Rule Discovery Process Based on Rough Sets under the Belief Function Framework

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Abstract. In this paper, we deal with the problem of rule discovery process based on rough sets from partially uncertain data. The uncertainty exists only in decision attribute values and is handled by the *Transferable Belief Model* (TBM), one interpretation of the belief function theory. To solve this problem, we propose in this uncertain environment, a new method based on a soft hybrid induction system for discovering classification rules called GDT-RS which is a hybridization of the *Generalization Distribution Table* and the *Rough Set* methodology.

Keywords: Rough sets, generalization distribution table, uncertainty, belief function theory, classification.

1 Introduction

The Knowledge Discovery from Databases (KDD) is usually a multi-phase process consisting of numerous steps, including attribute selection, discretization of real-valued attributes, and rule induction. Rough set theory constitutes a sound basis for KDD. It offers useful tools for discovering patterns hidden in data [10,12]. It can be used in different phases of the knowledge discovery process, like feature selection, data reduction, decision rule generation and pattern extraction. Techniques based on standard rough sets do not perform their tasks in an environment characterized by uncertain or incomplete data. Many researchers have adapted rough sets to this kind of environment [8,9]. These extensions deal with incomplete decision tables which may be characterized by missing condition attribute values and not with partially uncertain decision attribute. This kind of uncertainty exists in many real-world applications such as marketing, finance, management and medicine. For the latter, the diseases (classes) of some patients may be totally or partially uncertain. This kind of uncertainty can be represented by belief functions as in the Transferable Belief Model, one interpretation of the belief function theory [14]. In fact, this theory is considered as a useful tool for representing and managing totally or partially uncertain knowledge because of its relative flexibility [11]. The belief function theory is widely applied in machine learning and also in real life problems related to decision making and classification.

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In this paper, we deal with the problem of rule discovery process based on rough sets from partially uncertain data. The uncertainty exists only in decision attribute values and is represented by belief functions. To solve this problem, we propose under the belief function framework a new approach based on a soft hybrid induction system called GDT-RS. The GDT-RS system, presented originally in [4,19], is a combination of *Generalization Distribution Table* [20] and the *Rough Set* methodology [10]. It should be noted that our approach is complementary to the previous study of the relationship between rough sets and belief functions by Busse and Skowron [13]. Busse and Skowron's work can be used to enhance practical application of the proposed approach. The standard version of GDT-RS system deals with certain decision tables (known condition and decision attribute values) or incomplete decision tables (missing condition attribute values and known decision attribute). The advantage of our new approach named belief GDT-RS is that it can generate in an automatic way from decision table characterized by uncertain decision attribute a set of rules with the minimal description length, having large strength and covering all instances. There are some classification techniques such as Belief Decision Tree (BDT) [3,5,18] that can generate classification decision rules from this kind of databases. However to perform this task well, we need at first to build the decision tree and then prune it [16].

This paper is organized as follows: Section 2 provides an overview of the *Generalization Distribution Table* and *Rough Set* methodology (GDT-RS). Section 3 introduces the belief function theory as understood in the TBM. In Section 4, we propose a belief GDT-RS approach for discovering classification rules from partially uncertain data under the belief function framework. Finally, in Section 5, we carry experiments on real databases, based on two evaluation criteria: accuracy and time complexity. To evaluate our belief GDT-RS, we compare the results with those obtained from BDT after pruning.

2 Generalization Distribution Table and Rough Set System (GDT-RS)

GDT-RS is a soft hybrid induction system for discovering classification rules from databases with noisy data [4,19]. The system is based on a hybridization of the *Generalization Distribution Table* (GDT) and the *Rough Set* methodology (RS). The GDT-RS system can generate a set of rules with the minimal description length, having large strength and covering all instances.

2.1 Generalization Distribution Table (GDT)

Any GDT [20] consists of three components: possible instances, possible generalizations of instances, and probabilistic relationships between possible instances and possible generalizations. Possible instances, represented at the top row of *GDT*, are defined by all possible combinations of attribute values from a database. Possible generalizations of instances, represented by the left column of a GDT, are all possible cases of generalization for all possible instances. A wild card '*' denotes the generalization for instances. The probabilistic relationships between possible instances and possible generalizations, represented by entries G_{ij} of a given GDT. The prior distribution is assumed to be uniform if background knowledge is not available. Thus, it is defined by:

$$G_{ij} = p(PI_j|PG_i) = \begin{cases} \frac{1}{N_{PG_i}} & \text{if } PG_i \text{ is a generalization of } PI_j \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where PI_j is the j-th possible instance, PG_i is the i-th possible generalization, and N_{PG_i} is the number of the possible instances satisfying the i-th possible generalization,

$$N_{PG_i} = \prod_{k \in \{l | PG_i[l]=*\}} n_k \tag{2}$$

where $PG_i[l]$ is the value of the l-th attribute in the possible generalization PG_i, and n_k is the number of values of the k-th attribute.

2.2 Rough Sets (RS)

Let us recall some basic notions regarding rough sets and rule discovery from databases represented by decision tables [10]. A decision table (DT) is defined as A= (U, C, {d}), where $U = \{o_1, o_2, ...o_n\}$ is a nonempty finite set of n objects called *the universe*, $C = \{c_1, c_2, ...c_k\}$ is a finite set of k *condition* attributes and $d \notin C$ is a distinguished attribute called *decision*. The value set of d is called $\Theta = \{d_1, d_2, ...d_s\}$. By $IND(B)$ we denote the indiscernibility relation defined by B $\subseteq$ C, $[o_j]_B$ denotes the indiscernibility (equivalence) class defined by o_j, and U/B is the set of all indiscernibility classes of $IND(B)$.

2.3 Hybrid System GDT-RS

From the decision table (DT), we can generate decision rules expressed in the following form:

$$P \rightarrow Q \text{ with } S,$$

'if P then Q with strength S', where P is a conjunction of descriptors over C, Q denotes a concept that the rule describes, and S is a 'measure of the strength' of the rule. According to the GDT-RS, the strength S [4,19] is equal to:

$$S(P \rightarrow Q) = s(P) * (1 - r(P \rightarrow Q)) \tag{3}$$

where $s(P)$ is the strength of the generalization P (the condition of the rule) and r is the noise rate function. The strength of a given rule reflects incompleteness and noise. On the assumption that the prior distribution is uniform, the strength of the generalization $P = PG$ is given by:

$$s(P) = \sum_l p(PI_l|P) = \frac{1}{N_P} card([P]_{DT}) \tag{4}$$

where $[P]_{DT}$ is the set of all the objects in DT satisfying the generalization P and N_P is the number of the possible instances satisfying the generalization P which is computed using eqn. (2). The strength of the generalization P represents explicitly the prediction for unseen instances. On the other hand, the noise rate is given by:

$$r(P \rightarrow Q) = 1 - \frac{card([P]_{DT} \cap [Q]_{DT})}{card([P]_{DT})} \tag{5}$$

It shows the quality of classification measured by the number of the instances satisfying the generalization P which cannot be classified into class Q.

3 Belief Function Theory

In this Section, we briefly review the main concepts underlying the belief function theory as interpreted in the TBM [14]. Let Θ be a finite set of elementary events to a given problem, called the frame of discernment. All the subsets of Θ belong to the power set of Θ, denoted by 2^{Θ}. The impact of a piece of evidence on the subsets of the frame of discernment Θ is represented by a basic belief assignment (bba). The bba is a function $m : 2^{\Theta} \rightarrow [0, 1]$ such that:

$$\sum_{E \subseteq \Theta} m(E) = 1 \tag{6}$$

The value *m(E)*, called a basic belief mass (bbm), represents the portion of belief committed exactly to the event E. The bba's induced from distinct pieces of evidence are combined by the rule of combination [14]:

$$(m_1 \bigcirc\!\!\!\!\cap\, m_2)(E) = \sum_{F,G \subseteq \Theta : F \cap G = E} m_1(F) \times m_2(G) \tag{7}$$

4 Rule Discovery Process from Partially Uncertain Data

In this Section, we propose our method for discovering a set of classification rules from partially uncertain data. The uncertainty exists in decision attribute values and is represented by the TBM. This method is based on the hybrid system GDT-RS developed originally in [4,19]. Our solution, so-called belief GDT-RS can generate from partially uncertain databases a set of rules with the minimal description length, having large strength and covering all instances.

4.1 Uncertain Decision Table

Our uncertain decision table is given by $A = (U, C \cup \{ud\})$, where $U = \{o_j : 1 \leq j \leq n\}$ is characterized by a set of certain condition attributes C=$\{c_1$, c_2,...,$c_k\}$, and an uncertain decision attribute ud. We represent the uncertainty of each object o_j by a bba m_j expressing beliefs on decisions defined on the frame of discernment Θ=$\{ud_1$, ud_2,...,$ud_s\}$ representing the possible values of *ud*. These bba's are generally given by an expert (or several experts) and in addition to partial uncertainty, they can also present the two extreme cases of total knowledge and total ignorance.

Example: To illustrate this idea by a simple example, let us use Table 1 to describe our uncertain decision table. It contains eight objects, three certain condition attributes C={a, b, c} and an uncertain decision attribute *ud* with two values $\{yes,\ no\}$ representing Θ.

Table 1. An example of uncertain decision table

U	a	b	c	ud
o_1	0	0	1	$m_1(\{yes\}) = 0.95$ $m_1(\{no\}) = 0.05$
o_2	0	1	1	$m_2(\{yes\}) = 1$
o_3	0	0	1	$m_3(\{yes\}) = 0.5$ $m_3(\Theta) = 0.5$
o_4	1	1	0	$m_4(\{no\}) = 0.9$ $m_4(\Theta) = 0.1$
o_5	1	1	0	$m_5(\{no\}) = 1$
o_6	0	0	1	$m_6(\{no\}) = 0.9$ $m_6(\Theta) = 0.1$
o_7	0	2	1	$m_7(\{no\}) = 1$
o_8	1	1	1	$m_8(\{yes\}) = 1$

4.2 Belief GDT-RS Method

In this subsection, we detail the main steps of our belief GDT-RS method allowing to discover of classification rules from partially uncertain decision table under the belief function framework based on the hybrid system GDT-RS.

Step 1. Creation of the GDT: Since the GDT depends only on condition attributes, and not in decision attribute values, our GDT will have the same structure as in [20]. In fact, this step can be omitted because the prior distribution of a generalization can be calculated using eqns. (1) and (2).

Step 2. Definition of the compound objects: Consider the indiscernibility classes with respect to the condition attribute set C as one object, called the compound object o'_j . For objects composing each compound object, combine their bba's using the mean operator as follows:

$$m'_j(E) = \frac{1}{card(o'_j)} \sum_{o_j \in o'_j} m_j(E), \forall E \subseteq \Theta \tag{8}$$

In our case, the mean operator is more suitable to combine these bba's than the rule of combination in eqn. (7) which is proposed especially to combine different beliefs on decision for one object and not different bba's for different objects.

Let us continue with the same example. By applying *the step 2*, we obtain the following table:

Table 2. The compound objects

U	a	b	c	ud
$o'_1(o_1, o_3, o_6)$	0	0	1	$m'_1(\{yes\}) = 0.48$ $m'_1(\{no\}) = 0.31$ $m'_1(\{\Theta\}) = 0.21$
o'_2	0	1	1	$m'_2(\{yes\}) = 1$
o'_4 (o_4, o_5)	1	1	0	$m'_4(\{no\}) = 0.95$ $m'_4(\{\Theta\}) = 0.05$
o'_7	0	2	1	$m'_7(\{no\}) = 1$
o'_8	1	1	1	$m'_8(\{yes\}) = 1$

Step 3. Elimination of the contradictory compound objects: For any compound object o'_j from U and for each decision value ud_i, compute $r_{ud_i}(o'_j)$ representing a noise rate. If there exists a ud_i such that $r_{ud_i}(o'_j) = min\,\{r_{ud_{i'}}(o'_j)$ $|ud_{i'} \in \Theta\} < T_{noise}$ (threshold value), then we assign the decision class corresponding to ud_i to the object o_j. If there is no $ud_i \in \Theta$ such that $r_{ud_i}(o'_j) < T_{noise}$, we treat the compound object o'_j as a contradictory one, and set the decision class of o'_j to $\perp$(uncertain). The noise rate is calculated originally using eqn. (5). The latter is not appropriate in our uncertain context since the decision value is represented by a bba. So, we propose to compute the noise rate based on a distance measure as follows:

$$r_{ud_i}(o'_j) = dist(m'_j, m), \text{such that } m(\{ud_i\}) = 1 \tag{9}$$

Where $dist$ is a distance measure between two bba's.

$$dist(m_1, m_2) = \sqrt{\frac{1}{2}(\parallel \vec{m_1} \parallel^2 + \parallel \vec{m_2} \parallel^2 - 2 < \vec{m_1}, \vec{m_2} >)} \tag{10}$$

$$0 \leq dist(m_1, m_2) \leq 1 \tag{11}$$

Where $< \vec{m_1}, \vec{m_2} >$ is the scalar product defined by:

$$< \vec{m_1}, \vec{m_2} >= \sum_{i=1}^{|2^\Theta|} \sum_{j=1}^{|2^\Theta|} m_1(A_i) m_2(A_j) \frac{|A_i \cap A_j|}{|A_i \cup A_j|} \tag{12}$$

with A_i, $A_j \in 2^\Theta$ for $i, j = 1, 2, \cdots, |2^\Theta|$. $\parallel \vec{m_1} \parallel^2$ is then the square norm of $\vec{m_1}$. The idea is to use the distance between two bba's m'_j and a certain bba m (such that $m(\{ud_i\}) = 1$). With this manner, we can check that the decisions of all instances belong to the compound object are near from a certain case. So, it is considered as a not contradictory object. Many distance measures between two bba's were developed. Some of them are based on pignistic transformation [1,6,15,21]. For these distances, one unavoidable step is the pignistic transformation of the bba's. This kind of distances may lose information given by the initial bba's. However, the distance measures developed in [2,7] are directly defined on bba's. In our case, we choose the distance measure proposed in [2] which satisfies more properties such as non-negativity, non-degeneracy and symmetry.

By applying the *step* 3 to the Table 2, we obtain the Table 3:

Table 3. Contradictory and not contradictory compound objects

U	a	b	c	ud
$o'_1(o_1, o_3, o_6)$	0	0	1	$\perp$
o'_2	0	1	1	yes
$o'_4(o_4, o_5)$	1	1	0	no
o'_7	0	2	1	no
o'_8	1	1	1	yes

Step 4. Minimal description length of decision rule: Let U' be the set of all the compound object except the contradictory ones. Select one compound object o'_j from U', create a discernibility vector (the row or the column with respect to o'_j in the discernibility matrix) for o'_j. The discernibility matrix of A is a symmetric n*n matrix with entries a_{ij} as given below. Each entry thus consists of the set of attributes upon which objects o_i and o_j differ.

$$a_{ij} = \{c \in C | c(o_i) \neq c(o_j)\} \; for \, i, j = 1, ..., n \tag{13}$$

Next, we compute all the so-called local relative reducts for the compound object o'_j by using the discernibility function $f_A(o_j)$. It is a boolean function of k boolean variables corresponding to the k condition attributes defined as below:

$$f_A(o_j) = \bigwedge\{\bigvee a_{ij} | 1 \leq i \leq n, a_{ij} \neq \emptyset\} \tag{14}$$

The set of all prime implicants of $f_A(o_j)$ determines the sets of all reducts of o_j. According to the Table 3, the discernibility vector for the compound object o'_2 ($a_0b_1c_1$) is as follows: We obtain two reducts, {a, b} and {b, c} by applying the indiscernibility function : $f_A(o'_2)$=$(b) \wedge (a \vee c) \wedge (b)$= $(a \wedge b) \vee (b \wedge c)$

Table 4. Discernibility vector for o'_2

U'	$o'_1(\perp)$	$o'_2(yes)$	$o'_4(no)$	$o'_7(no)$	$o'_8(yes)$
$o'_2(yes)$	b	$\emptyset$	a,c	b	$\emptyset$

Step 5. Selection of the best rules: Construct rules from the local reducts for object o'_j, and revise the strength of each rule using eqn. (3). Select the best rules from the rules for o'_j having the best strength.

According to the same example, the following rules are acquired for object o'_2: $\{a_0b_1\} \rightarrow yes$ with S = $(\frac{1}{2}*1)*(1)$= 0.5 and $\{b_1c_1\} \rightarrow yes$ with S = $(\frac{1}{2}*2)*(1)$= 1. The rule $\{b_1c_1\} \rightarrow yes$ is selected for the compound object o'_2 due to its strength.

Let $U' = U' - \{o'_j\}$. $If\ U' \neq \emptyset$, then go back to *Step* 4. Otherwise, STOP.

As a result, we obtain a set of decision rules able to classify unseen objects shown in the Table 5.

Table 5. Decision rules

U	rules	strengths
o'_2, o'_8	$b_1 \wedge c_1 \rightarrow yes$	1
o'_4	$c_0 \rightarrow no$	0.167
o'_7	$b_2 \rightarrow no$	0.25

Note that the time complexity of the algorithm is $\mathrm{O}(mn^2 Nr_{max})$, where n is the number of instances in a given database, m stands for the number of attributes, Nr_{max} is the maximal number of reducts for instances. We can apply a method for attribute selection [17] in pre-processing stage before using our belief GDT-RS to avoid the costly calculation.

5 Experimentation

In our experiments, we have performed several tests on real databases obtained from the U.C.I. repository[1] to evaluate our proposed classifier based on our belief GDT-RS. A brief description of these databases is presented in Table 6. These databases were artificially modified in order to include uncertainty in decision attribute. We took different degrees of uncertainty (Low, Middle and High) based on increasing values of probabilities P used to transform the actual decision value d_i of each object o_j to a bba $m_j(\{d_i\}) = 1 - P$ and $m_j(\Theta) = P$. A larger P gives a larger degree of uncertainty.

- Low degree of uncertainty: we take $0 < \mathrm{P} \leq 0.3$
- Middle degree of uncertainty: we take $0.3 < \mathrm{P} \leq 0.6$
- High degree of uncertainty: we take $0.6 < \mathrm{P} \leq 1$

Table 6. Description of databases

Database	#instances	#attributes	#decision values
W. Breast Cancer	690	8	2
Balance Scale	625	4	3
C. Voting records	497	16	2
Zoo	101	17	7
Nursery	12960	8	3
Solar Flares	1389	10	2
Lung Cancer	32	56	3
Hyes-Roth	160	5	3
Car Evaluation	1728	6	4
Lymphography	148	18	4
Spect Heart	267	22	2
Tic-Tac-Toe Endgame	958	9	2

[1] `http://www.ics.uci.edu/~mlearn/MLRepository.html`

The relevant criteria used to judge the performance of our new method are the accuracy of the model (PCC[2]) and the time complexity (seconds). To more evaluate our belief GDT-RS, we compared its results[3] with those obtained from the BDT after pruning in averaging and conjunctive approaches [5,16]. We taked best results between the two approaches related to BDT. Table 7 summarizes the different results relative to our belief GDT-RS and to the BDT for all chosen databases using different degrees of uncertainty (Low, Middle, High) and according to two evaluation criteria: accuracy and time complexity. The latter is almost the same for the different uncertain cases. From the Table 7, we can conclude that belief GDT-RS gives better PCC's than the pruned BDT for all databases and for all degrees of uncertainty. Besides, we can also conclude that our new method is faster than the construction of the BDT after pruning. On the other hand, we note that the PCC slightly increases when the uncertainty decreases.

Table 7. The experimentation results relative to belief GDT-RS and BDT

Database	Belief GDT-RS PCC (%)			Pruned BDT PCC (%)			Belief GDT-RS Time complexity (seconds)	Pruned BDT Time complexity (seconds)
	Low	Middle	High	Low	Middle	High		
W. Breast Cancer	83.77	83.48	83.05	83.46	83.01	82.17	65	156
Balance Scale	81.46	80.21	80.03	78.15	77.83	77.76	42	139
C. Voting records	98.44	98.16	97.92	98.28	97.76	97.71	69	117
Zoo	93.52	93.47	92.87	91.94	91.36	91.41	34	103
Nursery	96.06	95.81	95.27	95.84	95.13	95.11	198	386
Solar Flares	89.67	89.61	89.56	85.78	85.61	85.46	123	160
Lung Cancer	75.50	75.50	66.33	66.33	66.33	66.33	21	56
Hyes-Roth	97.46	97.11	96.75	83.66	83.31	82.14	34	93
Car Evaluation	81.46	81.01	81.17	73.49	73.11	72.97	135	189
Lymphography	84.24	84.03	83.67	79.25	78.97	78.94	66	108
Spect Heart	87.34	87.28	87.07	83.46	83.01	82.17	72	111
Tic-Tac-Toe Endgame	86.26	86.21	86.18	83.91	83.75	83.42	106	149

6 Conclusion and Future Work

In this paper, we have proposed a method called belief GDT-RS of rule discovery process based on the hybrid system called GDT-RS, in order to generate a subset of classification rules from partially uncertain databases. Our belief GDT-RS allows dealing with uncertainty in decision attributes that may characterize objects of a decision table and where uncertainty is represented through the belief function theory. Experimentations done on real databases show interesting results, based on accuracy and time complexity, comparing with those obtained from BDT after pruning. Busse and Skowron [13] suggested the use of rough set theory to develop belief functions. We will explore the use of Busse and Skowron's proposal to compute the bba's in the uncertain decision attributes in the future applications.

[2] Percent of correct classification.

[3] A 10-fold cross validation process has been used for making all experimentations.

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