A STUDY ON MINING FUZZY CLASSIFICATION RULES WITH EXCEPTIONS

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Abstract - Now a days, searching of specific type of knowledge from the usual standards is very useful in several domains such as medical diagnosis, fraud detection , network traffic anomalies, economic analysis etc. Fuzzy association rules have been developed as a powerful tool for dealing with imprecision in databases and offering a comprehensive representation of found knowledge. Adding fuzziness to normal classification rules enable the rules to adapt to the real life decision making process. Besides, it also adds to the classification accuracy of obtained model and the rules look more accurate and reasonable. Further improvement in classification accuracy can be achieved by discovering exceptions corresponding to these fuzzy rules. Fuzzy rules augmented with exceptions (censors) are termed as Fuzzy Censored Classification Rules (FCCRs) and such kinds of rules are best at handling uncertainties like vagueness and ambiguity. These rules, being very efficient, have been widely used under exceptional circumstances. In this paper we have investigated all the algorithms used in past for discovering FCCRs. Based on review of literature, we have find out drawbacks and future direction with various issues.

***Keywords*:** CPR, Fuzzy Rules, FCCRs, Nature Inspired Algorithms.

1. Introduction

Data Mining is a step in KDD (Knowledge Discovery from Databases) which aims at finding knowledge in form of interesting patterns from the databases. Pattern discovery vary from one user to another depending on users' requirement. Classification is an important data mining task which extracts knowledge from the database in the form of If-Then Rules. Training data is used to create a classification model which is later applied to the test data to classify an unseen instance. A good classification model comprises of several If-Then production rules (PRs) which are simple, comprehensible, accurate and interesting. Interestingness is usually present in the form of exceptional instances which deviate from normal behavior but the traditional methods of classification rule discovery are least concerned with interestingness and leave out such instances during the rule discovery process. Several attempts have been made in past to modify these traditional techniques to incorporate exceptional instances for making the model more interesting and accurate and modified rules are often represented using If-Then-Unless form better known as CPRs (Censored Production Rules) framework.

However, nature of PRs or CPRs is such that they impose sharp cutoff on values that predicting attributes can take resulting in a model which is incapable of dealing with uncertainty and vagueness. Imposing sharp boundaries on predicting attributes' values is impractical and unreasonable in real life situations. Consider a classification rule of the form:

$$\text{If (Humidity} \leq 10) \text{ and (Temperature} \leq 25) \text{ then (Play\_outside} = \text{'yes')}$$

Rule says that a child is allowed to play outside provided humidity level is less than 10 and temperature is below 25. However, as per this rule the child is not allowed to play if humidity is 10.1 and temperature is 25.1 which definitely do not seem to be a justified decision. Augmenting fuzziness to the classification rules may improve real life decision making process and can make the rules more effective. A Fuzzy Classification Rule (FCR) takes the form:

$$\text{If X is } x_i \text{ and Y is } y_i \text{ then Class} = c_i$$

where 'X' and 'Y' are predicting attributes and 'Class' is class attribute and the attribute values of the predicting attributes such as x_i and y_i are fuzzy rather than crisp, meaning that predicting attributes take fuzzy values such as poor, excellent etc. instead of numerical values. A sample FCR may be given as:

$$\text{If (Humidity is moderate) and (Temperature is low) then (Play\_outside} = \text{'yes')}$$

Such a rule is certainly more relevant in context of daily life decision making process. However augmenting exceptions with FCRs may further improve the decision making process and make the rules more interesting. Consider an FCR with exception:

$$\text{If (Humidity is moderate) and (Temperature is low)}$$

$$\text{then (Play\_outside = 'yes') unless (Rainfall is false)}$$

Rule says that a child is allowed to play outside if humidity is moderate and temperature is low provided there is no rainfall. In presence of exceptional condition, Rainfall='True', decision of playing outside changes from 'yes' to 'no'. FCRs with exception conditions are termed as FCCRs (Fuzzy Censored Classification Rules) which integrates Fuzzy Rules with CPRs and posses more interestingness and information than the FCRs.

In this paper we have tried to investigate all the past works related to mining Fuzzy Censored Classification rules. We have also proposed possible modifications to existing techniques of mining FCCRs.

Rest of the paper is organized as follows: Section II discusses different past works related to mining FCCRs. Section III points direction for future research and suggests possible modifications in existing algorithms for mining FCCRs. Section IV concludes the paper.

2. Fuzzy Censored Classification Rule (FCCR)

To the best of our knowledge, first attempt to discover FCCRs dates back to 1992 when Dimiter et.al proposed a way to represent fuzzy rule with unless condition [1]. Authors have argued that fuzzy conditional statements of the form "If X is A then Y is B unless Z is C" can be represented by $R^* = R^+ \cap R^-$ where R^+ is equivalent to $A(x) \wedge C(z) \Rightarrow \sim B(y)$ and R^- is equivalent to $A(x) \wedge \sim C(z) \Rightarrow B(y)$. Such a rule helps in reasoning in the situations of incomplete information and resource constraints. Decision that Y is B can be concluded in case no information about Z is available. Later, in 1998, Fuzzy rule based classification system with reject option was proposed [2]. However such a system is limited to the situations where cost of misclassification is higher than the cost of rejection. α_{Classk}(Xp) is output value for class k when the new pattern Xp is presented as input vector to the fuzzy classification model and Xp is assigned the class with maximal value of α_{Classk}(Xp). Model rejects the input pattern provided the maximum value of α_{Classk}(Xp) is less than a minimum specified threshold, θ. Difference between largest and second largest value of α_{Classk}(Xp) is also sometimes used as rejection criteria.

Later in 2001, fuzzy exception learning was used to detect noise trading [3]. The proposed algorithm CELA(Competitive Fuzzy Exception Learning Algorithm) aims at discovering special circumstances, regimes, under which noise trading takes place. Discovering such special circumstances can be achieved by unmasking the fuzzy part (deterministic part). In context of financial market, regimes correspond to exceptional price developments and they are undesirable. An important modification to existing fuzzy exception discovery technique was proposed in 2004[4]. Authors have proposed a method to identify fuzzy model having maximal rules. Proposed model is multi-objective as it aims at achieving multiple goals viz. Maximum Rule, Accuracy and Interpretability. Extraction of the rules is followed by finding conflicts caused by them and these conflicts are resolved by including exceptions to the rules. Further, several strategies like rule reduction, rule merging and exception merging have been adopted to ensure interpretability of the model.

Rule plus Exception format, which is key to exception discovery, has been investigated by the authors in [5] in different contexts. As per authors, there exist two types of exceptions to a rule- the incorrectly covered exceptions and uncovered exceptions. Further, the discovered rules must be simple and number of exceptions discovered should be smallest possible. In 2007, an Ant Colony Optimization plug-in was proposed to enhance the interpretability of fuzzy rule bases with exceptions [6]. In 2008, authors extended their work to build a model which is enhancement of their previous work [7]. In particular, authors have worked on improving the interpretability and computational cost of the previous model. Restriction that defines feasible step of an ant has been relaxed which leads to increase in flexibility of rule base configurations thus providing interpretability improvement. Further, a local search technique has been incorporated to refine each solution provided by an ant. Attempts have been made to simplify the solution provided by ant by applying the concept of subasumption of a rule in rule base. Besides, computational cost of the previous algorithm has been diminished by pruning the construction graph which discards steps with low probability in selection procedure. Pheromone pruning has been used which sets a threshold for the pheromone level and all the edges of construction graph lying below the threshold are considered as infeasible transitions taken by an ant.

In [8], authors proposed an approach for the discovery of quantified rules with exceptions in the form of censored production rules (CPR) from the large set of discovered if-then rules.

A proper framework for discovering FCCRs has been proposed in [9]. Authors have proposed different parameters based on which exceptions can be discovered and also justified the needs and benefits of discovering FCCRs. In particular, the parameters γ_1 and γ_2 are used for exception discovery and are given by:

$$\gamma_1 = \frac{P \wedge D}{P}$$

$$\gamma_2 = \frac{P \wedge C}{P}$$

Where, P is the predicting part of an FCCR, D is the consequent part which holds frequently and C is the sensor part which holds rarely. Exceptions to a Fuzzy Classification Rule (FCR) exist subject to conditions: $\gamma_1 + \gamma_2 \leq 1$ && $\gamma_1 >> \gamma_2$. Authors have devised a genetic algorithm approach for discovery of FCCRs from the datasets and argued that proposed discovery will enhance the capabilities of automated and expert system and prove its worthiness in fuzzy control applications by predicting the behavior of system in rare circumstances. In [10], Bala et.al has proposed an extension to their work and used genetic algorithm approach for discovering tuned fuzzy classification rules with intra and inter-class exceptions. A three-phased approach has been used for discovery of (FCRs) augmented with intra- and inter-class exceptions. A pre-processing algorithm is suggested to tune DB in terms of the membership functions and number of linguistic terms for each attribute of a data set in the first phase. The second phase discovers FCRs employing a genetic algorithm approach. Subsequently, intra and inter-class exceptions are added to the rules in the third phase.

Exceptions i.e. censors add interestingness to the rule and rule out any possibility of misclassification even under rare circumstances. Intra-class exception refers to the attribute-value pair which, if appended to a decision rule, makes no change in the decision class whereas, augmenting inter-class exception to antecedent part alters the class of decision rule [11, 12]. A genetic algorithm based approach to discover intra-class exceptions has been proposed in [11]. It comprises of two stages: In first stage generalized rules are discovered and in second stage exceptions are appended to the rules. Michigan approach has been used in rule discovery meaning that the algorithm generates list of best rules and not the best rule list. Further, discovery of intra and inter-class exceptions using Nature Inspired Algorithms such as genetic algorithms and ACO have been investigated by the authors in [12]. Need for the exception discovery has been emphasized by the authors in [13, 14]. Suzuki et. al [13] have discovered exceptions in the form of rule pair . Rule triplet structure, which is an extension of rule pair structure, has been discussed in [14]. A brief summary of some of the appraised papers of this section is given in Table 1.

Table 1. List of appraised papers

Paper	Technique(s) used (if any)	Major Finding(s)
[1]		Proposed a different representation for representing fuzzy rules plus exception
[2]		Proposed a Fuzzy rule based classification system with reject option but limiting its use to the situations where cost of misclassification is higher than the cost of rejection
[3]	CELA	Use of fuzzy exception learning to detect noise trading
[4]		Multi-objective model to discover exceptions for fuzzy rules.
[6]	Ant Colony Optimization(ACO)	Use of Nature Inspired Algorithms, for the first time, for discovering interpretable fuzzy rule bases with exceptions.
[9]	Genetic Algorithm	(i) Fuzzy rules plus exception were given a new name, Fuzzy Censored Classification Rules (FCCRs) where a censor corresponds to exception. (ii) Use of parameters γ_1 and γ_2 for discovery of FCCRs.
[10]	Genetic Algorithm	(i) Use of GA for discovering tuned fuzzy classification rules with intra and inter-class exceptions. (ii) Use of 3-phased approach for discovering FCCRs.

3. Issues on FCCRs

One of the main problems when a discretization process into intervals is made from the continuous and irregular data set for numerical data is that of over- or underestimation of the boundary values. Fuzzy sets overcome this since they consider the natural boundaries of attributes when representing the attributes, obtaining thus a more adjusted description to reality. This way, we may find relations involving fuzzy items that cannot be discovered when employing crisp intervals. Moreover, data themselves can be vague or imprecise, and fuzzy sets can be used for describing them adequately. Particularly, discovering fuzzy exception and anomalous rules offers several benefits.

1) With these kinds of rules, we obtain a) what are the common or usual patterns in the data and b) the exceptions or anomalous rules representing a change in the common pattern. Therefore, they differ from those techniques that only search for the anomalies or outliers in the whole dataset.
2) They express a kind of knowledge, which is very useful in some domain areas, such as fraud detection, searching anomaly deviations, medicine, chemical processes, early warning detection, etc.
3) Since we use fuzzy rules, the obtained results are more understandable for humans in addition to having a more descriptive view of reality.

From the review of past works we can identify a number of possible modifications that are worth applying to all the existing algorithms and techniques of mining FCCRs. First could be improvement in interpretability of obtained rules. Interpretability of the model can be improved by modifying algorithms to generate more number of rules with fewer numbers of exceptions rather than fewer numbers of rules with larger number of exceptions. Excessive number of exceptions usually adds to the complexity of rules making the model less interpretable. Second, Nature Inspired Algorithms like GA and ACO have been limitedly used in past for mining FCCRs and hence it could be interesting to further investigate these algorithms because these algorithms are best at exploring search space and avoiding convergence to local optima. Third, a common step in discovering fuzzy rules is to fuzzify the predicting attributes using some membership function. In past, same membership function has been used to fuzzify all the predicting attributes irrespective of their nature. Accuracy of the obtained model can be enhanced if different membership functions are used for different predicting attributes.

4. Conclusion

Fuzzy rules are a suitable tool for representing infrequent information that can be present in the data. This is very useful in several area domains, particularly in those of fraud or crime detection. The reliability of these rules can be assessed by means of different measures. Several algorithms have been proposed in past to discover fuzzy rules plus exceptions, also called FCCRs. In this paper we have investigated all such algorithms and suggested possible modifications to existing approaches which, if adopted, may enhance the classification performance.

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