# A Comparison of Dynamic and Static Belief Rough Set Classifier

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**Abstract.** In this paper, we propose a new approach of classification based on rough sets denoted Dynamic Belief Rough Set Classifier (D-BRSC) which is able to learn decision rules from uncertain data. The uncertainty appears only in decision attributes and is handled by the Transferable Belief Model (TBM), one interpretation of the belief function theory. The feature selection step of the construction procedure of our new technique of classification is based on the calculation of dynamic reduct. The reduction of uncertain and noisy decision table using dynamic approach which extracts more relevant and stable features yields more significant decision rules for the classification of the unseen objects. To prove that, we carry experimentations on real databases using the classification accuracy criterion. We also compare the results of D-BRSC with those obtained from Static Belief Rough Set Classifier (S-BRSC).

**Keywords:** rough sets, belief function theory, uncertainty, dynamic reduct, classification.

## 1 Introduction

The rough set theory proposed by Pawlak [6] constitutes a sound basis for data mining. It offers solutions to the problem of discretization, decision rule generation and solves the problem of attribute selection. For the latter, one of the ideas was to consider as relevant features those in reduct of the information system [5,6,8]. In fact, a reduct is a minimal set of attributes that preserves the ability to perform classifications as the whole attribute set does. Another issue in real world applications is the uncertain, imprecise or incomplete data. This kind of uncertainty exists in real-world applications like in marketing, finance, management and medicine. For example, some condition or decision attribute values in a client's database, used by the bank to plan a loan policy, are partially uncertain. Nevertheless, finding reducts from uncertain and noisy data leads to results which are unstable and sensitive to the sample data. Using dynamic reducts [1] allows getting better performance in very large datasets. In fact, rules induced by means of dynamic reducts are more appropriate to classify new objects, since these reducts are more stable and appear more frequently in sub-decision systems created by random samples of a given decision system.

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For these reasons, we have previously developed an approach of feature selection based on rough set theory namely dynamic reduct [12] computed from uncertain data. In our context, the uncertainty appears only in decision attributes and is represented through the Transferable Belief Model (TBM), one interpretation of the belief function theory. In fact, this theory is considered as a useful model to represent quantified beliefs because it allows experts express partial beliefs in a much more flexible way than probability functions do. The belief function theory [7] is very applied in real world applications related to decision making and classification.

Due to the advantages of our dynamic feature selection approach [12], we propose in this paper a new approach of classification based on rough sets denoted Dynamic Belief Rough Set Classifier (D-BRSC) which is able to generate more stable decision rules from uncertain data which are better to classify unseen cases. The uncertainty exists only in decision attributes and is handled by the TBM. The feature selection step of the construction procedure of our new technique of classification is based on the calculation of dynamic reduct proposed originally in [12]. To evaluate our D-BRSC, we will carry experimentations on real databases using the classification accuracy criterion. Besides, we will compare the results with those obtained from Static Belief Rough Set Classifier (S-BRSC) [13].

This paper is organized as follows: Section 2 provides an overview of the rough set theory. Section 3 introduces the belief function theory as understood in the TBM. In Section 4, we propose under the belief function framework a new approach of classification called Dynamic Belief Rough Set Classifier (D-BSRC) based on dynamic approach of feature selection which is induced from uncertain data. Finally, we report results of experiments on real databases relative to our new approach Dynamic Belief Rough Set Classifier (D-BRSC) comparing with Static Belief Rough Set Classifier (S-BRSC) from [13].

## 2 Rough Sets

In this Section, we recall some basic notions related to information systems and rough sets [6]. An information system is a pair $A$ = (U, C), where $U$ is a non-empty, finite set called the *universe* and $C$ is a non-empty, finite set of attributes. We also consider a special case of information systems called decision tables. A decision table is an information system of the form $A$ = (U, C $\cup$ {d}), where $d \notin C$ is a distinguished attribute called *decision*. In this paper, the notation $c_i(o_j)$ is used to represent the value of a condition attribute $c_i \in C$ for $o_j \in U$.

For every set of attributes $B \subseteq C$, an equivalence relation denoted by $IND_B$ and called the B-indiscernibility relation, is defined by

$$IND_B = U/B = \{[o_j]_B | o_j \in U\} \tag{1}$$

Where

$$[o_j]_B = \{o_i | \forall c \in B\, c(o_i) = c(o_j)\} \tag{2}$$

Let $B \subseteq C$ and $X \subseteq U$. We can approximate $X$ by constructing the $B - lower$ and $B -$ *upper approximations* of $X$, denoted $\underline{\mathrm{B}}(\mathrm{X})$ and $\bar{\mathrm{B}}(\mathrm{X})$, respectively, where

$$\underline{\mathrm{B}}(X) = \{o_j | [o_j]_B \subseteq X\} \; and \; \bar{\mathrm{B}}(X) = \{o_j | [o_j]_B \cap X \neq \emptyset\} \tag{3}$$

### 2.1 Reduct and Core

A subset $B \subseteq C$ is a reduct of $C$ with respect to $d$, iff $B$ is minimal and:

$$Pos_B(\{d\}) = Pos_C(\{d\}) \tag{4}$$

Where $Pos_C(\{d\})$, called a positive region of the partition $U/\{d\}$ with respect to $C$.

$$Pos_C(\{d\}) = \bigcup_{X \in U/\{d\}} \underline{\mathrm{C}}(X) \tag{5}$$

The core is the most important subset of attributes, it is included in every reduct.

$$Core(A,\, d) = \bigcap RED(A,\, d) \tag{6}$$

Where $RED(A, d)$ is the set of all reducts of $A$ relative to $d$.

### 2.2 Dynamic Reduct

If $A = (U,\, C \cup \{d\})$ is a decision table, then any system $B = (U',\, C \cup \{d\})$ such that $U' \subseteq U$ is called a subtable of $A$. Let $F$ be a family of subtables of $A$ [1].

$$DR(A,\, F) = RED(A, d) \cap \bigcap_{B \in F} RED(B,\, d) \tag{7}$$

Any element of $DR(A,\, F)$ is called an $F$-dynamic reduct of $A$. From the definition of dynamic reducts, it follows that a relative reduct of $A$ is dynamic if it is also a reduct of all subtables from a given family F. This notation can be sometimes too restrictive, so we apply a more general notion of dynamic reduct. They are called $(F,\, \varepsilon)$-dynamic reducts, where $0 \leq \varepsilon \leq 1$. The set $DR_\varepsilon(A,\, F)$ of all $(F,\, \varepsilon)$-dynamic reducts is defined by:

$$DR_\varepsilon(A,\, F) = \left\{ R \in RED(A,\, d) : \frac{|\{B \in F : R \in RED(B,\, d)\}|}{|F|} \geq 1 - \varepsilon \right\} \tag{8}$$

## 3 Belief Function Theory

The belief function theory is proposed by Shafer [7] as a useful tool to represent uncertain knowledge. Here, we introduce only some basic notations related to the TBM [9], one interpretation of the belief function theory. Let $\Theta$, frame of discernment, be a finite set of exhaustive elements to a given problem. All the subsets of $\Theta$ belong to the power set of $\Theta$, denoted by $2^\Theta$. The bba (basic belief assignment) is a function representing the impact of a piece of evidence on the subsets of the frame of discernment $\Theta$ and is defined as follows:

$$m : 2^{\Theta} \rightarrow [0, 1]$$

$$\sum_{E \subseteq \Theta} m(E) = 1 \tag{9}$$

Where *m(E)*, named a basic belief mass (bbm), shows the part of belief exactly committed to the element $E$. The bba's induced from distinct pieces of evidence are combined by the rule of combination [9].

$$(m_1 \bigcirc\!\!\!\!\cap\, m_2)(E) = \sum_{F,G \subseteq \Theta : F \cap G = E} m_1(F) \times m_2(G) \tag{10}$$

## 4 Dynamic Belief Rough Set Classifier (D-BRSC)

In this Section, we propose a new approach of classification called Dynamic Belief Rough Set Classifier (D-BRSC) based on dynamic approach of feature selection. This classifier is built from uncertain data under the belief function framework. The uncertainty appears only in decision attribute and is handled by the TBM. Before describing the main steps of the construction procedure of D-BRSC especially the feature selection, we need at first to present the modified basic concepts of rough sets under uncertainty [11] such as decision table, tolerance relation, set approximation, positive region, reduct and core.

### 4.1 Basic Concepts of Rough Sets under Uncertainty

**Uncertain decision table** Our uncertain decision system 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 $\Theta$=$\{ud_1,\ ud_2,...,ud_s\}$ describing the possible values of $ud$. These bba's are given by an expert.

**Example:** Let us use Table 1 to describe our uncertain decision table. It contains eight objects, three certain condition attributes $C$=$\{Hair,\ Eyes,\ Height\}$ and an uncertain decision attribute $ud$ with two possible values $\{ud_1,\ ud_2\}$ representing $\Theta$. For the object $o_3$, 0.7 of beliefs are exactly committed to the decision $ud_1$, whereas 0.3 of beliefs is assigned to the whole of frame of discernment $\Theta$ (ignorance). With bba, we can represent the certain case, like for the objects $o_2$, $o_5$ and $o_7$. The decision rules induced from the uncertain decision table are denoted belief decision rules where the decision is represented by a bba: *If* $Hair = Blond$ *and* $Eyes = Brown$ *and* $Height = Short$ *Then* $m_3(\{ud_1\}) = 0.7 \quad m_3(\Theta) = 0.3$.

**Table 1.** Uncertain decision table

| U | Hair | Eyes | Height | ud |
|---|---|---|---|---|
| $o_1$ | Dark | Brown | Short | $m_1(\{ud_2\}) = 0.5 \quad m_1(\Theta) = 0.5$ |
| $o_2$ | Blond | Blue | Middle | $m_2(\{ud_2\}) = 1$ |
| $o_3$ | Blond | Brown | Short | $m_3(\{ud_1\}) = 0.7 \quad m_3(\Theta) = 0.3$ |
| $o_4$ | Blond | Brown | Tall | $m_4(\{ud_1\}) = 0.95 \quad m_4(\{ud_2\}) = 0.05$ |
| $o_5$ | Dark | Brown | Short | $m_5(\{ud_2\}) = 1$ |
| $o_6$ | Blond | Blue | Middle | $m_6(\{ud_2\}) = 0.95 \quad m_6(\Theta) = 0.05$ |
| $o_7$ | Dark | Brown | Tall | $m_7(\{ud_1\}) = 1$ |
| $o_8$ | Dark | Brown | Middle | $m_8(\{ud_1\}) = 0.975 \quad m_8(\Theta) = 0.025$ |

**Tolerance relation.** The indiscernibility relation for the decision attribute $U/\{ud\}$ is not the same as in the certain case. The decision value is represented by a bba. In our case, it will be denoted *tolerance relation*. So, we need to assign each object to the right tolerance class. The idea is to use the distance between the two bba's $m_j$ and a certain bba $m$ (such that $m(\{ud_i\}) = 1$). Many distance measures between two bba's were developed. Some of them are based on pignistic transformation [3,14]. This kind of distances may lose information given by the initial bba's. However, the distance measures developed in [2,4] 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. For every $ud_i$, we define a tolerance class as follows:

$$X_i = \{o_j | dist(m, m_j) < 1 - threshold\} \tag{11}$$

Besides, we define a tolerance relation as follows:

$$IND_{\{ud\}} = U/\{ud\} = \{X_i | ud_i \in \Theta\} \tag{12}$$

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

$$dist(m_1, m_2) = \sqrt{\frac{1}{2}(\| \vec{m_1} \|^2 + \| \vec{m_2} \|^2 - 2 < \vec{m_1}, \vec{m_2} >)} \tag{13}$$

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

$$< \vec{m_1}, \vec{m_2} > = \sum_{i=1}^{|2^\Theta|} \sum_{j=1}^{|2^\Theta|} m_1(A_i) m_2(A_j) \frac{|A_i \cap A_j|}{|A_i \cup A_j|} \tag{14}$$

with $A_i, A_j \in 2^\Theta$ for $i, j = 1, 2, \cdots, |2^\Theta|$. $\| \vec{m_1} \|^2$ is then the square norm of $\vec{m_1}$.

***Remark:*** It should be noted here that we replace the term equivalence class from the certain decision attribute case by tolerance class for the uncertain decision attribute, because the resulting classes may overlap.

**Example:** Let us continue with the same example to compute the tolerance classes based on the uncertain decision attribute $U/\{ud\}$. For the uncertain

decision value $ud_1$: (if we take threshold equal to 0.1, we btain these results)
$dist(m(\{ud_1\}) = 1, m_1) = 0.67$ (using eq. 13) $< 0.9$
$dist(m(\{ud_1\}) = 1, m_3) = 0.34 < 0.9$
$dist(m(\{ud_1\}) = 1, m_4) = 0.0735 < 0.9$
$dist(m(\{ud_1\}) = 1, m_7) = 0 < 0.9$
$dist(m(\{ud_1\}) = 1, m_8) = 0.065 < 0.9$
So, $X_1 = \{o_1, o_3, o_4, o_7, o_8\}$
The same for the uncertain decision value $ud_2$.
So, $X_2 = \{o_1, o_2, o_3, o_5, o_6\}$
$U/\{ud\} = \{\{o_1, o_3, o_4, o_7, o_8\}, \{o_1, o_2, o_3, o_5, o_6\}\}$

**Set approximation.** In the uncertain context, the two subsets *lower* and *upper* approximations are redefined using two steps:

1. We combine the bba's for each equivalence class from $U/C$ using the operator mean which is more suitable than the rule of combination in eq. 10 which is proposed especially to combine different beliefs on decision for one object and not different bba's for different objects.
2. We compute the new *lower* and *upper* approximations for each tolerance class $X_i$ from $U/\{ud\}$ based on uncertain decision attribute $ud_i$ as follows:

$$\underline{C}X_i = \{o_j | [o_j]_C \cap X_i \neq \emptyset \, and \, dist(m, m_{[o_j]_C}) \leq threshold\} \tag{15}$$

$$\bar{C}X_i = \{o_j | [o_j]_C \cap X_i \neq \emptyset\} \tag{16}$$

   We find in the new *lower* approximation all equivalence classes from $U/C$ included in $X_i$ where the distance between the combined bba $m_{[o_j]_C}$ and the certain bba $m$ (such that $m(\{ud_i\}) = 1$) is less than a *threshold*. However, the *upper* approximation is computed in the same manner as in the certain case.

**Example:** We continue with the same example to compute the new *lower* and *upper* approximations. After the first step, we obtain the combined bba for each equivalence class from $U/C$ using operator mean. Table 2 represents the combined bba for the equivalence classes $\{o_1, o_5\}$ and $\{o_2, o_6\}$. Next, we compute the *lower* and *upper* approximations for each tolerance class $U/\{ud\}$. We will use $threshold = 0.1$. For the uncertain decision value $ud_1$, let $X_1 = \{o_1, o_3, o_4, o_7, o_8\}$. The subsets $\{o_3\}$, $\{o_4\}$, $\{o_7\}$ and $\{o_8\}$ are included to $X_1$. We should check the distance between their bba and the certain bba $m(\{ud_1\}) = 1$.
$dist(m(\{ud_1\}) = 1, m_3) = 0.34 > 0.1$
$dist(m(\{ud_1\}) = 1, m_4) = 0.0735 < 0.1$
$dist(m(\{ud_1\}) = 1, m_7) = 0 < 0.1$
$dist(m(\{ud_1\}) = 1, m_8) = 0.065 < 0.1$
$\underline{C}(X_1) = \{o_4, o_7, o_8\}$ and $\bar{C}(X_1) = \{o_1, o_3, o_4, o_5, o_7, o_8\}$
The same for uncertain decision value $ud_2$, let $X_2 = \{o_1, o_2, o_3, o_5, o_6\}$
$\underline{C}(X_2) = \{o_2, o_6\}$ and $\bar{C}(X_2) = \{o_1, o_2, o_3, o_5, o_6\}$

**Table 2.** The combined bba for the subsets $\{o_1, o_5\}$ and $\{o_2, o_6\}$

| Object | $m(\{ud_1\})$ | $m(\{ud_2\})$ | $m(\Theta)$ |
|---|---|---|---|
| $o_1$ | 0 | 0.5 | 0.5 |
| $o_5$ | 0 | 1 | 0 |
| $m_{1,5}$ | 0 | 0.75 | 0.25 |
| $o_2$ | 0 | 1 | 0 |
| $o_6$ | 0 | 0.95 | 0.05 |
| $m_{2,6}$ | 0 | 0.975 | 0.025 |

**Positive region.** With the new *lower* approximation, we can redefine the positive region:

$$UPos_C(\{ud\}) = \bigcup_{X_i \in U/\{ud\}} \underline{C}X_i \tag{17}$$

**Example:** Let us continue with the same example, to compute the positive region of $A$. $UPos_C(\{\text{ud}\})=\{o_2, o_4, o_6, o_7, o_8\}$.

**Reduct and core.** Using the new formalism of positive region, we can redefine the reduct of $A$ as a minimal set of attributes $B \subseteq C$ such that:

$$UPos_B(\{ud\}) = UPos_C(\{ud\}) \tag{18}$$

$$UCore(A, ud) = \bigcap URED(A, ud) \tag{19}$$

Where $URED(A, ud)$ is the set of all reducts of $A$ relative to $ud$.

**Example:** Using our example, we find that $UPos_{\{Hair,\, Height\}}(\{ud\})=$ $UPos_{\{Eyes,\, Height\}}(\{ud\})=$ $UPos_C(\{ud\})$. So, we have two possible reducts $\{Hair, Height\}$ and $\{Eyes, Height\}$. The attribute $Height$ is the relative core.

### 4.2 The Construction Procedure of the D-BRSC

1. **Feature selection:** It is the more important step which consists of removing the superfluous condition attributes that are not in reduct. This leaves us with a minimal set of attributes that preserve the ability to perform same classification as the original set of attributes. However, our decision table shown in subsection 4.1 is characterized by a high level of uncertain and noisy data. One of the issues with such a data is that the resulting reducts are not stable, and are sensitive to sampling. The belief decision rules generated are not suitable for classification. The solution to this problem is to redefine the concept of dynamic reduct in the new context as we have done in [12]. The rules calculated by means of dynamic reducts are better predisposed to classify unseen objects, because they are the most frequently appearing reducts in sub-decision systems created by random samples of a

given decision system. According to the uncertain context, we can redefine the concept of dynamic reduct as follows:

$$UDR(A, F) = URED(A, ud) \cap \bigcap_{B \in F} URED(B, ud) \tag{20}$$

Where $F$ be a family of subtables of $A$. This notation can be sometimes too restrictive so we apply a more general notion of dynamic reduct. They are called $(F, \varepsilon)$-dynamic reducts, where $1 \geq \varepsilon \geq 0$. The set $UDR_\varepsilon(A, F)$ of all $(F, \varepsilon)$-dynamic reducts is defined by: $UDR_\varepsilon(A, F) =$

$$\left\{ R \in URED(A, ud) : \frac{|\{B \in F : R \in URED(B, ud)\}|}{|F|} \geq 1 - \varepsilon \right\} \tag{21}$$

2. **Eliminate the redundant objects:** After removing the superfluous condition attributes, we find redundant objects. They may not have the same bba on decision attribute. So, we use their combined bba's using the operator mean.
3. **Eliminate the superfluous condition attribute values:** In this step, we compute the reduct value for each belief decision rule $R_j$ of the form: **If** $C(o_j)$ **then** $m_j$. For all $B \subset C$, let $X = \{o_k \mid B(o_j) = B(o_k)\}$ **If** $Max(dist(m_j, m_k)) \leq$ threshold **then** $B$ is a reduct value of $R_j$.
   **Remark:** In the case of uncertainty, the *threshold* gives more flexibility to the calculation of tolerance class, set approximations and reduct value. It is fixed by the user and it should be the same value to be coherent.

## 5 Experimentations

In our experiments, we have performed several tests on real databases obtained from the U.C.I. repository[1] to evaluate D-BRSC. A brief description of these databases is presented in Table 3. These databases are artificially modified in order to include uncertainty in decision attribute. We take 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 $0 <$ P $\leq 0.3$
- Middle degree of uncertainty: we take $0.3 <$ P $\leq 0.6$
- High degree of uncertainty: we take $0.6 <$ P $\leq 1$

The relevant criterion used to evaluate the performance of D-BRSC is the classification accuracy (PCC[2]) of the generated belief decision rules. To further evaluate the new classifier, we will compare the experimental results relative to D-BRSC with those obtained from Static Belief Rough Set Classifier (S-BRSC) proposed originally in [13].

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[1] http://www.ics.uci.edu/ mlearn/MLRepository.html
[2] Percent of Correct Classification.

**Table 3.** 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 |

From Table 4, we can conclude that reducing uncertain and noisy database using dynamic feature selection approach is more suitable for classification of the unseen cases than the static approach. It is true for all chosen databases and for all degrees of uncertainty. For example, the PCC for Car Evaluation database under high degree of uncertainty is 84.17% with dynamic reduct and 72.77% with static reduct. We further note that the PCC slightly increases when the uncertainty decreases for the both approaches.

**Table 4.** Experimentation results relative to D-BRSC and S-BRSC

| Database | D-BRSC PCC (%) | | | S-BRSC PCC (%) | | |
|---|---|---|---|---|---|---|
| | Low | Middle | High | Low | Middle | High |
| W. Breast Cancer | 86.87 | 86.58 | 86.18 | 83.41 | 83.39 | 82.17 |
| Balance Scale | 83.46 | 83.21 | 83.03 | 77.3 | 77.83 | 77.76 |
| C. Voting records | 98.94 | 98.76 | 98.52 | 97.91 | 97.76 | 97.71 |
| Zoo | 96.52 | 96.47 | 95.87 | 90.22 | 90.41 | 90.37 |
| Nursery | 96.68 | 96.21 | 96.07 | 94.34 | 94.13 | 94.11 |
| Solar Flares | 88.67 | 88.61 | 88.56 | 85.72 | 85.61 | 85.46 |
| Lung Cancer | 75.77 | 75.50 | 75.33 | 66.43 | 66.08 | 66.08 |
| Hyes-Roth | 97.96 | 97.15 | 96.75 | 83.66 | 83.31 | 82.14 |
| Car Evaluation | 84.46 | 84.01 | 84.17 | 73.39 | 73.22 | 72.77 |
| Lymphography | 83.24 | 83.03 | 82.67 | 79.25 | 78.97 | 78.94 |
| Spect Heart | 85.34 | 85.28 | 85.07 | 83.54 | 83.21 | 82.17 |
| Tic-Tac-Toe Endgame | 86.26 | 86.21 | 86.18 | 83.93 | 83.72 | 83.47 |

## 6 Conclusion and Future Work

In this paper, we have proposed a new approach of classification called Dynamic Belief Rough Set Classifier (D-BRSC) based on rough sets induced from uncertain data under the belief function framework. This technique of classification is based on dynamic approach for feature selection. We have done experimentations on real databases to evaluate our proposed classifier based on classification accuracy criterion. To further evaluate our approach, we compare the results with those obtained from Static Belief Rough Set Classifier (S-BRSC). According to the experimentation results, we find that generating belief decision rules based on dynamic approach of feature selection is more suitable for classification process than static one.

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