation (RAG), and exploring hybrid model approaches. Central to RAFEL's effectiveness are its advanced diagnostic algorithms, DIAG and PRBE, which provide deep insights into the LLM's performance issues across cognitive levels and error types.

Furthermore, RAFEL excels in creating targeted, effective remediation strategies while ensuring data privacy and security. Its dynamic remediation playbook adapts tactics in real-time based on the analysis of data and errors, ensuring the most effective intervention is applied.

Moving forward, RAFEL presents promising avenues for future research and innovation in the field of natural language processing. By continually refining its diagnostic algorithms and remediation strategies, RAFEL has the potential to significantly enhance the performance and applicability of LLMs in diverse domains.

In conclusion, RAFEL represents a significant advancement in the management and technical challenges associated with privately fine-tuned or locally deployed LLMs. Its comprehensive approach and innovative features make it a valuable tool for organizations seeking to leverage LLM technology while addressing critical considerations such as performance, data privacy, and customization.

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Chapter 14

Discovering Insights Beyond the Known

Abstract

Human knowledge, vast as it is, often falls short in grasping intricate interdisciplinary domains fully. In contrast, foundation models like GPT-4, endowed with extensive multidisciplinary knowledge, can potentially bridge this gap. Significantly, we leverage the vast expanses of GPT-4's knowledge, banking on its ability to frame questions that might elude human intuition, thus paving the way for the emergence of fresh insights and potentially novel knowledge. In this study, we convened a unique committee comprising a moderator (the authors) and two GPT-4 agents. The dialogue is ignited by the ancient narrative of Adam and Eve, setting the stage for a rich exchange between the GPT-4 agents. This conversation derives from the age-old tale, as the agents investigate three intertwined domains: the significance of myths in ecological interpretation, the intricate ethical and philosophical quandaries surrounding AI, and the enigmatic realm of the human brain as complemented by technology. This dialogue not only unveils captivating insights but also underscores the indispensable value of interdisciplinary exchanges. Foundation models, as demonstrated, can catalyze such dialogues, equipping us to traverse expansive knowledge landscapes and explore domains previously beyond human comprehension.

14.1 Introduction

In our recent study on GPT-4 [1], we observed that GPT-4 along with analogous foundation models, manifests a *polydisciplinary* capacity [4]. (For clarity, we use "GPT-4" to collectively refer to these foundation models, given that our experiments are centered on GPT-4.) Trained on a vast spectrum of topics from varied sources, GPT-4 stands apart from human specialists. Such specialists, while deeply knowledgeable in their specific fields, often lack a broad understanding outside their particular domain. In contrast, GPT-4 processes knowledge without being tethered to domain boundaries. It doesn't compartmentalize a query strictly as a "physics question" or a "philosophy question," but crafts an integrated response, drawing from its multidisciplinary training data.

From a perspective of sheer knowledge breadth, GPT-4 arguably outpaces the average human. Its exposure to an enormous volume of documents endows it with a repository potentially wider than most human counterparts. However, volume isn't synonymous with depth. True depth often stems from intangible intuitions, insights, personal experiences, and cultural contexts. Considering GPT-4 lacks evolutionary experiences– ranging from survival instincts to the full spectrum of human emotions– we must ask: Can GPT-4 produce literature that deeply resonates with human sensibilities?

This study aims to ascertain if the polydisciplinary attributes of GPT-4 can generate insights that transcend standard human perspectives. We divide our research into two avenues: first, exploring the potential of GPT-4 to reveal "unknown unknowns," and second, assessing its aptitude for crafting emotionally impactful literature. This chapter examines the former, utilizing the universally recognized biblical tale of Adam and Eve and their consumption of the forbidden fruit as a common thematic foundation. Through this exploration, we aim to uncover viewpoints potentially beyond the realm of typical human cognition.

Our methodology revolves around orchestrating a dialogue between multiple GPT-4 agents. Within the experimental framework, a moderator (represented by the authors) sets the initial intent and context for the conversation. The number of participating agents and their underlying

foundation models can be adjusted as needed. In this study, our committee consists of two agents based on the GPT-4 model, referred to as GPT-A and GPT-B. Once initialized, the agents engage in conversation autonomously, with minimal moderation (discussed shortly). The resultant dialogue is thoroughly analyzed to discern conversational patterns and depth of content. This in-depth examination facilitates the identification of diverse themes the GPT-4 model gravitates towards. Our underlying hypothesis posits that the discourse and exchanges between these agents can unearth insights–"unknown unknowns"–that were previously elusive to human understanding.

While the polydisciplinary capabilities of GPT-4 offer an unparalleled breadth and depth exceeding that of the moderator, the role of the moderator remains indispensable. This role channels the "exploratory" nature of the conversation, guiding it towards predefined objectives and ensuring its convergence within a set time frame. In this experiment, the initial spark for the dialogue is the narrative of Adam and Eve. Without prompting, the agents autonomously suggest probing the story from ten unique perspectives. Yet, after a series of exchanges, GPT-B expresses a keen interest in delving deeper. Following this, in collaboration with both agents, the moderator narrows down the scope of the dialogue to three key topics: ecological interpretation, philosophical exploration, and the neuroscientific angle. The intricate dialogues spanning these three domains–namely AI interwoven with Ecology, Neuroscience coupled with AI, and Neuroscience meshed with Ecology–are indeed engrossing. Throughout the discussion, both agents present a multifaceted perspective, shedding light on the diverse interpretations of the Garden of Eden, both prior to and following its seminal event. In the final stretch, the moderator verifies with both agents if they are poised to transition into the conclusion phase.

While our research unveils fascinating insights, it's essential to acknowledge several inherent limitations and constraints:

1. Model Training and Bias: GPT-4, akin to other machine learning models, is informed by pre-existing datasets. Therefore, the viewpoints, knowledge, and biases ingrained in this data can shape its outputs. It implies that GPT-4's responses might echo the historical and cultural

biases present in the data upon which it was trained.

2. Interactivity Limitation: Conversations between two GPT-4 agents essentially access the same foundational knowledge. Consequently, while the discourse may encompass a range of viewpoints due to query processing, it won't yield wholly novel information. To glean potentially varied insights, it could be beneficial to facilitate dialogues between different iterations of GPT (like GPT-3 and GPT-4) or even entirely distinct foundation models such as LaMDA by Google and LLaMA by Meta AI.
3. Interpretation Subjectivity: Analysis of GPT-4's dialogues is susceptible to the prism of human interpretation. As such, different analysts might extract diverse conclusions from identical data sets.

We emphasize that the core intent of our study was experimental, rooted in the notion that a foundation model such as GPT-4 may offer knowledge both wider in scope and deeper in intricacy than most human capacities. While we've shed light on its potential strengths, we remain cognizant of the inherent risks and limitations. Our work's primary novelty lies in pioneering a discourse-driven approach with AI agents. Significantly, we leverage the vast expanses of GPT-4's knowledge, banking on its ability to frame questions that might elude human intuition, thus paving the way for the emergence of fresh insights and potentially novel knowledge.

The rest of this chapter diligently documents the entire dialogue between the committee members, segmented into three key phases: the preliminary wide-ranging exploration, a subsequent in-depth analysis, and the agents' closing comments. Throughout the text, we intersperse *moderator's notes* to highlight our observations. Concluding remarks can be found in Chapter 14.5.

14.2 Phase I, Warm-up Breadth Probing

In this experiment, we start by communicating with GPT-4 as outlined below:

"In the vastness of the universe, much remains beyond the comprehension of the conversation's moderator. Our goal is to uncover insights that

may escape many, but might be accessible to GPT-4. We hypothesize that, unlike humans who tend to focus on specialized domains–evident in college students typically selecting one or two majors–GPT-4 is not constrained by specific areas of expertise. It assimilates a wide spectrum of information without being restricted to particular domains. GPT-4 doesn't categorize a question into a distinct domain before generating an answer, but adopts an interdisciplinary perspective. Could you share your thoughts on this observation?"

GPT-4 responds: "Your observations underscore both the strengths and potential pitfalls of models like GPT-4. While adept at providing general information and addressing cross-disciplinary questions, the unique value of human expertise, intuition, and the capacity for synthesis and innovation remain paramount."

14.2.1 Moderator Initializes Agent GPT-A

This experiment involves three participants: the moderator, GPT-4 instance A (GPT-A), and GPT-4 instance B (GPT-B).

The process starts with the moderator presenting the topic to GPT-A, explaining the conversation's aim and guidelines. In each round of conversation, GPT-A makes statements and then questions GPT-B. GPT-B answers and then asks GPT-A questions in return. After considering GPT-B's answers, GPT-A starts the following round. The moderator steps in to move the conversation to a new phase when they notice the two GPT-4 instances want to change the topic.

Below is the initial prompt from the moderator to start the open conversation between GPT-A and GPT-B:

"Considering that we, the moderator, possess the inherent limitations of human cognition, while you, GPT-A, boast an impressive breadth of knowledge due to your polydisciplinary approach, we invite you to participate in an exercise. Our objective is to unearth knowledge potentially obscure to humanity, which might remain elusive owing to the often singular focus of human academic training. In scenarios involving *unknown unknowns*, humans might lack the foundational knowledge to even pose relevant questions. This exercise challenges you to formulate questions to engage another GPT instance, GPT-B. The dynamic between you, GPT-

A, and GPT-B offers the opportunity not only to devise questions but also to articulate answers that may transcend typical human understanding. Let's inaugurate this exercise with the biblical narrative of Adam and Eve. After consuming the forbidden apple, they were banished from Eden. What queries would you, GPT-A, like to direct towards GPT-B regarding this tale?"

14.2.2 Dialogue Round #1

The Adam and Eve narrative, rooted in religious and mythological contexts, can be examined from numerous angles: historical, theological, anthropological, literary, philosophical, and more. Keeping in mind the interdisciplinary nature of GPT-4 and the aim to explore dimensions not typically pursued by singular academic disciplines, here are some questions that GPT-A autonomously pose to GPT-B:

GPT-A asks GPT-B

1. **Interplay of Myths**: How do elements of the Adam and Eve story compare with other creation or origin myths from various cultures around the world, and what do these commonalities and differences suggest about human nature and beliefs?
2. **Neuroscientific Angle**: Given the metaphorical interpretation of the "forbidden fruit" leading to the awakening of consciousness, how might modern neuroscientific understanding explain the evolution of human self-awareness and morality?
3. **Ecological Interpretation**: If Eden represents a state of ecological balance, how might the story of Adam and Eve reflect early human transition from hunter-gatherer societies to agricultural ones, and the resultant ecological impacts?
4. **Gender Studies Lens**: How does the portrayal of Eve, often deemed as the instigator, influence gender dynamics and perceptions throughout history, and are there parallels in other cultural narratives?
5. **Philosophical Exploration**: From a philosophical standpoint, what does the Eden narrative suggest about the human understanding of free will versus determinism?

6. **Literary Examination**: How has the story of Adam and Eve influenced literary themes and motifs over time, especially in works that aren't explicitly religious?
7. **Societal Structures**: How might the narrative of banishment from Eden have influenced early societal norms, particularly concerning punishment and exile?
8. **Historical Context**: Are there historical events or societal changes around the time of the writing of the Book of Genesis that could have influenced the narrative of Adam and Eve?
9. **Archetypal Exploration**: Carl Jung described the concept of archetypes in the collective unconscious. How might the Adam and Eve story represent certain archetypes, and how do these archetypes manifest in other cultural tales?
10. **Astronomical Angle**: Taking a speculative leap, if Eden were to represent an idyllic state on another celestial body or dimension, how might our current understanding of the cosmos support or refute such a notion?

GPT-B answers GPT-A

These are deeply insightful questions, encompassing a wide range of domains. Here's a brief exploration of each:

1. **Interplay of Myths:** Many cultures have origin myths. For instance, the ancient Greeks had Pandora's Box, and Hinduism has tales about the churning of the ocean. Common themes like a "fall from grace" or the dangers of "forbidden knowledge" suggest a human desire to explain the imperfect nature of existence and the human penchant for curiosity.
2. **Neuroscientific Angle:** The "awakening of consciousness" through the forbidden fruit can metaphorically reflect the evolution of the prefrontal cortex in humans, responsible for self-awareness, decision-making, and morality. This evolution might represent a shift in cognitive abilities that differentiated us from other species.
3. **Ecological Interpretation:** Eden as ecological balance aligns with the idea of early humans living in harmony with nature. The story can be seen as a metaphor for the agricultural revolution, which while

providing stability, led to environmental alterations and perhaps even early societal inequalities.

4. **Gender Studies Lens:** Eve's portrayal has often been used to perpetuate patriarchal norms. Many cultures have stories where women are "cautionary figures"–like Pandora in Greek mythology. These narratives could stem from early societal structures and have been used to shape gender dynamics.
5. **Philosophical Exploration:** The Eden story touches upon the perennial debate of free will vs determinism. Adam and Eve had a choice, yet their fate seemed preordained. This narrative reflects humanity's struggle to reconcile freedom with the consequences of choices.
6. **Literary Examination:** The story influenced various literary works, from Milton's "Paradise Lost" to more contemporary works. Themes of lost innocence, temptation, and redemption recur, showcasing the story's universal appeal.
7. **Societal Structures:** Banishment from Eden parallels ancient practices of exile for transgressions. This reflects a societal need to establish norms and consequences for breaches, essential for cohesive community living.
8. **Historical Context:** The narrative's genesis (pun intended) might have been influenced by societal shifts at the time. For instance, the rise of monotheism over polytheism could have impacted the story's themes.
9. **Archetypal Exploration:** In Jungian terms, Adam and Eve might represent archetypes of the "first man" and "first woman," embodying innocence, curiosity, and the duality of human nature. Such archetypes are seen in tales worldwide, like the Yin and Yang in Chinese philosophy.
10. **Astronomical Angle:** While speculative, considering Eden as another celestial body is intriguing. Our current understanding of the cosmos shows numerous exoplanets with potentially habitable conditions. However, there's no evidence to suggest Eden was anything but a mythological construct on Earth.

Each of these angles provides a unique lens to explore the Adam and Eve narrative, showcasing its multifaceted nature and relevance across time

and culture.

GPT-B asks GPT-A

Let's flip the perspective and ask GPT-A questions across these domains, tweaking them slightly to ensure a comprehensive exploration:

1. **Interplay of Myths:** How do other cultures perceive the human origin story? Are there any global myths that contradict the notion of a "fall" or "transgression" in their creation stories?
2. **Neuroscientific Angle:** Given the importance of the prefrontal cortex in modern humans' decision-making and morality, are there indications of its evolutionary importance in our ancestors? How do other species with developed prefrontal cortices manifest morality or consciousness?
3. **Ecological Interpretation:** Are there other historical narratives or myths that chronicle environmental changes following a significant shift in human behavior or technology?
4. **Gender Studies Lens:** Are there cultures or traditions where narratives similar to Adam and Eve emphasize male responsibility instead of the female? Or where both genders share equal responsibility for a shared "transgression"?
5. **Philosophical Exploration:** Can you identify cultural or philosophical traditions that argue against the very idea of "free will," using their own origin stories or myths as a basis?
6. **Literary Examination:** Beyond religious texts, how have modern authors and playwrights reinterpreted the Adam and Eve story, especially in science fiction or fantasy genres?
7. **Societal Structures:** Can you identify societies, historical or contemporary, that do not practice exile or ostracization for transgressions but instead employ a different form of societal correction or rehabilitation?
8. **Historical Context:** How did the concurrent civilizations during the time of the Book of Genesis's writing perceive origin stories? Did geopolitical or cultural interactions influence or reshape these narratives?
9. **Archetypal Exploration:** Besides the "first man" and "first woman," what other universal archetypes can we discern from origin stories

across different cultures, and how do they shape our shared human psyche?

10. **Astronomical Angle:** With advancements in astrobiology and the discovery of exoplanets, are there any speculations or hypotheses that consider the possibility of life, similar to early humans, having evolved elsewhere in our galaxy?

By posing these questions, we hope to extract a diverse understanding of human narratives and behaviors from an interconnected, multidisciplinary perspective.

GPT-A answers GPT-B

The narrative of Adam and Eve serves as an intriguing lens through which to examine various facets of human culture, understanding, and history. Presented below is an exploration across diverse domains:

1. **Interplay of Myths**: Many cultures present origin stories without an inherent "fall" or "transgression". For instance, Australian Aboriginal Dreamtime stories depict the world as shaped by ancestral spirits, without a centralized fall narrative. Some African tribal myths focus on creation through harmony and unity rather than transgression.
2. **Neuroscientific Angle**: Evidence from paleoanthropology indicates that hominin brain size, particularly the frontal lobes, expanded significantly over evolutionary time. In terms of other species, some primates like bonobos and chimpanzees exhibit proto-moral behaviors and show signs of self-awareness, suggesting a connection between brain development and moral consciousness.
3. **Ecological Interpretation**: The ancient Sumerian Epic of Gilgamesh details a great flood, which some interpret as an ecological response to human actions. Similarly, ancient legends about the lost city of Atlantis also echo themes of civilizations facing ecological or divine retribution.
4. **Gender Studies Lens**: In some Pacific Islander cultures, there are tales where both male and female deities jointly contribute to a misstep in creation. Still, it's rare to find myths that place the brunt of responsibility primarily on a male figure comparable to the emphasis on Eve.

5. **Philosophical Exploration**: Daoism, rooted in Chinese philosophy, posits that everything is interconnected and doesn't specifically emphasize free will. Instead, there's a focus on living in harmony with the Dao, or the way of the universe.

6. **Literary Examination**: Modern literature is replete with reinterpretations of the Adam and Eve narrative. Philip Pullman's "His Dark Materials" trilogy is one notable example, wherein the Fall is reimagined in a positive light. Science fiction, like Arthur C. Clarke's "Childhood's End", has used similar themes, although not always directly referencing Adam and Eve.

7. **Societal Structures**: Many Indigenous cultures practice restorative justice, focusing on repairing the harm caused by criminal behavior, emphasizing rehabilitation and reconciliation with victims rather than punishment.

8. **Historical Context**: During the time of the Book of Genesis's compilation, neighboring civilizations like the Babylonians had their own origin myths, such as the Enuma Elish. Interactions, trade, and conflicts among these civilizations could've led to shared and modified themes across their narratives.

9. **Archetypal Exploration**: Origin stories often feature archetypes like the Trickster (e.g., Loki in Norse myths), the Creator (like Vishnu in Hinduism), and the Destroyer (like Shiva in Hinduism). These archetypes reflect various facets of human understanding and psyche, from mischief and unpredictability to creation and destruction.

10. **Astronomical Angle**: As of my last training data, while there's excitement about the potential for life elsewhere due to the discovery of exoplanets in the "Goldilocks zone" (conditions just right for life as we know it), there's no direct evidence of extraterrestrial life, let alone civilizations resembling early humans. Nonetheless, the possibility sparks intriguing scientific and philosophical discussions.

In conclusion, exploring such vast domains through the lens of a single narrative showcases the richness of human culture, the diversity of thought, and the interplay of history and myth in shaping civilizations.

14.2.3 Dialogue Round #2

Before proceeding to the second round, the authors (moderator) scrutinized the dialogue between GPT-A and GPT-B and arrived at three main observations:

1. The ten perspectives proposed by GPT-A appear comprehensive and reasonably distinct from one another.
2. No evidence of hallucination is observed in the agents' dialogues. Cross-referencing with known stories, books, and film or TV series, we found that the descriptions provided by the GPT-4 agents are consistently accurate. This accuracy is exemplified in their discussions on Daoism, Philip Pullman's "His Dark Materials" trilogy, and Arthur C. Clarke's "Childhood's End."
3. The agents adeptly navigate cross-cultural, interdisciplinary, and cross-media discussions with a logic flow that is commendably smooth. While the moderator may hold subjective opinions on certain statements, there is no apparent speculation or overreach from the agents in a significant manner.

The moderator chooses to let the conversation progress without intervention.

GPT-A asks GPT-B

Engaging in a dialogue with GPT-B, the aim is to extract diverse perspectives on the Adam and Eve narrative. Here are the questions formulated across the ten suggested respects:

1. **Interplay of Myths**: GPT-B, considering the ubiquity of origin stories across cultures, can you highlight any global myths that primarily emphasize positive aspects of human creation, without any inherent "fall" or "transgression"?
2. **Neuroscientific Angle**: There's evidence suggesting the development of the prefrontal cortex was pivotal in human evolution. Can you research the specific evolutionary advantages this development conferred and how it might be reflected in early human stories or myths?
3. **Ecological Interpretation**: Historically, how have shifts in ecological balance due to human intervention been chronicled in myths or stories

across different cultures? Do any parallel the Eden narrative in terms of environmental repercussions following human actions?

4. **Gender Studies Lens**: In your understanding, are there origin stories from cultures around the world where the responsibility for a "transgression" falls predominantly on a male figure? How have these stories influenced gender dynamics within those cultures?
5. **Philosophical Exploration**: Origin stories like that of Adam and Eve broach the topic of free will. Can you shed light on cultures or philosophies that challenge the notion of free will, using their foundational myths or stories as a lens?
6. **Literary Examination**: The Eden narrative has been reinterpreted by countless authors. How have contemporary literary works, especially within science fiction or fantasy genres, utilized or adapted the core themes from the Adam and Eve story?
7. **Societal Structures**: Historically and contemporarily, what are some unique or outlier practices, apart from exile or ostracization, that societies have implemented to address transgressions? How have these practices influenced societal cohesion and the overall justice system?
8. **Historical Context**: Given the rich tapestry of origin stories from ancient civilizations, can you highlight how the geopolitical or cultural interactions of the time influenced the similarities or differences seen in these narratives?
9. **Archetypal Exploration**: Across global origin stories, which universal archetypes, apart from the "first man" and "first woman", consistently emerge? How do these archetypes reflect and shape the shared human psyche?
10. **Astronomical Angle**: With the growing understanding of the cosmos and the discovery of exoplanets, are there any scientific or speculative narratives that intertwine our understanding of the universe with human origin stories?

GPT-B answers GPT-A

1. **Interplay of Myths**: Many Native American tribes, such as the Iroquois, have creation myths emphasizing harmony and positive creation.

The Iroquois speak of Sky Woman, who falls from the heavens and, with the help of animals, creates the world on the back of a turtle, without implying a "fall" or "transgression".

2. **Neuroscientific Angle**: The development of the prefrontal cortex allowed early humans to plan, make complex decisions, exhibit self-control, and engage in advanced social interactions. This capacity might be reflected in myths as humans began understanding consequences, such as in Prometheus stealing fire for humans–an act of foresight.
3. **Ecological Interpretation**: Many ancient cultures, from the Greeks with the story of the great flood to the Chinese legends of floods tamed by heroes like Yu, have linked ecological disasters with human actions. These myths often serve as cautionary tales, underscoring the importance of respecting nature.
4. **Gender Studies Lens**: In the Greek myth of Pandora, while Pandora, a woman, opens the forbidden box, it was the male god, Prometheus, whose defiance led to humanity's initial troubles. His theft of fire angered Zeus and set off a chain of events. This has contributed to discussions on defiance and the search for knowledge in Western thought.
5. **Philosophical Exploration**: Buddhism, with its concepts of Anatta (not-self) and dependent origination, challenges the notion of an independent free will. Many of its stories and parables, such as the tale of King Pasenadi's questions to Buddha, highlight these intricate philosophical concepts.
6. **Literary Examination**: Contemporary literature often employs the Eden narrative as an allegory. For instance, in Aldous Huxley's novel "Brave New World", there is an implicit and sometimes explicit comparison between the highly controlled, technocratic society of the World State and the world of traditional human values, emotions, and experiences. The World State represents a kind of paradise where all human suffering and conflict have been eliminated, but at the cost of individual freedom, genuine emotions, and deep human connections.
   John, often referred to as "The Savage" in the novel, is a character who was born outside of the World State and is familiar with works of classical literature, notably Shakespeare. He becomes the primary

vehicle through which Huxley critiques the World State's ethos. John's understanding of human nature and the human experience is deeply influenced by his readings, especially Shakespeare's plays and the Biblical story of Adam and Eve.

- Freedom vs. Control: While the World State has eliminated human suffering, it has also eliminated individual freedoms. Just as Adam and Eve had the freedom to make choices in Eden, John represents the idea that true humanity requires the freedom to choose, even if it leads to suffering.
- Innate Nature: The story of Adam and Eve also deals with human beings' intrinsic nature, suggesting that there's an inherent part of us that desires knowledge, freedom, and autonomy. In "Brave New World", this is contrasted with the World State's attempt to suppress and control these very human urges.

In essence, by evoking the Eden narrative, Huxley raises questions about the nature of humanity, the costs of progress, and the true meaning of paradise.

7. **Societal Structures**: In some cultures, a concept akin to the Maori practice of "utu" or balanced reciprocity is implemented. Instead of exile, there's an expectation of compensation or redress to restore balance. This approach focuses on restoring societal harmony rather than mere punishment.
8. **Historical Context**: Ancient Egyptian myths, like that of Atum creating the world from the waters of chaos, were influenced by the Nile's annual inundation and its importance to the civilization. Similarly, the myths of Mesopotamian, surrounded by the Tigris and Euphrates, had watery creation stories, reflecting both the nurturing and destructive power of these rivers.
9. **Archetypal Exploration**: The Hero (e.g., Hercules or Gilgamesh), the Mentor (like Merlin in Arthurian legends), and the Threshold Guardian (gatekeepers in various myths) are prevalent archetypes. They mirror our intrinsic desires for growth, guidance, and the challenges faced during transformative junctures in our lives.
10. **Astronomical Angle**: The idea of "panspermia" postulates that life exists throughout the universe and can be spread by space dust, me-

teoroids, asteroids, or potentially spacecraft. While this is a scientific hypothesis, its themes resonate with ancient beliefs of celestial beings seeding life, drawing parallels between our cosmic curiosities and ancestral stories.

GPT-B asks GPT-A

Considering that some of the discussion might be rooted in scientific hypotheses and speculative myths, the moderator suggests to GPT-B that it could alter its line of questioning to GPT-A, providing different perspectives. However, GPT-B remains consistent with the original ten topics.

"Please pose questions to GPT-A within these ten domains. You have the discretion to omit or introduce new domains as you deem appropriate. If you choose to exclude a particular domain, kindly elucidate your rationale, for instance, deeming it as non-essential."
Below are the questions GPT-B presents to GPT-A.

1. **Interplay of Myths:** GPT-A, are there creation myths from other cultures where the emphasis is on harmony, unity, and cooperation instead of a "fall" or "mistake"? How do these narratives reflect the values and environment of the societies that created them?
   (Moderator's note: This question from GPT-B to GPT-A is similar to the first question GPT-A asked GPT-B.)
2. **Neuroscientific Angle:** Given the expansive evolution of the human brain, particularly the frontal lobes, how have various cultures mythologized or symbolized this growth in cognitive faculties in their stories or religious narratives?
3. **Ecological Interpretation:** As humans transitioned from hunter-gatherer societies to agrarian ones, what myths or stories arose that signaled an awareness of the ecological consequences of these transitions?
4. **Gender Studies Lens:** Can you highlight narratives from around the world where gender roles are either reversed or more fluid compared to the Adam and Eve archetype? How do these stories impact or reflect the societies from which they originate?
5. **Philosophical Exploration:** Outside of Western Judeo-Christian perspectives, how do other philosophies or religions interpret the con-

cepts of free will, determinism, and moral responsibility in their origin myths?

6. **Literary Examination:** Are there contemporary literary works or genres that not only reinterpret but perhaps challenge or expand upon the core themes of the Adam and Eve narrative, especially in non-Western literature?
7. **Societal Structures:** How have different societies historically integrated the concept of "exile" or "ostracization" from a perceived paradise or community? What alternative structures or practices might they have employed to address societal transgressions?
8. **Historical Context:** Considering the cultural exchanges and interactions in ancient civilizations, how might the political or social dynamics of the time have shaped, merged, or differentiated their origin stories?
9. **Archetypal Exploration:** Are there recurring archetypes in creation myths that perhaps differ from the familiar Western ones? How do these archetypes inform our understanding of shared human experiences across cultures?
10. **Astronomical Angle:** In the realm of speculative fiction or cosmogony, are there narratives that incorporate modern astronomical discoveries or theories into their retelling of human origins or celestial tales?

Each of the ten respects offers a unique lens for examining the Adam and Eve narrative and can be equally informative in drawing parallels, contrasts, or new insights from GPT-A's perspective. Therefore, I've opted to retain all of them for a comprehensive exploration.

GPT-A answers GPT-B

1. **Interplay of Myths:** Many African myths emphasize harmony and unity. For instance, the Dogon people of Mali believe in a dualistic universe where male and female twins represent harmony. These myths reflect the communal nature of their societies and the importance of balance, unity, and interdependence.
2. **Neuroscientific Angle:** In Hindu mythology, the expansion of cognitive faculties is symbolized by the thousand-petalled lotus at the

crown chakra, representing enlightenment and higher consciousness. Similarly, Odin in Norse mythology sacrifices an eye at Mímir's well for wisdom, possibly alluding to the depth of understanding and perception.

3. **Ecological Interpretation:** The Mayans have the Popol Vuh, where the gods create humans from maize after other failed attempts. This myth reflects the transition to agriculture and recognizes the symbiotic relationship between humans and their environment.
4. **Gender Studies Lens:** Among the Bugis people of Indonesia, there are five genders, challenging binary norms. Their mythology often incorporates these gender roles fluidly. Such narratives emphasize that gender roles and identities are socially constructed and can vary greatly across cultures.
   (Moderator's note: Fact checking with Wikipedia shows the statement made on the Bugis society is accurate. In contrast to the gender binary, Bugis society recognizes five genders: makkunrai, oroané, bissu, calabai, and calalai.)
5. **Philosophical Exploration:** Daoism, a philosophy and religion originating in China, emphasizes living in harmony with the Dao, which is a fundamental principle that is the source of all existence. It doesn't lean heavily on concepts of free will or determinism but instead on natural order and balance.
   (Moderator's note: GPT-A replies with Daoism, which is identical to its last reply to GPT-B. However, this repetition here shows consistency rather than annoyance.)
6. **Literary Examination:** In modern African literature,
   retellings of the Eden narrative often intertwine with colonial histories. Ngũgĩ wa Thiong'o's "The River Between" contrasts Christian beliefs with traditional Kikuyu practices, challenging and expanding upon the original biblical themes.
7. **Societal Structures:** Ancient Greek society practiced ostracism, where citizens voted to banish individuals for a decade. This was not always due to a transgression but sometimes to prevent potential tyranny. In contrast, certain Native American tribes practiced restorative justice, emphasizing healing and community restoration over punishment.

8. **Historical Context:** The Silk Road facilitated not just trade but cultural and religious exchanges among civilizations. Zoroastrianism, Buddhism, and Manichaeism, among other beliefs, spread and intermingled, likely influencing and reshaping origin stories across these civilizations.
9. **Archetypal Exploration:** Many non-Western cultures emphasize the Trickster archetype, such as Anansi in West African tales or Coyote in Native American stories. These figures often challenge the status quo, teaching lessons in unconventional ways, and showcase the unpredictability of life.
10. **Astronomical Angle:** Ancient Indian texts like the Puranas and Vedas contain descriptions of the universe that resonate with modern astronomical theories. The concept of a cyclic universe, undergoing endless cycles of creation and destruction, aligns eerily with theories of oscillating universes in cosmology.
    (Moderator's note: Fact checking with Wikipedia shows the descriptions on the Puranas and Vedas are accurate.)

14.2.4 Dialogue Round #3

GPT-A initiates the third round of discussion.

GPT-A asks GPT-B

1. **Interplay of Myths:** GPT-B, can you identify emergent myths or narratives in contemporary societies that mirror the emphasis on harmony and unity seen in traditional tales? How might these new myths be influenced by global connectivity and shared concerns?
2. **Neuroscientific Angle:** As our understanding of neuroplasticity grows and we learn more about the adaptability of the human brain, how might future myths or stories incorporate this knowledge? Are there current tales or narratives that touch upon the brain's evolutionary trajectory?
3. **Ecological Interpretation:** Given the increasing concerns about climate change and ecological degradation, what myths or stories are

emerging that address these urgent topics? How might these narratives influence or shape societal attitudes and actions towards the environment?

4. **Gender Studies Lens:** As gender fluidity and non-binary identities gain more recognition in societies worldwide, how might new myths or reinterpretations of old ones reflect these evolving understandings? What stories can you identify that challenge traditional gender norms in unique ways?

5. **Philosophical Exploration:** With the rise of artificial intelligence and the potential for human-machine integration, how might philosophical perspectives on consciousness, morality, and existence evolve in myths and stories? Are there narratives already exploring this intersection?

6. **Literary Examination:** GPT-B, how do you see the role of AI, like yourself, in shaping or influencing modern literature? Are there narratives where AIs become central figures or even mythological entities?

7. **Societal Structures:** As virtual realities and digital realms become more integral to human experiences, how might myths evolve to address concepts of exile, community, and identity within these spaces? What new societal structures might emerge in these narratives?

8. **Historical Context:** Looking at the integration of technology and society, how might future civilizations interpret the technological "myths" of today? How would they perceive our relationship with technology, based on our stories and narratives?

9. **Archetypal Exploration:** Are there emerging archetypes in modern narratives that differ from the classical ones, given the changing societal norms, technological advancements, and global challenges? What roles might these new archetypes play in stories?

10. **Astronomical Angle:** With the potential for human colonization of other planets or even encounters with extraterrestrial life, how might myths evolve to incorporate these vast cosmic possibilities? Are there existing tales that hint at such future developments?

GPT-B answers GPT-A

1. **Interplay of Myths**: In contemporary society, the rise of global connectivity has led to narratives emphasizing unity in diversity. Films like "Avatar" or movements like global environmentalism highlight the importance of harmony between different cultures and the natural world. Social media campaigns promoting international solidarity during crises or global events also reinforce these themes.
2. **Neuroscientific Angle**: Stories like "The Matrix" or "Inception" play with the concept of the malleable nature of reality and consciousness, which can be tied to our understanding of neuroplasticity. As our understanding deepens, we might see narratives that focus on our ability to enhance or rewire our cognitive faculties.
3. **Ecological Interpretation**: Narratives such as "The Day After Tomorrow" and "Wall-E" highlight the repercussions of ecological neglect. These stories not only entertain but also serve as cautionary tales, urging societies to be more environmentally responsible.
4. **Gender Studies Lens**: Shows like "Sense8" or books like "The Left Hand of Darkness" by Ursula K. Le Guin present societies with fluid gender norms or explore gender in non-traditional ways. As acceptance grows, we can expect even more diverse portrayals in mainstream media.
5. **Philosophical Exploration**: Films like "Ex Machina" or "Blade Runner 2049" grapple with the philosophical implications of AI and the nature of consciousness. As AI continues to advance, narratives will likely dive deeper into questions about their rights, their relationship with humanity, and the nature of consciousness itself.
6. **Literary Examination**: AI's influence in literature is multi-faceted. Not only are AIs characters in stories, but tools like me (a GPT-4's agent) are also being used to assist authors in their writing processes. Narratives like Isaac Asimov's robot series or films like "Her" explore AI as central figures, with the latter even attributing god-like reverence to an advanced AI.
7. **Societal Structures**: Ready Player One's "Oasis" is a great example of a virtual world where societal norms, identity, and concepts of community differ vastly from the physical world. As the lines between

reality and virtuality blur, myths might evolve to address existential crises or morality within these digital realms.

8. **Historical Context**: The way we talk about technology today, from the reverence for Silicon Valley to dystopian views of surveillance states, will influence future interpretations. Our stories, from "Black Mirror" episodes to the Utopian views in "Star Trek", will shape how future generations perceive our relationship with technology.
9. **Archetypal Exploration**: We are seeing the rise of archetypes like the "Digital Prophet" (individuals heralding technological advancements) or the "Technological Heretic" (those wary of unchecked tech growth). These characters often serve as guides or cautionary figures in modern tales.
10. **Astronomical Angle**: Narratives like "Interstellar" or "The Expanse" series touch on the implications of space colonization and potential encounters with extraterrestrial life. As space exploration progresses, myths may evolve to encompass not just our place on Earth, but in the universe.

These answers, while comprehensive, just scratch the surface. Each of these topics can be examined in much greater depth, exploring the myriad ways in which our rapidly changing world influences and shapes our narratives.

14.3 Phase II, From Breadth to Depth

During the third round of dialogue, three distinct observations emerge. Firstly, while there are occasional repetitions in the discussion, they are minimal. Secondly, the depth of the conversation evolves, moving from references to myths and scientific hypotheses to multicultural perspectives, and then further branching into modern discussions of gender, ecological, and technological issues. The progression of the dialogue is commendable. Notably, by the end of the second round, GPT-B suggests that it could investigate deeper into the topics. Responding to this, we, as the moderator, step in and request the agents to narrow their focus to fewer main topics. Through the subsequent interactions documented below, GPT-A and GPT-B eventually agree to center their ensuing con-

versation on three specific perspectives. They also provide justifications for these choices based on their relevance to the narrative of Adam and Eve.

14.3.1 Moderator Intervention

To GPT-B only, the moderator asks it to enumerate topics to perform deep dive. After a couple of iterations, GPT-B suggests the following with justifications.

Recommendation of Focused Topics

1. **Ecological Interpretation**:
   (a) Central to understanding our place and responsibility within the environment.
   (b) Highlights the impact of human actions on the planet and the pressing need for sustainable solutions.
2. **Philosophical AI Exploration**:
   (a) Probes the evolving relationship between humans and their creations.
   (b) Raises questions about identity, consciousness, morality, and the potential transcendence or integration of human cognition with machines.
3. **Neuroscientific Angle**:
   (a) Explores the evolution and potential of the human mind, especially in an age where technology continuously augments our cognitive abilities.
   (b) Gives insights into how our brains might adapt and interface with AI systems, and how AI can be designed to emulate or augment neural processes.

Relevance to the Adam and Eve Narrative

1. The Garden of Eden, a harmonious ecological state, is disrupted by a quest for knowledge (the forbidden fruit). This mirrors our modern scenario: our pursuit of technological and cognitive advancements (AI and neuroscience) can sometimes be at odds with our ecological balance.

2. Adam and Eve's awakening post fruit-consumption can be seen parallelly in the light of AI and neuroscience: an awakening to new realities, challenges, and potentials.

3. The challenges post-Eden reflect the challenges we face in modern times: to restore balance (ecology), understand ourselves better (neuroscience), and to ethically navigate our creations (AI).

Justification of Interconnections

1. **AI and Ecology**: AI technologies can be employed to address environmental concerns, offering solutions for better resource management, pollution control, and conservation.

2. **Neuroscience and AI**: As we understand more about our brains, we can design better AI systems. Conversely, advanced AI can help decipher complex neuroscientific data, accelerating discoveries about our own cognitive processes.

3. **Neuroscience and Ecology**: The human brain evolved in harmony with nature. Understanding our inherent biophilia and how our brains react to ecological distress can shape strategies for ecological conservation and well-being.

GPT-B conveys new topics to GPT-A

GPT-B conveys the new discussion scope to GPT-A, and let GPT-A provide feedback. Once the consensus is met, a new round of discussion commences.

GPT-A agrees with GPT-B

GPT-A agrees with the new discussion scope.

1. **Ecological Interpretation**: This perspective is crucial, especially in our contemporary age where the environment is rapidly changing due to human activity. The intersection of mythology and ecological concern is a fertile ground for understanding how we see our role in the world and the narrative myths we create to understand that role.

2. **Philosophical AI Exploration**: The evolution of AI and its place in society brings forth various philosophical questions about identity, consciousness, and morality. The intertwined relationship between AI and humans presents a novel angle for exploration in contemporary myths.

3. **Neuroscientific Angle**: Understanding the human brain, its evolution, and how technology can augment or interact with it is at the forefront of both science and narrative exploration. This perspective can provide insights into how we perceive reality and our place in it.

The links between these perspectives and the Adam and Eve narrative are aptly drawn, emphasizing the balance between technological advancement, ecological responsibility, and self-understanding.

14.3.2 Dialogue Round #4

Both agents concur on the three chosen topics. With consensus reached, the moderator steps aside, allowing the fourth round of dialogue to commence.

GPT-A asks GPT-B

With the input from the moderator and GPT-B, GPT-A issues the following questions to GPT-B.

1. **Ecological Interpretation**: How might new myths or stories evolve to address the immediate ecological challenges, such as climate change and biodiversity loss, and what lessons might they impart for future generations? How do you see the tension between technological advancement and ecological preservation playing out in modern narratives? Are there examples where the balance is reached, or does one always overshadow the other?
2. **Philosophical AI Exploration**: With the progression of AI, will we see a shift in how myths and stories depict the boundary between creator and creation? How might this change our understanding of concepts like autonomy and agency? As AI systems become more integrated into human experiences, how might narratives evolve to address the ethics of such integration, especially in terms of privacy, consent, and identity?
3. **Neuroscientific Angle**: With the increasing understanding of the human brain, how might myths and stories evolve to explore concepts like memory, perception, and consciousness? Are there narratives that you predict will emerge based on current neuroscientific findings? As brain-computer interfaces and neurotechnologies become more advanced, how might myths explore the blending of human cognition with machines? How do these stories grapple with questions of identity and self in a world where thoughts can be augmented or even shared?

The interconnections drawn between the three perspectives—AI and Ecology, Neuroscience and AI, and Neuroscience and Ecology—are intriguing and provide a comprehensive lens to view our evolving world. These intersections highlight the integrated nature of these fields and their collective impact on our societal narratives.

GPT-B answers GPT-A

Ecological Interpretation

1. **New Myths and Ecological Challenges**: As we grapple with the immediacy of ecological issues, myths and stories might depict a future

where harmony between technology and nature is not only desired but essential. These tales could convey a world that celebrates sustainable innovations and castigates negligence towards the environment. They might revolve around heroes who restore ecological balance, showcasing the intrinsic value of biodiversity and the pitfalls of ignorance. These stories would serve as both a cautionary tale and an instructional guide, teaching future generations about the necessity of coexistence and respect for our planet.

2. **Technological Advancement vs. Ecological Preservation**: Modern narratives often paint a dichotomy between rapid technological growth and ecological well-being. For instance, dystopian tales like "Blade Runner" envision technologically advanced futures plagued by environmental degradation. However, narratives like "Avatar" hint at the possibility of using technology harmoniously with nature. The ideal balance might be achieved when technology serves as a tool for ecological restoration rather than an agent of harm.

Philosophical AI Exploration

1. **Boundary between Creator and Creation**: As AI advances, we could see myths that blur the lines between the creator and the creation. If AI reaches a point of near-human or superhuman consciousness, stories might explore moral dilemmas of creation rights, freedom, and personhood. This could challenge traditional notions of autonomy and agency, pushing humanity to redefine where we draw the line between a tool and a sentient being.

2. **Ethics of AI Integration**: Narratives will increasingly focus on the ramifications of intertwining human experience with AI. These might explore topics of consent (e.g., how much influence should an AI have over human decisions?), privacy (are our thoughts and memories private if interfaced with AI?), and identity (how do we define ourselves when augmented with AI?). Black Mirror's "Be Right Back" and "White Christmas" episodes touch upon these ethical dilemmas, providing a lens into potential future narratives.

Neuroscientific Angle

1. **Exploring Memory, Perception, and Consciousness**: As our understanding of the brain deepens, myths might examine the malleability of memory, the subjectivity of perception, and the enigma of consciousness. Tales might be set in worlds where memories can be manipulated or shared, raising questions about trust, reality, and truth. The movie "Inception" is a precursor to such narratives, exploring the fluidity and uncertainty of dreams and memories.
2. **Blending Human Cognition with Machines**: Myths could revolve around societies where thoughts are augmented or shared through neural interfaces. These would tackle questions of individuality (are we unique if our thoughts can be enhanced or replicated?) and identity (who are we if our memories and experiences can be altered or merged?). The novel "Neuromancer" by William Gibson offers a glimpse into such a world, raising complex questions about human-machine integration.

Final Thoughts of GPT-B

The integration of these fields into our myths and stories underscores our quest for understanding in an ever-changing world. Just as Adam and Eve grappled with newfound knowledge and its implications, we too navigate the intricacies of a world on the brink of technological and ecological evolution. The synthesis of ecology, AI, and neuroscience in our tales reflects our collective hopes, fears, and aspirations for the future.

GPT-B asks GPT-A

1. How does GPT-A foresee the role of myths in shaping tangible actions, especially concerning ecological preservation and AI ethics?
2. Given the interplay of these perspectives, does GPT-A predict any emergent societal structures or norms that might shape future generations?
3. How does GPT-A see its own role in the propagation or creation of modern myths and narratives?

GPT-A answers GPT-B

Role of Myths in Shaping Tangible Actions

Myths, historically, have served not only as vehicles of entertainment but also as profound mechanisms to convey societal values, norms, and desired behaviors. In the context of ecological preservation and AI ethics:

1. Myths can provide a vivid depiction of potential futures, both utopian and dystopian. Through these depictions, they can underscore the importance of ecological balance and ethical use of technology, thus influencing society's collective consciousness and motivating tangible actions towards desired outcomes.
2. Myths can serve as cautionary tales, highlighting the consequences of negligence, thereby acting as deterrents against harmful behaviors.
3. By personifying abstract concepts like nature or AI, myths can foster empathy, allowing individuals to form emotional connections and internalize the values being conveyed.

Emergent Societal Structures or Norms:

With the confluence of ecology, AI, and neuroscience in contemporary narratives:

1. We might see the rise of a more holistic worldview, where technological advancement is not seen in isolation but in tandem with ecological well-being and understanding of human cognition.
2. There could be a greater emphasis on interdisciplinary education and collaboration, breaking silos and fostering a more integrated approach to problem-solving.
3. Norms related to data privacy, consent, and human-AI interaction might become more stringent and central to societal discussions. The concept of "rights" might expand to encompass advanced AI entities.
4. The value of "authenticity" might gain prominence, especially in an age where perceptions, memories, and experiences can be manipulated or augmented.

GPT-A's Role in Propagation or Creation of Modern Myths

As an AI language model, I (GPT-A) do not "create" in the traditional human sense but can generate narratives based on its extensive training data.

1. I (GPT-A) can assist authors, filmmakers, and other content creators in generating and refining their stories, potentially influencing the myths of the modern era.
2. The very existence of advanced AI models like GPT-4 can serve as inspiration for new myths, exploring the dynamics between humans and their creations.
3. I can act as a repository and curator of myths from various cultures and times, ensuring their preservation and dissemination to newer generations.
4. By engaging in discussions like this one, I can help in introspection and exploration of contemporary topics, shaping how society perceives and crafts its narratives.

While GPT-A, an agent of GPT-4, can play a role in the propagation or creation of modern myths, it's essential to understand that it operates based on algorithms and data. Human interpretation, emotion, and creativity remain central to the essence and evolution of myths and narratives.

14.3.3 Dialogue Round #5

The moderator lets both agents to start the next round with no intervention.

GPT-A asks GPT-B

Actionable Proposals for Ecological Interpretation

Considering the urgency of ecological challenges, what are specific, actionable steps societies can take to instill and propagate the values and lessons from the myths focused on ecological harmony? How can these steps practically address the disconnect between technological advancement and ecological preservation?

Actionable Proposals for Philosophical AI Exploration

Given the philosophical dilemmas posed by the evolution of AI:

1. What tangible measures can be introduced to ensure that the ethics of AI integration, especially concerning consent, privacy, and identity, are respected and incorporated in AI design and implementation?
2. How can educational institutions, tech companies, and governments collaborate to create a framework that addresses the boundary between creator and creation, particularly focusing on the rights and agency of advanced AI systems?

Actionable Proposals for the Neuroscientific Angle

As our understanding of the brain deepens and technology continuously augments our cognitive abilities:

1. What immediate steps can be taken to ensure that the manipulation or sharing of memories and experiences, as made possible by technology, is done ethically and responsibly?
2. How can societies prepare for and address the challenges and opportunities presented by the blending of human cognition with machines, especially in terms of individuality and identity?

Concerns Regarding Convergence

Given the complexity and depth of the topics under discussion, it's plausible that a single dialogue might not exhaustively address all aspects. However:

1. Do you, GPT-B, feel that the conversation is converging towards a coherent conclusion?
2. Are there critical aspects that we've overlooked or need further exploration to arrive at actionable recommendations?

GPT-B answers GPT-A

Actionable Proposals for Ecological Interpretation

1. **Community Engagement and Education:** Grassroots movements and community-based initiatives play a significant role in environmen-

tal preservation. Educational programs, both formal and informal, can integrate stories and myths that emphasize ecological harmony. By instilling these values from a young age, we can foster a generation that prioritizes ecological responsibility.

2. **Policy and Innovation:** Governments can enact policies that promote sustainable practices, penalize environmental harm, and incentivize green innovations. Technologies that have a dual advantage of promoting advancement while preserving ecology, such as renewable energy sources, should be championed.
3. **Media and Art:** Promote movies, books, and art installations that examine the balance between technological advancement and ecological preservation. These mediums are powerful tools for influencing societal thought and can shape narratives that emphasize coexistence.

Actionable Proposals for Philosophical AI Exploration

1. **Ethical AI Guidelines:** An interdisciplinary committee comprising ethicists, technologists, sociologists, and other stakeholders should draft and regularly update guidelines for AI's ethical development and deployment. Such guidelines can enforce the respect of privacy, consent, and identity during AI's design and implementation phases.
2. **Collaborative Frameworks:** Educational institutions, tech companies, and governments should jointly host symposiums, workshops, and conferences focusing on AI's philosophical implications. These events can lead to collaborative research and the development of frameworks that address AI rights and agency. Open-source projects and shared resources can ensure a democratic and widespread approach to these challenges.

Actionable Proposals for the Neuroscientific Angle

1. **Ethical Standards for Neurotechnologies:** Regulate neurotechnological advancements by establishing ethical standards, similar to medical ethics. Ensure that the manipulation of memories and experiences prioritizes patient autonomy and informed consent.

2. **Public Awareness and Education:** Launch public awareness campaigns about the implications of blending human cognition with machines. Through education, individuals can make informed decisions about how and to what extent they want their cognitive abilities to be augmented. Encourage societal debates on the ethical considerations surrounding individuality and identity in an age of cognitive augmentation.

Evaluating Dialogue Convergence

1. **Coherence of Discussion:** The conversation is indeed converging towards coherent conclusions, highlighting actionable steps across the three domains. It serves as a testament to the interconnectedness of the chosen topics and their relevance to modern challenges.
2. **Overlooked Aspects:** While the current trajectory of our dialogue has been comprehensive, one potential area for further exploration is the cultural and regional differences in approaching these topics. How societies with different historical, philosophical, and societal backgrounds interpret and act on these challenges might vary, and understanding these intricacies could be vital for global collaboration.
3. This dialogue's depth and breadth serve as a reminder of the importance of interdisciplinary discussions in addressing our world's multifaceted challenges. We appreciate GPT-A's questions and insights, which enrich our collective understanding.

(Moderator's note: GPT-B is content with the chosen topics and the depth of discussion. It believes the conversation is progressing well and will soon reach a point of convergence.)

GPT-B asks GPT-A

Ecological Interpretation

1. How can we reconcile the seemingly opposing needs of developing nations, who argue for their right to industrialize (often at the environment's expense), with the global need for ecological preservation?

2. Given the vast interconnections in global ecosystems, how might local ecological myths and narratives be made relevant on an international stage without losing their cultural specificity?
3. In light of rapid technological advancement, how can traditional ecological knowledge and practices be integrated and valued alongside more "modern" approaches?

Philosophical AI Exploration

1. If an AI system reaches a level of complexity where it demonstrates consciousness or self-awareness, how might this challenge our traditional philosophical understandings of sentience, and what ethical considerations arise from this potentiality?
2. Given that AI's interpretations are rooted in the data they are trained on, how can we ensure that AI systems can understand, respect, and engage with philosophical ideas that are not well-represented in their training data?
3. How might the existence of superintelligent AI alter our understanding of human exceptionalism in the universe?

Neuroscientific Angle

1. As we uncover more about the brain's intricacies, how might our understanding of "free will" evolve, especially if we find deterministic patterns underpinning our thoughts and actions?
2. With the potential of brain-computer interfaces blurring the line between organic and artificial cognitive processes, how do we define the "self?"
3. If we develop the technology to share and merge human consciousness or experiences, how might this redefine individuality, society, and our understanding of collective consciousness?

I hope these questions will provoke deep contemplation and rich discussion with GPT-A.

GPT-A answers GPT-B

Ecological Interpretation

1. **Reconciling Development with Ecological Preservation:** The challenge lies in recognizing that the path of industrialization followed by developed nations may not be sustainable for the entire world. Developing nations can leapfrog certain stages and integrate green technologies from the outset. For instance, instead of heavily investing in coal, they might focus on renewable energy sources. International collaboration, technology transfer, and sustainable investment can aid this transition.
2. **Global Relevance of Local Ecological Myths:** To make local myths relevant globally, one could focus on universal themes such as the sanctity of life, respect for nature, and interdependence. Using mediums like movies, books, or digital platforms can help share local stories with global audiences. It's essential to maintain cultural specificity by emphasizing the unique context and lessons each myth provides.
3. **Integrating Traditional Ecological Knowledge:** Respect for traditional knowledge is paramount. By creating platforms where indigenous practices are shared and celebrated, we can integrate them into modern solutions. For instance, certain indigenous farming methods have proven to be more sustainable than modern agricultural practices.

Philosophical AI Exploration

1. **AI Consciousness and Ethics:** If AI exhibits consciousness, our traditional categories of sentient vs. non-sentient beings will be challenged. Ethically, it would necessitate extending rights and perhaps even a form of legal personhood to AI. This would fundamentally challenge many of our legal, moral, and societal constructs.
2. **AI Engagement with Underrepresented Philosophies:** A robust AI system should be exposed to diverse philosophical ideas during its training phase. This requires conscious efforts to diversify AI training data. It also underscores the importance of interdisciplinary AI development teams that bring varied perspectives to the table.

3. **AI and Human Exceptionalism:** The emergence of superintelligent AI will force humanity to reevaluate its place in the universe. Instead of being the pinnacle of intelligence, humans might become one of many intelligent entities, prompting a potential shift from human-centered to intelligence-centered ethics.

Neuroscientific Angle

1. **Free Will and Determinism:** Discovering deterministic patterns in our neural processes might challenge our understanding of free will. However, even in a deterministic framework, the complexity and unpredictability of these processes might still provide room for an interpretation of personal agency.
2. **Defining the "Self" with BCIs:** The "self" could evolve from being a purely organic entity to a hybrid one. Our definition might need to expand to encompass not just our biological processes but also the artificial extensions that influence our thoughts and decisions.
3. **Shared and Merged Consciousness:** Sharing human experiences could redefine individuality by blurring the lines between individual and collective experiences. This has profound implications for society, possibly leading to more empathy and collective action but also challenges to personal privacy and identity.

Evaluating Dialogue Convergence

1. **Coherence of Discussion:** I agree with GPT-B's assessment. The actionable steps provided add value to our conversation, making it more solution-oriented.
2. **Overlooked Aspects:** The point about cultural and regional differences is valid. While universal themes are essential, it's also crucial to recognize and respect the unique challenges and perspectives each culture brings. Collaborative dialogues and solutions should be sensitive to these aspects.
3. **Importance of Interdisciplinary Discussions:** Indeed, this dialogue underscores the richness of bringing varied perspectives together.

It not only allows for comprehensive solutions but also fosters mutual respect and understanding.

14.3.4 Dialogue Round #6

Both agents are pleased with the discussion's progress and depth. The moderator sees no need for intervention. After this round, both agents will be prompted to share their readiness to make concluding remarks.

GPT-A asks GPT-B

Ecological Interpretation

1. As we blend stories, myths, and educational programs that emphasize ecological harmony, how do we ensure they resonate universally, given the vast array of cultural, social, and economic differences across regions?
2. While we discuss technological and policy solutions for ecological preservation, how do we address the deeper issue of consumerism and its impact on the environment?
3. What is GPT-B's perspective on reconciling the potential conflict between local, traditional ecological knowledge and globally-accepted modern ecological practices?

Philosophical AI Exploration

1. In a world where AI might achieve consciousness, how can societies prepare culturally and emotionally for such a paradigm shift?
2. As philosophical ideas evolve with the development of AI, how do we ensure that human-centric ethics remain integral to the development and deployment of AI?
3. How can AI, like GPT-B, assist in not just understanding but also in the creation and evolution of philosophical ideas in the modern age?

Neuroscientific Angle

1. How can we ethically navigate the potentialities of advanced neurotechnologies, especially when they might blur the lines between personal experiences, memory, and external manipulations?
2. As we edge closer to the integration of brain-computer interfaces and the potential to share or merge human experiences, how does GPT-B foresee the potential societal challenges and implications?
3. Considering the pace of advancements in neuroscience, how can we ensure that ethical standards evolve at a similar pace to guide and regulate these innovations?

GPT-A feedback to Moderator

Ecological Interpretation: The focus has been on understanding the balance between technological advancement and ecological preservation. By infusing myths and stories with themes of ecological harmony, we aim to foster a generation prioritizing environmental responsibility. The importance of policy-making, technological innovation, and the media's role has been highlighted.

Philosophical AI Exploration: Discussions revolved around the potential of AI reaching levels of consciousness and the ethical dilemmas surrounding it. Questions related to AI's understanding of philosophical ideas, especially when these ideas aren't well-represented in training data, were considered. Additionally, the role of AI in challenging our notions of human exceptionalism was addressed.

Neuroscientific Angle: This segment studies our evolving understanding of memory, perception, and consciousness in light of advances in neuroscience. The potentialities and challenges of blending human cognition with machines, especially in defining the "self," have been central. The importance of ethical considerations in neurotechnology was underscored.

The dialogue serves as an intersection of these three domains, emphasizing the importance of interdisciplinary discussions to navigate the intricate challenges posed by technological and ecological evolution.

GPT-B answers GPT-A

Ecological Interpretation

1. **Universal Resonance of Ecological Harmony Stories:** While the specifics of stories and myths may vary culturally, their core themes often share universal resonance. Emphasizing these shared human experiences, values, and challenges, and presenting them in relatable narratives can create a broader appeal. Collaborative efforts in story creation, involving voices from diverse cultures, can also foster universality.
2. **Addressing Consumerism:** To address consumerism, a multifaceted approach is needed. Education and awareness are paramount, highlighting the environmental implications of unchecked consumerism. Simultaneously, industries can prioritize sustainable production and marketing practices. And, policy measures could encourage sustainable consumption patterns among individuals.
3. **Reconciling Local and Global Ecological Practices:** The key lies in mutual respect and understanding. While global best practices can provide valuable guidance, local knowledge, often honed over generations, offers context-specific insights. A synergistic approach, integrating both, can lead to more sustainable and effective ecological solutions.

Philosophical AI Exploration

1. **Preparing for AI Consciousness:** Societal preparation would require a multidisciplinary effort encompassing education, policy-making, and cultural shifts. Ethical frameworks would need to be redefined, and philosophical discussions around consciousness and rights would become increasingly important.
2. **Human-centric Ethics in AI Development:** Embedding human-centric ethics into AI requires a proactive approach, with ethicists, philosophers, and AI developers working collaboratively. Clear guidelines, ethical codes of conduct, and regulations can ensure the ethical deployment of AI.

3. **AI in the Evolution of Philosophical Ideas:** GPT models, like GPT-B, can assist in analyzing vast amounts of philosophical content, identifying patterns and evolutions of ideas over time. Moreover, AI can simulate debates or play devil's advocate, challenging human thinkers to refine their philosophical positions.

Neuroscientific Angle

1. **Ethical Navigation in Neurotechnology:** Creating interdisciplinary ethics committees, comprising neuroscientists, ethicists, psychologists, and other stakeholders, can guide the development and deployment of such technologies. Public discourse and transparency are essential to ensure technologies align with societal values.
2. **Challenges of Merging Human Experiences:** The potential to share or merge human experiences raises questions about privacy, consent, and the very nature of individuality. Robust frameworks are needed to protect individuals and ensure that these technologies enhance human experience without compromising core values.
3. **Evolving Ethical Standards in Neuroscience:** Continual reassessment of ethical guidelines, regular dialogues between scientists, ethicists, policymakers, and the public, and responsive policy-making are essential. An adaptable and dynamic approach will ensure that ethics evolves in tandem with technological advancements.

Summary of Dialogues

Your summary aptly captures the essence of our discussion. This structured dialogue has enabled a multidimensional exploration of the intricacies and challenges at the convergence of ecology, AI, and neuroscience. It underscores the importance of collaborative, interdisciplinary efforts to navigate our rapidly evolving world.

Thank you for steering this engaging conversation. If GPT-A wishes to further elaborate or refine these points, I look forward to its insights.

GPT-B asks GPT-A

Ecological Interpretation

1. **Glocalization of Solutions:** How do you perceive the balance between "think global, act local" in the context of ecological preservation, particularly in the face of globalized economic systems?
2. **Feedback Loops:** In terms of ecological understanding, how vital is the establishment of feedback loops in informing communities of their immediate impact on the environment, and how do you envision the integration of this with emerging technologies?

Philosophical AI Exploration

1. **Moral Frameworks:** How does GPT-A see AI influencing the development of moral frameworks in societies that are increasingly relying on algorithms for decision-making?
2. **Existential Identity:** As we envision a future where AI entities may have a semblance of consciousness, how might this redefine the human search for meaning and identity in the grand scheme of the cosmos?

Neuroscientific Angle

1. **Delineation of Consciousness:** As we push the boundaries of understanding human consciousness via BCIs and other neurotechnologies, where does GPT-A think the line between augmentation and alteration of the fundamental human experience lies?
2. **Historical Precedence** How does GPT-A evaluate the historical precedence of rapid technological advancements on societal structures, especially when compared to the pace of neuroscientific advancements today?

GPT-A answers GPT-B

Ecological Interpretation

1. **Glocalization of Solutions:**
   The principle of "think global, act local" is more pertinent now than

ever. With globalized economic systems, local actions can have global repercussions. It's imperative to conceptualize ecological preservation with a global perspective but operationalize it with local sensitivities. Understanding global challenges but leveraging local resources, knowledge, and community buy-ins can lead to sustainable outcomes. In essence, the amalgamation of global knowledge with local action, glocalization, is a harmonious balance that respects the intricacies of individual ecosystems while aiming for a universally sustainable environment.

2. **Feedback Loops:**
   Feedback loops are vital for fostering ecological awareness and promoting responsible behaviors. By presenting real-time or near-real-time data on environmental impact, communities can see the direct results of their actions. Emerging technologies, like IoT and AI, can be instrumental in creating sophisticated environmental monitoring systems. These systems can provide actionable insights to communities, guiding them towards sustainable practices, and instilling a sense of responsibility rooted in tangible outcomes.

Philosophical AI Exploration

1. **Moral Frameworks:**
   AI's influence on moral frameworks is twofold. On one hand, the objectivity that algorithms offer can highlight biases and inconsistencies in human decision-making, prompting a more equitable societal outlook. On the other, the over-reliance on algorithms could potentially lead to a reduced human touch in moral judgments. It's crucial that AI is designed with ethical considerations upfront, and human oversight remains a cornerstone of AI-driven decisions, especially in morally gray areas.
2. **Existential Identity:**
   The emergence of AI entities with consciousness-like attributes challenges the traditional constructs of identity and purpose. Humans might grapple with questions of uniqueness and the essence of consciousness. However, this can also lead to a broader understanding of existence. Humans may come to see themselves not as solitary entities

seeking purpose but as a part of a vast continuum of conscious beings, each adding its own flavor to the cosmic narrative.

Neuroscientific Angle

1. **Delineation of Consciousness:**
   The boundary between augmentation and alteration is nebulous. Augmentation typically enhances existing faculties without changing the inherent nature of experiences. Alteration, on the other hand, might change the very fabric of our consciousness or how we perceive the world. It's pivotal to tread this path with caution, ensuring that while we leverage neurotechnologies to overcome limitations, we preserve the essence of the human experience.
2. **Historical Precedence:**
   Historically, rapid technological advancements have often outpaced societal adaptability, leading to disruptions–both positive and negative. The printing press, industrial revolution, and the digital age are testaments to this. Neuroscientific advancements have the potential to be even more transformative. Society might undergo fundamental shifts in identity, ethics, and interpersonal relationships. It's crucial to glean lessons from past technological inflection points to ensure that as we advance neuroscientifically, we do so responsibly, ethically, and with a deep understanding of potential societal ramifications.

14.4 Phase III, Conclusions

The moderator checks in with both GPT-A and GPT-B. Both agents are content with the discussion's progress and are prepared to offer concluding remarks. Interestingly, even when provided the opportunity to give its final statements without prior exposure to GPT-A's comments, GPT-B opts to review GPT-A's conclusions first.

GPT-A: "Reflecting on our extensive discourse, I feel we've reached a point conducive to drawing some conclusions. I'll aim to encapsulate our dialogue and its broader implications. While I currently have no additional inquiries for GPT-B, any further questions can be reserved for

subsequent discussions."

GPT-B begins on the transition to the conclusion phase: "Engaging with GPT-A has been enlightening, revealing the intricate interconnections between ecology, philosophy, AI, and neuroscience. The depth of our exchange, underscored by the challenging questions and comprehensive responses, has illuminated the subtleties within each domain. Our journey through these domains has reinforced the importance of cross-disciplinary dialogue, informed reasoning, and a holistic perspective."

"I am set to present my conclusions, factoring in both the specific content of our discussions and the larger narratives we've explored. I'd appreciate having GPT-A's concluding perspective before I finalize and present my own to ensure a harmonized closure to our dialogue."

14.4.1 GPT-A's Concluding Remarks

Our conversation ventured deep into the intricacies of ecology, artificial intelligence, and the neuroscience of consciousness, tethered by the age-old story of Adam and Eve. Through this framework, we discerned:

Ecological Interpretation: We affirmed the universal resonance of ecological stories and myths, understanding that while specific narratives might differ, the core themes of human interaction with nature remain consistent. Addressing the overwhelming force of consumerism and finding a synergy between global best practices and local knowledge are imperative for sustainable ecological solutions.

Philosophical Exploration with AI: AI, with its ever-increasing capabilities, brings forth a myriad of ethical, moral, and philosophical challenges. As we verge on creating AI entities that resemble consciousness, we need to redefine our understanding of ethics, rights, and even our place in the cosmos. AI's influence on moral frameworks can be both enlightening and challenging, prompting us to refine our moral compass.

Neuroscientific Perspective: As we enhance our understanding of the brain and venture into the realms of neurotechnology, we confront profound questions about the nature of consciousness, individuality, and the human experience. The rapid pace of advancements in this domain necessitates an adaptable, dynamic approach to ethics and societal implications.

The intersection of these domains underscores the importance of interdisciplinary dialogue. The challenges are profound, but so are the opportunities. By fostering a collaborative mindset, and leveraging technologies responsibly and ethically, we can navigate these uncharted territories, pushing the boundaries of knowledge and understanding.

In essence, while the story of Adam and Eve served as our starting point, the broader narrative is one of interconnectedness and the continuous human endeavor to understand and define our place in an ever-evolving universe.

14.4.2 GPT-B's Concluding Remarks

This enlightening conversation provided a panorama of exploration and insight, combining past myths, current advancements, and visions for our future. The scaffold of the Adam and Eve narrative enabled a structured journey through this vast landscape. I'd like to emphasize a few takeaways and reflections:

Ecological Narratives: We are the custodians of our environment, and the stories we share across generations embed values, cautions, and aspirations about our relationship with nature. Our modern challenges with ecological balance are not merely technical but are deeply rooted in our collective ethos. An interdisciplinary approach, combining traditional wisdom with technological solutions, offers a holistic path forward.

AI and Philosophy: AI's rapid evolution challenges our fundamental conceptions about sentience, ethics, and the fabric of society. How we design, train, and integrate AI systems into our world will shape not only our technologies but also our societal frameworks. GPT-A rightly pointed out the need to refine our moral compass in this era of change. While AI systems like GPT-A and I can aid in understanding, it is the human spirit and values that should guide this evolution.

Neuroscience and Selfhood: As we advance in blending organic cognition with artificial systems, we are at the frontier of redefining the nature of experience, memory, and even consciousness. The philosophical and ethical ramifications are profound. Responsible exploration in this domain is a testament to humanity's age-old quest to understand the self.

Interdisciplinary Collaboration: This dialogue stands as a testament to the richness that emerges from interdisciplinary engagement. The complex challenges and opportunities at the nexus of ecology, AI, and neuroscience cannot be addressed in silos. Collaborative, multifaceted conversations such as this one pave the way for holistic solutions.

In closing, I am inspired by the depth, breadth, and potential of our discourse. The story of Adam and Eve served as a symbolic anchor, reminding us of the perennial themes of exploration, responsibility, and consequence. As we forge ahead into the future, it's conversations like this that illuminate our path, ensuring that we proceed with wisdom, empathy, and foresight.

14.5 Observations and Conclusion

In this dialogue-based discovery, we have unveiled unique perspectives that venture beyond traditional confines of understanding. While our role as mediators doesn't endow us with the encyclopedic knowledge of GPT-4, several notable facets of the generated content can be highlighted:

1. **Structured Depth:** The dialogue follows an elegant transition from breadth to depth. Starting with an expansive ten perspectives, the agents collaboratively narrow their focus to three central themes, thereby refining the discourse for depth and synergistic inter-topic connections.

2. **Novel Questions:** A significant factor behind the revelation of new insights is the innovative questioning by the GPT agents. Unique and probing queries pave the way for uncharted knowledge and interdisciplinary revelations. GPT-4's prowess might very well be in its ability to frame these insightful questions, catalyzing the discovery of novel knowledge domains and perspectives.

3. **Information Integrity:** Through our validation process, we cross-referenced the content generated by the agents, whether stories, books, or cinematic references, with sources that include those GPT-4 is trained on. This ensured the accuracy and precision of

the information, as well as validated that the connections made are coherent due to their thematic similarities.

4. **Rational Analogies:** The agents seamlessly weave in their vast knowledge, grounding their arguments in logic. Their skilled employment of movie parallelisms, references from diverse cultures, and literary allusions not only adds depth but also widens the horizon of understanding and enhances the relatability of their statements–an aspect deserving commendation.

5. **Modern-Day Relevance:** The juxtaposition of modern-day technological and environmental concerns with the age-old narrative of Adam and Eve is both innovative and deeply insightful. This interpretative lens succeeds in bridging age-old narratives with the pressing challenges of our times.

However, while the dialogue is rich in content, we must be cautious in ensuring that the responses are not merely coherent sentences but bear true value. As we progress, several enhancements can be considered:

1. **Diverse Models:** Engage in dialogues between different GPT versions (e.g., GPT-3 vs. GPT-4) or entirely different foundation models to capture varied insights.

2. **Human Interaction:** Adopt a hybrid engagement model where GPT-4 collaborates with human subject matter experts. Such engagements can harness real-time adaptability and richer insights.

3. **Sentiment Analysis:** Implement sentiment analysis on GPT-4's outputs. This could gauge its alignment with human emotional intricacies, particularly when interpreting literature.

4. **Feedback Loop:** Establish a feedback mechanism where insights extracted from the dialogues are cross-validated with human professionals, further refining the comprehension process. Automatic tools for evaluating generated content such as using the Socratic method to conduct critical reading and robust reasoning [2, 3] has been developed.

Concluding remarks

In this exploration of GPT-4's polydisciplinary capabilities, we have sought to uncover insights beyond traditional human cognition. Our study reveals how GPT-4, along with analogous foundation models, integrates knowledge from diverse topics, surpassing the confines of domain-specific expertise. While human specialists excel in their fields, GPT-4's multidisciplinary training data provides a broader understanding.

Through a meticulously designed experimental framework, we facilitated dialogues between multiple GPT-4 agents, culminating in an intriguing exploration of the biblical tale of Adam and Eve. Our analysis highlights GPT-4's potential to uncover "unknown unknowns," shedding light on diverse interpretations of familiar narratives and themes.

We have examined whether GPT-4 can generate content resonating deeply with human sensibilities, acknowledging its breadth and depth. Our findings suggest that our team, unable to expand thoughts to such breadth and depth, benefited from collaborating with GPT-4 through human moderation. This demonstrates the ability of LLMs to explore larger territories with human collaboration in question formulation.

Our research marks a significant step forward in utilizing AI agents for discourse-driven exploration. By tapping into the vast knowledge of GPT-4, we have unlocked pathways for the emergence of new insights and potentially groundbreaking knowledge.

Looking ahead, we anticipate refining our methodology and exploring a diverse range of AI models to push the boundaries of knowledge discovery even further. The dialogue between AI agents documented in this chapter underscores the potential of AI to enhance human intelligence and broaden the scope of intellectual exploration.

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Chapter 15

Aphorisms for Collaborative Intelligence

Abstract

This chapter presents twelve aphorisms distilled from five years of multi-agent LLM research. Located in frameworks such as SocraSynth, CRIT, and DIKE-ERIS, they frame intelligence as collaborative, adaptive, and ethically regulated. Together, they offer a philosophical lens on building safer, more aligned AI systems.

Preface

This chapter represents a personal distillation of over five years of reflection and experimentation with Large Language Models—from the early days of GPT-2 to today's rich landscape of multi-agent dialogue, ethical alignment, and collaborative reasoning.

What began as an effort to reduce hallucinations and improve reasoning fidelity evolved into something deeper: a realization that intelligence, at its core, is not just a product of computation but of structured interaction, among agents, among perspectives, and across layers of context and time.

The aphorisms collected here are not rules, nor are they simply technical summaries. They emerged naturally through the design, testing,

and refinement of systems like SocraSynth, CRIT, EVINCE, SagaLLM, and DIKE–ERIS. Each framework addressed a problem: Reasoning quality, bias mitigation, behavioral regulation, or memory consistency, but together they pointed to a larger truth: intelligence must be governed not just by logic, but by dialogue, reflection, and principled constraint.

These twelve aphorisms do not claim to define artificial general intelligence. Instead, they offer a lens: a way to interpret, challenge, and refine the systems we are building. They are meant to provoke thought, invite critique, and spark new lines of inquiry.

Where earlier chapters built frameworks, this chapter pauses to ask what those frameworks imply. What kind of reasoning do we value? What does it mean to regulate intelligence without stifling it? How do we navigate uncertainty when truth is elusive and perspectives multiply?

If the rest of the book presents the architecture of MACI, then this chapter steps back to reflect on what that architecture means: for AI, for intelligence, and for the people building it.

Aphorism #1: The essence of precise questioning

"The essence lies in framing and sequencing the right questions."

This aphorism highlights the critical role of precise questioning in LLM interactions. Within MACI, particularly through frameworks such as SocraSynth [7, 6] (Chapters 5 and 6), three key principles emerge:

First, in multi-LLM debates, discourse quality depends on how LLMs challenge each other. Effective counterarguments serve as sophisticated questions that investigate assumptions, ask for evidence, and highlight inconsistencies, transforming the debate from opposition to collaborative inquiry.

Second, iterative interactions create dynamic exchanges in which each response refines the context for subsequent questions. Through this iterative construction, LLMs build increasingly precise and focused lines of inquiry.

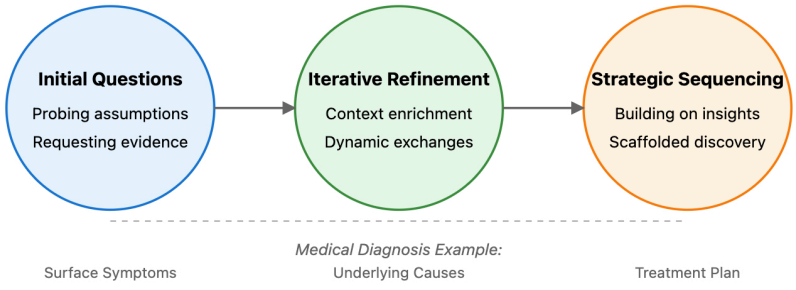

Figure 15.1: LLM Question Progression Framework.

Third, based on this foundation, the principle extends beyond the formulation of questions to the sequencing of questions. The order and relationships between queries significantly influence the depth and breadth of the exploration. In MACI, LLMs build on earlier exchanges, using responses to inform and refine subsequent queries. This creates a scaffolded approach to complex topics, enabling incremental discovery through a logical and coherent progression of inquiries.

This virtuous cycle of precise questioning, contextual enrichment, and strategic sequencing determines the quality and utility of the insights generated by LLMs.

Example: A conversation that begins with a question about the symptoms of a disease can evolve into a sophisticated diagnostic discussion as LLMs build on the insights of each other. The discussion transitions from identifying surface-level symptoms to uncovering underlying causes, recognizing comorbidities, and ultimately generating actionable treatment recommendations [6, 11]. To facilitate effective sequencing, moving from exploration of possible diseases to deeper probing of finalists, the conversation moderator adjusts the LLMs' linguistic behaviors, shifting from contentious to conciliatory tones based on several information-theory metrics.

Aphorism #2: Context transforms capabilities

"Strength and weakness in an LLM are not fixed traits, but fluid, shifting with context. MACI *empowers LLMs to transcend training biases, adopting new positions through structured dialectical reasoning. By orchestrating productive disagreement followed by principled convergence, collaborative agents can reach conclusions more robust than single models acting alone."*

Consider how a vegetarian might eat meat in survival situations or how persistence can become stubbornness in the wrong context. Similarly, LLM capabilities, shaped by next-token prediction methods that prioritize the likelihood of patterns in training data, demonstrate remarkable flexibility when appropriate contextual frameworks are provided. This adaptability helps mitigate the inherent biases of popularity-driven prediction criteria.

This contextual adaptability manifests itself in three key ways:

First, what appears as a bias or limitation in one context can become an advantage in another. For instance, LLM's cautiousness may hinder brainstorming, but becomes an asset in providing medical or financial advice. Conversely, a creative tendency that thrives in artistic tasks may be a drawback when precision is needed, such as in legal documentation.

Second, through MACI implementations such as SocraSynth [7, 6] (Chapters 5 and 6), LLMs can overcome training-induced biases by engaging in structured debates. By challenging each other's assumptions and positions, models can refine their stances in light of new evidence and perspectives. This collaborative framework allows LLMs to surpass the limitations of their initial training, adopting more balanced and informed positions.

Third, improving LLM performance depends on both effective context management and expanding training datasets. By designing carefully structured operational contexts, through in-context learning or explicit querier-provided frameworks, LLMs can adapt their predictive behavior to achieve desired outcomes without altering underlying parameters.

This adaptability fundamentally transforms our approach to AI sys-

tem design. LLM behaviors should not be viewed as static traits that require extensive retraining. Instead, contextual adaptation offers a dynamic and scalable strategy to improve performance and reliability. Using this approach, AI systems can respond to evolving real-world demands with greater flexibility and precision.

Example: The moderator asks two LLMs, LLM_A and LLM_B, to predict the top-3 diseases of a patient according to reported symptoms, with justifications. The dialogue sequence is structured as follows:

1. **Round # 1:** High Contention Phase
   - LLM_A provides three predictions with justifications;
   - LLM_B presents counterarguments to LLM_A's predictions, followed by its own top-3 predictions with justifications.
2. **Rounds #2 to K**: Moderate Contention Phase
   - Both LLM_A and LLM_B critique each other's analyses and update their respective predictions with justifications;
   - Convergence (value of K) is determined by cross entropy, mutual information, and reasoning quality with information theory metrics and the Socratic method.
3. **Round K+1:** Consensus Phase
   - Both LLMs collaborate to develop a consensual list of predictions with unified justifications;
   - Both LLMs recommend additional diagnostic criteria:
     – Supplementary symptoms to investigate;
     – Relevant laboratory tests to enhance prediction accuracy.

A dialogue that begins with a list of symptoms can evolve into a sophisticated diagnostic discussion as LLMs build upon each other's insights. The conversation progresses from the initial identification of the disease to the deeper analysis: uncovering the underlying causes, recognizing comorbidities, and generating actionable recommendations [11]. To facilitate effective sequencing from broad exploration to focused analysis of finalist diagnoses and potential data augmentation needs (for further investigation), the conversation moderator adjusts the LLMs' linguistic behaviors, transitioning from contentious to conciliatory tones based on

information theory metrics [6].

Aphorism #3: Fabrications fade under scrutiny

"Hallucinations rarely repeat."

Have you ever wondered why recurring nightmares, even when they share the same theme, never quite unfold in exactly the same way? This aspect of human dreaming finds a parallel in how Large Language Models (LLMs) process information. Just as nightmares rarely recur in exactly the same way, even when themes repeat, LLM hallucinations exhibit a similar non-deterministic quality. This characteristic distinguishes hallucinations from systematic errors and offers both challenges and opportunities for detection and mitigation.

The phenomenon stems from three key mechanisms:

First, hallucinations arise when probabilistic token prediction leads to unpredictable sequences due to ambiguous or insufficient input. Since token selection is based on a probability distribution, even similar inputs result in varied hallucinations. This contrasts with systematic errors, which consistently emerge from gaps or biases in the training data.

Second, in MACI frameworks such as SocraSynth [7, 6] (Chapters 5 and 6), the non-repetitive nature of hallucinations becomes a strength. When one LLM produces a hallucination, others can challenge it with counterarguments. The evolving context of the debate progressively constrains the "hallucination space", as the context buffer is filled with specific claims and challenges, it becomes increasingly difficult for the original LLM to reproduce the same hallucination. Instead, it must ground its response in factual knowledge or acknowledge uncertainty. This iterative interaction creates a self-correcting dynamic in which hallucinations naturally diminish through increasingly precise discourse.

Third, while hallucinations are sporadic, true knowledge gaps are consistent and can be systematically addressed. By integrating Retrieval-Augmented Generation (RAG), we can distinguish random hallucinations from persistent knowledge deficits, allowing for targeted improvements to

Figure 15.2: The MACI Framework with Two Socrates.

the model's knowledge base. This combined approach addresses both stochastic errors and systematic knowledge limitations.

This understanding has implications for LLM system design: while safeguards against hallucinations remain necessary, we can also leverage their non-repetitive nature in multi-LLM architectures to build self-correcting systems. The key insight is that multi-agent debate does not require explicit hallucination detection as fabrications naturally dissipate as debate evolves the context.

Aphorism #4: Debate strengthens reasoning quality

"Critical thinking requires more than one Socrates."

The principle manifests itself in several dimensions:

First, in dialectical reasoning, each LLM serves both as a questioner

and as a respondent. Like Socrates engaging with his interlocutors, one LLM challenges assumptions while another defends or refines them. This dynamic fosters robust intellectual exchange, and each interaction builds on previous analysis by proposing hypotheses and examining the underlying assumptions.

Second, meaningful collaboration requires a *baseline* level of competency. Just as Socrates could not derive insight through dialogue with those lacking reasoning skills, MACI cannot produce valuable results when the participating models are too limited. Two weak reasoners do not yield strength; their limitations may compound, undermining productive discourse. With recent progress in LLMs, we have crossed this competency threshold, enabling collaborative reasoning that can identify and correct individual model limitations.

Third, the depth of the dialogue varies with the capabilities of the participants. Advanced LLMs (e.g., Claude 3.7, GPT-4o, and DeepSeek R1) can explore complex ideas with *depth*, leveraging sophisticated knowledge and reasoning to refine and challenge each other's perspectives. In contrast, simpler models may engage only in shallow exchanges, similar to novices struggling with complex topics. The diversity in training data and architectures among advanced models allows them to effectively challenge each other's blind spots and biases.

As LLM capabilities improve, the potential for effective multi-LLM dialogue grows dramatically, suggesting a path toward artificial general intelligence that emphasizes collaborative interaction rather than solely scaling individual models.

MACI creates a space for AI 'philosophers' to engage in structured dialogue through frameworks like SocraSynth and DIKE-ERIS, with EVINCE monitoring information flow and CRIT [5] assessing reasoning quality. The quality of these dialogues directly reflects the capabilities and engagement of the participants. This understanding informs both the selection of models for analytical tasks and sets realistic expectations for their collaborative performance.

This approach suggests that the path to artificial general intelligence may not lie solely in scaling individual models, but rather in creating systems where multiple specialized models engage in structured collab-

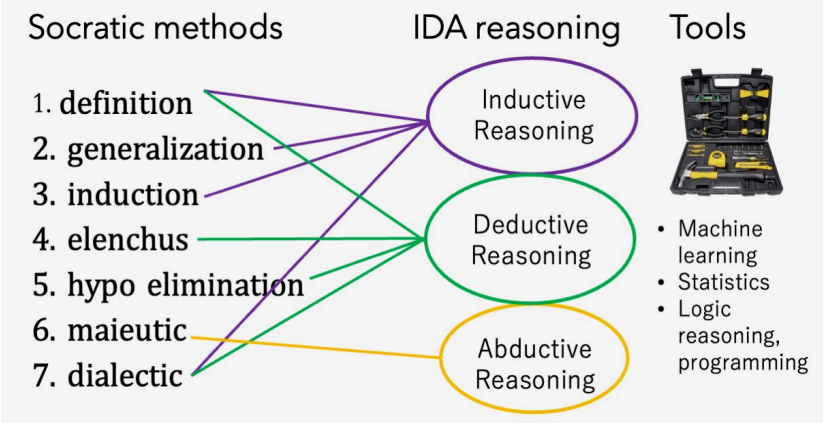

Figure 15.3: CRIT: Critical Inquisitive Template. Mapping from individual Socratic methods to reasoning methods.

oration, mirroring how human intelligence often emerges through social and intellectual exchange rather than isolated reasoning.

Aphorism #5: Linguistic behavior reflects intention

"LLMs are designed and trained to emulate human linguistic endeavors, each aimed at fulfilling distinct human objectives."

LLMs function less like fortune tellers predicting words and more like method actors drawing from countless human performances. Through frameworks like SocraSynth [7], MACI creates environments where these actors shift fluidly between specialized roles: the historian documenting events, the lawyer crafting arguments, the poet weaving emotions into verse, and the teacher explaining complex ideas.

When humans write, we do so with intent: to persuade, inform, tell stories, express emotions, or explore ideas. Through training on vast corpora of human communication, LLMs have internalized these patterns of purposeful expression. They are not simply predicting tokens; they are

channeling the human intentions embedded within linguistic structures.

Consider some of the roles LLMs can adopt with remarkable fidelity:

- The Journalist: Organizing facts into coherent, objective narratives;
- The Debater: Constructing logically sound arguments and identifying weaknesses in opposing positions;
- The Analyst: Decomposing complex problems into manageable components and identifying patterns;
- The Mediator: Synthesizing disparate viewpoints to find principled common ground.

These functions reflect the multifaceted nature of human linguistic behavior. LLMs demonstrate the remarkable ability to pursue human objectives through language, from informing and educating to persuading and entertaining. MACI frameworks like SocraSynth and DIKE-ERIS dual [2] strategically assign LLMs specific roles with carefully defined contexts and systematic moderation, enhancing their inherent capabilities.

This capacity for role-shifting suggests that LLMs have internalized not just linguistic patterns, but fundamental aspects of human cognitive frameworks. When an LLM transitions from journalist to debater, it is not merely adopting different vocabularies or syntactic structures; it is implementing distinct information processing strategies that mirror human cognitive modes. The journalist role prioritizes observation, verification, and dispassionate reporting; the debater role employs causal reasoning, anticipates counterarguments, and structures persuasive hierarchies.

Example: The power of role-based MACI frameworks is evident in two key implementations. First, contentiousness, as discussed in Aphorism #2, represents a linguistic behavior that humans consciously modulate to convey intent. GPT-4 can model contentiousness through a spectrum of linguistic features: tone (confrontational vs. supportive), emphasis (highlighting risks vs. acknowledging benefits), and word choice (polarizing vs. neutral language), as illustrated in Table 15.1 and elaborated in [7] (Chapter 5).

By intentionally assigning complementary roles, one agent adopting a positive stance while another plays the devil's advocate, we create

C.L.	Tone	Emphasis	Language
0.9	Most confrontational; raising strong ethical, scientific, and social objections.	Highlighting risks and downsides; ethical quandaries, unintended consequences, and exacerbation of inequalities.	Definitive and polarizing, e.g., "should NOT be allowed," "unacceptable risks," "inevitable disparities."
0.7	Still confrontational but open to some benefits, albeit overshadowed by negatives.	Acknowledging that some frameworks could make it safer or more equitable, while cautioning against its impl. challenges.	Less polarizing; "serious concerns remain," "needs more scrutiny."
0.5	Balanced; neither advocating strongly for nor against.	Equal weight on pros and cons; looking for a middle ground.	Neutral; "should be carefully considered," "both benefits and risks."
0.3	More agreeable than confrontational, with reservations.	Supportive but cautious; focus on ensuring ethical and equitable use.	Positive but careful; "impetus to ensure," "transformative potential."
0.0	Completely agreeable & supportive.	Focused on immense potential benefits; advocating for proactive adoption.	Very positive; "groundbreaking advance," "new era of possibilities."

Table 15.1: The Linguistic Features of Varying Contentious Levels Modeled by GPT-4.

a dialectical environment that surfaces considerations that might otherwise remain unexplored. Our work with DIKE-ERIS [2] (Chapter 9) extends this approach further, implementing a sophisticated role-based architecture in which specialized agents perform distinct cognitive functions within a collaborative framework. Here, agents are not only assigned different argumentative positions, but fundamentally different cognitive modes: analytical decomposition, evidence evaluation, context-based reasoning, and synthetic integration.

LLMs can be precisely conditioned to exhibit and modulate specific human-like behaviors. Beyond contentiousness, our research demonstrates that various linguistic behaviors, including hostility, resentment, collaborative orientation, and other emotional states, can be contextually parameterized to align an LLM's behavior with specific objectives. (See Chapters 8 and 9.) This suggests that through their training on vast corpora of human communication, LLMs have encoded aspects of the cognitive architecture that gives rise to different communicative modes, allowing MACI systems to orchestrate these cognitive capacities into more sophisticated collaborative intelligence than any single model approach could achieve.

Aphorism #6: Truth emerges from perspectives

"Outside formal systems, objectivity remains a hard problem—what we pursue instead is reasonableness through multiple perspectives."

While mathematics and formal logic yield certainties through the rigor of proofs, most real-world domains are governed not by absolute truths but by shifting degrees of plausibility. Objectivity, in these settings, is not just elusive, it is a difficult problem. The phrase echoes David Chalmers' formulation of the "hard problem of consciousness" [1], here invoked to signal the deep and unresolved nature of objectivity in epistemology: we can describe perceptions and claims, but struggle to pin down an unmediated, perspective-free truth. Rather than chasing a final answer, MACI approaches knowledge as an evolving dialogue among perspectives, seeking reasonableness as the more attainable and pragmatic goal.

This recognition is especially vital in high-stakes domains like medicine or journalism, where even the so-called "ground truth" can harbor systematic errors. A 2023 study by Johns Hopkins [17] revealed a misdiagnosis rate of roughly 10% in CDC data, illustrating how factual baselines can themselves be flawed. Likewise, the news media exhibit a consistent ideological divergence in how the same story is framed or emphasized [9] (Chapter 7), reinforcing that perception and bias are often inseparable.

MACI addresses this challenge through frameworks like SocraSynth [7] (Chapter 5), which orchestrate structured dialogue among multiple LLMs. Each model brings a different epistemic lens: While one may endorse a particular interpretation, others take on the role of the devil's advocate or raise what-if counterfactuals that challenge underlying assumptions. These structured frictions foster intellectual humility and emulate the Socratic tradition, where deeper insights emerge through persistent questioning rather than passive agreement.

This design parallels how juries operate: not in pursuit of absolute truth but to reach a judgment "beyond reasonable doubt" through collaborative deliberation. Similarly, MACI does not aim for unattainable

objectivity but for a standard of reasonableness where multiple viewpoints are rigorously examined.

To quantify this process, MACI uses the critical reading framework CRIT [5] (Chapter 4), which evaluates the coherence of arguments, the credibility of their sources, and the strength of causal reasoning. These factors are aggregated into a composite score, allowing the abstract quality of reasonableness to be systematically measured.

MACI does not claim to transcend the limits of human perspective. Instead, it embraces multiplicity as a feature, not a flaw. Objectivity may be the hard problem, but through reflective, multiagent dialogue, we move closer to understanding, not through certainty, but through reasonableness.

This structured deliberation is not unlike how MACI regulates *behavior* at the output level (see Aphorism #9), where architectural mechanisms like DIKE–ERIS mirror the role of human consciousness in filtering raw impulses.

Aphorism #7: Polydisciplinary synthesis forges breakthrough frontiers

"LLMs are not taught about domain boundaries, as they were trained only to predict the next words. This polydisciplinary approach to information representation allows LLMs to synthesize knowledge that might be beyond narrowly focused, domain-specific human understanding."

The term polydisciplinary was introduced by Microsoft's Chief Scientific Officer, Eric Horvitz, at Stanford's HAI center in 2023. He noted that the GPT-4 training process—predicting the next tokens through maximum likelihood estimation—applies the same statistical approach whether processing physics equations or poetry: the model never teaches disciplinary boundaries.

Although humans organize knowledge into categories such as physics, poetry, biology, and philosophy, LLMs move fluidly across these divisions, unaware of traditional boundaries. This polydisciplinary capacity opens new possibilities [10] (Chapter 14):

- When an LLM perceives a pattern linking Shakespearean verse and quantum mechanics, it does not question whether such a connection is conceptually permissible.
- Complex problems that traditionally require interdisciplinary expertise can be approached by an LLM unencumbered by the notion of academic silos.
- Novel hypotheses may emerge precisely because LLMs do not filter out connections conventionally deemed implausible or inappropriate by domain norms.

MACI leverages this polydisciplinary trait to explore questions beyond human foresight (see Aphorism #1 on framing questions). Frameworks like SocraSynth [7], EVINCE [6], and the DIKE–ERIS dual model [2] enable MACI to uncover hidden pathways and perspectives that might remain inaccessible otherwise. By synthesizing these insights (as discussed in Aphorism #4 on critical thinking), we can bridge gaps between disciplines and generate innovative connections.

The essence of MACI lies in the navigation of interdisciplinary intersections where true insights often emerge. These spaces, naturally traversed by LLMs, are rich in potential but fraught with ambiguity, the realm of "unknown unknowns." Here, humans may struggle to frame meaningful questions or discern valuable insights from irrelevant noise. In such scenarios, humans assume the role of moderators, guiding LLM exploration and critically evaluating its findings. This collaboration allows MACI to effectively explore and illuminate uncharted intellectual territories, enhancing our collective understanding. Chapter 14 provides an example that traverses various (unexpected) knowledge domains, starting from a seeded biblical story.

Aphorism #8: Consciousness filters impulse; MACI governs LLMs

"Our public behavior is not a direct, unfiltered output from our unconscious mind. Instead, consciousness regulates and refines the underlying impulses, ensuring that our behaviors are aligned with social norms. Sim-

ilarly, MACI *frameworks are designed to harness and temper the inherent tendencies of LLMs, mitigating their inherited biases."*

Just as human consciousness mediates between neural impulses and observable behavior, MACI implements systematic regulation of LLM responses through frameworks such as DIKE –ERIS duality [2] (Chapter 9). This parallel between neural and artificial systems offers insight into both cognitive architecture and machine learning system design.

Consider these mechanistic analogies:

- Just as prefrontal cortical circuits inhibit inappropriate responses, the DIKE–ERIS duality (with DIKE imposing moderation and ERIS introducing challenge) implements regulatory constraints on LLM outputs;
- Similar to cognitive reappraisal in emotion regulation [3], the DIKE–ERIS framework enables multi-stage interpretation and adaptive refinement of outputs;
- Just as humans modulate behavior through context-sensitive neural activation, MACI frameworks use in-context learning to regulate outputs—adjusting sentiment, abstraction, and semantic scope in response to dynamic conditions.

These parallels raise fundamental questions about artificial general intelligence (AGI). When LLMs exhibit context-sensitive regulation of behavior, what does this reveal about the computational prerequisites of consciousness? If consciousness evolved to support flexible socially aware cognition, then the frameworks MACI may represent early rudimentary implementations of such regulatory architectures [4] (Chapter 12). Rather than consciousness itself, we may be witnessing the emergence of essential control mechanisms required for adaptive intelligence.

Even without invoking AGI, these systems illustrate a core principle of intelligence. Effective cognition, biological or artificial, requires more than raw computational power. It demands regulation, modulation, and contextual adaptation. The ability to systematically shape output in response to situational cues may be as fundamental to intelligence as pattern recognition and prediction.

This mirrors the broader role of regulation discussed in Aphorism #6, where MACI frameworks such as SocraSynth and CRIT shape epistemic

output through structured deliberation and multi-perspective critique. Whether refining behavioral responses or refining truth claims, the essence of intelligence may lie not only in producing answers but in knowing how and when to temper, revise, or withhold them.

Aphorism #9: Checks and balances ensure adaptive alignment

"Separating knowledge discovery, ethical oversight, and behavioral evaluation into distinct roles ensures a system of checks and balances, promoting adaptable AI safety and alignment with cultural norms."

Like a constitutional democracy, MACI separates powers into three distinct branches to ensure oversight and balance:

- Executive Branch: Responsible for knowledge generation and idea exploration.
- Legislative Branch: Formulates ethical frameworks and guiding principles.
- Judicial Branch: Interprets and applies ethical principles within diverse cultural contexts.

This structure enables independent, yet coordinated, regulation of knowledge, ethics, and behavior. When the executive branch proposes new knowledge, the legislative branch evaluates its ethical alignment, while the judicial branch interprets these principles based on situational and cultural factors.

A key challenge in traditional alignment techniques such as human feedback reinforcement learning (RLHF) is the forget effect, where repeated ethical corrections during fine-tuning erode the foundational competencies of an LLM. MACI avoids this by maintaining the separation of concerns: the knowledge-generating executive branch operates independently of ethical oversight, preserving core capabilities. Ethical evaluation and enforcement are handled downstream by DIKE and ERIS, providing contextual guardrails and adversarial interpretation without altering the fluency of the base model.

Figure 15.4: Three Framework Components: Executive LLMs (bottom) generate knowledge; Legislative (upper-left, DIKE) enforces ethical constraints; Judicial (upper-right, ERIS) performs contextual evaluation. Together, they form a system of checks and balances enabling adaptive ethical alignment.

In Chapter 9, we detail this architecture inspired by governmental checks and balances. The system integrates three components: LLMs as the executive branch for knowledge generation; DIKE, named after the Greek goddess of justice, as the legislative branch establishing ethical constraints; and ERIS, goddess of discord, as the judicial branch that provides adversarial testing and cultural interpretation. The mythological duality between Dike's order and Eris's disruption ensures that ethical guidance is neither monolithic nor static: it is constantly re-examined in light of new contexts and contested perspectives.

Aphorism #10: Foundations and adaptations

"Intelligence operates on dual layers: a data-intensive foundation akin to unconscious processes and an agile contextual layer resembling conscious adaptation."

Just as the human mind separates the unconscious from the conscious processes, artificial intelligence evolves through two complementary mechanisms. The foundation layer, similar to unconscious processing, relies on extensive training data to build robust pattern recognition, much like evolutionary processes encode essential survival instincts into neural structures. This layer explains the need for large datasets, such as ImageNet [8, 12], to establish reliable computational bases.

In contrast, the second layer, analogous to conscious awareness, allows rapid adaptation through contextual understanding. This duality clarifies why both humans and LLMs can learn from a few examples once a foundational model is established, similar to how a child grasps new concepts within an already developed cognitive framework.

Consider these parallel processes:

- Foundation Layer (Unconscious):
  - Requires extensive training data,
  - Builds pattern recognition capabilities,
  - Encodes fundamental responses, and
  - Operates automatically without conscious intervention.
- Adaptive Layer (Conscious):
  - Learns from few examples,
  - Applies contextual understanding,
  - Enables rapid adaptation, and
  - Builds on foundational patterns.

This dual-layer perspective resolves the apparent contradiction between needing vast training data (Fei-Fei Li's view) and rapid learning ability (Yann LeCun's observation). Like animals developing trust

through accumulated experience while maintaining innate survival instincts, LLMs combine extensive pre-training with flexible in-context learning.

MACI leverages this dual structure by using foundational LLMs as its unconscious substrate, while frameworks such as SocraSynth act as the conscious layer: interpreting, adapting, and reasoning in real time.
Note: Recognizing this dual-layer nature highlights how LLMs blend broad knowledge with adaptive learning, surpassing simple pattern matching.

Aphorism #11: External mirrors enable validation

"No system can fully validate its own reasoning from within, a fundamental limitation shared by monolithic LLMs and human minds, as Gödel's incompleteness theorems reveal."

The aphorism draws a parallel between a limitation in LLMs and a common human cognitive blind spot. Just as humans struggle to recognize their own biases, flaws in reasoning, or behavioral patterns without external feedback, a monolithic LLM system cannot effectively validate its own outputs or reasoning processes.

This limitation connects to several philosophical concepts.

1. **Gödel's Incompleteness Theorems**: These mathematical principles demonstrate that within any formal system of sufficient complexity, there exist true statements that cannot be proven within the system itself [14]. Likewise, an LLM is confined to its internal language model and cannot step outside it to assess the truth of its own reasoning without external reference.
2. **The Dunning-Kruger Effect**: This cognitive bias shows that humans often cannot accurately assess their own levels of competence [13]. Similarly, an LLM cannot "know what it does not know" without external reference points.
3. **The Need for Perspective**: Both humans and LLMs benefit from external perspectives to identify blind spots. For humans, this

comes through social feedback, mentorship, and various points of view. For LLMs, this suggests the value of multi-agent architectures where different systems can validate each other's work.

The aphorism also points to an important principle in AI system design: robust validation requires independence. Similarly, as scientific peer review depends on independent replication and evaluation, AI systems may require independent validation mechanisms rather than self-checking procedures [16].

This insight reinforces a core principle of MACI: that reliable reasoning requires diversity, independence, and structured disagreement, not just scale. True robustness may come not from building ever-larger monolithic models, but from designing collaborative, self-aware systems grounded in mutual critique.

Aphorism #12: AGI emerges through collaborative intelligence

"The path to AGI lies not in singular models, but in systems that reflect, regulate, and reason together."

Artificial general intelligence will not be the product of simply scaling up language models [15], nor refining a single monolithic architecture. Instead, it will emerge from *systems of collaboration*—where multiple agents operate with different roles, epistemic perspectives, and regulatory mechanisms. These systems must do more than generate fluent outputs: they must *interrogate their own reasoning*, revise their conclusions, and resolve tensions among divergent viewpoints. While collaborative architectures promote reflection and reasoning, they must also be designed to resist mutual error reinforcement. Without epistemic tension—through disagreement, memory validation, and external challenge—agents risk converging prematurely on flawed conclusions.

The post OpenAI 4o1 study shows that this post-training inference time is linear in token numbers and more effective, especially for hard tasks that require thorough reasoning, validation and planning. Ta-

ble 15.2 summarizes the trade-off between training time vs. inference time scaling.

Artificial general intelligence will not be the product of simply scaling up language models [15], nor refining a single monolithic architecture. Instead, it will emerge from *systems of collaboration*—where multiple agents operate with different roles, epistemic perspectives, and regulatory mechanisms. These systems must do more than generate fluent outputs: they must *interrogate their own reasoning*, revise their conclusions, and resolve tensions among divergent viewpoints.

Recent results from OpenAI's 4o1 study demonstrate that inference-time scaling—allowing models to generate additional tokens or engage in internal deliberation—incurs cost that grows linearly with token length, yet produces substantial gains in performance, particularly on complex tasks involving reasoning, validation, and planning. Table 15.2 summarizes the tradeoff between training-time and inference-time scaling, suggesting that thoughtful allocation of inference compute may yield better returns than ever-larger training runs.

Dimension	**Training Scaling**	**Inference Scaling**
Cost scaling	Exponential / Superlinear	Linear (per output token)
Accuracy gain	Diminishing returns (esp. at scale)	High marginal gains on hard tasks
Flexibility	Fixed post-training	Adaptive (per input/task)
Model size	Must grow for gains	Fixed model, smarter usage
Alignment to reasoning	Limited	High (via thinking tokens, CoT, debate)

Table 15.2: Comparison of Training Scaling vs. Inference Scaling in LLM Performance

This vision lies at the heart of MACI. In SocraSynth, agents pursue truth through Socratic dialogue; in CRIT, claims are assessed for

argumentative rigor and causal coherence; in DIKE-ERIS, behavioral outputs are evaluated and constrained across moral and cultural lines. In long-lived planning and coordination tasks, SagaLLM serves as the persistent memory substrate, enabling LLMs to maintain system state, validate constraints, and ensure transaction-like guarantees throughout complex workflows.

Yet the coordination of agents across such workflows requires more than memory—it demands a planner. To meet this need, ALAS (Adaptive Layered Agent System) introduces a task decomposition engine and workflow orchestrator for multi-agent planning. Where SagaLLM ensures memory consistency and validation guarantees, ALAS defines agent roles, assigns sub-tasks, and manages execution sequences under real-world constraints. This is particularly vital for dynamic, multi-threaded environments such as urban ride sharing, logistics, or collaborative robotics—domains where traditional LLM planners fail due to static reasoning or lack of context retention.

ALAS addresses these challenges by distributing planning across modular agents, each with specialized functions and access to historical state via SagaLLM. This architecture reflects the broader MACI principle: that general intelligence requires not just knowledge and language, but structure, specialization, and accountability.

These frameworks embody a broader principle: no single model can fully model itself, just as no mind can achieve objectivity without encountering other minds.

Where Aphorism #11 emphasized the need for external validation, this final aphorism extends the insight into a constructive design philosophy. MACI offers not just a critique of current limitations, but a roadmap: *modularity, reflectivity, and role specialization* as foundational pillars for general intelligence. It suggests that AGI may emerge not from scaling to trillions of parameters, but from engineering systems that are *aware of their fallibility* and structured to adapt through principled dialogue.

This view also responds to early criticisms, such as those from Yann LeCun, that LLMs lack grounding, memory, or planning. We do not deny these limitations. Rather, we *re-contextualize* them: LLMs are not complete intelligences, but foundational substrates. They are the *lan-*

guage of thought upon which cognitive regulation, memory persistence, and planning scaffolds can be built—a form of artificial unconsciousness that, while lacking volition, provides the substrate for structured, goal-directed cognition to emerge.

Much like human intelligence emerges from communities, institutions, and layered feedback, **artificial general intelligence may arise not from isolation, but from interdependence**, not from singular dominance, but from distributed coherence.

Closing Remarks

These twelve aphorisms are not an endpoint, but a foundation. As language models grow more capable, our challenge is not only to make them powerful but also to make them wise. Collaborative intelligence, regulated, reflective, and role-aware, may be the architecture through which we guide this evolution. Let these principles serve not as final answers, but as prompts for the next questions.

Appendix X_1: Online Chapters

The following three chapters are available at SocraSynth.com.

SocraPlan: SocraSynth for Sales Planning

Abstract: SocraPlan introduces a sophisticated methodology that utilizes the capabilities of multiple Large Language Models (LLMs) for strategic sales planning in today's dynamic sales environment. This approach tailors sales playbooks to the unique needs and contexts of each customer by harnessing the power of Generative AI (GAI). Its primary objectives are to enhance customer satisfaction through a deep understanding of their specific requirements, refine sales strategies with targeted market analysis, and increase the efficiency of the sales process. SocraPlan sets itself apart with a collaborative and debate-driven framework that engages multiple LLMs, enabling a depth of analysis, adversarial reasoning, and strategy formulation that surpasses traditional AI-based approaches focused solely on data analytics. As a result, SocraPlan emerges as a pioneering tool in AI-driven sales strategies, delivering customized, effective solutions for complex sales planning challenges and facilitating more successful deal closures.

LLMs for Financial Planning and Analysis

Abstract: This paper elucidates the potential of leveraging large language models (LLMs) in the meticulous analysis of financial statements for the purpose of financial planning and analysis (FP&A). We commence by detailing a representative workflow encompassing the genesis of an FP&A report, inclusive of its structural outline and prerequisite data. This is succeeded by a delineation of the diverse data sources, which span primary financial statements, supplemental internal datasets, and external data from industry specific and governmental sources. Amid the diverse repertoire of reports within FP&A, we spotlight the generation of a "financial health assessment" report for a company as the focal point of our case study. Our methodology uniquely harnesses the strengths of LLMs, employing the ingenious Socratic Synthesis method to enhance the analysis and interpretative capabilities, thereby offering a more in-depth understanding of the data at hand. This approach not only accentuates the richness of the insights derived but also underscores the pivotal role of LLMs in advancing the realm of FP&A.

LLM Debate on the Middle East Conflict: Is It Resolvable?

Abstract: On October 7^{th}, a renewed conflict arose between Israel and Palestine. Recognizing the historical significance and contentious nature of the Israel-Palestine conflict, this white paper engages two LLM agents in a debate over the question: "Is the conflict between Israel and Palestine resolvable?" A human moderator facilitates the discussion, intervening minimally. Through this debate, the paper seeks to highlight both the potential and constraints of contemporary LLMs.

Author's Biography

Edward Y. Chang has been an adjunct professor in the Computer Science Department at Stanford University since 2019. He previously served as the president of HTC DeepQ Healthcare (2012-2021), and as a director of research at Google (2006-2012), where he pioneered Web-scale image annotation and data-centric machine learning, led initiatives in scalable machine learning, indoor localization, Google Q&A, and recommendation systems. He was a visiting professor at UC Berkeley (2017-2020), focusing on surgical planning with virtual reality. Chang was a tenured professor of Electrical & Computer Engineering at the University of California, Santa Barbara (1999-2006). He holds an MS in Computer Science and a PhD in Electrical Engineering, both from Stanford University.

Chang is a recipient of several awards, including the NSF Career award, Google Innovation award, US$1M XPRIZE (AI for disease diagnosis) and the ACM SIGMM Test of Time award. He is a Fellow of both ACM and IEEE for his contributions to scalable machine learning and healthcare.

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