Interactive Thought Networks (ITN): An Interactive Granular Computing Approach to Complex Reasoning in AI *the concept of a research seminar at KMMI UWM*

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Abstract

The ITN project introduces a ground-breaking approach to reasoning in artificial intelligence, combining advanced language models (LLMs) with granular computing theory. Addressing the limitations of traditional Chain of Thought (CoT) methods, ITN proposes dynamic, multidimensional networks of conceptual units, enabling AI to perform adaptive and contextual reasoning reminiscent of human cognition. Reasoning in ITN is based on information stored in informational layers of complex granules, the basic objects of Interactive Granular Computing (IGrC). IGrC is a generalization of the Granular Computing (GrC) model; complex granules in IGrC are linking abstract and physical objects contrary to information granules in GrC closed in the abstract space only.

This interdisciplinary research integrates linguistics, computer science, cognitive sciences, and mathematics to create AI capable of deep understanding of complex problems, creative problem-solving, and decision-making under uncertainty. The project encompasses both theoretical foundations for ITN and practical implementations, with potential applications in advanced data analysis, medicine, finance, and innovative problem-solving. The execution of tasks by complex granules in IGrC or their societies relies on computations performed over granular networks generated by the reasoning engines of these complex granules. These reasoning engines are based on what are known as complex games, which consist of families of transformations that are triggered by labeling them complex vague concepts. One of the challenges in this context is the adaptive learning of such games supported by LLMs.

One may justly term these calculus as deep granular networks.

The proposed research seminar combines theoretical foundations with practical workshops, aiming to develop the ITN concept and educate a new generation of AI researchers. Collaboration with experts in Retrieval-Augmented Generation (RAG) will provide participants with comprehensive understanding of cutting-edge AI techniques.

ITN has the potential to revolutionize the perception and creation of intelligent systems, paving the way for AI that transcends mere information processing to achieve advanced cognitive capabilities.

In section 2 the general idea of the ITN project is presented. The Department of Mathematical Methods in Computer Science (KMMI) plans to implement the project in the form of a research seminar described in section 5. The seminar will begin with sixteen sessions of 70 minutes each, conducted by Bert Gollnick `https://gollnickdata.de/#/aboutme` (two per day

on eight dates). Each session will last approximately 70 minutes. The eight meetings are tentatively planned for Wednesdays, starting at 16:30. Exact dates and times may be subject to change based on the finalization of the UWM student schedule. A detailed plan of the sessions is presented in section 5.2.

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1 Introduction

The issues concerning reasoning are central to the design and analysis of Intelligent Systems (IS's) [24, 27, 28]. A critical issue in developing reasoning methods for IS's, particularly dealing with complex phenomena, is identifying the objects upon which these methods should be based. The proposed project aligns with recent discussions surrounding IS's or the need to modify the Turing test (see, *e.g.*, [5, 25, 26, 29]). This project suggests grounding reasoning in objects that are not purely abstract but in what are known as complex granules, which connect abstract and physical objects. Reasoning is conducted on information stored in the informational layers of these granules, which are shaped by their interaction with the physical layers of complex granules. Consequently, reasoning methods that support the attentional behavior of complex granules in their interactions with the physical world, as well as the execution of transformations (actions) within that world, are essential.

The rapid development of large-scale language models (LLMs) such as GPT-4 opens new possibilities for natural language processing but also reveals their limitations. Existing reasoning mechanisms like *chain of thought* (CoT) work well for low-complexity tasks but face challenges with more demanding problems that require multidimensional and interacting network of thoughts analysis [8–23].

Advances in recent years indicate that processing multiple chains of thought significantly improves the quality of reasoning. A classic example illustrating the importance of this research direction can be found in [20]. The paper introduces Medprompt, a novel method that employs dynamic few-shot selection, self-generated chains of thought, and ensembling. Its main achievement demonstrates how generalist models can outperform specialized medical models through strategic prompting. A critical phase involves using k-nearest neighbors (KNN) in the embedding space to identify similar examples, significantly enhancing the model's performance on medical datasets and achieving state-of-the-art results without domain-specific tuning.

However, we can envision more complex processing of thoughts than presented in [8–23]. For example, we can apply more advanced machine learning algorithms, facilitate dynamic interactions among networks of thoughts, and introduce hierarchical meta-reasoning mechanisms for more effective attention control.

This is one of the key motivations behind the Interactive Thought Networks (ITN) proposed in our approach. ITN generalizes traditional methods, enabling the use of much more complex, dynamically interacting networks of thoughts. The project introduces a novel concept aimed at overcoming current limitations by implementing multidimensional, network-oriented reasoning processes based on granular computing, inspired in particular by Lotfi Zadeh's *computing with words* theory [30]:

> *Information granulation can be viewed as a human way of achieving data compression and it plays a key role in implementation of the strategy of divide-and-conquer in*

human problem-solving.

Granulation is inherent in human thinking and reasoning processes. Human ability to decompose complex, vague concepts using a divide-and-conquer strategy can be particularly beneficial when breaking down task specifications expressed by such concepts. This decomposition can also be facilitated through the use of LLM.

In the Department of Mathematical Methods in Computer Science (KMMI) at UWM, we have a unique record of research in logic and models of granular computing. For decades, we have collaborated with a leading expert in this field, Professor Andrzej Skowron [1–7]. Our intention is to undertake a research project aimed at applying the concepts of granular computing to enhance reasoning processes conducted by modern LLM models. To strengthen our technical competencies in implementing current LLM techniques (especially Retrieval-Augmented Generation (RAG)), we have established a promising collaboration with Bert Gollnick (`https://gollnickdata.de/#/aboutme`). As the first step in this partnership, Bert Gollnick will conduct 16 sessions (each lasting 70 minutes) to provide intensive training on the technical aspects of LLM/RAG implementation.

2 Interactive Thought Networks (ITN): proposal of new approach to improve complex reasoning by LLM/RAG

2.1 Vision

ITN aims to create artificial intelligence capable of dynamic and adaptive thinking akin to human thought processes within an environment of collaborating intelligent granules (e.g., agents, humans, robots, thought flows realized by intelligent IoT). Imagine an AI that not only solves problems but also builds complex networks of thought connections, adapting to changing data and requirements. Instead of linear chains of thought, ITN introduces interactive thought networks that allow exploration of complex relationships and dependencies between concepts. One could say that we aim at creating a model of thinking which attempts at creating an own world, or, a plethora of plausible worlds.

2.2 Motivation

The *chain of thought* mechanism works well for tasks requiring clear, linear steps toward a solution. However, in contexts requiring deep analysis, multi-level processing, and adaptive thought processes, CoT becomes insufficient. Granular computing enables dynamic information processing at various levels of detail, opening new possibilities in reasoning. In ITN, granules are treated as *thoughts* (multidimensional units of information) that can be connected, divided, and transformed into adaptive structures.

2.3 Granules as Thoughts

In the ITN context, granules represent thought units that can be organized into complex structures—networks of thoughts. This nonlinear structure allows modeling multi-level relationships between different elements, which significantly better reflects human cognitive processes.

Research Task: Investigate the effectiveness of granular structures compared to traditional *chains of thought* in complex logical and decision-making problems.

2.4 Key Innovations

2.4.1 From Linearity to Multidimensionality

ITN overcomes the limitations of linear reasoning methods by introducing dynamic knowledge graphs and semantic networks that better reflect complex relationships between thoughts.

Research Task: Develop and optimize dynamic knowledge graphs and integrate them with LLM models. This involves designing algorithms that can construct and modify these graphs in real-time, enabling the AI to explore multiple reasoning paths simultaneously.

2.4.2 Granular Revolution

Leveraging granular computing, ITN processes information at various levels of detail, offering flexibility and adaptability in analysis.

Research Task: Design and evaluate new algorithms for managing granules and dynamically organizing information. This includes creating methods for granule formation, decomposition, and recombination to adapt to different problem contexts.

2.5 Adaptive Thought Networks

Unlike linear *chains of thought*, ITN introduces mechanisms for dynamic organization and adaptation of granules, which can split, aggregate, and reorganize. This approach enables AI to explore new reasoning paths during problem-solving.

Research Task: Develop dynamic algorithms for creating adaptive thought networks inspired by neural structures. These algorithms should allow the AI to adjust its reasoning strategies based on feedback and changing data.

2.5.1 Integrating Granular Computing with LLMs

Modify existing LLM architectures to operate on granules and their dynamic structures effectively.

Research Task: Develop new training techniques and optimize language models incorporating granular computing. This may involve redefining the input-output structures of LLMs to handle granules and designing training datasets that reflect granular relationships.

2.6 Scalability and Flexibility

The dynamic organization of granules gives ITN unparalleled scalability in processing large datasets.

Research Task: Test and verify the scalability of the ITN system when processing big data. Address computational resource management to maintain performance with large and complex datasets.

2.7 Proposed Conceptual Approach

2.7.1 Replacing *Chain of Thought* with ITN Mechanisms

ITN offers a more flexible, multidimensional approach that enables deeper reasoning and modeling of complex relationships between granules of thought.

Research Task: Conduct comparative studies on the effectiveness of ITN vs. CoT in solving complex decision-making and analytical problems. Define clear evaluation metrics, such as accuracy, reasoning depth, and computational efficiency.

2.7.2 Adapting LLM Architecture

Transform current LLM models (e.g., GPT) to operate on granular thought structures, requiring new training and optimization algorithms.

Research Task: Design new LLM architectures based on granules and test their performance. Provide specific details on how existing architectures will be modified and how granules will be integrated into neural network structures.

2.7.3 Supporting Technologies

ITN will utilize advanced data structures like dynamic knowledge graphs and semantic networks for more sophisticated modeling of thought relationships.

Research Task: Develop and implement tools for dynamic knowledge management in thought networks. Address computational challenges and ensure that these tools are scalable and efficient.

2.8 Risk Management

Introducing new architectures and algorithms may come with unforeseen challenges.

Research Task: Identify potential risks, such as computational complexity and integration difficulties, and develop mitigation strategies to address them.

2.8.1 Interdisciplinary Integration

ITN combines linguistics, computer science, cognitive science, and mathematics, creating a unique research field at the intersection of many disciplines.

Research Task: Investigate the potential of integrating various methodologies, including symbolic AI and modern neural networks, in the context of granular reasoning. Provide concrete examples of how these integrations will occur, such as combining symbolic reasoning with neural computation in the processing of granules.

3 Potential Applications

3.1 Advanced Data Analysis

ITN enables discovering multidimensional patterns and dependencies in complex datasets.

Research Task: Test ITN applications in extensive data analysis, such as in medical or financial contexts. Evaluate its ability to uncover insights that traditional methods may miss.

3.1.1 Decision-Making in Uncertainty

With granular computing, ITN allows AI to handle ambiguity better, crucial in fields such as medicine or risk management.

Research Task: Develop tools to support decision-making in uncertain conditions. Assess ITN's performance in scenarios with incomplete or ambiguous data.

3.2 Creative Problem-Solving

ITN can generate innovative solutions by combining granules of thought in non-standard ways.

Research Task: Investigate ITN's ability to develop creative solutions in art, science, and design. Conduct experiments to compare its creativity with existing AI models.

3.3 Expected Benefits

3.3.1 Improved Reasoning Quality

ITN allows for a deeper understanding of problems and the generation of more accurate and creative responses.

Research Task: Evaluate the quality of AI responses operating within the ITN framework. Use standardized benchmarks and user studies to assess improvements over traditional models.

3.3.2 Scalability

Granular structures enable efficient management of vast amounts of data.

Research Task: Test the scalability of ITN in different environments. Measure performance metrics such as processing time and resource utilization.

3.3.3 Enhanced Interdisciplinary Collaboration

By integrating multiple fields, ITN fosters collaboration across disciplines, potentially leading to breakthroughs that single-discipline approaches might not achieve.

4 Seminar General Plan

To disseminate these ideas and gather feedback, we propose organizing a seminar with the following components:

4.1 Interactive Workshops

Incorporate hands-on sessions where participants can engage with preliminary models or simulations of ITN, fostering a deeper understanding of the concepts.

4.2 Expert Panels

Include discussions with experts in granular computing, cognitive science, and AI to provide diverse perspectives and uncover collaborative opportunities.

4.3 Case Studies

Present hypothetical or real-world scenarios where ITN could be applied, demonstrating its practical benefits over existing methods.

4.4 Evaluation Metrics Discussion

Facilitate a session to define clear metrics for comparing the effectiveness of ITN against traditional CoT methods, including benchmarks on specific tasks, performance measures, or user studies.

4.5 Risk Management Strategies

Discuss potential risks in implementing ITN and brainstorm mitigation strategies, ensuring the robustness of the project.

5 KMMI Seminar: Detailed Action Plan for October-December 2024

5.1 Objectives of the sessions

- Allow participants to implement a simple RAG system.
- Familiarize with contemporary tools used in this technology.
- Conduct experiments with modeling selected types of reasoning.

The sessions will take place over sixteen sessions, two per day on eight dates. Each session will last approximately 70 minutes. The eight meetings are tentatively planned for Wednesdays, starting at 16:30. Exact dates and times may be subject to change based on the finalization of the UWM student schedule. A detailed plan of the sessions is presented in section 5.2. Assuming the sessions start at 16:30, we plan to conduct them according to the following schedule for each daily meeting:

- 16:30-17:40: First lecture of the day
- 17:40-17:50: Break
- 17:50-19:00: Second lecture of the day

The primary goal is the practical part, as well as the explanation of the necessary theoretical knowledge to allow participants to acquire the skills to implement a simple RAG system independently. Towards the end of the project (i.e., around the end of November or the beginning of December 2024), we plan a buffer period for discussing technical issues that will cause the most problems for participants. Moreover, during the sessions, we plan to initiate discussions on the possibility of joint projects (e.g., experiments related to different types of reasoning or some other research projects focused on specific applications).

Date	General LLM/RAG topics	Specific LLM/RAG topics
02-10-2024	Introduction to contemporary tools and experiments with modeling reasoning	• What are Large Language Models? (Theory) • How are they trained? (Theory) • Which providers can be used? (Theory) • Quick demo of environment setup • Interacting with LLM via Python (Coding) • System-user-AI messages (Theory + Coding) • Using prompt templates (Coding) • Using chains (Coding)
09-10-2024	Theoretical foundations and practical aspects of vector databases for LLM and RAG systems	• Vector Database basics (Theory) • Differences between classical and vector DBs (Theory) • Data ingestion process (Theory) • Loading data (Coding) • Creating chunks (Coding) • Embeddings (Theory) • Creating chunk embeddings (Coding) • Choosing database providers (Theory) • Storing data in vector database (Coding) • Querying vector database (Coding)
16-10-2024	Modeling reasoning in LLMs and modern RAG systems	• What is RAG? (Theory) • How does RAG work? (Theory) • Implementing RAG in custom project (Coding)
06-11-2024	Vector databases in RAG systems and modeling reasoning	• Technical questions on RAG implementation • Tuning RAG systems (Theory, Coding) • Discussions on joint research projects
13-11-2024	RAG system design and modeling reasoning in specific domains	• Technical questions on implementation • Security and compliance in RAG systems • Demos of participants' RAG systems • Technical workshops
20-11-2024	Personalization of RAG systems	• Technical questions on implementation
27-11-2024	Buffer for discussions	• Demos and technical questions
04-12-2024	Buffer for discussions	• Demos and technical questions

5.2 Tentative Session Details

6 Key Books in Rough Set Theory and Granular Computing by KMMI UWM Department & Close Collaborators: An In-depth Analysis

This section provides an extended analysis of seven fundamental books in the fields of Rough Set Theory and Granular Computing, highlighting their main research theses and significant contributions to the field.

1. **Computing in Decision Approximation: An Application of Rough Mereology [2]**

   Author: Lech Polkowski

   Main Research Theses:

   - Rough mereology can be effectively applied to decision approximation problems.
   - The integration of rough set theory and mereology provides a powerful framework for handling uncertainty in decision-making processes.
   - Mereological approach offers unique insights into the structure of complex decision spaces.

   Key Contributions: Polkowski develops a comprehensive theoretical framework that combines rough set theory with mereology. This novel approach allows for a more nuanced understanding of decision approximation, particularly in scenarios where traditional methods struggle with ambiguity or incomplete information. The book presents rigorous mathematical foundations alongside practical algorithms, bridging the gap between theory and application.

   Significance: This work's major contribution is its unified approach to decision approximation, offering a new perspective on how to handle complex decision-making scenarios. It provides researchers and practitioners with a robust set of tools for tackling problems in areas such as artificial intelligence, machine learning, and data mining.

2. **Reasoning by Parts: An Introduction to Rough Mereology [3]**

   Author: Lech Polkowski

   Main Research Theses:

   - Reasoning about parts and wholes can be formalized using rough mereology.
   - Rough mereological approach provides a powerful framework for handling vagueness and uncertainty in reasoning processes.
   - The integration of rough set theory and mereology offers new insights into fundamental problems in AI and computer science.

   Key Contributions: This book lays the foundational groundwork for rough mereology, a field that combines elements of rough set theory with mereology. Polkowski introduces key concepts and demonstrates how this novel approach can be applied to various reasoning tasks. The author presents both the theoretical underpinnings and practical applications, making the work accessible to a wide audience.

Significance: The primary value of this work lies in its introduction of a new paradigm for reasoning under uncertainty. By formalizing the concept of "reasoning by parts," it opens up new possibilities for AI systems to handle complex, hierarchical structures and imprecise information in a more human-like manner.

3. **Logic: Reference Book for Computer Scientists [4]**

   Author: Lech Polkowski

   Main Research Theses:

   - Logic plays a crucial role in various aspects of computer science and AI.
   - Non-classical logics offer powerful tools for reasoning in complex, real-world scenarios.
   - The integration of different logical frameworks can lead to more robust and flexible computational systems.

   Key Contributions: This comprehensive reference book covers a wide range of logical systems and their applications in computer science. Polkowski provides in-depth discussions on classical logic, modal logics, fuzzy logics, and their relevance to AI and computational theory. The book also explores the connections between logic and other areas of computer science, such as database theory and programming languages.

   Significance: The main value of this work is its comprehensive and accessible treatment of logic in the context of computer science. It serves as an invaluable resource for researchers and practitioners, providing a solid foundation for understanding the logical underpinnings of various computational techniques and AI methodologies.

4. **Granular Computing in Decision Approximation: An Application of Rough Mereology [1]**

   Authors: Lech Polkowski, Piotr Artiemjew

   Main Research Theses:

   - Granular computing can significantly enhance decision approximation processes.
   - Rough mereology provides a robust framework for information granulation.
   - The integration of granular computing and rough mereology offers novel solutions to complex decision-making problems.

   Key Contributions: This book bridges the gap between theoretical foundations of granular computing and its practical applications. It introduces innovative approaches to information granulation based on rough mereology, demonstrating how these methods can be applied to real-world decision-making scenarios. The authors present a comprehensive framework that allows for more nuanced and flexible decision approximation, particularly in environments with uncertain or incomplete information.

   Significance: The work's main value lies in its ability to translate complex theoretical concepts into practical tools for decision support systems. It opens new avenues for research in artificial intelligence and data analysis, offering a granular approach to handling complex, multi-dimensional data.

5. **Interactive Granular Computations in Networks and Systems Engineering: A Practical Perspective [5]**

Author: Andrzej Jankowski

Main Research Theses:

- Granular computing offers a powerful approach to handling complexity in network and systems engineering.
- Interactive models based on granular computations can significantly enhance problem-solving in real-world scenarios.
- The integration of granular computing with other computational intelligence techniques leads to more robust and adaptive systems.

Key Contributions: Jankowski presents a practical framework for applying granular computing concepts to network and systems engineering problems. The book introduces novel interactive models and methods for dealing with complex systems, emphasizing the role of granular computations in solving real-world problems. It provides numerous case studies and examples, demonstrating the effectiveness of the proposed approaches.

Significance: The main value of this work lies in its practical orientation and its demonstration of how granular computing can be applied to solve complex engineering problems. It bridges the gap between theoretical concepts and practical applications, providing engineers and researchers with concrete tools and methodologies for tackling real-world challenges in network and systems design.

6. **Rough Sets and Intelligent Systems - Professor Zdzislaw Pawlak in Memoriam: Volume 1 [6]**

Editor: Andrzej Skowron

Main Research Theses:

- Rough set theory provides a powerful framework for dealing with imprecise and incomplete information.
- The integration of rough sets with other computational intelligence techniques leads to more robust intelligent systems.
- Rough set theory has wide-ranging applications across various domains of AI and data analysis.

Key Contributions: This volume, dedicated to the memory of Professor Zdzislaw Pawlak, covers fundamental aspects of rough sets and their applications in intelligent systems. It includes contributions from leading researchers in the field, discussing both theoretical developments and practical applications. The book explores topics such as rough set approximations, decision rules, data mining, and machine learning from a rough set perspective.

Significance: The primary value of this work is its comprehensive overview of the state-of-the-art in rough set theory and its applications. It serves as a crucial resource for researchers and practitioners, providing insights into the latest developments in the field and highlighting potential areas for future research.

7. **Rough Sets and Intelligent Systems - Professor Zdzislaw Pawlak in Memoriam: Volume 2 [7]**

Editor: Andrzej Skowron

Main Research Theses:

- Rough set theory continues to evolve, offering new perspectives on fundamental AI problems.
- The integration of rough sets with other AI techniques leads to more powerful and flexible intelligent systems.
- Rough set theory has significant potential for addressing emerging challenges in big data and complex systems analysis.

Key Contributions: This second volume continues to explore advanced topics in rough sets and intelligent systems. It focuses on recent developments and future directions in the field, showcasing the ongoing impact of Professor Pawlak's work on modern computational intelligence. The book covers topics such as granular computing, approximate reasoning, data mining, and pattern recognition, all from a rough set perspective.

Significance: The main value of this work lies in its forward-looking approach, highlighting emerging trends and potential future directions in rough set theory and its applications. It provides researchers with a roadmap for future investigations and demonstrates the continued relevance of rough set theory in addressing contemporary challenges in AI and data science. In particular, this book and [5, 25, 26] discuss the Interactive Granular Computing (IGrC) model aiming to put in sync issues of language and reasoning as well as perception and action. In IGrC, reasoning is conducted on networks of complex granules that connect abstract and physical objects. The reasoning methods support decision-making regarding the selection of transformations to be applied to the current granular network, facilitating the construction of approximate solutions for specific problems to be solved. This idea can be combined in a natural way with [14].

7 Key Publications on Chain of Thought Reasoning in AI and LLMs

This section presents a list of key publications on Chain of Thought (CoT) reasoning in AI and Large Language Models (LLMs), sorted by importance. The importance is determined based on the publication's impact on the field, its novelty, and its potential for future research and applications.

1. **Wei et al. (2022) [8]** *Main achievement:* Introduced the concept of Chain of Thought prompting, demonstrating its effectiveness in improving the reasoning capabilities of large language models.

2. **Wang et al. (2022) [9]** *Main achievement:* Proposed the self-consistency method to further improve Chain of Thought reasoning by considering multiple possible reasoning paths.

3. **Kojima et al. (2022) [10]** *Main achievement:* Explored the zero-shot reasoning capabilities of large language models using Chain of Thought prompting.

4. **Zhang et al. (2022) [11]** *Main achievement:* Introduced a method for automatically generating Chain of Thought prompts, eliminating the need for manual prompt creation.

5. **Nori et al. (2022) [20]** *Main achievement:* The paper introduces Medprompt, a novel method using dynamic few-shot selection, self-generated chains of thought, and assembling. Its main achievement showcases how generalist models can outperform specialized medical

models through strategic prompting. A critical phase involves using k-nearest neighbors (KNN) in the embedding space to identify similar examples, for example, selection, significantly enhancing the model's performance on medical datasets and achieving state-of-the-art results without domain-specific tuning. This approach significantly improves performance on medical datasets, surpassing prior state-of-the-art models.

6. **Yao et al. (2023) [12]** *Main achievement:* Extended the Chain of Thought concept to a tree structure, allowing for exploration of multiple reasoning paths and selection of the optimal path for problem-solving.

7. **Zhou et al. (2022) [13]** *Main achievement:* Introduced the "least-to-most prompting" technique, which decomposes complex problems into simpler subtasks, improving language models' reasoning abilities in complex tasks.

8. **Yao et al. (2022) [14]** *Main achievement:* Presented the ReAct framework, which combines reasoning with acting, enabling language models to interact with their environment and solve problems more effectively through simultaneous planning and execution.

9. **Gao et al. (2022) [15]** *Main achievement:* Integrated program generation with language models, allowing them to write and execute code as part of the reasoning process, significantly improving results in tasks requiring mathematical and logical computations.

10. **Lewkowycz et al. (2022) [16]** *Main achievement:* Applied Chain of Thought to solving quantitative and mathematical problems, showing significant advances in language models' abilities to handle complex calculations.

11. **Nye et al. (2021) [17]** *Main achievement:* Explored the use of "scratchpads" as a form of intermediate computation, closely related to Chain of Thought reasoning, allowing models to store and manipulate intermediate results.

12. **Drozdov et al. (2022) [18]** *Main achievement:* Introduced a method for compositional Chain of Thought prompting, combining multiple chains of thought to solve complex tasks requiring multi-step reasoning.

13. **Press et al. (2022) [19]** *Main achievement:* Investigated challenges related to compositionality in language models and proposed methods to improve their ability to understand and generate compositional structures by reducing the "compositionality gap".

14. **Huang et al. (2023) [21]** *Main achievement:* Applied Chain of Thought prompting to the specific task of answering survey questions, demonstrating its effectiveness in the context of qualitative data analysis.

15. **Fu et al. (2023) [22]** *Main achievement:* Explored how smaller language models can be adapted to multi-step reasoning tasks through techniques inspired by Chain of Thought.

16. **Creswell and Shanahan (2022) [23]** *Main achievement:* Discussed methods for ensuring that the reasoning process of large language models is faithful and reliable, which is crucial for practical applications of Chain of Thought.

8 Conclusion

Interactive Thought Networks (ITN) represents not just the next step in AI development but a significant leap that can define the future of intelligent systems. By integrating granular computing with advanced language models, ITN opens the door to a new era in AI, where machines not only process data but genuinely "think."

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