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Optimizing Fuzzy Rule based Classifier for Multi Label Classification using ACO

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***Abstract*— Ant Colony Optimization (ACO) studies artificial systems that take inspiration from the behavior of real ant colonies and which are used to solve discrete optimization problems. This paper proposes an extension of Multilabel classification algorithm based on ant colony optimization with novel quality function to handle continuous valued attributes using the concept of fuzzy logic. Fuzzy classification rules are generated by using the concept of fuzzy heuristic, fuzzy entropy and fuzzy quality with confidence of a rule. Extension of Ant-Miner to cope with multi-label classification, called MuLAM (Multi-Label Ant-Miner). In MuLAM, each ant constructs a set of fuzzy rules – A rule can predict a single class attributes or multiple class attributes, depending on which value will give a better rules for the data mining. pheromone matrix used by MULAM for each of the class attributes. Hence, when a rule is create, the terms of its antecedent are used to update only the pheromone matrices of the class attribute(s) predicted by that rule. Discover fuzzy rule based classifier for multi label data set maximum accuracy.**

***Index Terms*— Data Mining, Classification, Fuzzy Logic, Optimization Problem,Ant colony optimization, Fuzzification, Multilabel classification.**

I. INTRODUCTION

Data mining is a powerful tool that can help you find patterns and relationships within your data. But data mining does not work by itself. It does not eliminate the need to know your business, to understand your data, or to understand analytical methods. Data mining discovers hidden information in your data, but it cannot tell you the value of the information to your organization [1].The data analysis task is classification, where a model or classifier is constructed to predict categorical labels. A classification task begins with training data for which the target values are known. The discovered knowledge is often represented in the form of IF (conditions) THEN (class) classification rules, which has the advantage of representing a comprehensible model to the user Ant Colony Optimization (ACO) concepts inspired by the behaviour of natural ants

II. Multi Label Classification and Fuzzy Logic

Multilabel classification assigns to each sample a set of target labels. This can be thought as predicting properties of a data-point that are not mutually exclusive, such as topics that are relevant for a document. Multi output – multi class classification and multi-task classification means that a single estimator has to handle several joint classification tasks. This is a generalization of the multi-label classification task, where the set of classification problem is restricted to binary classification, and of the multi-class classification task. The output format is a 2d array or sparse matrix.

ACO has been used successfully in data mining field to extract rule based classification systems. Ants often find the shortest path between a food source and the nest of the colony without using visual information[2]. In order to exchange information about which path should be followed, ants communicate with each other by means of a chemical substance called pheromone.

ACO is a rule based classification approach. It differs from other rule based approaches in a way that it uses quality of highly accurate rule as a measure to generate other successive rules. As a result, search space of rules is intelligently explored. In any rule based classifier, prediction of class label attribute is done by applying classification rules. These rules are generated as a part of classification model when learning algorithm is applied on training data set. Rules are developed one by one iteratively in more general to more specific order. The goal of any rule based classification model is to cover all variety of data from training set and they should not over fit it. Further they should be optimal in nature so that providing less information about unseen data; closest class label value should be predicted. As the no. of attributes are added, rule generating may become exponential because each attribute has no. of distinct values and each <attribute, value> is a candidate to appear in rule. ACO helps here for not only generating rules in intelligent way but it also prunes them.

A new ant colony algorithm tailored for a kind of classification task in data mining called multi-label classification. In essence, this is a more challenging version of the conventional (single-label) classification task, as follows. In conventional classification the goal is to predict a single class for an example (a record or case), based on the values of predictor attributes describing that example. By contrast, in multi-label classification there are two or more classes to be predicted for an example.

A more detailed discussion of the differences between single-label and multi-label classification will be discussed later in report. For now it should be noted that multi label classification is an active and increasingly important research area, due to the growing interest in datasets which naturally have multiple classes to be predicted, particularly in the areas of text mining and bioinformatics. Ant-Miner addresses the conventional, single-label classification task. It discovers classification.

Rules of the Form:

IF (conditions) THEN (predicted class) with the meaning that, if an example satisfies the conditions in the rule antecedent, that example is assigned the class predicted by the rule consequent. In the rules discovered by Ant-Miner, each consequent contains exactly one predicted class whereas our objective is to find a new algorithm which extends his rule representation to allow more than one predicted classes in the rule consequent.

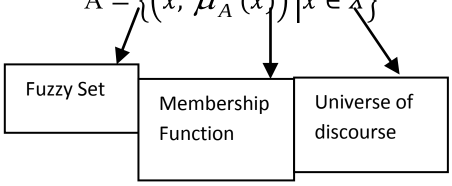
Multi-label classification involves the simultaneous prediction of the value of two or more class attributes, rather than just one class attribute as in conventional classification. Proposed a major extension of Ant-Miner to cope with multi-label classification, called Multi-Label Ant-Miner).

In Multi label ant miner each ant constructs a set of rules – rather than a single rule – where different rules predict different class attributes. A rule can predict a single class attribute or multiple class attributes, depending on which option will lead to better rules for the data being mined.uses a pheromone matrix for each of the class attributes. Hence, when a rule is built, the terms in its antecedent are used to update only the pheromone matrix of the class attribute(s) predicted by that rule.

Difference between crisp, random, and fuzzy variables: a uniform probability distribution, a probability distribution, a membership functions associated with its domain respectively.

A fuzzy set Ã in X is expressed as a set of ordered pairs:

$$\tilde{A} = \left\{ \left(x,\ \mu_A\,(x) \right) \middle| x \in X \right\}$$



2.1 Why Fuzzy Logic required?

Drawback of crisp logic: The membership function of crisp logic fails to distinguish between members of the same set. Fuzzy logic deals with smooth transition. It is flexible, conceptually easy to understand, tolerant of imprecise data, based on natural language.

2.2 Types of fuzzy sets: Membership function [16] [17]

There are different shapes of Membership Functions (MFs); triangular, trapezoidal, Gaussian, bell-shaped, etc.

1) Triangular MF: A triangular MF is specified by three parameters {a, b, c} as follows: By using min and max, we have an alternative expression for the preceding equation:

$$trimf(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

The parameters {a, b, c} (with a < b < c) determine the x coordinates of the three corners of the underlying triangular MF. Fig.2. (a) illustrates a triangular MF defined by triangle (x; 20, 60, 80).

2) Trapezoidal MF: A trapezoidal MF is specified by four parameters {a, b, c, d} as follows: An alternative concise expression using min and max is:

$$trapmf(x; a, b, c, d) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

The parameters {a, b, c, d} (with a < b <= c < d) determine the x coordinates of the four corners of the underlying Trapezoidal MF Fig.2. (b) Illustrates a trapezoidal MF defined by trapezoid (x; 10, 20, 60 95).

Note that a trapezoidal MF with parameter {a, b, c, d} reduces to a triangular MF when b is equal to c.

3) Gaussian MF: A Gaussian MF is specified by tow parameters:

$$gaussmf(x; a, b, c) = e^{-\frac{1}{2}}\left(\frac{x-c}{\sigma}\right) * \left(\frac{x-c}{\sigma}\right)$$

A Gaussian MF is determined complete by c and σ; c represents the MFs centre and σ determines the MFs width. Fig.2. (c) plots a Gaussian MF defined by Gaussian(x; 50, 20).

4) Generalizes MF: A Gaussian MF is specified by tow parameters: A generalized bell MF (or Bell-shaped Function) is specified by three parameters {a, b, c}: I.1.1

$$gbellmf(x; a, b, c) = \frac{1}{1+\left|\frac{x-c}{b}\right|}2\text{b}$$

Where the parameter b is usually positive. (If b is negative, the shape of this MF becomes an upside-down bell.)Fig.2. (d) shows generalized bell MF. Note that this MF is a direct generalization of the Cauchy distribution used in probability theory, so it is also referred to as the Cauchy MF. Because of their smoothness and concise notation, Gaussian and bell MFs are becoming increasingly popular for specifying fuzzy sets.

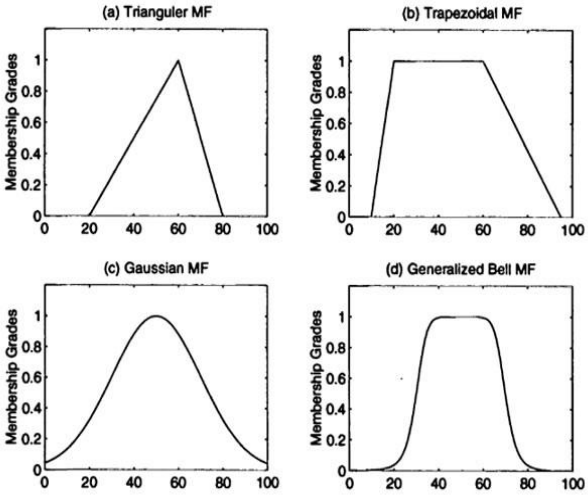


Figure 2.4:Parameterized MFs

III. ANT-MINER AND MULTI LABEL ANT-MINER

3.1 Basic Ant-Miner Algorithm

Ant-Miner Algorithm [4] provide step by solution for discover rule .The goal of Ant-Miner is to extract classification rules from data in the form of:

IF <term1 AND term2 AND … > THEN < class >.

The algorithm is inspired by both researches on the behavior of real ant colonies and some data mining concepts as well as principles. Algorithm consists of several steps:

3.1.1. Rule construction

First Ant starts with empty rule and Ant adds one term at a time to rule choice depends on two factors: Heuristic function (problem dependent) η Pheromone associated with term τ.

3.1.2. Rule pruning[10]

Some irrelevant terms may be added during previous phase so, Remove irrelevant, unduly included terms in rule Thus, improving simplicity of rule Iteratively remove one-term-at-a-time Test new rule against rule-quality function:

This Process repeated until further removals no more improve quality of the rule.

3.1.3. Pheromone updating

Increase pheromone in trail followed by current ant according to Quality of found rule.

$\tau_{ij}(t+1) = \tau_{ij}(t) + \tau_{ij}(t) * Q, \ \forall i, j \in R$ The authors of the accepted manuscripts will be given a copyright form and the form should accompany your final submission.

3.1.4. Normalization

Normalize the amount of pheromone value at iteration for each predictor attribute

3.1.5. Stopping Criteria

1. Num. of rules >= Num. of ants
2. Convergence is met
    a. Last *k* ants found exactly the same rule,
       k = No_rules_converg
3. List of discovered rules is updated
4. Pheromones reset for all trails

3.2 Algorithm

Algorithm 1: Basic Ant-Miner Algorithm

Step1: The training set is classifying the rule based on
Predictor attributes and class label.
Step2: Count the value of predictor attributes and Class label
Step3: Find the probability of term based on class Label.
Step4: Find the entropy (Information gain) of value For predictor attributes based on class label
Step5: Find the Heuristic function for each value of Predictor attributes
Step6: Multiply Heuristic function with amount of Pheromone (for single ant, in first iteration Amount of pheromone is same of different Value)
Step7: Choose best attribute value by maximum
Step8: Repeat for each predictor attribute
Step9: Discover the Rule.
Step10: Find Quality of rule
[Quality= Sensitivity * Specificity]
Step11: Update pheromone value (Iteration=2)
Step12: Normalize the amount of pheromone value At second iteration for each predictor Attribute.

3.3 Limitation of Ant-Miner

Ant-Miner's limitation[9] – It cannot cope up with multi label data set.

Solution: Data classification by Multi label Ant-Miner:

Multi-label classification[5] involves the simultaneous prediction of the value of two or more class attributes, rather than just one class attribute as in conventional classification. Proposed a major extension of Ant-Miner to cope with multi-label classification, called Multi-Label Ant-Miner).

IV. UNITS

In Multi label ant miner each ant constructs a set of rules – rather than a single rule – where different rules predict different class attributes. A rule can predict a single class attributes or multiple class attributes, depending on which option will lead to better rules for the data being mined. Uses a pheromone matrix for each of the class attributes. Hence, when a rule is built, the terms in its antecedent are used to update only the pheromone matrix of the class attribute(s) predicted by that rule.

Limitation of Multi label Ant-miner:

1. Generated fuzzy rules are not simplified, easy to implement.
2. [Quality = Sensitivity * Specificity]. This rule quality function is not accurate and reliable compared to confidence of rule.

IV. PROPOSED METHOD OF FUZZY MULTI LABEL CLASSIFICATION: FAMC

1. The proposed work is extracts the classified rules using fuzzy based ant miner algorithm[3] is called Fuzzy Ant Multi-label Classifier (FAMC).
2. Obtaining multi-label rules based on new quality function deals with confidence which is more reliable compared to specificity.
3. Confidence measures on validity of the rule.
4. It is one kind of probability that if body occurs also head occurs.
5. Confidence as a conditional probability that a transaction having A also contains B = P (B|A).
6. Confidence indicates rule's strength

Fuzzy set divides into training and testing data set. After then apply Ant-Miner algorithm with novel quality measure and optimize discover rules.

V. RESULT AND DISCUSSION

V.1 Implementation details

Description of requirements	
Data set	Emotions.arff
Classifier	FAMC (Fuzzy Ant Multi-Label Classifier)
Platform	Windows
Language	eclipse-java-luna-SR2-win32-x86_64
Tool	MEKA
Simulator	MATLAB

Table 5.2 Description of requirements

V.2 RESULTS

Implementation has been done for best fuzzy classification rules with its novel quality. FACM algorithm applied to Flags dataset, which is first fuzzified numeric data by using fuzzification process in java and then its numeric attribute values are replace by linguistics word for smooth transition and discover fuzzy classification rules using code of FAMC algorithm.

= Discovered Model =

Rule 1:

IF landmass = 4 AND

zone = 2 AND

area > 7.0 AND

population<= 28.5AND

language = 72 AND
bars = 3 AND
stripes = 5 AND
colors = 6 AND
circles = 3 AND
crosses = 2 AND
quarters = 0 AND
sunstars = 12
THEN
religion = 2
Existing method Quality: 0.055

= Discovered Model =

Rule 1:
IF landmass = F1Low:F1High AND
zone = F2Low AND
area = F3Low AND
population = F4Low AND
language = F5Low:F5Med AND
bars = F6Low AND
stripes = F7Low AND
colors = F8Low AND
circles = F9Low AND
crosses = F10Low AND
quarters = F11Low AND
sunstars = F12Low
THEN
religion = Muslim
Novel Quality: 0.077

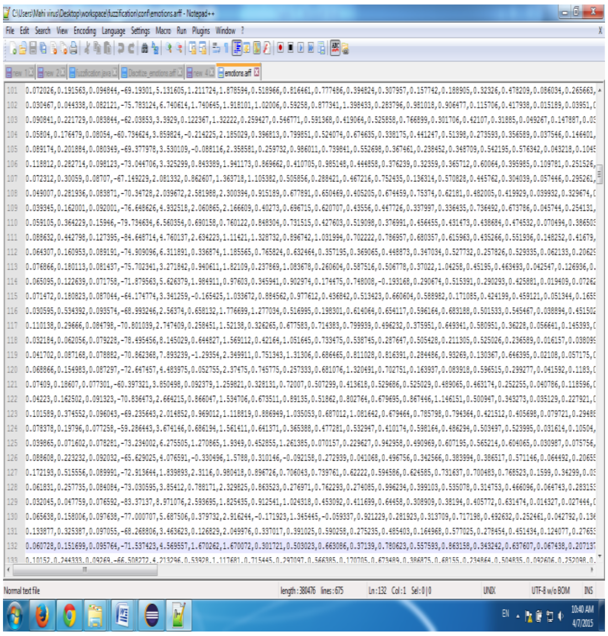


Fig. 5.1 shows the original input file.

In this emotions data set 78 attributes are present and that divided in two category 72 predictor attributes and 6 class label attribute are shown in input file.

For e.g. simple classification rule and fuzzy classification rule

Above rules and quality of rule shows that improved quality of fuzzy classification rules for multi-label dataset by using novel quality measure deals with confidence instead of specificity in existing method quality measure

VI. CONCLUSION

The goal of Ant-Miner is to discover classification rules in data sets. and Ant-Tree-Miner, for the induction of decision trees in the context of the classification task in data mining. An extension to Ant-Miner, named cAnt-Miner, which copes with continuous attributes during the rule construction process.
An extension of classification learning algorithms based on ant colonies in order to process continuous valued attributes is proposed. These parameters are fuzzified on the fly according to the concepts of fuzzy logic. Fuzzy Ant Classifier (FAMC) method takes under account the novel fuzzy quality with confidence of a rule which is more reliable compared to specificity The primary goal of this thesis is to develop accurate, comprehensible and efficient classification algorithm based on ACO for multi-label dataset. Experiments and comparison show that the proposed algorithm exhibit better quality when compared with original Ant-Miner algorithm commonly used for such purposes.
VI.1 The proposition of this algorithm and the resulting experimentation shows that obvious improvement compared to basic Ant-Miner and basic multi-label classification.

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