A strategy of attribute reduction based on partition

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Abstract

The attribute reduction is an important pre-processing step for data mining. In order to avoid striking equivalence classes repeatedly for positive region or information entropy reduction it is proposed to calculate attribute reduction by constructing partition directly. At the same time the judgments of the absolute reduction and the relative reduction based on the equivalent division are proved. And the data description quality for the relative reduction has been defined. It is shown that striking minimum relative reduction of decision table is in the cost of the relative decline of description quality for classification.

Keywords: attribute reduction, partition, rough sets, data mining

1 Introduction

The attribute reduction is an important pre-treating step in the process of data mining [1]. It can reduce the data scale for the following mining effectively [2, 3]. But finding a minimum attribute set is a NP-hard problem due to the combinatorial explosion of properties [4]. It has been the main problem of various reduction algorithms to get results quickly and accurately.

There are three classical methods for attribute reduction, such as distinguish matrix [5], positive region [6] and information entropy [7]. However, the reduction algorithm based on distinguish matrix is only suitable for processing small decision tables relatively because of the matrix calculation increasing the space overhead. So the reduction for large data tables is on the basis of the positive region or information entropy mainly [8]. But calculating equivalence classes is a basic and essential step whether it is positive attribute reduction or information entropy. To avoid duplication of obtaining equivalence classes, it is proposed to reduce directly in the process of equivalence classes obtained. This can decrease computational overhead for the positive region and information entropy reduction.

2 The concept of attribute reduction

The target of attribute reduction is to delete irrelevant or unimportant attributes. There is same basic category between the original set and the set having removed some attributes. Those attributes removed do not change the overall description of the domain. Any object of the information system is on behalf of a class with the same regularity properties after reduction. So the number and composition of the object have been simplified for the information system. This will reduce the time and space overhead for the subsequent data processing. The knowledge used in rough set and equivalence relation is shown as follows:

Definition 1 [9] The information system can be represented as a quadruplet $S=(\tilde{X},R,V,f)$, where, $\tilde{X}$ represents a non-empty finite set of objects named domain. $\tilde{X}=\{X_1,X_2,\cdots,X_N\}$. X_i is an object. R is attribute set. V represents the set of the property value. V_a is range of the attribute $a\in R$. f is an information function $\tilde{X}\times R\to V$, $a\in R$, $X\in\tilde{X}$, $f_a(X)\in V_a$.

Definition 2 [9] Let A is an attribute set of the information table. a is on behalf of a particular attribute value. The objects X_i, X_j are named equivalence relation with respect to the property A. If X_i,X_j satisfies the relation as follows:

The equation $f_a(X_i)=f_a(X_j)$ founded for $\forall a\in A$, $A\subset R$, $X_i\in\tilde{X}$, $X_j\in\tilde{X}$. This relation is also known as indistinguishable relationship expressed as:

$$IND(A)=<X_i,X_j>\Big|<X_i,X_j>\in\tilde{X}\times\tilde{X},\quad \forall a\in A, f_a(X_i)=f_a(X_j). \tag{1}$$

Definition 3 [9] Let object $X\in\tilde{X}$. The set posed by the elements having the same values with X of $\tilde{X}$ on the attribute collection B will be named equivalence class of relation $IND(B)$ as $[X]_B$.

$$[X]_B=\{X_i\,|<X,X_i>\in IND(B)\}, \tag{2}$$

$[X]_B$ is also known as the basic concept or category of the attribute set B.

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Definition 4 [9] The partition related to attribute set B on the basis of domain $\tilde{X}$ is expressed as:

$$\pi_B = \tilde{X} / B = \{E_i \,|E_i = [X_i]_B, i = 1, 2, \cdots\}, \quad (3)$$

the partition has the properties as $E_i \neq \varnothing$. If $i \neq j$ then $E_i \cap E_j = \varnothing$ and $\tilde{X} = \bigcup E_i$.

Definition 5 [10] The entropy $H(P)$ of knowledge P defined as:

$$H(P) = -\sum_{i=1}^{n} p(X_i)\log_2(p(X_i)), \quad (4)$$

where, P is an attribute set of domain $\tilde{X}$.

Definition 6 [10] The partitions of the indistinguishable relationship about attribute set P and Q expressed as $\tilde{X} / IND(P) = \{X_1, X_2, \cdots, X_n\}$ and $\tilde{X} / IND(Q) = \{Y_1, Y_2, \cdots, Y_m\}$. The conditional entropy $H(Q|P)$ about Q related to P defined as:

$$H(Q|P) = -\sum_{i=1}^{n} p(X_i)\sum_{j=1}^{m} p(Y_j|X_i)\log_2(p(Y_j|X_i)), \quad (5)$$

where, $p(Y_j|X_i) = |Y_j \cap X_i| / |X_i|$. $i = 1, 2, \cdots, n$. $j = 1, 2, \cdots, m$.

Definition 7 [10] Let P and Q are equivalence relation clusters on the basis of domain $\tilde{X}$. The P positive domain of Q defined as $POS_P(Q)$.

$$POS_P(Q) = \bigcup_{X \in \tilde{X}/IND(Q)} P_{-}(X), \quad (6)$$

where, $P_{-}(X) = \bigcup\{Y|Y \in \tilde{X}/IND(P) \wedge Y \subseteq X\}$.

Definition 8 [10] $\tilde{X}$ is a domain. P and Q are attribute sets on the basis of $\tilde{X}$. $r \in P$. If $POS_P(Q) = POS_{(P-\{r\})}(Q)$ then relation r of P is absolutely unnecessary property related to Q. Or r of P is absolutely necessary property. If any $r \in P$ is necessary absolutely that the attribute set P is independent according to Q.

Lemma 1 [10] $\tilde{X}$ is a domain. P is conditional attribute set of $\tilde{X}$. The necessary and sufficient condition that r in P is necessary absolutely is $H(\{r\}|P-\{r\}) = 0$.

Lemma 2 [10] $\tilde{X}$ is a domain. P is conditional attribute set of $\tilde{X}$. d is decision attribute and domain $\tilde{X}$ is consistency with respect to $\{d\}$ on P. Then the necessary and sufficient condition that r with respect to $\{d\}$ is necessary absolutely is $H(\{d\}|P) = H(\{d\}|P-\{r\})$.

Lemma 3 [10] $\tilde{X}$ is a domain. P is conditional attribute set of $\tilde{X}$. d is decision attribute and domain $\tilde{X}$ is consistency with respect to $\{d\}$ on P. Then the necessary and sufficient condition that p with respect to $\{d\}$ is independent is $H(\{d\}|P) \neq H(\{d\}|P-\{r\})$ for any attribute $r \in P$.

Lemma 4 [10] $\tilde{X}$ is a domain. P is conditional attribute set of $\tilde{X}$. d is decision attribute and domain $\tilde{X}$ is consistency with respect to $\{d\}$ on P. Then the necessary and sufficient conditions that $Q \subseteq P$ with respect to $\{d\}$ is a reduction are two things as following:

1) $H(\{d\}|Q) = H(\{d\}|P)$.
2) Q with respect to $\{d\}$ is independent.

3 Reduction description based on partition

The relationship with equal value is an equivalence relation in an attribute information table. Any of equivalence relations will form a partition on the object belonged to the domain. This partition means a kind of classification model corresponding to the domain. The reduction result for attribute information table contains the minimum number of attributes. All of attributes in the reduction set are necessary absolutely. These attributes have same classification compared to all attributes on the domain objects. Generally there are two reduction forms as the absolute reduction and the relative reduction. The absolute reduction process applies to general information processing system. In this system all the properties aren't distinguish, and the reduction contains only part of properties. The relative reduction is suitable for handling special information table as the decision table. The properties are divided into condition attribute and decision attribute in this table. There are multiple properties but only one decision attribute in the table usually. For multi-attribute decision table, the process is needed to convert it into a single decision table at first. The condition attributes and the decision attributes formed a classification model for domain respectively. The reduction means to strike a condition attribute set containing the minimum attributes for the decision table. The result with respect to the decision classification is consistent with all the condition properties and expresses as a subset of condition attribute set. If the relativity of the decision attributes isn't considered the absolute reduction is the relative reduction also. Either the absolute reduction or the relative reduction has similarities to strike a minimum reduction. And the results of the reduction may be multiple normally.

Definition 9 $\tilde{X}$ is a domain. P and Q are attribute sets on the basis of $\tilde{X}$. And $Q \subseteq P$. If $\pi_{IND(Q)} = \pi_{IND(P)}$ and for either attribute $r \in Q$ the formula

$\pi_{IND(Q)} \neq \pi_{IND(Q-\{r\})}$ is founded. Then Q is an absolute reduction with respect to P.

Definition 10 $\tilde{X}$ is a domain. P and Q are attribute sets on the basis of $\tilde{X}$. And $Q \subseteq P$. d is decision attribute. If $POS_P(\{d\}) = POS_Q(\{d\})$ the Q is a relative reduction with respect to P.

In short, the main problem of attribute reduction is committed to strike less conditions meeting the consistent classification. The absolute reduction is suitable for general information table. The information table reduced can be used for finding association rules, clustering and other data mining process. The relative reduction is applicable to special information table like decision table. The classification rules can be generated with respect to the decision attributes through reduction. But the absolute reduction does not mean the relative reduction. The absolute reduction has strong constraint.

3.1 ABSOLUTE REDUCTION BASED ON PARTITION

The indistinguishable relation of the absolute reduction set will generate classification with objects on the domain. If a property a has r value that it will form a partition $\tilde{X}/\{a\}$ involving r equivalence classes for all objects of the domain. $\tilde{X}/\{a\} = \{X_1, X_2, ..., X_r\}$. When the rest of properties add to the equivalence classes as a part of the division the classes will be split likely. So the classification will be refinement further. When adding an attribute does not change the equivalence classes of division this property having no contribution to the classification is unnecessary. If the division generated by the distinguished relationship on the attribute set is smallest that the remaining properties can be reduced as unnecessary attributes.

Definition 11 The information system is a quadruplet $S = (\tilde{X}, R = C \cup D, V, f)$, where $IND(P)$ and $IND(Q)$ are indistinguishable relationships on C and $\tilde{X}/IND(P) = \{X_1, X_2, ..., X_m\}$, $\tilde{X}/IND(Q) = \{Y_1, Y_2, ..., Y_n\}$. For any $X_i \in \tilde{X}/IND(P)$ there is a $Y_j \in \tilde{X}/IND(Q)$ making $X_i \subseteq Y_j$ established. And there are $X_k \in \tilde{X}/IND(P)$ and $Y_r \in \tilde{X}/IND(Q)$ making $X_i \subseteq Y_j$ established at least. So the partition $\tilde{X}/IND(P)$ is more refined than $\tilde{X}/IND(Q)$. Or $\tilde{X}/IND(P)$ is a subdivision of $\tilde{X}/IND(Q)$.

Theorem 1 The information system $S = (\tilde{X}, C, V, f)$. $C' \subseteq C$. The necessary and sufficient condition that the property $r \in C - C'$ is unnecessary absolutely is $\pi_{C'} = \pi_{C' \cup \{r\}}$.

Proof (Sufficiency) Let $\pi_{\{r\}} = \{B_1, B_2, \cdots B_k\}$ and $\pi_D = \{C_1, C_2, \cdots C_m\}$. According to the system S, if $\pi_{C'} = \pi_{C' \cup \{r\}}$ then $IND(C') = IND(C' \cup \{r\})$. Let $\pi_{C'} = \pi_{C' \cup \{r\}} = \{A_1, A_2, \cdots A_n\}$. And the partition $\pi_{C'}$ is more refined than $\pi_{\{r\}}$. From the definition 4 of equivalence division, either $A_i \subseteq B_j$ or $A_i \cap B_j = \varnothing$ has been established for any A_i or B_j. So $p(B_j | A_i) = 1$ or $p(B_j | A_i) = 0$. From the Equation (5) it is known that $H(\{r\} | C') = -\sum_{i=1}^{n} p(A_i) \sum_{j=1}^{m} p(B_j | A_i) \log(p(B_j | A_i)) = 0$.

According to Lemma 1 that attribute r is absolutely unnecessary relative to C'.

(Requirement) If the attribute r is absolutely unnecessary relative to C' then $IND(C') = IND(C' \cup \{r\})$. From one to one relationship between the equivalence relation and the division the equation $\pi_{C'} = \pi_{C' \cup \{r\}}$ is founded.

Theorem 1 illustrates that both equivalent division reduction and information entropy reduction are similar to for determining the absolute necessary properties. The process for seeking absolute reduction based on equivalent partition is shown according to the data in Table 1.

TABLE 1 Information table of sample (1)

$\tilde{X}$	a_1	a_2	a_3
x_1	1	1	1
x_2	0	0	0
x_3	2	1	3
x_4	1	0	3
x_5	1	1	1
x_6	3	2	2
x_7	3	0	0
x_8	0	0	0

From Table 1, $R = \{a_1, a_2, a_3\}$. Beginning from the attribute a_1 for division construction, the division formed by increasing properties a_2 and a_3 sequentially is shown as:

$$\tilde{X}/\{a_1\} = \{\{x_1, x_4, x_5\}, \{x_2, x_8\}, \{x_3\}, \{x_6, x_7\}\},$$

$$\tilde{X}/\{a_2\} = \{\{x_1, x_3, x_5\}, \{x_6\}, \{x_2, x_4, x_7, x_8\}\},$$

$$\tilde{X}/\{a_1, a_2\} = \{\{x_1, x_5\}, \{x_4\}, \{x_2, x_8\}, \{x_3\}, \{x_6\}, \{x_7\}\},$$

$$\tilde{X}/\{a_1, a_2, a_3\} = \{\{x_1, x_5\}, \{x_4\}, \{x_2, x_8\}, \{x_3\}, \{x_6\}, \{x_7\}\}.$$

From the result of division, it is seen that the distribution of equivalence classes division has not changed by adding a_3. So the attribute a_3 is unnecessary absolutely. $\{a_1, a_2\}$ is independent because of

$\tilde{X}/\{a_1,a_2\} \neq \tilde{X}/\{a_1\}$ by removing a_2. As same time, $\tilde{X}/\{a_1,a_2\} \neq \tilde{X}/\{a_2\}$ by removing a_1. An absolute reduction of R in Table 1 is $\{a_1,a_2\}$. By similar method $\{a_1,a_3\}$ is the other absolute reduction of R too. It can be seen that the absolute reduction of the information system is not the only.

From the above analysis, removing unnecessary property does not change the original classification ability of the information system because this attribute is not able to provide new information for further subdivision to the objects of the domain. And the results are the same on the contrary. So seeking absolute reduction process can be carried out by dividing the refinement. At first any of property is selected to make division according to their different values by scanning information system vertically. Then adding the remaining property individually will divide refinement in equivalence class set until the division does not change.

An absolute reduction set contains minimum attributes for all objects described on the field. But the relative reduction issues tend to be more concerned in the application process. This problem is what conditions would lead to the decision situation occurred.

3.2 RELATIVE REDUCTION BASED ON PARTITION

Both condition attribute set and decision attribute set will be formed division on the domain for special information system like decision table. At this time the relationship between one classification and another tends to be more concerned. At this point the attribute reduction goal is to focus on finding some necessary properties from condition set. The classification capability of these properties is same as all conditions relative to decision attribute. This leads to the concept of relative reduction.

In a decision table, P is condition attribute set and Q is decision attribute set. According to the definition 7 refining division will lead to changes in the positive region $POS_P(Q)$. The attributes that does not belong to the positive region originally are likely to fall in the region. When all equivalence classes refined fall within the equivalence classes corresponding decision this condition set is a reduction. The following theorem will be founded.

Theorem 2 The information system $S=(\tilde{X},R,V,f)$. $R=C\bigcup D$. The domain $\tilde{X}$ is consistent with respect to the decision attribute set D, $C^{'}\subseteq C$, π_D is a partition formed by decision attribute. $\pi_{C^{'}}$ and π_C are division formed by indistinguishable relationship on the condition attribute set $C^{'}$ and C. If both of conditions are true as following that the attribute set $C^{'}$ is a D reduction of C.

1) $\pi_{C^{'}}$ is a subdivision of π_D.

2) $\neg\exists r((r\in C^{'})\wedge\pi_{C^{'}-\{r\}}$ is a subdivision of π_D).

Proof:

Let $\pi_{C^{'}}=\{X_1^{'},X_2^{'},\cdots,X_m^{'}\}$, $\pi_C=\{X_1,X_2,\cdots,X_n\}$. $\pi_D=\{Y_1,Y_2,\cdots,Y_k\}$. The equation $POS_C(D)=\tilde{X}$ is founded because of the domain $\tilde{X}$ is consistent with respect to the decision attribute set D. So $\pi_{C^{'}}$ is a subdivision of π_D.

For any $X_i^{'}\in\pi_{C^{'}}$ there is $Y_j\in\pi_D$ making the equation $X_i^{'}\subseteq Y_j$ established because $\pi_{C^{'}}$ is a subdivision of π_D. At the same time knowing from Definition 4 that $X_i^{'}\bigcap Y_l=X_i^{'}$ or $X_i^{'}\bigcap Y_l=\varnothing$ is founded for any $Y_l\in\pi_D$. So $p(Y_l|X_i^{'})=1$ or $p(Y_l|X_i^{'})=0$. From the Equation (5) and $C^{'}\subseteq C$,

$H(D|C^{'})=-\sum_{i=1}^{n}p(X_i)\sum_{j=1}^{k}p(Y_j|X_i)\log(p(Y_j|X_i))=0$. In the same way $H(D|C)=0$ because $\pi_{C^{'}}$ is a subdivision of π_D.

Assuming there is a property $a\in C^{'}$ making the equation $H(D|C^{'})=H(D|C^{'}-\{a\})$ established. In other words the conditional entropy of attribute set $C^{'}$ is equal to the entropy of $C^{'}-\{a\}$ with respect to the decision attribute set D. And because the domain $\tilde{X}$ is consistent with respect to the decision attribute set D that the attribute a is unnecessary by Lemma 2. a in $C^{'}$ does not affect its classification with respect to D. Then $\pi_{C^{'}}=\pi_{C^{'}-\{a\}}$ or $\pi_{C^{'}-\{a\}}$ is a subdivision of π_D. This conflicts to the condition (2) that $\neg\exists r((r\in C^{'})\wedge\pi_{C^{'}-\{r\}}$ is a subdivision of π_D). So the assumption does not hold. And any $r\in C^{'}$ the formula $H(D|C^{'})\neq H(D|C^{'}-\{r\})$ is founded. By Lemma 3 it is shown that $C^{'}$ is independence. So $C^{'}$ is a reduction by Lemma 4.

Theorem 2 illustrates that the attribute reduction is a subset of the condition attribute set C with respect to the decision set D. And the result of the reduction is relatively consistent with the division to the domain forming by all attributes of C. But the reduction does not include redundant attributes. Therefore, the attribute reduction based on the partition can be expressed as to strike a subset $C^{'}$ of the condition attribute set C. This subset $C^{'}$ is consistent with C for classification relative to the decision D.

4 The description of the reduction quality for data classification based on the equivalent division

In general case, the attribute information table containing more attributes of the universe is more detailed for object description. But too much attributes will influence the comprehensive feature extraction for domain objects. Attribute reduction to facilitate the comprehensive knowledge extraction will lead to a quality decline on the object description in the domain. At present the property set of the absolute reduction forms smaller classification to the universe objects. This reduction is more detailed to the object description. In contrast the description to relative reduction on the domain object is rough. The data description quality for relative reduction is defined as follows.

Definition 12 The information system $S=(\tilde{X},R,V,f)$. $R^{'}$ is absolute reduction set and $C^{'}$ is relative reduction set, $\pi_{R^{'}}=\{X_1,X_2,\cdots,X_n\}$, $\pi_{C^{'}}=\{Y_1,Y_2,\cdots,Y_m\}$. The definition description of the quality of the classification to the domain as follows:

$$r_{C^{'}}(R^{'})=\left|\pi_{C^{'}}\right|/\left|\pi_{R^{'}}\right|. \quad (7)$$

It is shown in Table 2 by adding a row of decision attributes to Table 1.

TABLE 2 Information table of sample (2)

$\tilde{X}$	a_1	a_2	a_3	d
x_1	1	1	1	0
x_2	0	0	0	1
x_3	2	1	3	0
x_4	1	0	3	0
x_5	1	1	1	0
x_6	3	2	2	1
x_7	3	0	0	1
x_8	0	0	0	1

In Table 2, $R=\{a_1,a_2,a_3,d\}$. The division is constructed with the beginning of the property a_1 with respect to the decision attribute $\{d\}$. Part of the division is shown as following:

$$\tilde{X}/\{d\}=\{\{x_1,x_3,x_4,x_5\},\{x_2,x_6,x_7,x_8\}\},$$

$$\tilde{X}/\{a_1\}=\{\{x_1,x_4,x_5\},\{x_2,x_8\},\{x_3\},\{x_6,x_7\}\},$$

$$\tilde{X}/\{a_1,a_2\}=\{\{x_1,x_5\},\{x_4\},\{x_2,x_8\},\{x_3\},\{x_6\},\{x_7\}\},$$

$$\tilde{X}/\{a_1,a_3\}=\{\{x_1,x_5\},\{x_3\},\{x_4\},\{x_6\},\{x_7\},\{x_2,x_8\}\}.$$

The results can be drawn from the result. The absolute reduction generated by Table 2 is $\{a_1,a_2\}$ or $\{a_1,a_3\}$. The partition $\tilde{X}/\{a_1,a_2\}$ or $\tilde{X}/\{a_1,a_3\}$ is finer than $\tilde{X}/\{a_1\}$. But $\tilde{X}/\{a_1\}$ is subdivision of $\tilde{X}/\{d\}$ also and the classification can be done with respect to the decision attribute $\{d\}$. It is shown that the relative reduction results of Table 2 is $\{a_1\}$ by Theorem 2. The description classification quality of $\{a_1\}$ can be calculated by the Equation (7). $r_{\{a_1\}}(\{a_1,a_2\})=r_{\{a_1\}}(\{a_1,a_3\})=0.67$. Therefore striking minimum relative reduction of decision table is in the cost of the relative decline of description quality for classification. To improve the quality described on the domain objects some of the properties need to be increased on the results of the relative reduction for further refinement. The finer division are more specific for domain description.

Striking minimum attribute reduction and seeking higher classification description quality of the decision table cannot be taking into account. In the actual application this will be weighed in accordance with the characteristics of the field.

5 Conclusions

In classical rough set theory, attribute reduction is on the basis of positive region, distinguish matrix and information entropy. However calculating the distinguish matrix is excessive. And calculating equivalence classes is important basic steps for positive region or information entropy. The determination and proof for refinement reduction are given from absolute and relative reduction. It is shown that striking minimum relative reduction of decision table is in the cost of the relative decline of description quality for classification. These results must be processed according to the knowledge of specific fields.

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