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A New Proposal Classification Method Based on Fuzzy Association Rule Mining for Student Academic Performance Prediction

Cu Nguyen Giap*, Doan Thi Khanh Linh

Vietnam University of Commerce, 79 Ho Tung Mau, Cau Giay, Hanoi,Vietnam

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Abstract: Predicting student academic performance (SAPP) is an important issue in modern education system. Proper prediction of student performance improves construction of education principle in universities and helps students select and pursue suitable occupation. The predictions approaching fuzzy association rules (FAR) give advantages in this circumtance because it give the clear data-driven rules for prediction outcome. Applying fuzzy concept brings the linguistic terms that is close to people thought over a quantitative dataset, however an efficient mining mechanism of FAR require a high computing effort normally. The existing FAR-based algorithms for SAPP often use Apriori-based method for extracting fuzzy association rules, therefor they generate a huge number of candidates of fuzzy frequent itemsets and many redundant rules. This paper presents a new proposal model of predictor using FAR to elevating prediction performance and avoids extraction of the fixed set of FAR before prediction progress. Indeed, a modification tree structure of a FP-growth tree is used in fuzzy frequent itemset mining, when a new requirement raised, the proposed algorithm mines directly in the tree structure for the best prediction result. The proposal model does not require to pre-determine the actecedent of prediction problem before the training phrase. It avoids searching for non-relative rules and prunes the conflict rules easily by using a new rule relatedness estimation.

Keywords: Classification, fuzzy, fuzzy association rule, student academic performance prediction.

1. Introdution

Predicting student academic performance (SAPP) is an important matter in education [1]. It predicts future performance of a student after being enrolled into a university and determines who would do well and who would have bad scores. These predicted results help making admission decisions more efficiently and improve quality of academic services [2]. Particularly, administrators can evaluate performance of students in next semesters by changing their education principle to fit their students' features. Lecturers are possible to select suitable learning strategies for students having different scores and estimate how they would make the students getting better within certain of extent [3]. Such the benefit impulses the development of computerized methods that could predict the results with high reliable accuracy [4].

The most efficient tools that were appeared in many papers regarding SAPP is Neuro-fuzzy inference system, which combines neural network and fuzzy systems in order to utilize

* Corresponding author. Tel.: 84-943335958.
Email: cunguyengiap@tmu.edu.vn

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the advantages from both methods [5, 6]. There have been many neuro-fuzzy models namely Adaptive Neuro-Fuzzy Inference System (ANFIS), Coactive Neuro-Fuzzy Inference System (CANFIS), Hierarchical Adaptive Neuro-Fuzzy Inference System (HANFIS), Multi Adaptive Neuro-Fuzzy Inference System (MANFIS) [7-9].

The neutral network-based algorithms have high accuracy, however they still have a weak point that is they do not clearly interpret the precedences of predicted results. Fuzzy association rules (FAR) based approaches take an advantage in this aspect by giving data-driven rules for any prediction. The existing FAR based algorithms for SAPP used Apriori-based methods for extracting fuzzy association rules [10, 11]. These approaches have to generate a huge number of candidates of fuzzy frequent itemsets and many redundant rules. The most well-known approach that avoids redundant candidates in mining frequent itemset from crisp dataset is using FP-growth tree structure, however this structure does not fit for mining fuzzy frequent itemset [12]. In [12-14] the modifications of FP-growth tree struture are presented, which adapts with mining fuzzy frequent itemset. MFFP-tree and CMFFP-tree are efficient structures to store and extract frequencies of fuzzy.

This study has presented a new efficient model approaching FAR to elevating prediction performance in education database. Using fuzzy concept in association rule mining maps the linguistic terms over a quantitative dataset contributes and lets people understand outcome rules easier, however the extraction of fuzzy frequent itemset is not convenient as extraction of frequent itemset in quatitative data. First and foremost, fuzzilizers require deep expert knowledge in application in order to generate good fuzzy membership function, however this prerequisite is not satisfy in many application areas. In new proposal model, FCM algorithm is used to determine the fuzzy set centers and a standard fuzzy membership function is chosen by user, and then fuzzy membership function parameters are automatically optimized by a genetic algorithm. Secondary, in a FAR prediction system, avoiding redundant rules is an important issues also. In new proposal model, there is no need to extract a fixed set of fuzzy association rules before performing prediction. Indeed, a modification tree structure of FP-growth tree is constructed that can be used to mine fuzzy frequent itemset with a backtracking algorithm. As a new requirement of prediction raised, an proposed algorithm mines directly from the tree structure for the best predicted result.

The new proposal model has three main improvements: The model does not require for pre-determine the antecedent of prediction problem before the training phrase; Avoiding estimation of non-relative rules and pruning the conflict rules easily by using a new rule relatedness score; The modification tree structure accumulates the knowledge during the time then when the training set expanding the quality of prediction model is improved. This proposal model has potential application on many areas where the deep research is not performed and expert knowledge of fuzzy member function is missed. In that case, automatic fuzzy association rule mining technique generates rules to help people make rational decision or gives fundamental knowledge to emerge further study.

In the rest, we have briefly reviewed formal extended definitions of fuzzy association rule and related works in the second part and described the proposal model comprehensively in the third part. We have also introduced new rule relatedness estimation method in the fourth part and summated several important points in our study and future works in final part.

2. Background and relate works

2.1. Fuzzy association rule

Fuzzy association rule is extended from crisp association rule by extending the membership function. An indicate member function is the function defined in a set X that indicates membership of an element in subset A of X, having the value 1 for all elements of A and 0 for elements are not in A.

$$\iota_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases}$$

The fuzzy member function is an extension of member function above, which indicates membership of an element x in X with the fuzzy set $\tilde{A}$. The fuzzy member function is normally formed $\mu_A(x)$ that represents the membership degree of an element x in fuzzy set $\tilde{A}$. The value 0 means that x is not a member of the fuzzy set; the value 1 means that x is fully a member of the fuzzy set. The values between 0 and 1 characterizes fuzzy members, which belongs to the fuzzy set only partially.

As a fuzzy membership function is formed for each attribute of a quantitative dataset, this crisp dataset is transformed into a fuzzy dataset by transformed each transaction one after the other. The final target is clustering the finite set of n elements $X = \{x_1, \ldots, x_n\}$ into the set of c fuzzy cluster $C = \{c_1, \ldots, c_c\}$ regards several factors. The fuzzy set corresponding to original set of elements, now, represents the memberships of each element to c fuzzy cluster, which expressed by a patition matrix μ sizes $n \times c$, where $\mu_{ij} \in [0,1]\ \forall\, i \in \{1, n\}$and $j \in \{1, c\}$.

2.2. Fuzzy association rule

Given a fuzzy dataset $D_f = \{t_1, t_2, \ldots, t_N\}$ contains N transactions of fuzzy item sets X_f, which is transformed from a crisp dataset. A fuzzy association rule is formed as $A \Rightarrow B$, where $A, B \subseteq X_f; A \cap B = \emptyset$; and $A \cup B$does not contain any pair items come from the same attribute in original crisp dataset.

The well-known extensions of support and confidence measurements for a fuzzy association rule are defined as follow:

$$D_f supp(A \Rightarrow B) = \frac{\sum_{i=1}^{n} A(x) \otimes B(y)}{|D_f|}$$

And

$$D_f conf(A \Rightarrow B) = \frac{\sum_{i=1}^{n} A(x) \otimes B(y)}{\sum_{i=1}^{n} A(x)}$$

Where $\otimes$ is a T-norm.

Mining fuzzy association rule problem concerns on figure out fuzzy association rules have high support and confidence. In detail, the target is figuring out all rules have:

$D_f supp(A \Rightarrow B) \geq Min\_supp$;

$D_f conf(A \Rightarrow B) \geq Min\_conf$

Where Min_supp and Min_conf are thresholds defined by users.

In this study, minimum T-norm is applied, therefor a fuzzy frequent itemset is extended from frequent itemtset as following definition.

Definition 1: The frequency of a fuzzy item is calculated by the following formulas.

$$f(A(x)) = \sum_{i=1}^{n} A(x)$$

Where

$$A(x) = \min\{a_i(x_i)\}\ \forall\, a_i \in A$$

2.3. General fuzzy association rule

Definition 1: Given a fuzzy association rule formed as $A \Rightarrow B$, and $A' \Rightarrow B$,where $A, A', B \subseteq X_f; A \cap B = \emptyset; A' \cap B = \emptyset$; and $A \cup B$; $A' \cup B$ do not contain any pair items come from the same attribute in original crisp dataset. The rule $A' \Rightarrow B$ is said as a more general rule of $A \Rightarrow B$ if A' is a subset of A.

2.4. Relate works

Since the fuzzy concept is introduced by Lotfi A. Zadeh, it is widely applied in many areas including SAPP. Recently, many researchers have solved the SAPP problem by apply fuzzy association rule [15-19]. The authors presented a fuzzy rule-based approach to aggregate student academic performances. The membership values produced in this paper were more meaningful than the values produced by statistical standardized-score. Ramjeet Singh Yadav et al [15] proposed a Fuzzy Expert System (FES) for student academic performance evaluation based on Fuzzy Logic techniques. A suitable Fuzzy Inference mechanism and associated rule has been discussed in the paper. It introduces the principles behind Fuzzy Logic and illustrates how these principles could be applied by Educators to evaluate the student's academic performance. Chiang and Lin [16] presented a method for applying the Fuzzy Set Theory to teaching and assessment. Bai and Chen [17] presented a new method for evaluating student's learning achievement using Fuzzy Membership Functions and Fuzzy Rules. Chang and Sun [18] composed a method for fuzzy assessment of learning performance of Junior High School Students. Ma and Zhou [19] introduced a Fuzzy Set approach to the assessment of student centered learning. Those methods are based on Apriori algorithm.

Apriori described the background knowledge of association rule including the fundamental definitions and properties of frequent itemset. The most important point in his research is the closure of frequent item-sets that leaded to the first algorithm for mining association rules using searching on lattice space layer to layer for frequent candidates. These candidates are checked to be added into frequent item-sets or ignored. The association rules are generated from frequent item-sets by a simple algorithm. In SAPP, Apriory-based method for extracting fuzzy association rules are described more clearly in [10, 11]. This method has to check all k-item-sets (k=1-n) to figure out the fuzzy frequent itemsets. The approach using the Apriori closure is easily implemented however it has too many candidates to check as calculating the k-item-sets.

The above approaches have to scan an input database many time to calculate itemset frequency that costs much computing time. The well-known technique that improves performance of frequent itemset extractor is using FP-growth tree struture. However, this tree structure is not easily apply in fuzzy frequent itemset mining due to the difference between itemset's frequency and fuzzy itemset's frequency. In [12-14] several modifications of FP-growth tree struture are introduced to adapt with mining fuzzy frequent itemset. MFFP-tree and CMFFP-tree are efficient structure to store and extract the frequency of fuzzy itemsets from a fuzzy sets. MFFP-tree stores the frequency of an itemset in a branche as the normal FP-growth tree, however this algorithm requires the input transactions must be reorder all its items' member values in decending order. This order makes the finall tree structure more complex than FP-growth tree constructed in original way [13]. CMFFP-tree stores the frequency of an itemset in a branche as the normal FP-growth tree also, however in each node of the tree structure the number of frequence has to be stored is equal to the node level in the tree. This cost much more memory than the original FP-growth tree [14].

In order to improve the quality of SAPP using Fuzzy association rules, in our proposal model has the mechanism for learning fuzzy membership function based on FCM and optimize by Genetic algorithm [20]. Beside, in the model a MFFP-tree structure is construted and when a required prediction appears the predictor mines directly from the tree structure for the best evaluate result. Moreover, the model also uses a new method to score the fitness of a rule for prediction. This method scores a rule via not only its confident, support values but also the length of antecedent [21] and how this rule fits to an particular input transaction.

3. A new proposal model for Classification based on Fuzzy association rule mining

The new model for a student performance prediction system has two stages. The first stage constructs a modification of FP-growth tree for a fuzzy dataset, which called a trainning progress. The fuzzy dataset is not exist beforehand but it is result of a fuzzilizer that us a fuzzy membership function constructed by FCM algorithm and a chosen type of member function by user. The second stage using the modification FP-growth tree to predict the result of an application domain that is transformed from a quantitave dataset by the same fuzzilizer above, which called a predicting progress.

Stage 1. The outline of the first stage is showed in the figure 1.

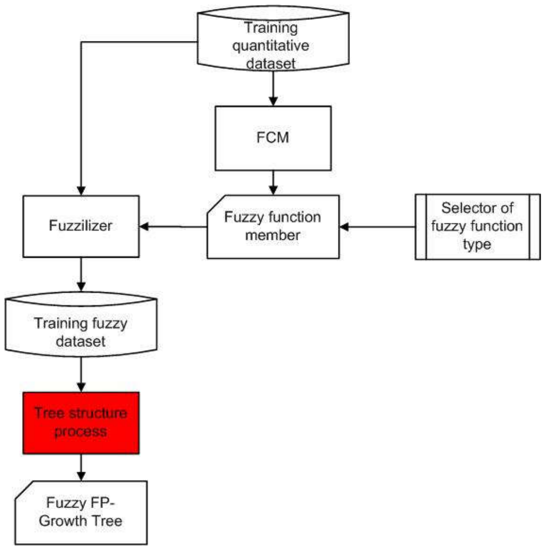

Figure 1. Workflow of Training progress.

For each contribution of transaction in crisp dataset, the target of first stage is clustering the finite set of n elements $X = \{x_1, \dots, x_n\}$ into the set of c fuzzy cluster $C = \{c_1, \dots, c_c\}$ regards several factors. The fuzzy set corresponding to original set of elements, now, represents the memberships of each element to c fuzzy cluster, which is expressed by a patition matrix W sizes $n \times c$, where $\mu_{ij} \in [0,1]\ \forall\, i \in \{1, n\} \text{and } j \in \{1, c\}$.

The first stage uses fuzzy c-means (FCM) algorithm improved by Bezdek to construct a partition matrix satisfies that the following object function is minimized.

$$J_m = \sum_{i=1}^{n}\sum_{j=1}^{c} \mu_{ij}^{m}\left\|x_i - c_j\right\|^2$$

Where:

$$w_{ij}^{m} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}};\ c_j = \frac{\sum_{i=1}^{N} u_{ij}{}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}{}^{m}}$$

The membership values μ_{ij} are depended on the fuzzifier $m \in R \text{ with } m \geq 1$. As the fuzzifier $m = 1$, the membership values equal to 0 or 1, in this case, the fuzzy cluster becomes a crisp partition. w_{ij}^{m} and c_j are updated repeatedly untill $max_{ij} = \{|\mu_{ij}^{k-1} - \mu_{ij}^{k}|\} < \varepsilon$ where ε is a error boundary and k is an iteration step.

FCM sets membership values to all attributes of a crisp dataset, however this algorithm needs a large training dataset to have good quality. Therefore using direct FCM to fuzzilize a crisp testing dataset is not suitable when the testing dataset is small. Indead, after the FCM algorithm learns and returns fuzzy centers for all fuzzy clusters, a type of fuzzy membership function is chosen by user to form a fuzzy membership fuction. The user know insights of application domain then his can chose the most suitable type of fuzzy membership function for applied domain.

In fact, a significant fuzzy association rules are generated from frequent fuzzy item-sets based on a simple algorithm, therefore the challenge here is finding frequent fuzzy item-sets. In this study, we have proposed an algorithm that using a modification of FP-growth tree to store frequent fuzzy items and seek for frequent item-sets. For example: given a crisp dataset as follow.

A modification of FP- growth tree called MFFP-tree contains a FP-structure tree and a table of fuzzy items, in order to construct a FP-tree the proposed algorithm has to access entire database one time only. The item table stores all fuzzy items in the descending order, the frequence of each item and a pointer points to the first node on the FP-tree has the same name.

Table1. Scrisp dataset

TID	Items
1	B:4, C:9
2	A:8, B:2, C:3
3	A:3, C:10, D:2, E:3
4	A:7, C:9
5	A:5, B:3, C:5, D:5
6	A:5, C:10, E:9

Table 2. After a fuzzy clustering stage, we have the corresponding fuzzy dataset

TID	Items
1	(0.4/B.Low, 0.6/B.Middle), (0.4/C.Middle, 0.6/C.High)
2	(0.6/A.Middle, 0.4/A.High), (0.8/B.Low, 0.2/B.Middle), (0.6/C.Low, 0.4/C.Middle)
3	(0.6/A.Low, 0.4/A.Middle), (0.2/C.Middle, 0.8/C.High), (0.8/D.Low, 0.2/D.Middle), (0.6/E.Low, 0.4/E.Middle)
4	(0.8/A.Middle, 0.2/A.High), (0.4/C.Middle, 0.6/C.High)
5	(0.2/A.Low, 0.8/A.Middle), (0.6/B.Low, 0.4/B.Middle), (0.2/C.Low, 0.8/C.Middle), (0.8/D.Low, 0.2/D.Middle)
6	(0.2/A.Low, 0.8/A.Middle), (0.2/C.Middle, 0.8/C.High), (0.4/E.Middle, 0.6/E.High)

Table 3. The frequence of fuzzy items are count as follow

Item	count	Item	count	Item	Count
A.Low	1.0	C.Low	0.8	E.Low	0.6
A.Middle	3.4	C.Middle	2.4	E.Middle	0.8
A.High	0.6	C.High	2.8	E.High	0.6
B.Low	1.8	D.Low	1.6		
B.Middle	1.2	D.Middle	0.4		
B.High	0.0	D.High	0.0		

Table 4. The table of frequent fuzzy items regard to threshold 1.5.

Item	count	Occurence frequency
A.Middle	3.4	5
C.Middle	2.4	6
C.High	2.8	4
B.Low	1.8	3

MFFP-tree involves a root node called a null node (signs as {}) and a set of precedent trees that are subtrees of root node. The transactions in database are going to insert into FP-tree by their own items in alpabetical order. Except root node, each node on FP-tree has a name comes from linguistic items, and its membership value and an array of frequences of all super item-sets contain the node labels regard to all nodes stay on the same branch from root. Each element in this array includes the prefix of the precendents in the such branch and it frequences. Besides, the node has pointers point to parent node, children nodes and the node with the same name on the tree.

MFFP-tree is constructed from the transactions with respect to frequent items only. The transactions are reordered base on the frequencies of its items. If there are items have the same frequencies in a transaction, they are ordered based on the order of header table.

Table 5. The table of fuzzy dataset after reordering.

TID	Items
1	(0.6/C.High, 0.4/C.Middle, 0.4/B.Low)
2	(0.8/B.Low, 0.6/A.Middle, 0.4/C.Middle)
3	(0.8/C.High, 0.4/A.Middle, 0.2/C.Middle)
4	(0.8/A.Middle, 0.6/C.High, 0.4/C.Middle)
5	(0.8/A.Middle, 0.8/C.Middle, 0.6/B.Low)
6	(0.8/A.Middle, 0.8/C.High, 0.2/C.Middle)

The algorithm using to construct MFFP-tree has read 1 transaction at a time and maps it to a path of FP-tree like. The algorithm is depicted as follow.

Algorithm: construct MFFP –tree
Input: set of transactions T of fuzzy dataset.
Ouput: MFFP-tree {
root = {}; // init empty t
foreach transaction t_i in T {
For(j=0; j< $|t_i|$; j++) {
currnode = root;
current_element = e_{ij};
if (current_element is not a child of currnode) {
//put current_element as a child of currnode
node newnode =Insert(current_element, currnode);
node* Point=last_insert(current_element);
point = & newnode;
currnode= newnode;
}
else {
// update frequency of node has label equal to current_element
node temp =find(current_element, currnode);
update(current_element, temp);
currnode= temp; }
}
return root;
}
}

Algorithm: last_insert (element x)
Input: an element x of header table
Output: the pointer of the last inserted node of tree has the lable equal to x.
{
for (i =0; i< length(header_table); i++)
If(header_table[i] == x) {
node* temp = header_table[i].pointer;
while(temp->next !=NULL)
temp= temp->next;
return temp;
}
return null;
}

Stage 2: The second stage uses the MFFP-tree above to extract the most relavant item of a prediction requirement. The outline of the second stage process is showed in the figure below.

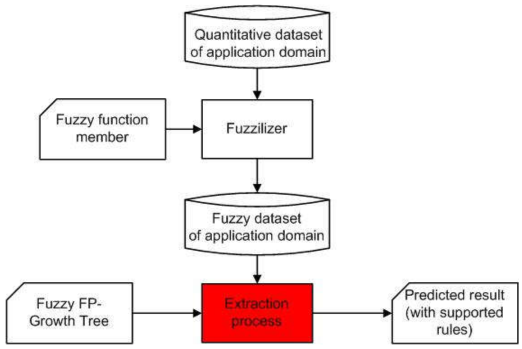

Figure 2. Workflow of predicting progress.

In above progress, a quatitative dataset of an application domain is converted into a fuzzy set by the fuzzilizer constructed in the first stage. Therefore, the most important here is figuring out the algorithm for extraction process. The extraction process is used to ditermine the most general fuzzy association rule relates to a prediction. This process has borrow several ideas from MFFP-growth mining algorithm but it is modified to extract the highest supported and general degree rule only.

The extraction process has two main steps, the first one extracts entire relevant frequent itemsets involve all fuzzy items generated from crisp predicted items from MFFP-tree and the second step extracts the highest confident rule from frequent itemsets.

Algorithm: extracting_relevant_frequents
Input: MFFP-tree {root}, min support threshold minsupp, min confidence threshold minconf, crisp input transaction for predict T and crisp predict requirements Y={y}.
Output: Predicted result and its rules-based information.
{
Call P={p/p is fuzilized from y };
Reorder(P) by membership value in desending order;
Call FI ={}; // init a empty set of frequent itemset
foreach(p in P) {
Call S ={}; // S is supper set of p;
foreach node link by p {
Foreach each supper set Si of p, calculate it support supp(Sij);

If (Si < S) increase supp(Si) by supp(Sij).
Else Add Si with supp(Sij) to S; }
foreach Si in S
If(Supp(Si) > minsup) add Si to FI
} **return** predicting(FI, T,Y);
}
Algorithm: predicting(FI, T,Y)
Input: frequent itemsetses FI, input transaction T and output items Y
Output: Predicting result of Y and rule-based information.
{
Reorder FI by support;
Call P={p/p is set of lable for items of Y };
Reorder(P) by membership value in desending order;
foreach yi item in Y {
Double maxscore_yi = 0;
Chosen_rule_yi = null;
foreach Si itemset of FI {
if(Si include one lable from yi) {
Generate rule: r (Si/yi->yi);
Score(r,T);
if(score(r,T) > maxscore) {
maxscore = score(r,T);
chosen_rule = r;
}
}
}
} **return** all chosen_rule_yi and maxscore_yi;
}

In above predicted algorithm, the important point to choose a rule is a score of a rule corresponding with input transaction. This score is estimate by a formula presented in next session.

4. Rule-based evaluation

In a crisp data, a predicting result is generated depend on the rule-based score, however when we extend a crisp data into a fuzzy data, the input transaction also contains values that make a bias onto a special input label. Therefore, the evaluation has to combine both issues.

In order to combine both issues in one evaluation unit, a new score has introduced:

$$Score(r,T) = \alpha.pref(r,T) + (1-\alpha)memb(r,T)$$

The parameter $\alpha \in [0,1]$ show that predictor bias to preference of a rule. In general, a rule that has higher preference and has antecedent closer to input transaction will has higher score, in other words, this rule is more likely to used on predictor.

Normally, a rule has the highest confidence is interest, however there might be exist more than one elligible rule for prediction. In that case, the rule has higher support is prefered because this rule is more common than are other rules in dataset. Beside, in the same condition, a rule has longer antecedence is prefered because this rule gives more evidence for the prediction.

For a rule: r{A->B} and prediction requirement T, the preference of r is estimated by the following formulas:

$$pref(r,T) = \begin{cases} \beta.\frac{supp(A \cup B)}{supp(A)}.supp(A \cup B) + (1-\beta).\frac{|A|}{|T|} & if\ (supp(A \cup B) < 1) \\ conf(r) & if\ (supp(A \cup B) = 1) \end{cases}$$

The parameter $\beta \in [0,1]$ show the bias between support value of a rule and length of rule antecedant. If β goes closer to 1, it means that predictor prefers on rule's support, otherwise predictor prefers on length of rule antecedent. Beside, as the $supp(A \cup B) = 1$, the rule r is existed in all transaction then other aspects are not considered, indead the $pref(r,T) = conf(r) = 1$.

The membership value or A in T is calculate by following formulas:

$$memb(r,T) = 1 - \frac{1}{|A|}\sum_{1}^{i}|1 - w_{ai}|$$

The membership value of antecedence A of rule r in transaction T is calculated by the power of each item in itemset A in transaction T. The $memb(r,T) = 1$ when all items in A have the membership value w_{ai} equal to 1. It means that the antecedent A perfectly fits to transaction T.

5. Conclusion

This study has proposed a new prediction model for Student Academic Performance Prediction based on the appoaching of fuzzy concept in association rule mining. The proposal model has two main stage, the first one including a fuzzilier that transforms a crisp dataset into fuzzy dataset and then a constructor generates a MFFP-tree from such dataset. The second stage convert an input transaction into fuzzy transaction and estimate score of rules relates to input transaction. A rule with highest score is chosen for prediction and explanation of predicted result.

The proposed model has three main contributions over the existing approaches: The model does not require for pre-determine the antecedent of prediction problem before the training phrase. It avoids searching for non-relevant rules and easily prunes the conflict rules by estimating the rule score for each predicted input. The modification tree accumulates knowledge during the time then if the training set is expanded the quality of prediction model will be improved consequently. This proposed model has also higher opportunity to use in areas where the deep research has not been performed or expert knowledge of fuzzy member function is missed. In that case, automatic fuzzy association rule mining technique generates rules to help people make rational decision or gives fundamental knowledge to emerge further study.

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