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A Comparative Analysis of Feature Selection Algorithms Based on Rough Set Theory

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Abstract: Rough set theory introduced by Pawlak in 1982 has been applied successfully in all the fields. It creates a framework for handling imprecise and incomplete data in information systems. A Rough Set is a mathematical tool to deal with Uncertainty and vagueness of an information system. An information system can be presented as a Table with rows analogous to objects and columns analogous to attributes. Each row of the table contains values of particular attributes representing information about an object. Based on rough sets theory, this study proposes Modified Quickreduct algorithm and discusses the performance study of various reduct algorithms for constructing efficient rules. The experiments were carried out on data sets of UCI machine learning repository and the Human Immuno deficiency Virus(HIV) data set to analyze the performance study. Generally, in rule generation for taking decision from the information system, the reduct plays a vital role. The reduct algorithm that generates the least number of rules is considered an efficient one.

Key words: Data mining, rough set, feature selection, rule induction

INTRODUCTION

Data mining: Data mining refers to extracting or mining knowledge from large amounts of data. There are many other terms carrying a similar or slightly different meaning to Data mining, such as knowledge mining from databases, knowledge extraction, data pattern analysis, data archaeology and data dredging. Data mining can also be termed as Knowledge Discovery in Databases (KDD)[1].

KDD is the process of identifying valid, novel, potentially useful and ultimately understandable patterns in data. Data mining is not a single technique, some commonly used techniques are: Statistical Methods, Case-Based Reasoning (CBR), Neural Networks, Decision Trees, Rule Induction, Bayesian Belief Networks (BBN), Genetic Algorithms, Fuzzy Sets and Rough Sets.

Rough set: Rough set theory was initially developed[2,3] for a finite universe of discourse in which the knowledge base is a partition, which is obtained by any equivalence relation defined on the universe of discourse. In rough sets theory, the data is organized in a table called decision table. Rows of the decision table correspond to objects and columns correspond to attributes. In the data set, a class label indicates the class to which each row belongs. The class label is called as decision attribute, the rest of the attributes are the condition attributes. Here, C is used to denote the condition attributes, D for decision attributes, where $C \cap D = \Phi$ and t_j denotes the j^{th} tuple of the data table. Rough sets theory defines three regions based on the equivalent classes induced by the attribute values: lower approximation, upper approximation and boundary. Lower approximation contains all the objects, which are classified surely based on the data collected and Upper approximation contains all the objects, which can be classified probably, while the boundary is the difference between the upper approximation and the lower approximation. Hu[4] presented the formal definitions of rough set theory. Kusiak[5] described the basic concepts of rough set theory and other aspects of Data mining.

Let U be any finite universe of discourse. Let R be any equivalence relation defined on U. Clearly, the equivalence relation partitions U. Here, (U, R) which is the collection of all equivalence classes, is called the approximation space. Let W_1, W_2, W_3, ..., W_n be the elements of the approximation space (U, R). This collection is known as knowledge base. Then for any

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subset A of U, the lower and upper approximations are defined as follows:

$$\underline{R}A = \cup \{W_i / W_i \subseteq A\} \quad (1)$$
$$\overline{R}A = \cup \{Wi / Wi \cap A \neq \emptyset\} \quad (2)$$

The ordered pair ($\underline{R}A$, $\overline{R}A$) is called a rough set. After defining these approximations of A, the reference universe U is divided into three different regions: the positive region $POS_R(A)$, the negative region $NEG_R(A)$ and the boundary region $BND_R(A)$, defined as follows:

$$POS_R(A) = \underline{R}A \quad (3)$$

$$NEG_R(A) = U - \overline{R}A \quad (4)$$

$$BND_R(A) = \overline{R}A - \underline{R}A \quad (5)$$

Hence, it is trivial that if BND(A) = Φ, then A is exact. This study provides a mathematical tool that can be used to find out all possible reduces.

Feature selection: Feature selection process refers to choosing subset of attributes from the set of original attributes. Feature selection has been studied intensively in the past one decade[6-9]. Besides the brief introduction given here, the extensive literature of Rough sets theory can be referred to Orlowska[10], Peters[11], Polkowski[12] for recent comprehensive overviews of developments.

The purpose of the feature selection is to identify the significant features, eliminate the irrelevant of dispensable features and build a good learning model. The benefits of feature selection are twofold: it considerably decreases the computation time of the induction algorithm and increases the accuracy of the resulting mode.

A decision Table may have more than one reduct. Anyone of them can be used to replace the original Table. Finding all the reduces from a decision table is NP-Hard[13]. Fortunately, in many real applications it is usually not necessary to find all of them. It is sufficient to compute only one reduct[4]. A natural question is which reduct is the best if there exist more than one reduct. The selection depends on the optimality criterion associated with the attributes. If it is possible to assign a cost function to attributes, then the selection can be naturally based on the combined minimum cost criteria. In the absence of an attribute cost function, the only source of information to select the reduct is the contents of the data Table[9]. N. Zhong[14] applied Rough Sets with Heuristics(RSH) and Rough Sets with Boolean Reasoning(RSBR) are used for attribute selection and discretization of real-valued attributes. For simplicity, we adopt the criteria that the best reduct is the one with the minimal number of attributes and that if there are two or more reducts with the same number of attributes, then the reduct with the least number of combinations of values of its attributes is selected.

Data mining process: The process of the data mining methodology is depicted in the following block diagram.
Data Preparation

In the first stage, the data sets viz., Iris, Pima, Bupa and New-thyroid obtained from UCI machine learning repository[15] and the HIV data set are considered for this study. The HIV database consists of information collected from the HIV Patients at Voluntary Counselling and Testing Centre (VCTC) of Government Hospital, Dindigul District, Tamilnadu, India, a well-known centre for diagnosis and treatment of HIV. The advantage of this data set is that it includes a sufficient number of records of different categories of people affected by HIV. The set of descriptors presents all the required information about patients. It contains the records of 500 patients. The record of every patient contains 49 attributes and this has been reduced to 22 attributes after consulting the Physician. The details of attributes are given as follows: The continuous attributes are Age, Sex, Marital-Status, Occupation(OCCU), Area, Loss-of-Weight(LW), Continuous-Fever(CF), Continuous-Cough(CC), Skin-Disease(SD), Oral-Thrush(OT), Tuberculosis(TB), Diarrahoea(D), Anaemia, Sexual–Transmission-Disease(STD), Swelling-on-Neck(SWELL), Different-Count(DC), Total-Count(TC), Erythrocyte-Rate(ER), Creatinine, Loss-of-Appetite(LA), Lymphodenopathy and the decision attribute Result (Positive, Negative, Suspect).

In our experiments, no condition attribute value is unknown. If some values existed in the input data files, the input data files were preprocessed to remove them. All inconsistent rows in the decision table is eliminated.

Reduct algorithms: The Quickreduct, Variable Precision Rough Set have been studied and the Modified Quickreduct was introduced for computing reducts.

Quickreduct algorithm(QR): The reduction of attributes is achieved by comparing equivalence relations generated by sets of attributes. Attributes are removed so that the reduced set provides the same predictive capability of the decision feature as the original. A reduct is defined as a subset of minimal cardinality R_{min} of the conditional attribute set C such that $\gamma_R(D) = \gamma_C(D)$.

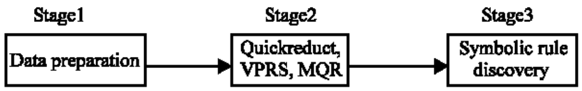

Fig. 1: Data mining process

$$R = \{X : X \subseteq C;\ \gamma_X(D) = \gamma_C(D)\} \qquad (6)$$

$$R_{min} = \{X : X \in R;\ \forall Y \in R;\ |X| \leq |Y|\ \} \qquad (7)$$

The intersection of all the sets in R_{min} is called the core, the elements of which are those attributes that cannot be eliminated without introducing more contradictions to the dataset. In this method a subset with minimum cardinality is searched for.

The problem of finding a reduct of an information system is the subject of much research[16,17]. Jensen[18-20] have developed the Quickreduct algorithm to compute a minimal reduct without exhaustively generating all possible subsets and also they developed Fuzzy-Rough attribute reduction with application to web categorization. K. Thangavel[21,22] applied Rough Sets for feature selection in Medical databases like Mammograms and HIV etc. The most basic solution to locating such a subset is to simply generate all possible subsets and retrieve those with a maximum rough set dependency degree. Obviously, this is an expensive solution to the problem and is only practical for very simple datasets. Most of the time only one reduct is required as, typically, only one subset of features is used to reduce a dataset, so all the calculations involved in discovering the rest are pointless. The pseudo code of the Quickreduct algorithm is given below:

QUICKREDUCT(C,D)
C, the set of all conditional features;
D, the set of decision features.
(a) $R \leftarrow \{\}$
(b) Do
(c) $T \leftarrow R$
(d) $x \in (C-R)$
(e) if $\gamma_{R\cup\{x\}}(D) > \gamma_T(D)$
where $\gamma_R(D)$=card($POS_R(D)$) / card(U)
(f) $T \leftarrow R\cup\{x\}$
(g) $R \leftarrow T$
(h) until $\gamma_R(D) == \gamma_C(D)$
(i) return R

Variable Precision Rough Set(VPRS): Variable Precision Rough Sets (VPRS)[23] extend rough set theory by the relaxation of the subset operator. It was proposed to analyze and identify data patterns which represent statistical trends rather than functional. The VPRS study may also be found in[24-26]. As yet, there have been no comparative experimental studies between rough set methods and the VPRS method. The main idea of VPRS is to allow objects to be classified with an error smaller than a certain predefined level. This introduced threshold relaxes the rough set notion of requiring no information outside the dataset itself. Let $X,Y \subseteq U$, the relative classification error is defined by

$$c(X,Y) = 1-\{\ |X \cap Y| / |X|\ \} \qquad (8)$$

Observe that $c(X,Y) = 0$ if and only if $X \subseteq Y$. A degree of inclusion can be achieved by allowing a certain level of error, β in classification:

$$X \subseteq_\beta Y \text{ iff } c(X,Y) \leq \beta,\ 0 \leq \beta < 0.5 \qquad (9)$$

Using $\subseteq \beta$ instead of $\subseteq$, the β-upper and β-lower approximations of a set X can be defined as:

$$\underline{R}_\beta X = \cup\ \{ [x]_R \in U/R \mid [x] \subseteq_\beta X\} \qquad (10)$$

$$\overline{R}_\beta X = \cup\ \{ [x]_R \in U/R \mid c([x]_R, X) < 1-\beta\ \} \qquad (11)$$

Note that $\underline{R}_\beta X = \underline{R}X$ for β=0. The positive, negative and boundary regions in the original rough set theory can now be extended to:

$$POS_{R,\beta}(X) = \underline{R}_\beta X \qquad (12)$$

$$NEG_{R,\beta}(X) = U - \overline{R}_\beta X \qquad (13)$$

$$BND_{R,\beta}(X) = \overline{R}_\beta X - \underline{R}_\beta X \qquad (14)$$

Consider a decision table $A = (U, C \cup D)$, where C is the set of conditional attributes and D the set of decision attributes. The β-positive region of an equivalence relation Q on U may be determined by

$$POS_{R,\beta}(Q) = \cup\ X \in U / Q\underline{R}_\beta X \qquad (15)$$

where R is also an equivalence relation on U. This can then be used to calculate dependencies and thus determine β-reducts. The dependency function becomes:

$$\gamma_{R,\beta}(Q) = |\ POS_{R,\beta}(Q)\ | / |U| \qquad (16)$$

It can be seen that the QUICKREDUCT algorithm outlined previously can be adapted to incorporate the reduction method built upon the VPRS theory. By supplying a suitable β-?value to the algorithm, the β-lower approximation, β-positive region and β-dependency can replace the traditional calculations. This will result in a more approximate final reduct, which may be a better generalization when encountering unseen data. However, the variable precision study requires the additional parameter β which has to be specified from the start. By repeated experimentation, this parameter can be suitably approximated. However, problems arise when searching for true reducts as VPRS incorporates an element of inaccuracy in determining the number of classifiable objects.

Modified Quickreduct Algorithm(MQR): In quickreduct algorithm, the vertical reduct is possible, when only the unwanted attributes are eliminated. As in the normalization process in the data base system, the size of the information system can also be reduced horizontally by eliminating the objects which are involved in the construction of the lower approximation. The steps of the proposed algorithm namely "Modified Quickreduct Algorithm" are described as follows:

- Create an empty set R and T.
- Eliminate all inconsistent rows in the decision table(i.e. the rows with similar condition attribute values, but different decision attribute values).
- Select an attribute at a time, this attribute results in the greatest increase in $\gamma_p(Q)$.
- Remove all consistent rows for the above particular attribute, till it reaches its maximum possible value for the data set.

The step by step procedure of the Modified Quickreduct Algorithm is detailed below:

- $R \leftarrow \{\}$
- do
- eliminate inconsistency in decision table
- $T \leftarrow R$
- eliminate all consistent instances: $U = U - POS_R(D)$, where $POS_R(D) = \cup \underline{Px}$
- $\forall a \in (C - R)$
- if $\gamma_{R \cup \{a\}}(D) > \gamma_T(D)$ where $\gamma_R(D) = card(POS_R(D)) / card(U)$
- $T \leftarrow R \cup \{a\}$
- $R \leftarrow T$
- until $\gamma_R(D) = \gamma_C(D)$
- return R

Rule extraction: In this stage , reduced data obtained from stage 2 is applied to the rule extraction algorithm to formulate the efficient rules (Table 1). The rule extraction algorithm uses the following Heuristic Study:

- Merge identical rows, that is rows with similar condition and decision attribute values.
- Compute the core of every rows.
- Merge duplicate rows and compose a table with reduct value.

Example: A system of 8 objects consisting of four conditional attributes and a decision attribute, borrowed from[4] is taken into consideration and is presented in Table 1.

In Table 1, the following substitutions LOW=1, MEDIUM=2, HIGH=3, COM=1 and SUB=2 can be used and the above reconstructed Table is presented in Table 2.

Table 1: Car data set

Object	Weight	Door	Size	Cylinder	Mileage
1	Low	2	Com	4	High
2	Low	4	Sub	6	Low
3	Medium	4	Com	4	High
4	High	2	Com	6	Low
5	High	4	Com	4	Low
6	Low	4	Com	4	High
7	High	4	Sub	6	Low
8	Low	2	Sub	6	Low

Table 2: Reconstructed table

Object	Weight	Door	Size	Cylinder	Mileage
1	1	2	1	4	3
2	1	4	2	6	1
3	2	4	1	4	3
4	3	2	1	6	1
5	3	4	1	4	1
6	1	4	1	4	3
7	3	4	2	6	1
8	1	2	2	6	1

Table 3: Reconstructed Table with consistent instances

Object	Weight	Door	Size	Cylinder	Mileage
1	1	2	1	4	3
2	1	4	2	6	1
6	1	4	1	4	3
8	1	2	2	6	1

Table 4: Attribute reduction

Object	Weight	Size	Mileage
1	1	1	3
2	1	2	1
3	2	1	3
4	3	1	1
5	3	1	1
6	1	1	3
7	3	2	1
8	1	2	1

Table 5: Merge identical rows

Object	Weight	Size	Mileage
1, 6	1	1	3
2, 8	1	2	1
3	2	1	3
4, 5	3	1	1
7	3	2	1

Table 6: Core

Object	Weight	Size	Mileage
1, 6	*	1	3
3	*	1	3
2, 8	*	2	1
7	*	2	1

Table 7: Merge duplicate rows

Object	Weight	Size	Mileage
1, 6, 3	*	1	3
2, 8, 7	*	2	1
4, 5	3	1	1

Apply the Modified Quickreduct Algorithm for the above decision system. Initially, R ← {} and T ← R.

Ind(Weight) = {1, 2, 6, 8}, {3}, {4, 5, 7}.
Ind(Mileage) = {1, 3, 6}, {2, 4, 5, 7, 8}.
Pos(Weight)/(Mileage) = Ind(Weight) ⊆ Ind(Mileage)
= {3, 4, 5, 7}
γ(Weight) / (Mileage) = 4 / 8. Therefore R ← {Weight} and T ← R, until γ(Weight) / (Mileage) = γ(Weight, Door, Size, Cylinder) / (Mileage). This condition proves false, because γ(Weight, Door, Size, Cylinder) / (Mileage)= 8/8.
Eliminate all consistent instances: U = U – $POS_R(D)$.
U = {1, 2, 3, 4, 5, 6, 7, 8} – {3, 4, 5, 7} = {1, 2, 6, 8}. Again reconstruct the decision system with consistent instances and present as in Table 3.

Take the next combination and find out the degree of dependency as follows:

γ(Weight, Door) / (Mileage) = 0 / 8 and if γ(Weight, Door) / (Mileage) > γ(Weight) / (Mileage), this condition proves false. Again take the next combination and find out the degree of dependency as follows:
γ(Weight, Size) / (Mileage) = 8 / 8, and if γ(Weight, Size) / (Mileage) > γ(Weight) / (Mileage), this condition proves true, therefore R ← {Weight, Size}, T ← R. Until γ(Weight, Size) = γ(Weight, Door, Size, Cylinder) / (Mileage). This condition also proves true, and the final reduct set for the above table is {Weight, Size}. Hence, Table 2 can be reduced into Table 4 using the attribute reduct {Weight, Size}.

Apply the rule extraction algorithm[27] in Table 4. Merge identical objects of Table 4. In take the condition attributes of {WEIGHT, SIZE} as presented in Table 4. If any identical pair occurs, merge it. It is shown in Table 5.

Compute the core of every object in Table 5 and present it as in Table 6.

In the next step, merge duplicate objects with same decision value and compose a table with the reduct value. That is, the merged rows are {{1, 6},{3}} and {{2, 8}, {7}} as presented in Table 7.

Table 7 shows the new set of objects which contains the rules of Table 2. Decision rules are often presented as implications and are often called "if….then…" rules. We can express the rules as follows:

If Size = 1 Then Mileage = 3
If Size = 2 Then Mileage = 1
If Weight = 3 and Size = 1 Then Mileage = 1

EXPERIMENTAL ANALYSIS

The Quickreduct, VPRS, Modified Quickreduct algorithm and the Rule Extraction Algorithm have been implemented using MATLAB for databases available in the UCI data repository and the HIV data directly collected from the 500 HIV patients. The Comparative Analysis of Quickreduct, VPRS and Modified Quickreduct is tabulated in Table 8 as follows:

From the above Table, it is evident that Modified Quickreduct algorithm produces minimal reduct for large data sets. The reduced attributes obtained from HIV data set after applying Modified Quick Reduct Algorithm is Age, Occupation, Area, Loss-of-Weight, Continuous-Fever, Continuous-Cough, Skin-Disease, Tuberculosis, Diarrahoea, Anaemia, Sexual–Transmission-Disease, Swelling-on-Neck, , Loss-of-Appetite. The important rules of positive and suspected cases are as follows:

Rule 1: IF AREA=rural, STD=yes, TB=yes, D=yes THEN RESULT =positive

Rule 2: IF AREA=rural, STD=yes, D=yes THEN RESULT =positive

Rule 3: IF OCCU=cooly, STD=yes, SD=yes, CF=yes THEN RESULT =positive

Rule 4: IF STD=yes, LW=yes, D=yes, TB=yes THEN RESULT = positive

Rule 5: IF OCCU=cooly, AREA=rural, STD=yes, SD=yes, TB=yes THEN RESULT = positive

Rule 6: IF AREA=rural, CF=yes, CC=yes, STD=yes THEN RESULT = positive

Rule 7: IF STD=yes, ANAEMIA=yes, SWELL=yes, DC=high THEN RESULT = positive

Rule 8: IF STD=yes, SD=yes, TB=no THEN RESULT =suspect

Rule 9: IF AREA=urban, OCCU=driver, STD=yes, CF=no, CC=no THEN RESULT=suspect

Rule 10: IF STD=yes, SD=no, LW=yes THEN RESULT =suspect

Rule 11: IF STD=yes, TB=yes, CC=no THEN RESULT =suspect

Table 8: Comparison of various reduct algorithms for rule generation

			QR		VPRS β =0.4		MQR	
Data sets	Instances	Features	Reduct	Rule	Reduct	Rule	Reduct	Rule
Car	8	4	2	3	3	4	2	3
Iris	150	4	3	39	3	31	3	17
Pima	768	8	5	40	6	37	3	27
Bupa	345	6	4	47	4	31	3	25
New-Thyroid	215	5	3	64	4	60	3	22
HIV	500	21	17	23	14	19	13	13

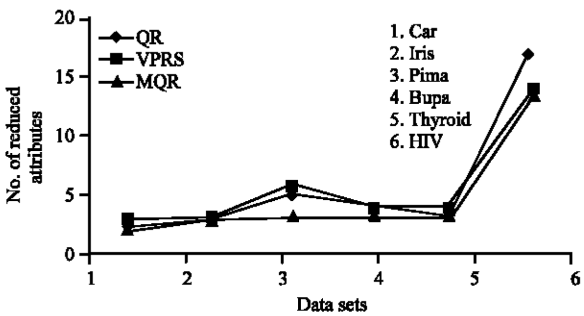

Fig. 2: Performance analysis of the quickreduct, variable precision rough set and modified quickreduct

The Performance Analysis of the Quickreduct, Variable Precision Rough Set and Modified Quickreduct is also depicted in Fig. 2.

It is observed from the graph that the Modified Quickreduct produces minimal reduct for the data sets like Pima, Bupa and HIV. In the case of Car, Iris and New-Thyroid data sets, the same number of reducts is obtained in Quickreduct and Modified Quickreduct, perhaps the reason may be the Car, Iris and New-Thyroid information system consists of small data.

CONCLUSION

The Modified Quickreduct has been proposed and compared with the Quickreduct and Variable Precision Rough Set. It was observed that the Modified Quickreduct generates minimal reduct for large data sets. The rule induction was performed by using minimal reduct set generated by Modified Quickreduct and it was identified that less number of rules were produced when compared with the rules generated by the reducts using Quickreduct and Variable Precision Rough Set.

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