ICIC Express Letters
Volume **13**, Number **4**, April **2019**

ICIC International ©2019 ISSN 1881-803X
pp. **269–277**

DATA ANALYSIS USING ROUGH SET THEORY AND Q-LEARNING ALGORITHM

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Received October 2018; accepted December 2018

Abstract. *Data mining or knowledge discovery is the process of analyzing data, extracting relationships between them and summarizing them into useful information. This paper introduces methodology for medical data analysis by using both rough set theory and reinforcement learning. The rough set theory is applied in order to find all the reducts of the data containing minimal subset of attributes. The reinforcement learning based on Q-learning algorithm is used for classification of a dataset. The reducts will be used as actions in our reinforcement framework. A comparison will be set between the obtained results, using the proposed method with support vector machine and standard rough sets approaches. The experimental results have shown that the proposed method has higher classification accuracy rates.*

Keywords: Knowledge discovery (data mining), Rough set theory, Attributes reduction, Reinforcement learning, Q-learning algorithm, Medical data analysis

1. **Introduction.** Data mining or knowledge discovery is the process of analyzing large data in order to extract useful information. In other words, it is the process of collection and exploration of datasets and building models through huge data stores to discover previously unknown outline [1-3]. In medical field, the process of analyzing data and extracting required knowledge from the data set requires advanced techniques, because these data are very essential for the medical decision [4]. In the dataset, some attributes may be redundant, one can find a reduced set of attributes by removing superfluous attributes, without losing the classification power based on feature reduction process [5]. Feature reduction or attribute reduction is an important step in data mining and classification tasks. It aims at selecting a subset of important and discriminative features [6].

In the classification process, the dimensionality reduction removes the feature that is unnecessary, irrelevant or unimportant, which leads to speeding up learning concept and improves the quality of classification. Rough set theory enables the discovery of data dependencies and the reduction of the number of attributes contained in a dataset using the data alone, which require no additional information [7,8].

In recent years, attribute reduction based on rough set theory has attracted many researchers and was used in different domains. The authors in [9] improved the performance of the classifier by using rough set theory based on features selection to find the irrelevant and redundant features and remove them. The authors in [10] used the feature reduction in order to improve predictive accuracy in medical diagnosis problem. The authors in [11] used the feature reduction method for assigning predefined categories to web pages. The authors in [12] used feature reduction based on rough set theory to cope with a

DOI: 10.24507/icicel.13.04.269

huge dataset to delete and eliminate the redundant and useless features. The authors in [13] proposed a method for cancer diagnosis by gene selection by using feature reduction technique.

In artificial intelligence, there are several methods for classification, such as support vector machine (SVM), decision tree, and Naïve Bayes. In this work, reinforcement learning approach was applied to the classification process based on Q-learning technique. However, there are a small number of researches that use reinforcement learning in classification tasks. Reinforcement learning is a learning approach that learns from interaction with the environment in order to achieve long-term goals [14,15].

Broadly speaking, approaches of reinforcement learning can be divided into direct approach (model-free) and indirect approach (model-based). In the direct approach (model-free) the optimal policy is learned by the direct interaction between the agent and the environment, such as Q-learning algorithm proposed by Waking (1989), temporal difference (TD) learning proposed by Barto et al. (1983) and state-action-reward-state-action (SARSA) proposed by Rummery and Niranjan (1994). The indirect approach (model-based) constructs transition model for environment and uses it instead of interacting directly with the world [16,17].

Reinforcement learning has been used in many fields. The author in [18] used reinforcement learning algorithm for similar objects segmentation in image sequences. In [19], reinforcement learning approach is successfully used in the field human-robot interaction (HRI). The authors in [20] proposed an access control scheme of devices using Q-learning to solve the overload problem in "Machine Type Communication" applications that connect a huge number of devices into one network. The authors in [21] designed the neural network for image classification tasks by using reinforcement learning.

In the literature there are works that combine RST and Q-learning; in [22], the authors proposed an efficient real-time intrusion detection system (IDS) where RST is applied on discrete data for selecting set of reduct. On the other hand, reduct is not exceptional and so the reduct which makes available highest classification correctness is chosen to build the rule base classifier to classify the system traffic information either normal or anomaly. For the test data, concerning the similar cut value may produce unusual reduct, resulting in fall of classification correctness. Consequently, discretization and article assortment are not to be taken care of as independent events to classify network data precisely. In the proposed method, Q-learning algorithm has been modified to become skilled at different cut value for each restricted attribute and equivalent reduct and correctness are estimated to form the reward matrix. Modified Q-matrix estimates optimum cut standards for each characteristic to accomplish highest classification correctness in detecting intrusions using network traffic data. The system is finished when two consecutive cut produces similar correctness or monotonically decreasing correctness.

This paper presents the medical data analysis approach based on the rough set theory as an attribute reduction technique and the Q-learning approach for classification of a dataset. First, rough set theory was used to find all reducts of the data which contain minimal subset of attributes from dataset that will be used as actions in our reinforcement framework. The methodology is implemented on two datasets taken from UCI Machine Learning Repository. In addition, a comparison is set between the result obtained from the proposed method with standard rough sets approaches and the support vector machine (SVM).

The remaining portion of the paper is organized as follows. Definitions of rough set theory and reinforcement learning are presented in Section 2. The proposed methodology is given in Section 3. Section 4 analyzes the experimental results. Section 5 gives the conclusion.

2. Concepts and Definitions.

2.1. Rough set theory. Rough set theory (RST) is a method of data analysis that was introduced by Pawlak (1980). RST offers mathematical tools to handle vagueness and imprecise information in data. The base advantage of rough set theory is that it does not require any preliminary or additional information about data [23,24].

The basic concepts of rough set theory.

Information system

Information system is used for representing data that will be used by rough set theory.

$$IS = (U, A) \tag{1}$$

where U is non-empty finite set of objects, and A is non-empty finite sets of attributes.

Decision system

There are two types of attributes in the decision table: condition attributes and decision attribute.

$$DS = (U, C \cup \{d\}) \tag{2}$$

where C is called condition attributes, and $d \notin C$ is called decision attribute.

Indiscernibility relation

Indiscernibility relation is a central concept in rough set theory, and is considered as a relation between two objects or more, where all the values are identical in relation to a subset of considered attributes. Indiscernibility relation is equivalence relation, where all identical objects of set are considered as an elementary.

Approximation of sets

Let $IS = (U, A)$ be information system, $B \subseteq A$, and $X \subseteq U$, X can be approximated using only the information contained in B by constructing the B-lower, B-upper and B-boundary approximation of X, where B-lower approximation of X is the collection of objects that can be definitely be classified as elements of set X, B-upper approximation of X is the collection of objects that can only be classified as possible elements of X and the B-boundary region is the difference between the upper and lower approximation.

Reduct and core

Reduct is a minimal subset of attributes, which give the same quality of approximation (discernibility) as the whole set of attributes, and the attributes that recur in all reducts are called a core.

2.2. Reinforcement learning. Reinforcement learning is the problem faced by an agent that learns a behavior through trial-and-error interactions with a dynamic environment [25].

The elements of reinforcement learning. Additional to agent and environment, there are four sub-elements of reinforcement learning system: a policy, a reward function, a value function and, optionally, a model of the environment [14,26].

The policy

It is the core of a reinforcement learning that determines an agent is behavior to take actions which maximize the total reward. In some cases, the policy may be a table, and in other cases may be a function.

The reward function

It defines the objective of a reinforcement learning problem. A reinforcement learning agent is sole objective that is to maximize the total reward it receives over the long run. In other words, the reward function defines for an agent what events are good or bad.

The value function

Whereas a reward function specifies what is good in an immediate sense, a value function indicates what is good for the whole task execution.

The model

It is something that mimics the behavior of the environment. For example, given a state and an action, the model might predict the resultant next state and next reward.

3. Proposed Methodology.

This section describes the details of the proposed methodology for the medical data analysis used in this study. Attributes reduction approach was used to obtain a set of reductions from given data. The set of reductions will be used as actions set in our reinforcement learning framework, where we have used Q-learning algorithm in classification of a dataset.

3.1. Attributes reduction.

We have used rough set theory to generate a subset of attributes (reduct) from the original dataset. The steps of this theory are transforming dataset into decision table $D = (U, A \cup \{d\})$, where U is a non-empty finite set of objects and A is a finite sets of attributes and $\{d\}$ is decision attribute, where $d \notin A$, computing set of reduct for attributes of dataset using the genetic algorithm to search a minimal representation of original dataset.

3.2. Classification process.

This work employed Q-learning algorithm for classifying the patients in the dataset. Q-learning algorithm is a from model-free reinforcement learning. In Q-learning, the agent maintains a table or matrix of $Q(S, A)$; where S is the set of states and A is a set of actions. The basic idea of the Q-learning algorithm is the interaction between the environment and the agent. At each iteration, the agent observes the current state s_t and chooses the action a_t. After performing the action, the agent moves to the next state s_{t+1} and receives the reward r, updating the $Q(s_t, a_t)$ table based on the iteration equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)\right] \quad (3)$$

where α $(0 \le \alpha \le 1)$ is the learning rate and γ $(0 \le \gamma \le 1)$ is the discount factor. When the learning rate is 0, the Q-matrix is never updated. When the learning rate is set to a high value, the learning occurs quickly. The discount factor determines the importance of future rewards. A null factor will make the agent consider current rewards only, while a big factor will achieve a high long-term reward [27]. In this work, the states are the patients in the dataset, and the actions are the set of reducts.

The pseudo-code of Q-learning algorithm is shown below.

1. Initialize Q-matrix of size (states x actions) to 0s
2. For each episode in range max_episodes:
3. For patient in patients set:
4. Start at patient 1 (state 1).
5. Choose the best action from the Q-matrix for the given patient.
6. Apply the chosen action to the current patient to reducing the attributes.
7. Apply the custom function defined below to the reduced attributes to obtaining a classification.
8. Obtain a reward of +1 if the classification is correct, −1 otherwise, and move to the next patient.
9. Update the Q-matrix using the following rule:

Q(current-patient) = reward + gamma * maximum Q(next-patient)

The custom function was used to determine the thresholds to decide classification, where the median for each attribute of the given reduct was calculated, and using the median value as the threshold to decide the classification. The algorithm of the custom function is described as follows.

Input: reduct

Output: classification: 1 or 2, where class 2 points to the disease existing, and class 1 does not.

For each attribute in a reduct:

Calculate the median from the dataset

Compare the attribute to its median value from the dataset, if the attribute is bigger than the median, the class is 2, otherwise it is 1.

At the start of the Q-learning algorithm, the agent does not have any knowledge about environment and chooses randomly between actions, since the Q-matrix is initialized to zeros. **For example:** If the agent is at the first state, which corresponds to the first row in the Q-matrix and takes the action (the reduct) $\{0, 1, 4\}$, that corresponds to taking the mean of the attributes 0, 1 and 4 in the dataset. In this step the median is calculated by the agent for the action's attributes, and the median value is used as a threshold to decide the diagnosis (classification); either 1 or 2. Based on this diagnosis that the agent gives, it receives a reward from the environment where correct classification leads to positive reward (+1) and incorrect classification leads to negative reward (-1), and then the Q-matrix is updated using the Q-algorithm update rule to reinforce the actions that leads to larger rewards and correct classifications.

4. **Experiments and Results.** The proposed algorithm was implemented in python 3.6, windows 7, and the set of reducts was obtained from datasets using (ROSETTA system: A Rough set Toolkit for Analysis of Data). The proposed method was tested on two datasets that were obtained from UCI Machine Learning Repository. The first dataset is liver disorder dataset which contains 7 attributes and 345 patients [28]. The second dataset is Statlog (Heart) dataset which contains 14 attributes and 270 patients [29]. Attributes of dataset 1, and dataset 2 are shown in Table 1.

Table 1. The attributes of the dataset 1 and dataset 2

No	Dataset 1 attributes of liver disorder dataset	Dataset 2 attributes of Statlog (Heart) dataset
0	Mean corpuscular volume	Age
1	Alkaline phosphatase	Sex
2	Alanine aminotransferase	Chest pain type
3	Aspartate aminotransferase	Resting blood pressure
4	Gamma-glutamyl trans peptidase	Serum cholesterol
5	Drinks number of half pint equivalents of alcoholic	Fasting blood sugar
6	Class	Resting electrocardiographic results
7		Maximum heart rate achieved
8		Exercise induced angina
9		Old peak
10		The slope of the peak exercise ST segment
11		Number of major vessels (0-3) colored by fluoroscopy
12		Thal
13		Class

First, a set of reducts based on rough set theory was generated, which will be used as actions in our reinforcement learning framework.

The set of reducts which was obtained from dataset 1 is:

$\{\{1,3,5\}, \{1,4,5\}, \{1,3,4\}, \{0,1,3\}, \{2,3,4\}, \{0,1,4\}, \{0,2,4\}, \{1,2,3\}, \{0,1,5\}, \{0,1,2\}, \{1,2,4\}\}$.

The set of reducts which was obtained from dataset 2 is:

$\{\{4,7\}, \{3,7\}, \{4,10\}, \{4,9\}, \{4,11\}, \{4,12\}, \{2,4\}, \{0,4\}, \{0,7\}, \{4,6\}, \{3,4\}, \{4,8\}, \{0,3,9\}, \{0,9,11\}, \{3,8,9\}, \{0,3,11\}, \{7,9,10\}, \{7,9,11\}, \{0,10,11\}, \{0,8,9\}, \{5,7,9\}, \{7,9,12\}, \{1,7,9\}, \{0,3,10\}, \{2,7,9\}, \{6,7,9\}, \{0,2,9\}, \{0,2,11\}, \{2,3,9\}, \{2,3,6,10\}, \{0,1,9,10\}, \{0,2,8,10\}\}$.

After obtaining the set of reducts, reinforcement learning approach based on Q-learning algorithm for medical dataset classification problem was used. A problem was formulated by creating the Q-matrix. In Q-matrix the columns will be actions (the reducts), and the rows will be the states (the set of patients in the dataset). The Q-matrix $(n * m)$ is represented in the following equation:

$$\text{Q-matrix} = \begin{bmatrix} Q(s_1,a_1) & Q(s_1,a_2) & \dots & Q(s_1,a_m) \\ Q(s_2,a_1) & Q(s_2,a_2) & \dots & Q(s_2,a_m) \\ \vdots & \vdots & \ddots & \vdots \\ Q(s_n,a_1) & Q(s_n,a_2) & \dots & Q(s_n,a_m) \end{bmatrix} \tag{4}$$

where m is number of the actions, and n is number of the states.

The experiment setting for the Q-learning algorithm is listed as follows: the reward $r = +1$ if correct classification, $r = -1$ otherwise, the discount factor $\gamma = 0.1$ means that the immediate reward is the only important one, the learning rate $\alpha = 0.9$ means that the Q-matrix has made quickly update. Therefore, learning can occur quickly and the Q-matrixes are all initialized as 0. To balance between exploitation and exploration in learning process the e-greedy exploration strategy is used where $e = 0.5$.

For displaying the results of the implementation of Q-learning algorithm on medical dataset classification problem, patients of dataset 1 and dataset 2 were presented as shown in Figure 1. Then the agent classifies each patient of them. After the classification is done, every correctly classified patient is coloured green, and each wrongly classified patient is coloured red. The results after the agents are trained for some number of iterations are shown in Figure 1.

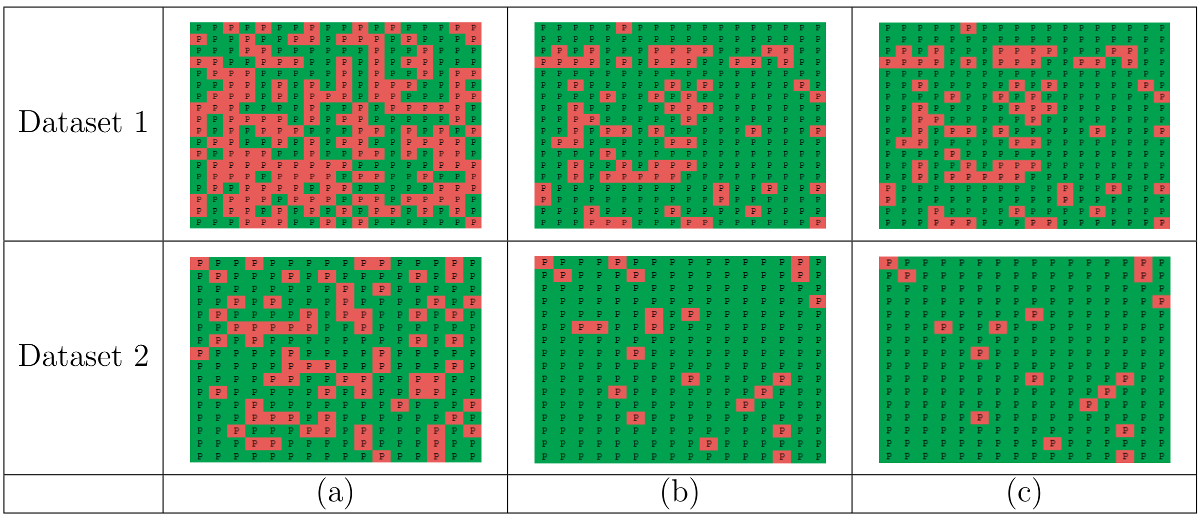


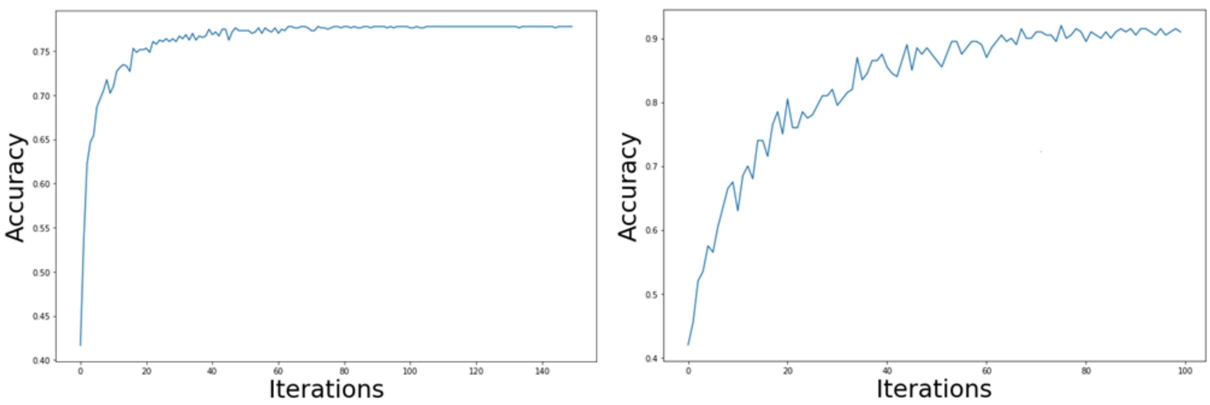
Figure 1. (color online) The results after the agents are trained for some number of iterations in (a) after 10 iterations, (b) after 100 iterations and (c) after 1000 iterations, where “P” is the patient, and “P” green point to the classification patient is correct, and “P” red point to the classification is incorrect

To evaluate the performance of the proposed method, the accuracy of classification was computed, where an accuracy is the proportion of the correct classified samples to the total number of samples. The accuracy is defined as:

$$Accuracy = (TP + TN)/N \tag{5}$$

where TP is the number of true positive, TN is the number of true negative, and N is the total number of instances in the test set.

The accuracy rate which was obtained using our proposed method after iterations of the learning process is 49% after 10 iterations, 77% after 100 and 1000 iterations in the dataset 1, and in the dataset 2 is 72% after 10 iterations, 92% after 100 and 1000 iterations. The relationship between the number of iterations and accuracy is shown in Figure 2, where the accuracy was observed reaching its maximum after about 100 iterations in the dataset 1, and reaches its maximum after about 80 iterations in the dataset 2.



(a) (b)

FIGURE 2. The relationship between the number of iterations and accuracy: (a) dataset 1; (b) dataset 2

TABLE 2. A comparison among our proposed method, rough sets and SVM

	Accuracy		
	Classification method		
	Rough sets	SVM	Our proposed method
Dataset 1	64%	66%	**77%**
Dataset 2	50%	83%	**92%**

As shown in Table 2, our method was compared with standard rough sets approaches and support vector machine (SVM), where we have split the data into 80% training and 20% testing for both methods. Our proposed method achieved better results than rough sets and SVM methods, where our proposed method achieved a classification accuracy of 77% in dataset 1, which is better than rough sets and SVM methods which achieved 64% and 66% respectively. In addition, our proposed method also achieved better results than rough sets and SVM methods in dataset 2, where it has accuracy of 92% compared with 50% and 83% by rough sets and SVM methods. It implies that the proposed algorithm has proven to be capable of proving a high performance compared to the current technologies used in the same domain.

5. **Conclusion.** In this paper, a medical data analysis approach was presented by using both rough set theory and reinforcement learning. Rough set theory was used to obtain a set of reducts (subset of attributes) from the original attributes, and reinforcement

learning based on Q-learning algorithm in classifying medical dataset was used. In our reinforcement framework, the reducts were used as actions and the patients in the dataset as states. The experimental results show that the proposed method overcomes rough sets and SVM. In the future, we plan to apply the idea of Q-learning with neural network to medical images analysis.

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