Rough Sets and their Applications

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Abstract. The paper discusses basic concepts of rough set theory. Starting point of the theory are data tables which are used to define rudiments of the theory: approximations, dependency and reduction of attributes, decision rules and others. Various applications of the theory are outlined and future problems pointed out.

Keywords. Rough sets, fuzzy sets, vagueness, decision tables, decision rules, data mining.

1 Introduction

Rough set theory is a new approach to imperfect knowledge. Particularly it offers a new perspective to vagueness and uncertainty, fundamental issues discussed in modern philosophy, logic and AI. Recently, researcher interested in cognitive sciences, machine learning, data mining and others contributed essentially to this area. The most important contributions, no doubt, are fuzzy set theory and the theory of evidence.

Rough set theory is still another look on vagueness and uncertainty. Although it is somehow related to fuzzy set theory [5, 6, 14, 33, 37, 40, 51, 58, 61, 62, 72, 95, 107, 111, 112] and the evidence theory, [76] it can be viewed as a independent discipline in its own rights.

We witnessed a rapid grow of interest in rough set theory and its application, world wide. Many international workshops, conferences and seminars included rough sets in their programs. Over a thousand papers have been published on rough sets and their applications so far.

Rough set theory hinges on the assumption that every object of the *universe of discourse* has some characteristic features, which are represented by information (knowledge, data) about the object. Objects having the same features are indiscernible. The indiscernibility relation leads to the so called "boundary-line" approach to vagueness, first formulated by father of modern logic, Gotlob Frege [17]. According to Frege "the concept without a sharp boundary", i.e. vague concept, must have boundary-line examples which cannot be classified, neither to the concept nor to its complement. Thus from philosophical point of view rough set theory can be understood as a special case of Frege's idea.

Practically, rough set theory can be seen as a new approach to data analysis, known recently as also data mining. In general, data mining is a methodology for discovering hidden patterns in data. Rough set theory has proved to be useful in data mining, and it "... constitutes a sound basis for data mining applications" [13]. The theory offers mathematical tools to discover hidden patterns in data. It identifies partial or total dependencies (i.e. cause-effect relations) in data bases, eliminates redundant data, gives approach to null values, missing data, dynamic data and others.

Many real life, nontrivial applications of this methodology for knowledge discovery have proved it usefulness. Rough set theory has been successfully applied in many areas. Medicine [57, 59, 68, 77, 78, 79, 92, 93, 97, 100, 101, 102, 103, 106], pharmacology [30, 31], banking, financial and market analysis [3, 19, 20, 82, 83, 84] are areas where rough set approach showed its advantages. Very interesting results have been also obtained in speaker independent speech recognition and acoustics [9, 10, 11, 12, 29]. The rough set approach seems also important for various engineering applications, like machine diagnosis [54], process control [1, 8, 36, 40, 43, 69, 90, 91, 96, 114, 115, 119], material science [28], databases [4, 7, 16, 18, 27, 74, 85] and others [2, 22, 23, 24, 25, 26, 67, 73, 86, 113]. More about applications of rough set theory can be found in [34, 35, 39, 41, 42, 56, 58, 65, 80, 81, 99, 104, 105, 117].

Rough set theory, has also links between Boolean reasoning methods [75], statistics [15, 32, 87, 94], neural networks [44, 45, 46, 48, 49, 50, 52, 53, 88, 110], mathematical morphology [70], mereology [71], just to name few.

The theory is not competitive but rather complementary to other methods and can also be often used jointly with other approaches (e.g. fuzzy sets, genetic algorithms, statistical methods, neural networks etc.)

Rough set theory has been generalized in many ways, but we are going to present in this paper basic concepts of this theory only. Rudiments of rough set theory can be found in [63, 66, 78, 89]. Readers interested in more advanced results are advised to consult suitable literature.

2 Information Tables

The basic concepts of rough set theory can be formulated in quite general terms, but in order to give more intuitive insight into the theory we will start our consideration from *data tables* called *information tables*, *information systems* or *attribute-value systems*. Column of the table are labeled by *attributes*, rows by *objects* and entries of the table are *attribute values*. An example of information table is shown below.

Table 1. An example of an information table

	H	M	T	F
p1	no	yes	high	yes
p2	yes	no	high	yes
p3	yes	yes	v. high	yes
p4	no	yes	normal	no
p5	yes	no	high	no
p6	no	yes	v. high	yes

Columns of the table are labeled by attributes Headache (H), Muscle-pain (M), Temperature (T) and Flu (F) and rows – by patients (objects) *p*1, *p*2, *p*3, *p*4, *p*5 and *p*6.

Each row of the table can be seen as information about specific patient. For example patient *p*2 is characterized in the table by the following attribute-value set

{(Headache, yes), (Muscle-pain, no), (Temperature, high), (Flu, yes)}.

Let us observe that each subset of attributes divides the set of all objects in the table into classes having the same features, i.e. clumps of objects which are indiscernible in view of the available data. For example, in the table patients *p*2, *p*4 and *p*6 are indiscernible with respect to the attribute Headache, since all they have the same value of this attribute. Similarly, patients *p*3 and *p*5 are indiscernible in terms of attributes Headache and Temperature, etc. Thus each subset of attributes induces on the set of objects an equivalence relation, whose equivalence classes form *granules* (*blocks*, *clusters*) of objects having the same features. These granules will be referred to as *elementary sets*, which are basic building bricks of rough set theory.

Now we present the above concepts formally.

Let $S = (U, A)$ be an information table, where U and A, are finite, non-empty sets called the *universe*, and a set *attributes* respectively. With every attribute $a \in A$ we associate a set V_a of its *values*, called the *domain* of a. Any subset B of A determines a binary relation $I(B)$ on U which will be called an *indiscernibility relation*, and is defined as follows:

$(x, y) \in I(B)$ if and only if $a(x) = a(y)$ for every $a \in A$, where $a(x)$ denotes the value of attribute a for element x.

Obviously $I(B)$ is an equivalence relation. The family of all equivalence classes of $I(B)$, i.e., partition determined by B, will be denoted by $U/I(B)$, or simple U/B; an equivalence class of $I(B)$, i.e., block of the partition U/B, containing x will be denoted by $B(x)$.

If $(x, y) \in I(B)$ we will say that x and y are *B-indiscernible*. Equivalence classes of the relation $I(B)$ (or blocks of the partition U/B) are refereed to as *B-elementary sets*.

In the table patients $p2$, $p3$ and $p5$ are indiscernible with respect to the attribute Headache, patients $p3$ and $p6$ are indiscernible with respect to attributes Muscle-pain and Flu, and patients $p2$ and $p5$ are indiscernible with respect to attributes Headache, Muscle-pain and Temperature. Hence, for example, the attribute Headache generates two elementary sets $\{p2, p3, p5\}$ and $\{p1, p4, p6\}$, whereas the attributes Headache and Muscle-pain form the following elementary sets: $\{p1, p4, p6\}$, $\{p2, p5\}$ and $\{p3\}$.

3 Approximation of Sets

It can be seen from Table 1 that the concept "flu", i.e. the set $\{p1, p2, p3, p6\}$ (or the concept "not flu", i.e. the set $\{p4, p5\}$) cannot be defined in terms of attributes Headache, Muscle-pain and Temperature, because patients $p2$ and $p5$ have the same symptoms, i.e. values of attributes Headache, Muscle-pain and Temperature, but $p2$ has flu and $p5$ has not. Therefore we propose to define two set, called the *lower* and the *upper approximation* of a concept, which can be defined in terms of features contained in the table. The lower approximation of a concept is the set of all objects which can be *surely* classified as belonging to the concept, whereas the upper approximation of set is the set of all objects which *possible* belong to the concept – in view of available data.

Formally approximations are operations on sets defined as follows:

$$B_*(X) = \{x \in U : B(x) \subseteq X\},$$

$$B^*(X) = \{x \in U : B(x) \cap X \neq \emptyset\},$$

which assign to every subset X of the universe U two sets $B_*(X)$ and $B^*(X)$ called the *B-lower* and the *B-upper approximation* of X, respectively.

The set

$$BN_B(X) = B^*(X) - B_*(X)$$

will be referred to as the *B-boundary region* of X.
If the boundary region of X is the empty set, i.e., $BN_B(X) = \emptyset$, then the set X is *crisp* (*exact*) with respect to B; in the opposite case, i.e., if $BN_B(X) \neq \emptyset$, the set X is *rough* (*inexact*) with respect to B.

Rough set can be also characterized numerically by the following coefficient

$$\alpha_B(X) = \frac{card(B_*(X))}{card(B^*(X))},$$

called *accuracy of approximation*. Obviously $0 \leq \alpha_B(X) \leq 1$. If $\alpha_B(X) = 1$, X is *crisp* with respect to B (X is *precise* with respect to B), and otherwise, if $\alpha_B(X) < 1$, X is *rough* with respect to B (X is *vague* with respect to B).

Let us depict above definitions by examples referring to Table 1. Consider the concept "flu", i.e., the set $X = \{p1, p2, p3, p6\}$ and the set of attributes

B = {Headache, Muscle-pain, Temperature}. Hence $B_*(X)$ = {$p1$, $p3$, $p6$} and $B^*(X)$ = {$p1$, $p2$, $p3$, $p5$, $p6$}. For this case we get α_B ("*flu*") = 3/5. It means that the concept "flu" can be characterized partially employing symptoms, Headache, Muscle-pain and Temperature. Taking only one symptom B = {Headache} we get $B_*(X) = \emptyset$, $B^*(X) = U$ and α_B("*flu*") = 0, which means that the concept "flu" cannot be characterized in terms of attribute Headache only i.e., this attribute is not characteristic for flu whatsoever. However, taking the attribute

B = {Temperature} we get $B_*(X)$ = {$p3$, $p6$}, $B^*(X)$ = {$p1$, $p2$, $p3$, $p5$, $p6$} and $\alpha_B(X)$ = 2/5, which means that the single symptom Temperature is less characteristic for flu, than the whole set of symptoms, but also characterizes flu partially.

4 Rough Membership Function

Rough sets can be also defined using a *rough membership function*, defined as

$$\mu_X^B(x) = \frac{card(B(x) \cap X)}{card(B(x))}.$$

Obviously

$$\mu_X^B(x) \in [0,1].$$

Value of the membership function $\mu_X^B(x)$ is kind of conditional probability, and can be interpreted as a degree of *certainty* that x can be classified as X, employing set of attributes B.

The rough membership function, can be used to define approximations and the boundary region of a set, as shown below:

$$B_*(X) = \{x \in U : \mu_X^B(x) = 1\},$$

$$B^*(X) = \{x \in U : \mu_X^B(x) > 0\},$$

$$BN_B(X) = \{x \in U : 0 < \mu_X^B(x) < 1\}.$$

The rough membership function can be generalized as follows [71]:

$$\mu(X, Y) = \frac{card(X \cap Y)}{card\ X},$$

where X, $Y \subseteq U$, $X \neq \emptyset$.

Function $\mu(X,Y)$ is an example of a *rough inclusion* [71] and expresses the degree to which X is included in Y. Obviously, if $\mu(X, Y) = 1$, then $X \subseteq Y$.

If X is included in a degree k we will write $X \subseteq_k Y$.

The rough inclusion function can be interpreted as a generalization of the mereological relation "part of", and reads as "part in a degree".

For example, $p1$ belongs to the concept "flu" (i.e. the set {$p1$, $p2$, $p3$, $p6$}) with degree 1, whereas $p2$ belongs to this set with degree 0,5.

5 Dependency of Attributes

Our main problem can be also formulated in another way. Instead of using approximations of sets we can use the concept of *dependency of attributes*.

Intuitively, a set of attributes D (called *decision attributes*) depends totally on a set of attributes C (called *condition attributes*), denoted $C \Rightarrow D$, if all values of attributes of D are uniquely determined by values of attributes of C. In other words, D depends totally on C, if there exists a functional dependency between values of D and C. In Table 1 there are not total dependencies whatsoever. If in Table 1, the value of the attribute Temperature for patient $p5$ were "no" instead of "high", there would be a total dependency {Temperature}$\Rightarrow$ {Flu}, because to each value of the attribute Temperature there would correspond unique value of the attribute Flu.

Formally dependency can be defined in the following way.

Let D and C be subsets of A. We say that *D depends totally* on C, if and only if $I(C) \subseteq I(D)$. That means that the partition generated by C is finer than the partition generated by D.

We would need also a more general concept of dependency of attributes, called a *partial dependency* of attributes. For example, in Table 1, the attribute Temperature determines uniquely only some values of the attribute Flu. That is, (Temperature, very high) implies (Flu, yes), similarly (Temperature, normal) implies (Flu, no), but (Temperature, high) does not imply always (Flu, yes). Thus the partial dependency means that only some values of D are determined by values of C.

Formally, the above idea can be formulated as follows.

Let D and C be subsets of A. We say that *D depends in degree k*, $0 \le k \le 1$, on C, denoted $C \Rightarrow_k D$, if

$$k = \gamma(C, D) = \frac{card(POS_C(D))}{card(U)} = \frac{\sum_{x \in U/D} card(C_*(X))}{card(U)},$$

where

$$POS_C(D) = \bigcup_{X \in U/I(D)} C_*(X).$$

The expression $POS_C(D)$, called a *positive region* of the partition U/D with respect to C, is the set of all elements of U that can be uniquely classified to blocks of the partition U/D, by means of C.

Notice that for $k = 1$ we get the previous definition of total dependency.

For dependency {Headache, Muscle-pain, Temperature}$\Rightarrow$ {Flu} we get $k = 4/6 = 2/3$, because four out of six patients can be uniquely classified as having flu or not, employing attributes Headache, Muscle-pain and Temperature.

If we were interested in how exactly patients can be diagnosed using only the attribute Temperature, that is – in the degree of the dependence {Temperature} $\Rightarrow${Flu}, we would get $k = 3/6 = 1/2$, since in this case only three patients $p3$, $p4$ and $p6$ out of six can be uniquely classified as having flu. In contrast to the previous case patient $p4$ cannot be classified now as having flu or not. Hence the single attribute Temperature offers worse classification than the whole set of attributes Headache, Muscle-pain and Temperature. It is interesting to observe that neither Headache nor Muscle-pain can be used to recognize flu, because for both dependencies {Headache}$\Rightarrow${Flu} and {Muscle-pain}$\Rightarrow${Flu} we have $k = 0$.

6 Reduction of Attributes

Another important issue in our approach is data reduction. For example, it is easily seen that if we drop in Table 1 either the attribute Headache or Muscle-pain we get the data set which is equivalent to the original one, in regard to approximations and dependencies. That is we get in this case the same accuracy of approximation and degree of dependencies as in the original table, however using smaller set of attributes.

This concept can be formulated more precisely as follows. Let $C \Rightarrow_k D$. A minimal subset C' of C, such that $\gamma(C, D)= \gamma(C', D)$ is called a *reduct* of C.

It is easily seen that in Table 1 we have two reducts, {Temperature, Muscle-pain} and {Temperature, Headache}.

Thus a reduct is a set of condition attributes that preserves the degree of dependency. It means that a reduct is a minimal subset of condition attributes that enables the same decisions as the whole set of condition attributes.

Obviously a set of condition attributes may have more then one reduct. Intersection of all reducts is called the *core*. The core in Table 1 is the attribute Temperature. Thus the core is the set of attributes that cannot be eliminated from the information table without changing its dependencies and approximations.

7 Decision Rules and Consistency Factor

It we distinguish in an information table two classes of attributes, *condition* and *decision* attributes, such tables are called *decision tables*. For example in Table 1 attributes Headache, Muscle-pain and Temperature are condition attributes, whereas the attribute Flu – is a decision attribute.

Each row of a decision table determines a *decision rule*, which specifies *decisions* (*actions*) that should be taken when conditions pointed out by condition attributes are satisfied. For example, in Table 1 the condition (Headache, no), (Muscle-pain, yes), (Temperature, high) determines uniquely the decision (Flu, yes). Decision rules 2) and 5) in Table 1 have the same conditions by different decisions. Such rules are called *inconsistent* (*nondeterministic*, *conflicting*, *possible*); otherwise the rules are referred to as *consistent* (*deterministic*, *non conflicting*, *sure*). Decision tables containing inconsistent decision rules are called *inconsistent*; otherwise the table is *consistent*.

Decision rules are often presented as implications and are called "*if..., then*..." rules. For example rule 1) in Table 1 can be presented as implication

if (Headache, no) and (Muscle-pain, yes) and (Temperature, high) then (Flu, yes).

To express this idea more precisely we need a formal language associated with any information table $S = (U, A)$. The language is defined in a standard way and we assume that the reader is familiar with the construction.

Given $x \in U$ and $B \subseteq A$ by $\Phi_x^B = \wedge_{a \in B}(a, v)$ we mean a formula such that $a(x) = v$ and $v \in V_a$.

Every dependency $C \Rightarrow_k D$ determines a set of *decision rules*

$$\{\Phi_x^C \rightarrow \Phi_x^D\}_{x \in U} .$$

We say that a decision rule $\Phi_x^C \rightarrow \Phi_x^D$ is *true* in *S*, if $|\Phi_x^C|_S \subseteq |\Phi_x^D|_S$, where $|\Phi_x^C|_S$ denotes the *meaning* of Φ_x^C in *S*, defined in a usual way.

Let $C_S(x) = |\Phi_x^C|_S$ .Hence the decision rule $\Phi_x^C \rightarrow \Phi_x^D$ is true in *S* if $C_S(x) \subseteq D_S(x)$.

A decision rule $\Phi_x^C \rightarrow \Phi_x^D$ is *true in a degree l* in *S*, if $l = \mu(C_S(x), D_S(x)) > 0$, i.e., $C_S(x) \subseteq_l D_S(x)$.

Rough inclusion in this case boils down to the rough membership function. As a consequence rough membership can be interpreted as a generalized truth value.

The degree of truth of a decision rule can be also interpreted as a certainty factor of the rule.

Let us observe that the rough membership can be interpreted both as conditional probability and at the same time as partial truth value.

The above considerations lead to a inference rule, called the *rough modus ponens*, defined as below:

$$\frac{\pi(\Phi_x^C);\ \mu(\Phi_x^C, \Psi_x^D)}{\pi(\Psi_x^C)},$$

where

$$\pi(\Phi_x^C) = \frac{card(|\Phi_x^C|_S)}{card(U)},$$

$$\mu(\Phi_x^C, \Psi_x^D) = \frac{card(|\Phi_x^C \wedge \Psi_x^D|_S)}{card\,|\Phi_x^C|_S}$$

and

$$\pi(\Psi_x^D) = \pi(\sim \Phi_x^C \wedge \Psi_x^D) + \pi(\Phi_x^C) \cdot \mu(\Phi_x^C, \Psi_x^D),$$

or

$$\pi(\Phi_D^x) = \sum_{y \in D(x)} (\pi(\Psi_y^C) \cdot \mu(\Psi_y^C,\ \Phi_y^D)) .$$

The number $\pi(\Phi_x^C)$ can be interpreted as the probability, that *x* has the property Φ_x^C, and the number $\mu(\Phi_x^C,\ \Psi_x^D)$ – as *certainty factor* of the decision rule $\Phi_x^C \rightarrow \Psi_x^D$.

Hence the inference rule, the *rough modus ponens*, enables us to calculate the probability of conclusion Ψ_x^D as a function of the probability of the premise Φ_x^C and the certainty factor $\mu(\Phi_x^C, \ \Psi_x^D)$ of the decision rule $\Phi_x^C \rightarrow \Psi_x^D$.

8 Conclusions

Rough set theory attracted researchers and practitioners all over the world. They contributed essentially to its theoretical foundations as well as to wide range of non trivial applications of the theory. Besides, software based on rough set approach to data analysis has been developed in many countries.

The theory has many important advantages. Some of them are listed below.

- Provides efficient algorithms for finding hidden patterns in data.
- Finds minimal sets of data (data reduction).
- Evaluates significance of data.
- Generates minimal sets of decision rules from data.
- It is easy to understand.
- Offers straightforward interpretation of obtained results.

Despite many serious achievements in rough set theory further investigations are here still needed. Particularly its algebraic, logical and probabilistic aspects require more research.

Beside pure theoretical research many problems related closer to applications require due attention.

Despite of many valuable methods of efficient, optimal decision rule generation methods from data, developed in recent years based on rough set theory – more research here is needed, particularly, when quantitative attributes are involved. In this context also further discretization methods for quantitative attribute values are badly needed. Comparison to other similar methods still requires due attention, although important results have been obtained in this area. Particularly interesting seems to be a study of the relationship between neural network and rough set approach to feature extraction from data.

Rough control and rough databases seem very promising domains of research and applications in the years to come.

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