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DECISION SUPPORT IN DATA MINING USING ROUGH SET THEORY

Priyanka [1] ,Pritika Saini[2], Niti Sethi [3]
(Deptt. of Computer Science, M.Tech Scholar, Maharishi Dayanand university, Rohtak, India) [1]
(Deptt. of Computer Science, Assistant Professor in SGT Institute of Engineering &Technology in MD University, India) [2]
(Department of Computer Science, M.Tech Scholar, Maharishi Dayanand university, Rohtak, India)[3]

Abstract-Data mining deals with finding patterns in data that are by user-definition, interesting and valid. It is an interdisciplinary area involving databases, machine learning, pattern recognition, statistics, visualization and others. Decision support provides a selection of data analysis, simulation, visualization and modeling techniques, and software tools such as decision support systems, group decision support and mediation systems, expert systems, databases and data warehouses. Independently, data mining and decision support are well-developed research areas, but until now there has been no systematic attempt to integrate them. In a DSS, decision making process is intimately related to some factors which determine the quality of information systems and their related products. Traditional approaches to data analysis usually cannot be implemented in sophisticated Companies, where managers need some DSS tools for rapid decision making. In traditional approaches to decision making, usually scientific expertise together with statistical techniques are needed to support the managers. However, these approaches are not able to handle the huge amount of real data, and the processes are usually very slow. Today, data mining and knowledge discovery is considered as the main module of development of advanced DSSs. In this research, Using rough set theory approach, relay decision rule extraction is naturally a byproduct of the data reduction process involved and easily understood. Rule extraction technique is inherent to the machine learning process of rough set theory. Thus, the inherent capability of rough set theory to discover fundamental patterns in relay data has essentially mooted this study.

Index terms- Approximation, Data Extraction, Data mining, Decision Tables, Rough set, Rule Extraction.

1.Introduction

Modern organizations use several types of decision support systems to facilitate decision support. For the purposes of analysis and decision support in the business area in many cases Data Mining using Rough Set Theory is used. data mining is a powerful tool for nontrivial extraction of implicit, previously unknown, and potentially useful information from large data sets. Data mining is used in a process called Knowledge discovery in databases (KDD). The discovered knowledge can be rules describing properties of data or relationships among data, frequently occurring patterns, clustering of the objects in the data set, etc. Most data mining systems in use have been designed using variants of traditional machine learning techniques.

Using an approximation concept, rough set theory is able to remove data redundancies and consequently generate decision rules. In contrast to crisp sets, a rough set has boundary line cases – events that cannot be certainly classified either as members of the set or of its complement. Rough set theory is an alternative intelligent data analysis tool that can be employed to handle vagueness and inconsistencies. Recently, there has been a growing interest in rough set theory among researchers in modern intelligent information systems. The theory has found many real life applications in many areas. The primary applications of rough sets so far have been in data and decision analysis, databases, knowledge-based systems, and machine learning.
The rest of the paper is organized as follows: In the next section, data mining and knowledge discovery are reviewed. In section 3, the main aspects of rough set theory are explained. Section 4 uses rough set theory for rule extraction. Section five presents rule-structuring algorithms. Finally, in section six, conclusion and potential future works are presented .

2.Data Mining

Data mining is the process of posing various queries and extracting useful information, patterns, and trends often previously unknown from large quantities of data possibly stored in a database. Essentially, for many organizations, the goals of data mining include improving marketing capabilities, detecting abnormal patterns, and predicting the future based on past experiences and current trends. By increasing the size of a database, its supporting decision-making becomes more difficult. Moreover, the data might be from multiple sources and multiple domains. Thus, the integrity of a data also should be considered in a database approach. Data mining encompasses a range of techniques, which aim to extract value from volume and form the foundation of decision making.

Data mining takes advantage of advances in the fields of artificial intelligence (AI) and statistics. The challenges in data mining and learning from data have led to a revolution in the statistical sciences (Hasti & Tibisharani, 2002). Both disciplines have been working on problems of pattern recognition and classification. Both communities have made great contributions to the understanding and application of different paradigms, such as neural nets and decision trees

A. Data Mining and KDD

Historically, the notion of finding useful patterns in data has been given a variety of names, including data mining, knowledge extraction, information discovery, information harvesting, data archaeology, and data pattern processing. The term *data mining* has mostly been used by statisticians, data analysts, and the management information systems (MIS) communities. It has also gained popularity in the database field. The phrase *knowledge discovery in databases* was coined at the first KDD workshop in 1989 (Piatetsky-Shapiro 1991) to emphasize that knowledge is the end product of a data-driven discovery.In our view, KDD refers to the overall process of discovering useful knowledge from data, and data mining refers to a particular step in this process. *Data mining* is the application of specific algorithms for extracting patterns from data. The distinction between the KDD process and the data-mining step (within the process) is a central point of this article. The additional steps in the KDD process, such as data preparation, data selection, data cleaning, incorporation of appropriate prior knowledge, and proper interpretation of the results of mining, are essential to ensure that useful knowledge is derived from the data. Blind application of data-mining methods (rightly criticized as data dredging in the statistical literature) can be a dangerous activity, easily leading to the discovery of meaningless and invalid patterns.

B. Data Mining Steps

- **Stage 1: Exploration.** This stage usually starts with data preparation which may involve cleaning data, data transformations, selecting subsets of records

- **Stage 2: Model building and validation.** This stage involves considering various models and choosing the best one based on their predictive performance

- **Stage 3: Deployment.** That final stage involves using the model selected as best in the previous stage and applying it to new data in order to generate predictions or estimates of the expected outcome.

C. Data mining technologies and techniques

As shown in Figure 4, data mining is an integration of multiple technologies. These include data management such as database management, data warehousing, statistics, machine learning, decision support, visualization, and parallel computing [5]. Data mining methods and tools can be categorized in different ways]. In application, data mining methods can be classified as clustering, classification, summarization, dependency modeling, link analysis and sequence analysis. Some methods are traditional and established and some are relatively new.

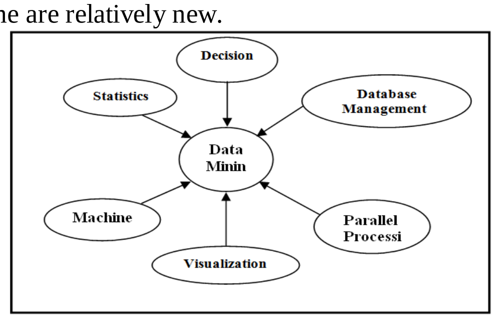

Figure1. Data mining technologies and techniques

3. Rough Set Theory

Rough Set Theory, proposed in 1982 by Zdzislaw Pawlak, is in a state of constant development. Its methodology is concerned with the classification and analysis of imprecise, uncertain or incomplete information and knowledge, and of is considered one of the first non-statistical approaches in data analysis. The main concepts related to Rough Set Theory are presented as the following:

A. Set

A set of objects that possesses similar characteristics it is a fundamental part of mathematics. All the mathematical objects, such as relations, functions and numbers can be considered as a set. However, the concept of the classical set within mathematics is contradictory; since a set is considered to be "grouping" without all elements are absent and is know as an empty set (Stoll, 1979). The various components of a set are known as elements, and relationship between an element and a set is called of a pertinence relation. Cardinality is the way of measuring the number of elements of a set. Examples of specific sets that treat vague and imprecise date are described below.

a. Fuzzy Set

Proposed by mathematician Loft Zadeh in the second half of the sixties, it has as its objective the treatment of the mathematical concept of vague and approximate, for subsequent programming and storage on computers. In order for Zadeh to obtain the mathematical formalism for fuzzy set, it was necessary to use the classic set theory, where any set can be characterized by a function. In the case of the fuzzy set, the characteristic function can be generalized so that the values are designated as elements of the Universe Set U belong to the interval of real numbers [0,1]. The characteristic Function Fuzzy is µA: U □ [0,1], where the values indicate the degree of pertinence of the elements of set U in relation to the set A, which indicated as it is possible for an element of x of U to belong to A, this function is known as Function of Pertinence and the set A is the Fuzzy Set (Zadeh, 1965).

b. Rough Set

An approach first forwarded by mathematician Zdzislaw Pawlak at the beginning of the eighties; it is used as a mathematical tool to treat the vague and the imprecise. Rough Set Theory is similar to Fuzzy Set Theory, however the uncertain and imprecision in this approach is expressed by a boundary region of a set, and not by a partial membership as in Fuzzy Set Theory. Rough Set concept can be defined quite generally by means of interior and closure topological operations know approximations (Pawlak, 1982).Observation:

It is interesting to compare definitions of classical sets, fuzzy sets and rough sets. Classical set is a primitive notion and is defined intuitively or axiomatically. Fuzzy set is defined by employing the fuzzy membership function, which involves advanced mathematical structures, numbers and functions. Rough set is defined by topological operations called approximations, thus this definition also requires advanced mathematical concepts.

B. Information system or information table

An information system or information table can be viewed as a table, consisting of objects (rows) and attributes (columns). It is used in the representation of data that will be utilized by Rough Set, where each object has a given amount of attributes (Lin, 1997). These objects are described in accordance with the format of the data table, in which rows are considered objects for analysis and columns as attributes (Wu et al., 2004). Below is shown an example of an information Table.

Table 1. Information Table

Patie-nt	Attributes			
	Head-ac-he	Vomiting	Temperat-ure	Viral illness
1	No	Yes	High	Yes
2	Yes	No	High	Yes
3	Yes	Yes	Very High	Yes
4	No	Yes	Normal	No
5	Yes	No	High	No
6	No	Yes	Very High	Yes

C. Approximation Spaces and Set Approximations

In this approach, vagueness is expressed by a boundary region of a set. Rough set concept can be defined by means of topological operations, *interior* and *closure*, called *approximations*. Now, we describe this problem more precisely. Let a finite set of objects U and a binary relation $R \subseteq U \times U$ be given. The sets U, R are called the *universe* and an *indiscernibility relation*, respectively. The discernibility relation represents our lack of knowledge about elements of U. For simplicity, we assume that R is an equivalence relation. A pair (U,R) is called an *approximation space*, where U is the universe and R is an equivalence relation on U. Let X be a subset of U, i.e. $X \subseteq U$. Our goal is to characterize the set X with respect to R.

In order to do it, we need additional notation and basic concepts of rough set theory which presented below.

By $R(x)$ we denote the equivalence class of R determined by element x. The indiscernibility relation R describes - in a sense - our lack of knowledge about the universe U. Equivalence classes of the relation R, called *granules*, represent an elementary portion of knowledge we are able to perceive due to R. Using only the indiscernibility relation, in general, we are not able to observe individual objects from U but only the accessible granules of knowledge described by this relation.

• The set of all objects which can be with *certainty* classified as members of X with respect to R is called the *R-lower approximation* of a set X with respect to R, and denoted by $R_*(X)$, i.e.

$R_* X = \{x: R(x) \subseteq X\}$.

• The set of all objects which can be only classified as *possible* members of X with respect to R is called the *R*-

upper approximation of a set *X* with respect to *R*, and denoted by $R^*(X)$, i.e.

$R^*(X) = \{x: R(x) \cap X \neq \emptyset\}$.

• The set of all objects which can be decisively classified neither as members of *X* nor as members of - *X* with respect to *R* is called the *boundary region* of a set *X* with respect to *R*, and denoted by *RN* (*X*) *R* , i.e. $RN_R(X) = R^*(X) - R_*(X)$

Now we are ready to formulate the definition of the rough set notion.• A set *X* is called *crisp* (*exact*) with respect to *R* if and only if the boundary region of *X* is empty.

• A set *X* is called *rough* (*inexact*) with respect to *R* if and only if the boundary region of *X* is nonempty.

The definitions of set approximations presented above can be expressed in terms of granules of knowledge in the following way. The lower approximation of a set is union of all granules which are entirely included in the set; the upper approximation − is union of all granules which have non-empty intersection with the set; the boundary region of a set is the difference between the upper and the lower approximation of the set.Figure presents the graphical illustration of the set approximations defined above

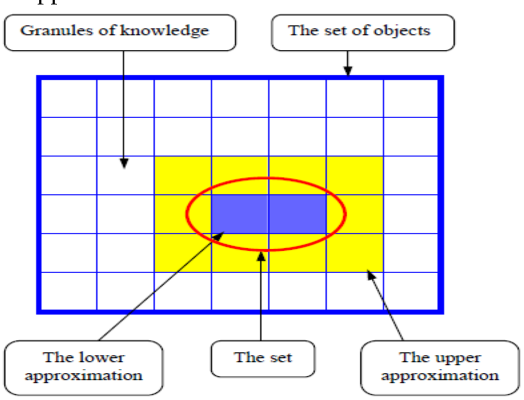

Figure 2. Approximations.

It is interesting to compare definitions of classical sets, fuzzy sets and rough sets. Classical set is a primitive notion and is defined intuitively or axiomatically. Fuzzy sets are defined by employing the fuzzy membership function, which involves advanced mathematical structures, numbers and functions. Rough sets are defined by approximations. Thus this definition also requires advanced mathematical concepts.

It is easily seen that the lower and the upper approximations of a set are, respectively the interior and closure of this set in the topology generated by the indiscernibility relation. One can define the following four basic classes of rough sets, i.e., four categories of vagueness:

1. A set X is roughly R-definable, iff $R_*(X) \neq \emptyset$ and $R^*(X) \neq U$.

2. A set X is internally R-undefinable, iff $R_*(X) = \emptyset$ and $R^*(X) \neq U$.

3. A set X is externally R-undefinable, iff $R_*(X) \neq \emptyset$ and $R^*(X) = U$.

4. A set X is totally R-undefinable, iff $R_*(X) = \emptyset$ * and $R^*(X) = U$.

The intuitive meaning of this classification is the following.

A set *X* is roughly *R-definable* means that with respect to *R* we are able to decide for some elements of *U* that they belong to *X* and for some elements of *U* that they belong to –*X*.

A set *X* is internally *R*-undefinable means with respect to *R* we are able to decide for some elements of *U* that they belong to –*X*, but we are unable to decide for any element of *U* whether it belongs to *X*.

A set *X* is externally *R*-undefinable means that with respect to *R* we are able to decide for some elements of *U* that they belong to *X*, but we are unable to decide for any element of *U* whether it belongs to –*X*.

A set *X* is totally *R*-undefinable means that with respect to *R* we are unable to decide for any element of *U* whether it belongs to *X* or –*X*.

D. Decision tables and decision algorithms

A decision table contains two types of attributes designated as the condition attribute and decision attribute. In Table 1, the attributes of headache, vomiting and temperature can all be considered as condition attributes, whereas the viral illness attribute is considered a decision attribute.Each row of a decision table determines a decision rule, which specifies the decisions (actions) that must be taken when conditions are indicated by condition attributes are satisfied, e.g. in Table 1 the condition (Headache, no), (vomiting, yes), (Temperature, high) determines the decision (Viral illness, yes). Table 1 shows that both patient2 and patient5 suffer from the same symptoms since the condition attributes of headache, vomiting and temperature possess identical values; however, the values of decision attribute differ. These set of rules are known as either inconsistency, non-determinant or conflicting. These rules are known as consistency, determinant or non conflicting or simply, a rule. The number of consistency rules, contained in the decision table are known as a factor of consistence, which can be denoted by $\gamma(C, D)$, where C is the condition and D the decision. If $\gamma(C,D) = 1$, the decision table is consistent, but if $\gamma(C,D) \neq 1$ the table of decision is inconsistent.

Given that Table 1, $\gamma(C,D) = 4/6$, that is, the Table 1 possesses two inconsistent rules (patient2, patient5) and four consistent rules (patient1, patient3 patient4, patient6), inside of universe of six rules for all the Table 1 (Ziarko & Shan, 1995). The decision rules are frequently shown as implications in the form of "if... then... ". To proceed is shown one rule for the implication viral illness:

If
Headache = no and
Vomiting = yes and
Temperature = high
Then
Viral Illness = yes

A set of decision rules is designated as decision algorithms, because for each decision table it can be associated with the decision algorithm, consisting of all the decision rules that it occur in the respective decision table. A may be made distinction between decision algorithm and decision table. A decision table is a data set, whereas a decision algorithm is a collection of implications, that is, a logical expressions (Pawlak, 1991).

4. Data and Rule Extraction

Data analysis is accomplished, using a Rough Set approach for the elimination of redundant data and the development of a set of rules that it can aid the doctor in the elaboration of the diagnosis. Below the Table 3 is shown with the patients data set and respective symptoms, and the data are of the discreet type.

Information system or information table

Table 2. Patients with respective symptoms

Pa-tient	**Conditional Attributes**	**Decision Attribute**		
	blotched_red_skin	muscu-lar_pain_articulations	Temper-ature	Den-gue
P1	No	No	Normal	No
P2	No	No	High	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes
P5	No	Yes	Very High	Yes
P6	Yes	Yes	High	Yes
P7	Yes	Yes	Very High	Yes
P8	No	No	High	No
P9	Yes	No	Very High	Yes
P10	Yes	No	High	No
P11	Yes	No	Very High	No
P12	No	Yes	Normal	No
P13	No	Yes	High	Yes
P14	No	Yes	Normal	No
P15	Yes	Yes	Normal	No
P16	Yes	No	Normal	No
P17	Yes	No	High	No
P18	Yes	Yes	Very High	Yes
P19	Yes	No	Normal	No
P20	No	Yes	Normal	No

Where, B are all of the objects or registrations of the system, given set B={P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18, P19, P20} the set conditional attributes is represented byC={blotched_red_skin,muscular_pain_articulations,Temperature}and the set D represented the decision attribute, where D={dengue}. The set A or Table 3, can be shown in relation to the function of nominal values of considered attributes, in the Table 3:

Table 3. Nominal Values of Attributes

	Attributes	Nominal Values
Conditional Attributes	blotched_red_skin,	Yes, No
	muscular_pain_articulations	Yes, No
	Temperature	Normal, High,Very High
Decision Attributes	Dengue	Yes, No

Approximation

The lower and the upper approximations of a set are interior and closure operations in a topology generated by a indiscernibility relation. Below is presented and described the types of approximations are followed using in Rough Set Theory; the approximations concepts are applied in the Table 4, shown to proceed:

8. Table 4 organized in relation decision attribute

Patient	**Conditional Attributes**			**Decision Attribute**
	blotched_red_skin	muscular_pain_articu lations	Temperature	Dengue
P1	No	No	Normal	No
P2	No	No	High	No
P8	No	No	High	No
P10	Yes	No	High	No
P11	Yes	No	Very High	No
P12	No	Yes	Normal	No
P14	No	Yes	Normal	No
P15	Yes	Yes	Normal	No
P16	Yes	No	Normal	No
P17	Yes	No	High	No
P19	Yes	No	Normal	No
P20	No	Yes	Normal	No
P3	No	No	Very High	Yes
P4	No	Yes	High	Yes
P5	No	Yes	Very High	Yes
P6	Yes	Yes	High	Yes
P7	Yes	Yes	Very High	Yes
P9	Yes	No	Very High	Yes
P13	No	Yes	High	Yes
P18	Yes	Yes	Very High	Yes

a. Lower Approximation set B”

- Lower Approximation set (B”) of the patients that are definitely have dengue are identified as B” = {P3,P4,P5,P6,P7,P13,P18}

- Lower Approximation set (B”) of patients that certain have not dengue are identified as B” = {P1 ,P2 ,P8 ,P10 ,P12, P14, P15, P16, P17, P19,P20}

b. Upper Approximation set B*

- Upper Approximation set (B*) of the patients that possibly have dengue are identified as B* = {P3,P4,P5,P6,P7, P9, P13,P18}

- Upper Approximation set (B*) of the patients that possibly have not dengue are identified as B* = {P1, P2, P8, P10, P11, P12, P14, P15, P16, P17, P19, P20}

c. Boundary Region (BR)

- Boundary Region (B*) of the patients that not have dengue are identified as:

BR={P1,P2,P8,P10,P11,P12,P14,P15,P16,P17,P19,P20}-{P1,P2,P8,P10,P12,P14,P15,P16,P17,P19,P20} = {P11};

- Boundary Region (B*), the set of the patients that have dengue are identified as: BR = {P3,P4,P5,P6,P7, P9, P13,P18} - {P3,P4,P5,P6,P7,P13,P18} = {P9}

Observation: Boundary Region (BR), the set constituted by elements P9 and P11, which cannot be classified, since they possess the same characteristics, but with differing conclusions differ in the decision attribute.

Quality of approximations

The two coefficients of quality of approximation are:- Imprecision coefficient, using Eq. (1)):

• for the patients with possibility of they are with dengue αB(X) = =7/8;

• for the patients with possibility of they are not with dengue αB(X) = 8/12.

- Quality Coefficient of upper and lower approximation, using Eq. 2 and 3:

• αB(B*(X)) =8/20, for the patients that have the possibility of they be with dengue;

• αB(B*(X)) =11/20, for the patients that not have the possibility of they be with dengue;

• αB(B”(X)) =7/20, for the patients that have dengue;

• αB(B"(X)) =8/20, for the patients that not have dengue.

Observations:

1. Patient with dengue: αB(B"(X))=7/20, that is, 35% of patients certainly with dengue.

2. Patient that don't have dengue: αB(B"(X)) = 11/20, that is, approximately 55% of patients certainly don't have dengue.

3. 10% of patients (P9 and P11) cannot be classified neither with dengue nor without dengue, since the characteristics of all attributes are the same, with only the decision attribute (dengue) not being identical and generates an inconclusive diagnosis for dengue.

Data reduction in information system

The form in which data is presented within an information system must guarantee that the redundancy is avoided as it implicates the minimization of the complexly computational in relation to the creation of rules to aid the extraction knowledge. However, when the information system possesses redundancy situations, it is necessary to treat it One of the ways of accomplishing this is to use the concept of reduct, without altering the indiscernibility relations. A reduct is a set of necessary minimum data, since the original proprieties of the system or information table are maintained. Therefore, the reduct must have the capacity to classify objects, without altering the form of representing the knowledge.

The process of reduction of information is presented below in Table 3, it can be observed that the data is of a discreet type.

a. Verification inconclusive data

Step 1 – Analysis of data contained in Table 3 shows that possess information inconclusive, being that the values of conditional attributes same and the value of decision attribute is different.

Conclusion of Step 1: The symptoms of patient P9 and patient P11 are both inconclusive, since they possess equal values of conditions attributes together with a value of decision attribute that is different. Therefore, the data of patient P9 and patient P11 will be excluded from Table 3.

b. Verification of equivalent information

Step 2 – Analysis of data that possesses equivalent information.

5. Decision rules

With the information reduct shown above, it can be generated the necessary decision rules for aid to the dengue diagnosis. The rules are presented to proceed:

Rule-1 R1: If patient
blotched_red_skin = No and
muscular_pain_articulations = No and
temperature = Normal
Then dengue = No.

Rule-2 R2: If patient
blotched_red_skin = No and
muscular_pain_articulations = No and
temperature = Very High
Then dengue = Yes.

Rule-3 R3: If patient
blotched_red_skin = No and
muscular_pain_articulations = Yes and
temperature = High
Then dengue = Yes.

6. Conclusion

This study, it has discussed the Rough set theory, was proposed in 1982 by Z. Pawlak, as an approach to knowledge discovery from incomplete, vagueness and uncertain data. The rough set approach to processing of incomplete data is based on the lower and the upper approximation, and the theory is defined as a pair of two crisp sets corresponding to approximations.

The main advantage of rough set theory in data analysis is that it does not need any preliminary or additional information concerning data, such as basic probability assignment in Dempster-Shafer theory, grade of membership or the value of possibility in fuzzy set theory. The Rough Set approach to analysis has many important advantages such as (Pawlak, 1997): Finding hidden patterns in data; Finds minimal sets of data (data reduction); Evaluates significance of data; Generates sets of decision rules from data; Facilitates the interpretation of obtained result Different problems can be addressed though Rough Set Theory, however during the last few years this formalism has been approached as a tool used with different areas of research. There has been research concerning be relationship between Rough Set Theory and the Dempster-Shafer Theory and between rough sets and fuzzy sets. Rough set theory has also provided the necessary formalism and ideas for the development of some propositional machine learning systems.

Rough set has also been used for knowledge representation; data mining; dealing with imperfect data; reducing knowledge representation and for analyzing attribute dependencies.

Rough set Theory has found many applications such as power system security analysis, medical data, finance, voice recognition and image processing; and one of the research areas that has successfully used Rough Set is the knowledge discovery or Data Mining in database.

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