

# Applying Fuzzy Data Mining for an Application CRM

Chien-Hua Wang and Chin-Tzong Pang

**Abstract**—In the era of great competition, understanding and satisfying customers' requirements are the critical tasks for a company to make a profits. Customer relationship management (CRM) thus becomes an important business issue at present. With the help of the data mining techniques, the manager can explore and analyze from a large quantity of data to discover meaningful patterns and rules. Among all methods, well-known association rule is most commonly seen. This paper is based on Apriori algorithm, using data mining to discover fuzzy classification rules. The mined results can be applied in CRM to help decision maker make correct business decisions for marketing strategies.

**Index Terms**—Customer relationship management (CRM), Data mining, Apriori algorithm, Fuzzy classification rules.

## I. INTRODUCTION

CUSTOMER relationship management (CRM) is an important information system architecture as an enterprise enters e-Business [15]. Its purpose is to effectively collect, store, analyze data to come up with a core integration profile for customers through IT, such as the Internet, Data Warehouse, Data Mining etc. The results gained are to support enterprises dealing one on one interactions and customized marketing, sales and after-sales service. Through different media such as the Call Center, the Internet, Telephoning, Faxing and Salespeople, enterprises can interact, connect, trade and wait on their customers to attract new customers and secure old ones to enhance customer satisfaction, customer loyalty and profitability [21-22].

The relationship between customers and enterprises is a vital surviving factor for enterprises. When, enterprises accumulate some great amount of unhandled data such as customer transactions, one must know that this kind of data means little help to decision makers. In order to reach maximal efficient interactions between customers and enterprises, enterprises need to adopt data mining technology, such as association rules, classifications and clusters to discover useful information in databases, as well as acquire valuable information to provide enterprises with sound management skills and perfect core competitiveness in business[4].

Additionally, in terms of decision making, one has to take users' perception and cognitive uncertainty of subjective decisions into consideration. Zadeh proposed the Fuzzy Theory [26] in 1965 to deal with cognitive uncertainty of vagueness

and ambiguity [25]. Since linguistic variables and linguistic values [27-29] can be described with fuzzy concepts to subjectively correspond with the possible cognition of a decision maker, they are handy in carrying out analysis of decisions-making. Fuzzy data mining has then recently become an important research matter.

In this paper, we used a two-phase data mining technique to discover fuzzy rules for customer's classification problems [6]. This method is based on the Apriori algorithm. Firstly, the first-phase finds frequent fuzzy grids by dividing each quantitative attribute with a user-specified number of various linguistic values. Secondly, the second-phase generates effective fuzzy classification rules from those frequent fuzzy grids. In addition, the fuzzy support and the fuzzy confidence, which have been defined previously [5, 10, 11], are employed to determine which fuzzy grids are frequent and which rules are effective by comparison with the minimum fuzzy support (min FS) and the minimum fuzzy confidence (min FC), respectively.

The remaining parts of this paper are organized as follows. The association rule and grid partition method are briefly introduced in Section II. Notation and the algorithm are introduced in Section III. An example is given to illustrate the proposed algorithm in Section IV. Experimental results to demonstrate the performance of the proposed fuzzy data mining algorithm are stated in Section V. The conclusion is given in Section VI.

## II. LITERATURE REVIEW

### A. Customer relationship management (CRM)

CRM aims for enterprises to focus on customers, the most essential core of business operations, and tries to establish a "Learning Relation" with customers. Through customers' responses to certain products and services, enterprises make customers their center to adjust management and operations effectively. By so doing, enterprises obtain the know-how to improve the quality of products and service [16]. In other words, via constant communication and thorough understanding, enterprises acquire new ways to secure existing customers, gain new customers to motivate customers' contribution and loyalty to enterprises [1, 14, 17].

1) *Customer Satisfaction*: Customer satisfaction is the satisfaction degree when products purchasing and service offering are taking place. Cardozo [2] painted out customer satisfaction increases customers' second purchasing behavior as well as the desire to purchase more products. Spreng [20] further thought customers perceive a state of sense and sensibility after the process of evaluating items and purchasing them.

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Customer satisfaction is to strengthen the relation with existing customers, which is a cost-saving approach to encourage "repurchasing tendency". Through their word-of-mouth, enterprises are likely to win new customers and pronounce prominent influence for profitability [24]. Some known factors to affect customer satisfaction are products, service, and corporate images. Products are divided into software and hardware, including quality, function, performance, efficiency, and price. Service is the serving attitude of servers, such as clothes, word usages, greetings, smiles and product-related knowledge. Corporate images include environmental awareness and the contribution to the society. The measuring method uses scales of service quality to proceed with customers' perception and expectancy of certain service and the degree of satisfaction is thus gained.

2) *Customer Loyalty*: Customer loyalty means the repeated purchasing behavior a customer demonstrates to particular companies, products or services. Jones and Sasser [12] assumed customer loyalty is customers' willingness to purchase the same products or services in the future. Customer loyalty can also be shown short-term and long-term. Short-termers represent customers waver when there are better alternatives whereas long-termers stay and seldom change. Because of this, enterprises learn only with good service and novelty can they secure customer loyalty.

### B. Grid partition method

The concepts of linguistic variables were proposed by Zadeh [26-28]. Formally, a linguistic variable is characterized by a quintuple [19, 30] denoted by  $(x, T(x), U, G, M)$ . Here,  $x$  is the name of the variable;  $T(x)$  denotes the set of names of linguistic values or terms, which are linguistic words or sentences in a natural language [3] of  $x$ ;  $U$  denotes a universe of discourse;  $G$  is a syntactic rule for generating values of  $x$ , and  $M$  is a semantic rule for associating a linguistic value with a meaning. Using the grid partition methods, each attribute can be partitioned by various linguistic values. This grid partition method has been widely used in pattern recognition and fuzzy reasoning. For example, there are the applications to pattern classification by [8-9], to fuzzy neural networks by [13], and to the fuzzy rule generation by [23].

In the grid partition method,  $K$ -various linguistic values are defined in each quantitative attribute.  $K$  is also pre-specified before performing the proposed method. For example,  $K = 3$  and  $K = 4$  for  $x_1$  that ranges from 0 to 60 are depicted in Fig. 1 and 2, respectively. If  $x_1$  is "age", then linguistic values (i.e.,  $A_{11}$ ,  $A_{12}$ ,  $A_{13}$ ) with triangle-shaped membership functions depicted in Fig. 1 can be linguistically interpreted as *young*, *medium*, and *old*, and those (i.e.,  $A_{11}$ ,  $A_{12}$ ,  $A_{13}$ ) depicted in Fig. 2 can be interpreted as *young*, *mediumyoung*, *medium*, and *old*.

In this method, symmetric triangle-shaped linguistic values are used for simplicity. When a linguistic value is not yet determined if it is frequent, it is called a candidate 1-dim fuzzy grid. For a quantitative variable, say  $x_k$ ,  $\mu_{ki_k}$  is represented as follows [5-9 ]:

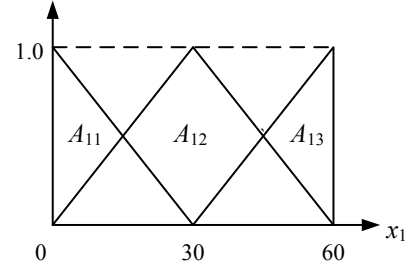


Fig. 1:  $K = 3$  for " $x_1$ "

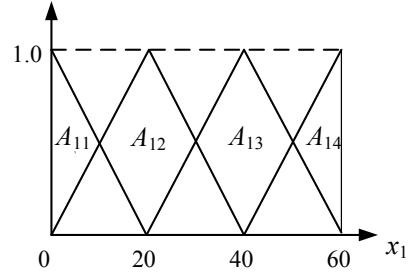


Fig. 2:  $K = 4$  for " $x_1$ "

$$\mu_{ki_k}(x) = \max\left\{1 - \frac{|x - a_{i_k}|}{b^{K_i}}, 0\right\} \quad (1)$$

where

$$a_{i_k} = \frac{m_i + (m_a - m_i)(i_k - 1)}{K_k - 1}, \quad (2)$$

$$b^{K_i} = \frac{(m_a - m_i)}{K_k - 1} \quad (3)$$

where  $m_a$  and  $m_i$  are the maximum and the minimum values of the domain interval of  $x_k$ , respectively.  $(A_{11}, A_{23})$  is called a candidate 2-dim fuzzy grid that can be generated by using  $A_{11}$  and  $A_{23}$ . In other words, candidate 1-dim fuzzy grids can be further employed to generate the other candidate or frequent fuzzy grids with higher dimensions [6-7].

In regard to categorical attributes, each has a finite number of possible values, with no ordering among values (such as color or profession). If the distinct attribute values are  $n'$  ( $n'$  is finite), this attribute can only be partitioned by  $n'$  linguistic values. For example, since the attribute "Class" is categorical, and the linguistic sentence of each linguistic value may be stated as follows:

$$\begin{aligned} A_{2,1}^{Class \text{ label}}: & \text{ class 1} \\ A_{2,2}^{Class \text{ label}}: & \text{ class 2} \end{aligned}$$

where, it should be noted that the maximum number of dimensions for a single fuzzy grid  $d$  [6-7].

### III. RESEARCH METHOD

In this section, we describe the individual phase of the method in section 3.1 and 3.2.

TABLE I: Initial table FGTTFS for an example

Fuzzy grid	FG						TT		FS
	$A_{3,1}^{x_1}$	$A_{3,2}^{x_1}$	$A_{3,3}^{x_1}$	$A_{3,1}^{x_2}$	$A_{3,2}^{x_2}$	$A_{3,3}^{x_2}$	$t_1$	$t_2$	
$A_{3,1}^{x_1}$	1	0	0	0	0	0	$\mu_{3,1}^{x_1}(t_{11})$	$\mu_{3,1}^{x_1}(t_{21})$	FS( $A_{3,1}^{x_1}$ )
$A_{3,2}^{x_1}$	0	1	0	0	0	0	$\mu_{3,2}^{x_1}(t_{11})$	$\mu_{3,2}^{x_1}(t_{21})$	FS( $A_{3,2}^{x_1}$ )
$A_{3,3}^{x_1}$	0	0	1	0	0	0	$\mu_{3,3}^{x_1}(t_{11})$	$\mu_{3,3}^{x_1}(t_{21})$	FS( $A_{3,3}^{x_1}$ )
$A_{3,1}^{x_2}$	0	0	0	1	0	0	$\mu_{3,1}^{x_2}(t_{12})$	$\mu_{3,1}^{x_2}(t_{22})$	FS( $A_{3,1}^{x_2}$ )
$A_{3,2}^{x_2}$	0	0	0	0	1	0	$\mu_{3,2}^{x_2}(t_{12})$	$\mu_{3,2}^{x_2}(t_{22})$	FS( $A_{3,2}^{x_2}$ )
$A_{3,3}^{x_2}$	0	0	0	0	0	1	$\mu_{3,3}^{x_2}(t_{12})$	$\mu_{3,3}^{x_2}(t_{22})$	FS( $A_{3,3}^{x_2}$ )

### A. Determining frequent fuzzy grids

Without loss of generality, given a candidate  $k$ -dim fuzzy grid  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$ , where  $1 \leq i_1, i_2, \dots, i_k \leq K$ , the degree which  $t_p$  belongs to this fuzzy grid can be computed as  $\sum_{p=1}^n \mu_{A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}}(t_p)$ . The fuzzy support [5-7, 10-11] of  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$  is defined as follows:

$$\begin{aligned}
 & FS(A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}) \\
 &= \sum_{p=1}^n \mu_{A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}}(t_p) / n \\
 &= \left[ \sum_{p=1}^n \mu_{K,i_1}^{x_1}(t_{p1}) \cdot \mu_{K,i_2}^{x_2}(t_{p2}) \cdot \dots \cdot \mu_{K,i_k}^{x_k}(t_{pk}) \right] / n
 \end{aligned} \quad (4)$$

The algebraic product uses a  $t$ -norm operator in the fuzzy intersection. When  $FS(A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k})$  is larger than or equal to the user-specified min FS, that  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$  is a frequent  $k$ -dim fuzzy grid. for any two frequent grids, such as  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$  and  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{k,i_{k+1}}^{x_{k+1}}$ , since  $\mu_{A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{k,i_{k+1}}^{x_{k+1}}}(t_p) \leq \mu_{A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}}(t_p)$  ( $1 \leq p \leq n$ ), thus  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{k,i_{k+1}}^{x_{k+1}} \subseteq A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$  holds. But it should note that any subset of a frequent fuzzy grid must also be frequent. This is different from the Apriori property, but we may view it as a special property for mining frequent fuzzy grids.

Next, utilizing the Table FGTTFS generates frequent fuzzy grids. FGTTFS consists of the following substructures [6-7].

- 1) Fuzzy grid table (FG): each row represents a fuzzy grid, and each column represents a linguistic value.
- 2) Transaction table (TT): each column represents ( $t_p$ ), and each element records the membership function degree of the corresponding fuzzy grid.
- 3) Column FS: stores the fuzzy support corresponding to the fuzzy grid in FG.

An initial tabular FGTTFS is shown in TABLE I as an example, from which we can see that there are two sample  $t_1$  and  $t_2$ , with two attributes  $x_1$  and  $x_2$ . Assume both  $x_1$  and  $x_2$  are divided into three linguistic values (i.e.,  $K = 3$ ), and  $x_2$  is the attribute of class labels. Because each row of FG is a bit string consisting of 0 and 1,  $FG[u]$  and  $FG[v]$  (i.e.,  $u$ th row and  $v$ th row of FG) can be paired to generate certain

desired results by applying the Boolean operations. But any two linguistic values defined in the same attribute cannot be contained in the same candidate  $k$ -dim fuzzy grid ( $k \geq 2$ ).

Further, a candidate  $k$ -itemset can be derived by joining two frequent ( $k-1$ ) itemsets, and they share ( $k-2$ ) itemsets in the Apriori algorithm. In this method, a candidate  $k$ -dim ( $2 \leq k \leq d$ ) fuzzy grid can be viewed as to be derived by joining two frequent ( $k-1$ )-dim fuzzy grids, and share ( $k-2$ ) linguistic values. However, this method will encounter one selection of many possible combinations to avoid redundant computations. To solve this problem, we apply exist integers  $1 \leq e_1 \leq e_2 \leq \dots \leq e_k$ , such that  $FG[u, e_1] = FG[u, e_2] = \dots = FG[u, e_{k-2}] = FG[u, e_{k-1}] = 1$  and  $FG[v, e_1] = FG[v, e_2] = \dots = FG[v, e_{k-2}] = FG[v, e_{k-1}] = 1$ , where  $FG[u]$  and  $FG[v]$  correspond to frequent ( $k-1$ )-dim fuzzy grids and  $FG[v, e_k]$  stands for the  $e_k$ th element of the  $v$ th rows of FG, thus  $FG[u]$  and  $FG[v]$  can be paired to generate a candidate  $k$ -dim fuzzy grid.

### B. Determining effective fuzzy rules

The general type of one fuzzy classification rule denoted by  $R$  is stated as Eq.(5).

$$\begin{aligned}
 \text{Rule } R : & A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \Rightarrow A_{C,i_\alpha}^{x_\alpha} \\
 & \text{with } CF(R)
 \end{aligned} \quad (5)$$

where  $x_\alpha$  ( $1 \leq \alpha \leq d$ ) is the class label and  $CF(R)$  is the certainty grade of  $R$ . The above rule can be interpreted as: if  $x_1$  is  $A_{K,i_1}^{x_1}$  and  $x_2$  is  $A_{K,i_2}^{x_2}$  and  $\dots$  and  $x_k$  is  $A_{K,i_k}^{x_k}$ , then  $x_\alpha$  is  $A_{C,i_\alpha}^{x_\alpha}$  with certainty grade  $CF(R)$ . Where the left-handed-side of " $\Rightarrow$ " is the antecedence of  $R$ , and the right-handed-side is the consequence. Since  $(A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{C,i_\alpha}^{x_\alpha}) \subseteq (A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k})$  holds,  $R$  can be generated by  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{C,i_\alpha}^{x_\alpha}$  and  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k}$ . Moreover, the fuzzy confidence of  $R$  is defined as follows [5-7, 10-11]:

$$FC(R) = \frac{FS(A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{C,i_\alpha}^{x_\alpha})}{FS(A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k})} \quad (6)$$

When  $FC(R)$  is larger than or equal to the user-specified min FC, we can say that  $R$  is effective.  $FC(R)$  can further be used as the grade of certainty of  $R$  (i.e.,  $CF(R) = FC(R)$ ). Similarly, we also can use Boolean operations to obtain the antecedence and consequence of each rule.

However, some redundant rules must be eliminated in order to achieve compactness. Assume there exist two rules, such as  $R$  and  $S$ , having the same consequence, and the antecedence of  $R$  is contained in that of  $S$ , then  $R$  is redundant and can be discarded, whereas  $S$  is temporarily reserved. This is because the minimization of the number of antecedent conditions should be considered.

At the same time, Ishibuchi et al. [9] and Nozaki et al. [18] further demonstrated that the performance of fuzzy rule-based systems can be improved by adjusting the grade of certainty of each rule. Therefore, it is possible to improve the classification ability of this method by incorporating the adaptive rules proposed by Nozzki et al [18]. into the proposed learning algorithm. Next, we determine the class label of  $t_p$  by applying fuzzy rules derived by the learning algorithm. Without loss of generality, if the antecedent part of a fuzzy associative classification rule  $R_\tau$  is  $A_{K,i_1}^{x_1} \times A_{K,i_2}^{x_2} \times \dots \times A_{K,i_k}^{x_k} \times A_{K_\tau,i_\tau}^{x_\tau}$ , then we can calculate  $\omega_\tau$  of  $R_\tau$  as Eq.(7).

$$\omega_\tau = \mu_{K_1,i_1}^{x_1}(t_{p1}) \cdot \mu_{K_2,i_2}^{x_2}(t_{p2}) \cdot \dots \cdot \mu_{K_\tau,i_\tau}^{x_\tau}(t_{p\tau}) \cdot FC(R_\tau) \quad (7)$$

Then  $t_p$  can be determined to categorize the class label which is the consequent part of  $R_\beta$ , when

$$\omega_\beta = \max_j \{\omega_j | R_j \in TR\} \quad (8)$$

where TR is the set of fuzzy rules generated. The class label of  $t_p$  is determined and adaptive rules can be employed to adjust the fuzzy confidence of the "firing" rule  $R_\tau$ . This is if  $t_p$  is correctly classified then  $R_\tau$  is increased; otherwise,  $R_\tau$  is decreased.

#### IV. RESEARCH RESULT

The transaction data set of this paper is obtained from a 3C hypermarket in Kinmen. The time is from October, 2010 to November, 2010. There are about 527 data. It is a transaction data set. The original data set contains as follows:

- 1) Name;
- 2) Sex;
- 3) ID number;
- 4) Birth data;
- 5) Telephone number;
- 6) Address;
- 7) Average year income;
- 8) Category.

TABLE II: Format of data transaction

Sex	Age	Average year income	Customer satisfaction	Customer Loyalty	Category
Man	41 ~ 45	30K ~ 35K	0.76	0.24	B
Man	21 ~ 25	15K under	0.66	0.83	C
Woman	15 ~ 20	15K under	0.78	0.69	A
Man	26 ~ 30	25K ~ 30K	0.52	0.84	D
⋮	⋮	⋮	⋮	⋮	⋮

Through data preprocessing, we clear data of noise and inconsistency and delete unnecessary items. Next, by data transformation, we discretize birth date and average year income. In addition, customer loyalty is obtained from times of purchase and customer satisfaction is obtained from the scale. And then we use the method of normalization. The data formats of generation are shown as TABLE II.

Customer satisfaction and customer loyalty are fuzzified, and the linguistic values are shown in Fig 3, and 4.

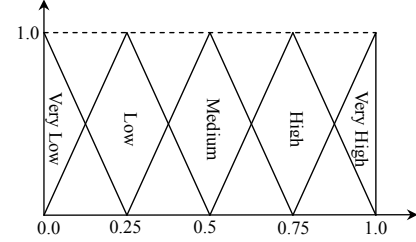


Fig. 3: Linguistic values of customer satisfaction

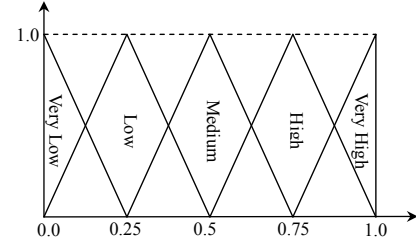


Fig. 4: Linguistic values of customer loyalty

In the experiment, for the partition number  $k$ , we adopt Hu's suggestion which is known as set 5 [6]. And the minimum support and minimum confidence are set as 0.3 and 0.4. The results are as follows:

- 1) IF Age  $\geq 41$  AND Sex = Man AND Average year income = 30K ~ 35K AND Customer satisfaction = Very High AND Customer loyalty = High, THEN Class A with  $CF = 0.7752$ ;
- 2) IF Age = 26 ~ 30 AND Sex = Woman AND Average year income = 20K ~ 25K AND Customer satisfaction = High AND Customer loyalty = Medium, THEN Class B with  $CF = 0.6615$ ;
- 3) IF Age = 21 ~ 25 AND Sex = Man AND Average year income = 26K ~ 30K AND Customer satisfaction = High AND Customer loyalty = Medium, THEN Class B with  $CF = 0.6259$ ;
- 4) IF Age = 21 ~ 25 AND Sex = Man AND Average year income = 20K ~ 25K AND Customer satisfaction = Medium AND Customer loyalty = High, THEN Class C with  $CF = 0.5818$ ;
- 5) IF Age = 36 ~ 40 AND Sex = Woman AND Average year income = 20K ~ 25K AND Customer satisfaction = Medium AND Customer loyalty = Medium, THEN Class C with  $CF = 0.4974$ ;

From the above five rules findings, Sex = Man and Customer satisfaction and Customer loyalty over Medium, the  $CF$  is least which is over 0.62. Next, the Sex = Woman and Customer satisfaction and Customer loyalty over Medium, the  $CF$  is least which is over 0.49. Because  $CF$  increases the strength of the classified rule, when the value of  $CF$  is higher and higher, the category is classified with more certainty. Thus,  $CF$  is an index of threshold restriction. And, the five rules above are the output as meta- knowledge concerning the given transaction.

Also, the original transaction database is compared with that of the two-phase method and fuzzy  $c$ -mean for accuracy, the results is shown as TABLE III. The two-phase method is better than fuzzy  $c$ -mean from TABLE III. The result corresponds with Hu's research.

TABLE III: Accuracy of the comparison

	Two-phase method	Fuzzy $c$ -mean
Accuracy rates	95.68	92.41

## V. CONCLUSIONS

In this competitive society, how to attract new customers and secure old customers play important roles in enterprises. CRM is believed to utilize proper analytic tools with restricted resources to acquire the most valuable customers and increase their desires to purchase more.

In this paper, we use two-phased method to find fuzzy rules for classification problems which is based on the processing of the Apriori algorithm. First, the first-phase finds frequent fuzzy grids by dividing each quantitative attribute with a user-specified number of various linguistic values. And the second-phase generates effective fuzzy classification rules from those frequent fuzzy grids. The research results generate five fuzzy classification rules which are the output as meta-knowledge concerning the given transaction. In addition, this method compares to fuzzy  $c$ -mean. The results demonstrate that the two-phased method for fuzzy classification is better in accuracy rates.

Since fuzzy knowledge representation can facilitate interactions between the expert system and users, this method may be further viewed as a knowledge acquisition tool to discover fuzzy association rules to perform the Market Basket Analysis (MBA), which helps users make preferable decisions.

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