Constructing the Classification systems using Association rule mining for Predictive Analysis

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Abstract -- **Association rule mining is one of the most significant techniques of data mining. It finds all the rules existing in the transactional database that satisfy some minimum support and minimum confidence constraints. Classification using Association rule mining is another major Predictive analysis technique that aims to discover a small set of rule in the database that forms an accurate classifiers. The combined approach that integrates association rule mining and classification rule mining called Associative Classification (AC). This is new classification approach. It is a promising approach in data mining that utilizes the association rule discovery techniques to construct classification systems, also known as associative classifiers. The integration is done by focusing on mining a special subset of association rules called classification association rule (CAR). And then classification is being performed using these CAR. Given the readability of the associative classifiers, they are especially fit to applications where the model may assist domain experts in their decisions. It introduces a new associative classifier that takes advantage of weighted association rule mining. The model can be applied in any domain to improve the prediction accuracy. It consists of the terms and the basic concepts to define attribute weight, record weight, weighted support and weighted confidence for associative classifiers. The technique for Weighted Association Rule Mining is known as (WARM) and the technique for associative classifiers is termed as Weighted Associative Classifier (WAC) and also discusses the fuzzy associative classifier with as well as without weighted concept**

Index Terms - **Associative Classifiers, WARM , WAC, FAC, WFAC**

I. INTRODUCTION

Data mining is a powerful new technology with great potential to help companies focus on the most important information in the data they have collected about the behavior of their customers and potential customers. It discovers information within the data that queries and reports can't effectively reveal. It is used to discover patterns and relationships in the data in order to help make better business decisions. Data mining can help spot sales trends, develop smarter marketing campaigns, and accurately predict customer loyalty. Association rules are useful for analyzing and predicting customer behavior. They play an important part in shopping basket data analysis, product clustering, catalog design and store layout.It is used to build programs capable of machine learning. Machine learning is a type of artificial intelligence (AI) that seeks to build programs with the ability to become more efficient without being explicitly programmed.

Classification is another central task in data mining. Given a collection of records in a data set, each record consists of a group of attributes and one of the attributes is the class label. The classification task involves constructing a model from the classified objects, in order to classify previously unseen objects as accurately as possible[14].This process involves prediction of future class labels, whereas association rule mining involves only the description of the relationships among items in a database. In addition, there is one and only one pre-specified target class in classification, however, the target classes for association rule are not pre specified. A new approach that integrates association rule mining and classification called associative classification has been proposed [4] Many experimental studies[6] showed that associative classification approach, which builds more accurate classifiers than traditional classification techniques such as decision trees (Quinlan, 1993). Moreover, many of the rules found by associative classification methods cannot be discovered by traditional classification algorithms [3]. Given the readability of the associative classifiers, they are especially fit to applications were the model may assist domain experts in their decisions.

This paper is organized as follows: Section I is an introduction of association and classification. Section II discusses the associative classification and weighted associative classification and also relating with the Fuzzy associative classification based on the weight and without weight for performance analysis carried in recent years. Finally Section III concludes the paper.

II. LITERATURE SURVEY

1 Associative Classification

Associative classification (AC) mining is an integrated approach in data mining that utilizes the association rule discovery techniques to construct classification systems. An

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AC task is different from association rule discovery. The most obvious difference between association rule discovery and AC is that the latter considers only the class attribute in the rules consequent. Table 1 shows the main important differences between AC and association rule discovery, where overfitting prevention is essential in AC, but not in association rule discovery as AC involves using a subset of the discovered set of rules for predicting the classes of new data objects. Overfitting often occurs when the discovered rules perform well on the training data set and badly on the test data set. This can be due to several reasons such as a small amount of training data objects or noise. The problem of constructing a classifier using AC can be divided into four main steps, as follows. [5]

- **Step 1**: The discovery of all frequent ruleitems.
- **Step 2**: The production of all CARs that have confidences above the minconf threshold from frequent ruleitems extracted in Step 1.
- **Step 3**: The selection of one subset of CARs to form the classifier from those generated at Step 2.
- **Step 4**: Measuring the quality of the derived classifier on test data objects.

Figure 1 shows the general steps used in the AC approach, in which the first step is similar to the discovery of frequent itemsets in association rule discovery, which is a challenging problem[1][5]. Methods that find the complete set of frequent ruleitems, generally separate ruleitems that are potentially frequent and then work out their frequencies in the training data set (Step 1). Once all frequent ruleitems are identified, for each ruleitem that passes the minconf threshold, a single rule is generated of the form, X→C where C is the largest frequency class associated with itemset X in the training data set (Step 2). The problem of generating the classification rules is straightforward, once all frequent ruleitems are identified, In Step 3, a selection of an effective ordered subset of rules is accomplished using various methods discussed in this paper, and in the final step the quality of the selected subset is measured on an independent test data set.

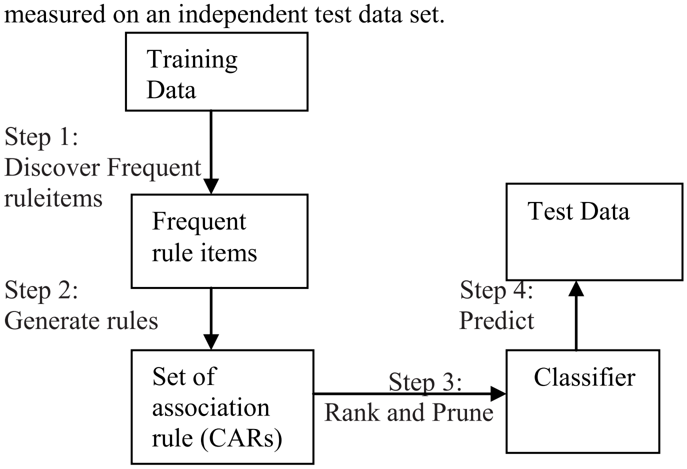

Fig.1 Associative classification Steps.

Table - 1 The main differences between AC and association rule discovery

Association rule Discovery	Associative classification
No class attribute involved (unsupervised learning)	A class must be given (supervised learning)
The aim is to discover associations between items in a transactional database.	The aim is to construct a classifier that can forecast the classes of test data objects.
There could be more than one attribute in the consequent of a rule.	There is only attribute(class attribute) in the consequent of a rule
Overfitting is usually not an issue	Overfitting is an important issue

2. Weighted Associative Classfiers (WAC)

A weighted association rule (WAR) is an implication X→Y where X and Y are two weighted items. A pair (i_j, w_j) is called a weighted item where i_j **ε** I and w_j **ε** W is the weight associated with the item i_j. A transaction is a set of weighted items where $0<w_j<=1$. Weight is used to show the importance of the item.In weighted association rule mining problem each item is allowed to have a weight. The goal is to steer the mining process to those significant relationships involving items with significant weights rather than being flooded in the combinatorial explosion of insignificant relationships

Associative classifiers are especially fit to applications where the model may assist the domain experts in their decisions. There are many domains such as medical, where the maximum accuracy of the model is desired and hence the accuracy of the associative classifiers. In a proposed system a new framework (associative classifier) that uses weighted association rule mining (WARM).[10] In any prediction model all attributes do not have same importance in predicting the class label. So the different weights can be assigned to different attributes according to their predicting capability. It introduces a new associative classifier that takes advantage of weighted association rule mining. The model can be applied in any domain to improve the prediction accuracy. It consists of the terms and basic concepts to define attribute weight, record weight, weighted support and weighted confidence for associative classifiers. Technique for Weighted Association Rule Mining is known as (WARM) and technique for associative classifiers is termed as Weighted Associative Classifier (WAC).

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2.1 System model

Data mining community proposed the concept of weighted association rule mining to deal with the case where items are given weights to reflect their importance. More weights can be assigned to these important attributes and according to their importance less weight to the other attributes. Assigning different weights to different attribute and using weighted association rule mining; the selection of significant item sets is steered to those item sets having relationship to high weight item. Hence integrating WARM with classifiers may improve the prediction accuracy as the accuracy of the model depends on how strong rules are used for classification.[10]
In the proposed system a new Weighted Associative Classifier (WAC) that generates classification rules using weighted support and Confidence framework. The naïve approach is generating strong rules instead of weak irrelevant rules. The importance of weighted Association rule in classification problem (Wang 2000)

2.2 System Overview of WAC

A weighted associative classifiers consists of training dataset as T = {r_1, r_2, r_3…. r_i…} with set of weight associated with each {attribute, attribute value} pair. Attribute weight is assigned depending upon the domain. For example item in supermarket can be assigned weight based on the profit on per unit sale of an item. In web mining visitor page dwelling time can be used to assign weight In medical domain symptoms can be assigned weight by expert doctor[12]. In associative classification rule mining, the association rules are not of the form
X →Y rather they are subset of these rules where Y is the class label. Weighted support WSP of rule X→Class_label, where X is set of non empty subsets of attribute-value set, is fraction of weight of the record that contain above attribute-value set relative to the weight of all transactions. Performing the Post processing techniques for weighted associative classification (pruning, rule ranking, and rule selection to reduce the generated rules) and builds the classifier using the rules and make decisions.
The training dataset are stored in the database. Assigning the weight for each attributes in the training dataset with the specified condition.

1.3 System Design

To create the attribute value pair based on the training dataset and generates the candidate set for all attribute set and calculate the record weight. After generating the candidate set, removing

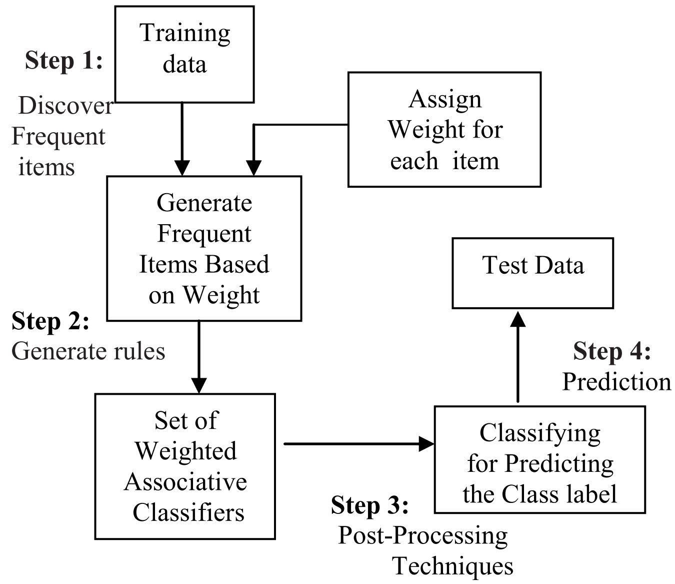

Fig 2: Weighted Associative Classification

the attribute set which does not satisfy the given minsup and minconf values and calculate the record weight for the candidate set. Based on the record weight for each attribute set along with the class label condition, calculating the weighted support and weighted confidence. After that rules to be generated that indicates for predicting the class_label.
From the training dataset, assigning the different weights for each attribute in the dataset with the specified condition is used in the predicting the class_label. The weighting attributes are inserted into the database. For example, in heart disease identification ECG ,Blood pressure plays the major role. Hence the attribute value associated with this test value holds maximum weightage. With the help of physician, weights to the attribute can be assigned.

Table 3 Sample Database for Heart patient.

R_ID	Age	Smoking habits	Hyper tension	BMI	Heart Disease
1	42	Yes	Yes	40	Yes
2	62	Yes	No	28	No
3	55	No	Yes	40	Yes
4	62	Yes	Yes	50	Yes
5	45	No	Yes	30	No

Weight of different attribute in predicting the probability of Heart Disease is given in Table 4

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Table 4 Weight of symptoms for Heart disease (attribute weight).

S.No	Symptoms	Weights
1	Age<40	0.1
2	40<age<58	0.2
3	Age>58	0.3
4	Smoking_habits =yes	0.8
5	Smoking_habits = no	0.7
6	Hypertension = yes	0.6
7	Hypertension = no	0.5
8	BMI<=25	0.1
9	26<= BMI<=30	0.3
10	31<=BMI<=40	0.5
11	BMI>=40	0.8

The Candidate set will be constructed using the weighted attribute in the database with the specified conditions.[11] Attribute value pairs along with weights have been created and find their all possible combinations for generating the candidate sets and also calculate the attribute set weight and record weight. For calculating the attribute weight, look up the database for finding the weighted attribute.

Attribute set weight is denoted as W(X) is calculated as the average of weights of enclosing attribute.

$$W(X) = \frac{\sum_{i=1}^{|x|} \text{weight}(a_i)}{\text{Number of attributes in x.}}$$

The tuple weight or record weight can be defined as type of attribute weight. It is average weight of attributes in the tuple. If the relational table is having n number of attribute then Record weight is denoted by $W(r_k)$ and given by

$$W(r_k) = \frac{\sum_{i=1}^{|r_k|} \text{weight}(a_i)}{\text{Number of attributes in a record}}$$

After generating the candidate set from the training dataset, attribute set weight is calculated by the average of of weights of enclosing attribute and record weight is calculated by the average weight of attributes in the tuple.

The Candidate set generation examples are based on the training dataset shown as in table 5

Table 5 Candidate set Generation

S.no	Candidate set generation	Record weight
1	{ age,"med"),(smoking_habits, "yes") }	0.2+0.8/4 = <u>0.25</u>
2	{ (age, "old"),(Hypertension, "yes")}	0.3+0.6/4 = <u>0.23</u>
3	{ (smoking_habits, "yes"), (Hypertension,"no")}	0.8 +0.5/4 = <u>0.33</u>
4	{(age, "old"), BMI,"med"),Hypertension,"yes")}	0.3+0.3+0.6/4 = <u>0.30</u>
5	{(age,"high"),(smoking_habits, "yes"), (Hypertension,"yes")}	0.3 + 0.8 +0.6/4 = <u>0.43</u>
6	{(age, "old"), (BMI, "very high"),(smoking_habits,"yes") ,(Hypertension,"yes")	0.3+0.5+0.6+0.8= <u>0.55</u>

After generating the Candidate sets, calculating the record weight for all attribute pairs and find the weighted support. Removing the attribute set which is not satisfying the minsup thresholds values. Weighted support WSP of a rule X→ Class_label, where X is set of non empty subsets of attribute-value set, is the fraction of weight of a record that contain above attribute-value set relative to the weight of all transactions.

Weighted Support can be calculated as by using the formula,

$$WSP(X \rightarrow \text{Class\_label}) = \frac{\sum_{i=1}^{|X|} \text{weight}(r_i)}{\sum_{i=1}^{|n|} \text{weight}(r_i)}$$

After calculating the record weight for candidate generation, calculate the weighted support for given class label condition. A special subset whose right hand side is restricted to the class attribute is used for classification. This subset of rules is referred as the Class Association Rules (CARs).

Consider a rule R (Hypertension="yes") → Heart_Disease="yes" then Weighted Support of R is calculated as

$$WSP(R) = \frac{\text{Sum of Record Weight having the condition Hypertension='yes" true and also given class label Heart\_Disease}}{\text{Sum of Weight of all transactions}}$$

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$$WSP(R) = \frac{0.53+0.50+0.50}{0.53+0.48+0.50+0.50+0.45}$$

$$WSP(R) = \underline{0.62}$$

After calculating the weighted support, find the weighted confidence. Removing the attribute set which is not satisfying the minconf thresholds values. It is the ratio of weighted support(X U Y) and the weighted support(x).

Weighted Confidence can be calculated as by using the formula

$$WC(R) = \frac{\text{Weighted Support (X U Y)}}{\text{Weighted Support (X)}}$$

The Weighted confidence of the rule R (Hypertension = "yes") → Heart_Disease="yes" can be calculated as :

$$WC(R) = \frac{\text{Sum of Record Weight having the condition Hypertension='yes" true and also the class label Heart Disease}}{\text{Sum of Record Weight having the condition Hypertension="yes" true}}$$

$$WC(R) = \frac{0.53+0.50+0.50}{0.53+0.50+0.50+0.45}$$

$$WC(R) = \underline{0.77}$$

Likewise calculating the Weighted support and Weighted confidence for all transactional attribute set and finally the rules are generated. CAR Rules are of the form $((A_i,v_i)\ldots,(A_j,v_j)) \rightarrow c$ where c ε Class-Label. Where left hand side is itemset and right hand side is class. And set of all attribute and class label together form $((A_i,v_i)\ldots,(A_j,v_j))$, c) called rule attribute. Rule attribute ((Ai, vi), …,(Aj vj), c) passes the minsup threshold if support count of $((A_i,v_i)\ldots,(A_j,v_j), c) \geq$ minsup and also passes the minconf threshold if confidence count of $((A_i,v_i)\ldots,(A_j,v_j), c) \geq$ minconf. Based on these class_label will be predicted.
For generating a rule from attribute set, each one satisfies the given minimum support and minimum confidence value. The example are shown in below as

Consider the rule R (Smoking_habits = "yes", Hypertension = "yes") → Heart_Disease ="yes" calcul$_k$ate the Weighted Support and Weighted Confidence and also give the minimium support and confidence values for generating a rule.

<u>Weighted Support</u>

$$WSP(R) = \frac{0.53+0.50}{0.53+0.48+0.50+0.50+0.45}$$

$$WSP(R) = \underline{0.42} \geq \text{minsup}$$

Weighted support of the rule attribute should be greater than or equal to given minsup threshold. It does not satisfy the condition of minsup, removing the attributes from the transactional attribute set. Likewise given the condition for weighted confidence and predict the class label.

<u>Weighted Confidence</u>

$$WC(R) = \frac{0.53+0.50}{0.53+0.50+0.45}$$

$$WC(R) = \underline{0.70} \geq \text{minconf}$$

2.3 Predicting the class label

Predictive analysis is an area of statistical analysis that deals with extracting information from data and using it to predict future trends and behavior patterns. The core of predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting it to predict future outcomes. It is important to note, however, that the accuracy and usability of results will depend greatly on the level of data analysis and the quality of assumptions.
The objective of this module is, predicting the class label that is patients risk level based on the rule generated in the previous module. This module can be tested using the test data set where we were aware of the correct class label. The predicted class label will be compared with the existing value of the class label, to compute the classification accuracy. Based on the classification accuracy further enhancement can be taken place. The system can predict if the patient is likely to have a certain disease. Considering the output of the classification model, the physician can make a better decision on the treatment to be applied to this patient.

3. Fuzzy Weighted Associative Classification (FWAC)

A data mining for Discovering Fuzzy Association Rules is proposed in [13]. The authors have given the technique to find Fuzzy Association Rules without using the user supplied support values which are often hard to determine. The other unique feature of the work is that the conclusion of a fuzzy association rule can contain linguistic terms.

Fuzzy Weighted Association Rule Mining with Weighted Support and Confidence Framework is proposed in [13]. The authors have addressed the issue of invalidation of downward

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closure property (DCP) in weighted association rule mining where each item is assigned a weight according to their significance. Formulae for fuzzy weighted support and fuzzy weighted confidence for Boolean and quantitative items with weighted settings is proposed. The methodology follows an Apriori like approach and avoids the pre and post processing as opposed to most weighted ARM algorithm, thus eliminating the extra steps during rules generation.

Fuzzy Weighted Association Classification with Fuzzy Weighted Support and Confidence Framework is proposed by Sunita et al. in [12].Fuzzy logic is incorporated to split the domain of quantitative attribute into intervals, and to define a set of meaningful linguistic labels represented by fuzzy sets and use them as a new domain.

A fuzzy dataset consists of fuzzy relational database D={ r_1, r_2, r3…. ri…rn} with a set of attributes I=(I_1, I_2, ……I_m}, each I_K can be associated with a set of linguistic labels L={l_1, l_2,……l_L } for example L={young, Middle, Old}.Let each I_k is associated with fuzzy set F = {(I_k,l_1), (I_k,l_2), (I_k,l_3), ……(I_k,l_L)}. So that a new Fuzzy Database D'' is defined as {(I_1, l_1)…. (I_1, l_L) …. (I_k, l_1),…(I_k, l_L),…(I_m, l_1)…(I_m , l_L) } .Each attribute Ii in a given transaction tk is associated (to some degree) with Several fuzzy sets. The degree of association is given by a *membership degree* in the range [0..1]. tk[$\mu(I_i, l_j)$] will denote the degree of membership for Fuzzy Attribute Ii to fuzzy set lj in transaction tk.

Table-6 Data Base with continuous domain

R_ID	Age	Blood Pressure	BMI	Heart Disease
1	42	90-130	40	Yes
2	62	80-120	28	No
3	55	80-122	40	Yes
4	62	92-135	50	Yes
5	45	92-135	30	No

Y-young	***H-High***	***M-Mild***
M-Middle	***L-Low***	***M1-Moderate***
O- Old	***N-Normal***	***S-Severe***

Table-7 Transformed Binary Database D' from D

R_ID	Age			Blood Pressure			BMI			Heart Disease
	Y	M	O	H	L	N	M	M1	S	
1	0	1	0	1	0	0	0	1	0	Yes
2	0	0	1	0	0	1	0	1	0	No
3	0	1	0	1	0	0	0	1	0	Yes
4	0	0	1	1	0	0	0	0	1	Yes
5	0	1	0	1	0	0	1	0	0	No

Table-8 Database D'' with Fuzzy Items.

R_ID	Age			Blood Pressure			BMI			H_D
	Y	M	O	H	L	N	M	M1	S	
1	0.2	0.7	0.1	0.4	0	0.6	0.3	0.3	0.1	Y
2	0.0	0.3	0.7	0.1	0.1	0.8	0.1	0.1	0.1	N
3	0.1	0.3	0.6	0.2	0.0	0.8	0.3	0.3	0.1	Y
4	0.0	0.3	0.7	0.5	0.0	0.5	0.2	0.2	0.7	Y
5	0.1	0.8	0.1	0.6	0.0	0.4	0.2	0.2	0.1	N

Table 6 shows the Example database D with continuous Domain of quantitative attribute. In Table 7 the transformed binary database (D') is shown in which the quantitative attributes have been partitioned by converting it into categorical attribute. Consider attribute *Age* in Table 6 again, three new attributes (e.g. *((Age*, young), (Age, middle) and (*Age, old)* in place of *Age* may be used to constitute a new database (D__) with partial belongings of original attribute values toeach of the new attributes. Table 8 illustrates an example of the new database obtained from the original database, given fuzzy sets {*Young*, *Middle, Old*} as characterized by membership functions shown in Figure 3 for attribute age. Similarly the other quantitative attribute ie Bloodpressure and BMI (Obesity) are also partitioned and membership values are assigned by using corresponding membership function.

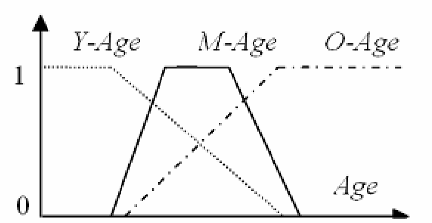

Fig 3: Fuzzy Sets *Y-Age*, *M-Age* and *O-Age*.

Here Fuzzy logic is incorporated to split the domain of quantitative attribute into intervals, and to define a set of meaningful linguistic labels represented by fuzzy sets and use them as a new domain. In this case it is possible that one item may appear with different label of same attribute.[13] Hence the item sets are needs to be restricted to contain at most one item set per attribute because otherwise the rules of the form {(Age, Middle),(Age, old)….. _ class_label } have no meaning. The triangle and trapezoidal are the two important membership functions that can be used to find the degree of association for the different attribute.[14]

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Definition 1. **Fuzzy Attribute Weight**:
We assign a weight $W(I_i, l_j)$ to each fuzzy Item $I(I_i, l_j)$ where ($1 \le i \le n$), ($1 \le j \le L$) and ($0 \le w \le 1$). Table 4 shows the random weight assigns to different fuzzy attribute for heart disease

Table-9 Weight of symptoms for heart disease (attribute weight).

S.No	Symptoms	Weights
1	Age,young	0.1
2	Age,middle	0.2
3	Age,old	0.6
4	BP,Normal	0.3
5	BP,Low	0.2
6	BP,High	0.7
7	BMI,Mild	0.3
8	BMIModerate	0.5
9	BMI,Severe	0.7

Definition 2. Fuzzy Attribute set Transaction Weight: Weight of attribute set X a particular transaction tk is denoted by t_k[FATW(X)] and is calculated as the product of membership degree of attribute in given fuzzy set in the transaction tk and weight of fuzzy attribute; of all enclosing Fuzzy attribute in the set. And is given by

$$tk[FASTW(X)] = \prod_{i=1}^{|X|} (\forall (I_i, l_j) \in X) \; [t_k[\mu (I_i, l_j)] \times W(I_i, l_j)]$$

Consider the 2 attribute set **(**Age , old), (BP, high) **in transaction1**

FASTW ((Age, old), (BP, high)) = (0.1×0.6) (0.4×0.7) = 0.34

Definition 3. Fuzzy Attribute Set Weight: Fuzzy Weight of attribute set X is calculated as sum of FASTW all transaction and is denoted by FASW(X). And is given by

$$FASW(X) = \sum_{k=1}^{|D''|} t_k \, [FASTW(X)]$$

$$FSAW(X) = \sum_{k=1}^{|D''|} \prod_{i=1}^{|X|} (\forall (I_i, l_j) \in X) \; [tk[\mu (I_i, l_j)] \times W(I_i, l_j)]$$

Consider the 2 attribute set **(**Age , old), (BP, high).

FASW ((Age, old), (BP, high)) = [(0.1×0.6)(0.4×0.7) + (0.7×0.6) (0.1×0.7) + (0.6×0.6) (0.2×0.7) + (0.7×0.6)(0.5×0.7) + (0.1×0.6) (0.6×0.7)] = **2.34**

Definition 4 Fuzzy Weighted Support
In associative classification rule mining, the association rules are not of the form X →Y rather they are subset of these rules where Y is the class label.Fuzzy Weighted support FWS of rule X→Class_label, where X is set of non empty subsets of fuzzy weighted attribute. Fuzzy Weighted Support FWS of a rule X→Class_label is calculated assum of weight of all transaction in which the given class label is true, divided by total number oftransaction, denoted by FWS(X→Class_label). And is given by

$$FWS(X \rightarrow Class\_label) = \frac{\sum_{\forall\, t_k \text{ having Given class\_label}} t_k[FASTW(X)]}{\text{Number of records in } D''}$$

where t_k is all transaction for which the given class_label is true

$$FWS(X \rightarrow Class\_label) = \frac{\sum_{\forall\, t_k \text{ having Given class\_label}} \prod_{i=1}^{|X|} \forall\, (I_i, l_j) \in X \; [\mu (I_i, l_j) \times W(I_i, l_j)]}{n}$$

Consider the attribute set X= [**(**Age, old), (BP, high)**]** and a rule r =[(Age, old), (BP,high)_(Heart_disease= ”yes”) the Fuzzy Weighted Support of a rule is given by
FWS((Age, old),(BP, high)_ (Heart_disease=”yes”))

$$\frac{[(0.1\times0.6)(0.4\times0.7)+(0.6\times0.6)(0.2\times0.7)+(0.7\times0.6)(0.5\times0.7)]}{5}$$

FWS(r) = 0.27 (27%)

Definition 5 Fuzzy Weighted Confidence
Fuzzy Weighted Confidence of a rule X→Y where Y represents the Class label can be defined as the ratio of Fuzzy Weighted Support of (XUY)

$$\text{Fuzzy Weighted Confidence} = \frac{\text{Fuzzy Weighted Support } (X \cup Y)}{\text{Fuzzy Weighted Support } (X)}$$

$$FWC(X) = \frac{\sum_{\forall\, t_k \text{ having given class\_label}} \prod_{i=1}^{|X|} \forall\, (I_i, l_j) \in X \; [\mu(I_i, l_j) \times W(I_i, l_j)]}{\sum_{K=1}^{|D''|} \prod_{i=1}^{|X|} (\forall (I_i, l^j) \in X) \; [\mu (I_i, l_j) \times W(I_i, l_j)]}$$

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Consider the attribute set X= [(Age, old), (BP, high)] and a rule r =[(Age, old), (BP,high)_(Heart_disease= "yes") the Fuzzy Weighted Confidence of a rule is given by
FWC[(Age, old), (BP, high)_ Heart_disease="yes")] =

[(0.1×0.6)(0.4×0.7)+(0.6×0.6)(0.2×0.7)+(0.7×0.6)(0.5×0.7)]
[(0.1×0.6)(0.4×0.7)+(0.7×0.6)(0.1×0.7)+(0.6×0.6)(0.2×0.7)+(0.7×0.6)(0.5×0.7)+(0.1×0.6)(0.6×0.7)]

FWC(r) = 1.37/ 2.34

FWC(r) = 0.585(58%)

III. Conclusion

A weighted associative classifiers where attributes are allowed to have weight depending upon their importance in predicting the class labels Each Fuzzy attribute is allowed to have weight depending upon their importance in predicting the class labels. A Conceptual model has been presented that allows development of an efficient and applicable algorithm in future that can capture real-life situations and can produce more accurate classifiers such as in Medical data mining. Hence using weighted and Fuzzy weighted Association Rule as a Classification rule will improve the classification accuracy. In future work, one of existing associative classifiers is to be chosen or new algorithm needs to be developed that can be integrated with weighted association rule miner and evaluate the performance analysis. Using association rule mining for constructing classification systems is a promising approach. Given the readability of the associative classifiers, they are especially fit to applications were the model may assist domain experts in their decisions.

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