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HYBRID DIMENSION MINING BY FUZZY ASSOCIATION RULE

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ABSTRACT

Mining hybrid dimension fuzzy association rule is one of the important processes in data mining . Apriori algorithm concerned with handling single level, single dimensional association rules. this paper is presenting, a new modification in joining process to reduce the redundant generation of sub items during pruning the candidate itemsets, which can obtain higher efficiency of mining that of original algorithm when the dimension of data is high. Hybrid dimensional association rules are obtaining by using improved joining method of Apriori Algorithm. Support and confidence are the two most important quality measures for evaluating the interestingness of association rules. Crisp set have a well defined universe of members .Crisps sets allow only full membership or no membership at all, where as fuzzy sets allow partial membership. In fuzzy data there are three values namely 0 indicating that an attribute is not a member of the set, values between 0 & 1 indicating that an attribute is partially a member of the set involving partial membership. It means that an attribute is definitely a member of the set involving full membership. This Approach can be characterized by generating hybrid dimensional association rules mining as a generalization of inter-dimension and intra-dimension rule. In this project, two measures support and confidence are calculated for hybrid dimensional association rules by using fuzzy concept. Fuzzy concept is used to acquire an accurate hybrid dimension association rule by calculating Support and Confidence.

Keywords : Multidimensional Transactional Database, Inter Dimensional Join, Intra Dimensional Join, Fuzzy Set, Crisp Set, Multi Valued Attribute, Hybrid Dimensional Association Rules.

I INTRODUCTION

Data Mining is the process of extracting hidden patterns from data. Data Mining is an important technique to transform data into information. It is used in marketing, surveillance, fraud detection and scientific discovery .Data Mining is a type of information extraction system. Information extraction system differs from information retrieval .Information retrieval is basically like processing a query on a database but information extraction is one step ahead. It gets relevant patterns or trends from the information retrieved.

Differences between them are as follow:

1. Information retrieval gets sets of relevant documents from the database so that we can analyze the document
2. Information extraction gets facts out of the document retrieved so that we can analyze the facts.

Data mining techniques can yield the benefits of automation on the existing software and hardware platforms, and can be implemented on new systems as existing platforms are upgraded and new products developed. When data mining tools are implemented on high performance parallel processing systems, they can analyze massive databases in minutes. Faster processing means that the user can automatically experiment with more models to understand complex data. High speed makes it practical for users to analyze huge quantities of data. Larger databases, in turn, yield improved predictions.

Databases can be larger in both depth and breadth:

Columns: Analysts must often limit the number of variables they examine when doing hands-on analysis due to time constraints. Yet variables that are discarded because they seem unimportant may carry information about unknown patterns. High performance data mining allows users to explore the full depth of a database, without preselecting a subset of variables.

Rows: Larger samples yield lower estimation errors and variance. Allow users to make inferences about small but important segments of a population.

These above two points proven the fact that the database for have both depth and breadth in terms of column data and row data respectively.

II ASSOCIATION RULE MINING IN DATA MINING

The discovery of association rules constitutes an important task in the process of data mining. Association rules are an important class of regularities with in data which have been extensively studied by the data mining community. The general objective is to find frequent co-occurrences of items within a set of transactions. The found co-occurrences are called associations. The idea of discovering such rules is derived from market basket analysis where the goal is to mine patterns describing the customer's purchase behavior.

Today, mining this type of rules is a very important discovery method in the KDD [3] Process. A simple association rule could look as follows:

Cheese→Beer [Support=0.1, confidence=0.8].Put simply, this rule expresses a relationship between Beer and Cheese. The support measure states that beer and cheese appeared together in 10% of all recorded transactions. The confidence measure describes the chance that there is beer in a transaction provided that there is also cheese. In this case, 80% of all transactions involving cheese also involved beer. We can thereby assume that people who buy cheese are also likely to buy beer in the same transaction. Such information can aid retail companies to discover cross-sale opportunities and guide the category management in this way. In addition, it enables companies to make recommendations which can be especially useful for online retail shops.

Association rule mining is user-centric because its objective is the elicitation of interesting rules from which knowledge can be derived [2]. Interestingness of rules means that they are novel, externally significant, unexpected, nontrivial, and actionable. An association mining system aids the process in order to facilitate the process, filter and present the rules for further interpretation by the user.

III TERMINOLOGY

The problem of mining association rules as follows:I= {i1, i2, i3........,im}is a set of items={t1,t2,t3.......tm}is a set of transactions, each of which contains items of the item set I . Thus, each transaction t_i is a set of items such that $t_i \subseteq I$. An association rule is an implication of the form: $X \rightarrow Y$, where $X \subseteq I$, $Y \subseteq I$ and $X \cap Y = \emptyset$. X (or Y) is a set of items, called item set [3]. An example for a simple association rule would be {*bread*}→{*butter*} .This rule says that if bread was in a transaction, butter was in most cases in that transaction too. In other words, people who buy bread often buy butter as well. Such a rule is based on observations of the customer behavior and is a result from the data stored in transaction databases.

Looking at an association rule of the form $X \rightarrow Y$, X would be called the antecedent, Y the consequent. It is obvious that the value of the antecedent implies the value of the consequent. The antecedent, also called the "*left hand side*" of a rule, can consist either of a single item or of a whole set of items. This applies for the consequent, also called the "*right hand side*", as well. The most complex task of the whole association rule mining process is the generation of frequent item sets. Many different combinations of items have to be explored which can be a very computation-intensive task, especially in large databases. As most of the business databases are very large, the need for efficient algorithms that can extract item sets in a reasonable amount of time is high.

Often, a compromise has to be made between discovering all item sets and computation time. Generally, only those item sets that fulfill a certain support requirement are taken into consideration**. Support and confidence are the two most important quality measures for evaluating the interestingness of a rule.**

Support: The support of the rule $X \rightarrow Y$ is the percentage of transactions in T that contain $X \cap Y$. It determines how frequent the rule is applicable to the transaction set T. The support of a rule is represented by the formula

Supp (x→y) = $|x \cap y| / n$

Where $|X \cap Y|$is the number of transactions that contain all the items of the rule and n is the total number of transactions. The support is a useful measure to determine whether a set of items occurs frequently in a database or not. Rules covering only a few transactions might not be valuable to the business. The above presented formula computes the relative support value, but there also exists an absolute support. It works similarly but simply counts the number of transactions where the tested item set occurs without dividing it through the number of tuple.

Confidence: The confidence of a rule describes the percentage of transactions containing X which also contain Y.

Conf (x→y) = $|x \cap y| / |x|$

This is a very important measure to determine whether a rule is interesting or not. It looks at all transactions which contain a certain item sets or the transactions also including all the items contained in the consequent.

IV HYBRID DIMENSIONAL ASSOCIATION RULES

1. Inter-dimensional Association

Considering each database attribute or warehouse dimension as a predicate, we can therefore mine association rules containing multiple predicates, such as

Age(x, "20….29") ^occupation(x,"student") →buys(x, "laptop")

Association rules that involve two or more dimensions or predicate can be referred to as multidimensional association rule. Above rule contains three predicates (age, occupation, and buys) each of which occurs only once in the rule, hence, we say that it has **no repeated predicate**s. Multidimensional association rules with no repeated predicates are called Interdimensional association rule.

2. Intra-dimensional Association

Mining Multidimensional association rules contain a single predicate with multiple occurrence of values are called Intradimensional association rule

3. Hybrid-dimensional Association

Multidimensional association rules with repeated predicates, which contain multiple occurrence of some predicates are called Interdimensional association rule.

Hybrid –dimensional association rule contains repeated occurrence of its multi valued combined with single valued attributes.

Hybrid –dimensional mining is a very promising area and has wide applications in real life scenario. For example, in a super market, a store manager may ask a question like, what group of customers would like to buy what group of items? .In the same way, a medical officer may ask " What type of patient undergoing what other type of treatment?" .Each attribute of database or dataset and warehouse can also be termed as predicate.

V INTERESTINGNESS OF ASSOCIATION RULES

So far, we have discussed the algorithms from generating frequent item sets to finally discovering rules. During our experiments with real data, sometimes, more than a thousand rules can be found even from a small size of data. Are all the rules discovered interesting enough to be presented to the user? Not necessarily, whether a rule is interesting or not can be judged either subjectively or objectively. Ultimately, only the user can judge if a given rule is interesting or not, and this judgment, being subjective, may differ from one user to another. However, objective interestingness criterion, based on the statistics "behind" the data, can be used as one step towards the goal of weeding out uninteresting rules from presentation to the user. How can we tell which rules are really interesting? Example:

"Carry Bags"→ "Sport Wear"

the support of this rule is 50%, confidence is 66.7%. We can say that rule 4.11 is a strong association rule based on the support-confidence framework. However, this rule is incomplete and misleading since the overall support of "Carry Bags" is 75%, even greater than 66.7%. In other words, a customer who buys "Carry Bags" is less likely to buy "Sport Wear" then a customer about whom we have no information. The truth here is that there is a negative dependence between buying "Carry Bags" and buying "Sport Wear". To help filter out such misleading strong association rules A → B, we need to study how the two events A and B are correlated. We want to find the dependence of a given rule in order to give a more precise characterization of the rule.

Definition: - We define the interestingness of events x, y to be

$$I(x, y) = \frac{P(x,y)}{P(x)\,P(y)}$$

Where, p(x) is the possibility of event x.

The fact that the interestingness of events x and y is less than 1 indicates negatively correlation, since the nominator is the actually likely hood of both events happen, and the denominator is what the likely hood would have been in the case when the two activities are independent. In the above example, we can see that the interestingness of "Carry Bags", "Sport Wear" is:

P ("Carry Bags", "Sport Wear") /P ("Carry Bags") × P ("Sport Wear")

$$=0.5/0.75\times0.75=0.89<1$$

It means that buying "Carry Bags" is negative associated with buying "Sport Wear", so this rule is not interesting enough to be reported.

Combining the computation into association mining and returning those rules having positive dependence will reduce the size of results and make those generated rules more precise. We notice that p(x) is the support of item x in term of association rules. Therefore, we have the following definition:

Definition:-We define the interestingness of a rule A→B to be

$$I(A\rightarrow B) = \frac{Support(A,B)}{Support(A).Support(B)}$$

This step is to compute of interestingness of each rule and filter out those rules whose interestingness is less than 1.

VI PROBLEMINTRODUCTION

Mining association rules from database is a time-consuming process. Finding the large item set fast, is the crucial step in the association rule algorithm. The problem of discovering association rules can be generalized into two steps:

1. Finding large item sets i.e. frequent itemsets
2. Generating association rules from these item sets.

The research work also put some light over the challenges facing in mining association rules in data items. The subsequent sections discuss some of the motivations regarding the research topic.

The problem of discovering association rule was introduced by Rakesh Agrawal et al (1993). He searched for relationship among attributes/items with a specific strength (support & confidence) was initiated on a flat table with domain. Apriori algorithm invented as a solution, detailed in Rakesh Agrawal et al (1994). Most of the existing algorithm is derived from Agrawal's Apiori algorithm for searching frequent itemset that satisfied minimum support.

In the data mining, the problem of mining AR quite interesting and AR mining is a popular method for discovering interesting relations between variables in databases. Such information can be used as the basis for decisions about marketing activities, etc. As the size of data stored in databases and data warehousing increases a lot, it is very important to develop powerful, fast, efficient and accurate algorithms. The popularity induced demand for the ARM algorithms. It widely used to find of hidden patterns and relationships among data items. ARM algorithms turned out to be very popular but the judgment of efficiency ARM algorithms started when algorithms have to deal with very huge databases with thousands of items, here the problems occurred, as it has to be very accurate and process fast and consume fewer resources to obtain FIS.

Many algorithms for generating association rules were presented over time. Constant efforts have been going on for improvement of ARM algorithm. Some well known algorithm are Apriori, FP-Growth, DHP,CHARM , Sampling, Partitioning, etc. ,but they only do half the job, since there are various fields untouched that needs improvements.

This research work proposed a new system to generate association rules among multi dimensional transaction database. Hybrid dimensional association rules are generating by making an improvement in joining process in Apriori Algorithm.

FL provides the opportunity for modeling conditions that are inherently imprecisely defined. Fuzzy techniques in the form of approximate reasoning provide decision support and expert systems with powerful reasoning capabilities. The permissiveness of fuzziness in the human thought process suggests that much of the logic behind thought processing is not traditional two valued logic or even multivalve logic, but logic with fuzzy truths, fuzzy connectiveness, and fuzzy rules of inference. A fuzzy set is an extension of a crisp set. Crisp sets allow only full membership or no membership at all, whereas fuzzy sets allow partial membership. So, in this proposed work we measuring the interestingness of association rules by calculate accurate value of support and confidence by using fuzzy concept.

VII ALGORITHM

1. Finding frequent co-occurrence of items with in a set of transaction

According the above analysis, Proposed project design the

(a) Finding out frequent 1-itemset L_1.

(b) Compass the original transaction database according to the located frequent 1-itemsets.

(c) Generate candidate 2-itemsets C2 from frequent 1-itemsets L_1. Here is the process: Differentiate the two random frequent 1-itemsets l_1, l_2 (l_1, 1_2 ε L_1), which are going to proceed with natural join. If l_1 and l_2 are both subordinate attributes, the join is not allowed, and the connection is allowed on other occasions.

(d) Generate frequent 2-itemsets from candidate 2-itemsets.

(e) Start from frequent 2-itemsets, take advantage of the iterative approach to generate frequent k-itemsets L_k from frequent (k-1)-itemsets L_{k-1}, (k≥3). Before making the natural joining to generate candidate k-itemsets C_k, differentiate the intra-dimensional join from the Interdimensional join first, and then proceed with the join under certain condition following actualization flow of the algorithm:

(f) Generate association rules from frequent itemsets.

Figure (i) show the logic flow of the improved Apriori Algorithm.

Figure (ii) and Figure (iii) give the actualizing flow of the main process.

--

L **1** = find-frequent-l-itemsets (D);

2) //compress the transaction database, according

/I to the generated frequent l-itemsets

D'= trans-compression@);

3) //generate candidate 2-itensets

Q=apriori_genl (L_1);

4) //generate frequent 2-itemsets

L=find_frequent_2_itensets (D');

5) //generate candidate k-itemsets C_k from frequent

/ (K-1)-itemsets **L_k- I**

For **(k=3;** L k - i # Θ***; k+ +)*** do

6) //generate all the candidate k-itemsets& by joining

Begin

Ck = **Apriori-gen(L_k-1);**

7)//use the **Apriori** property to eliminate

//candidates having a subset that **is** not frequent

For each transaction t E D'do

8) Begin (the t equal to each record)

9) Ct =subset (C_k, t);

10) For each candidate C ε C_t

11) C.count ++,

12) end

13) //all those candidate k-itemsets

L_k = {C ε C_k| C.count>=min Sup)

/ / C_k**satisfying** minimum support from the

/I set of frequent k-itemsets **Lk**

End

14) Answer = U **k** $\mathbf{L_k}$**;**

15) // generate rules from all frequent itemsets

For each large itemsets L_k ε Answer, **(K≥2)** do

16) gen rules (Lk, L_k)

Figure: (i)-The logic flow of the improved Apriori Algorithm

Procedure apriori_gen(L_{k-1} : frequent itemsets)

{

C[k] = n u l l ;

For each l_1 ε L_{k-1}

For each L_2 ε L_{k-1}

if is Inner Join (l_1) o r is Inner Join (1_2)

// i f l_1 or 1_2 can make intra dimension join

// is Inner Join (l_1) is a bool f u n c t i o n ,$l_1$is parameter,

//its 'function is to judge whether

/ / an item l_1 can make intra dimension join ,

/ / if the return value is 'true', it's allowed.

then {

c = $\mathbf{l_1} \bowtie l_2$ ***;***

Insert into C[k]: }

f o r e a c h CεC[k]

for each (k-1)-subset **s** o f c

if S € L_{k-1}

then delete from C[K]

}

Figure (ii):- **Apriori_genl () progress flow**

The following text gives a simple practical example to explain the generating process of the frequent itemsets, which are obtained from hybrid-dimension association rules mining.

```
Procedure Apriori-gen(L_{k-1}:frequent-itemsets)
{
C[k] = null;
For each 1_1 ε L_{k-1}
For each 1_2 ε L_{k-1}
If
then //if make Intradimensional join
{
if ( I_1[ l ]=I_2 [ l])^ (I_1[2]=1_2[2])^----------
 ------------^(l_1(K-2) = l_2(K-2)) ^( l_1(K-1) = l_2(K-1))
Then
{
c = 1_1 ►◄ l2;
Insert  in t o C [ k ];
}
}

else //if make inter dimension join
{
if ( I_1[ 2 ]=I_2 [ l])^ (I_1[3]=1_2[2])^----------
 ------------^(l_1(K-1) = l_2(K-2)) ^( l_1(1) = l_2(K-1))
then {
c = 1_1 ►◄ l2;;
Insert into[k];}
}
for each c ε c[k]
for each (k-1)-subset s of c
ifs  € Lk-i
then delete c from C[k];}
```

Figure (iii):-**Apriori-gen l () progress flow**

Above algorithm is use to finding frequent itemsets of a multidimensional transaction database. Generating frequent itemsets is use for finding Hybrid dimensional association rules for illustrating this approach an example is shown in below.

VIII ILLUSTRATIVE EXAMPLE

An illustrate example is given to understand well the concept of the proposed method and how to calculate support and confidence of the multidimensional association rule mining is performed. Obtain accurate value of support and confidence by using fuzzy concept.

In Table (a), we show a multidimensional transaction database Product Order, which includes two subordinate attributes: Age. Area and one main attribute OrderID. In order to simplify the implement process of algorithm, we preprocessed some attributes before algorithm executes, which are shown as Table. 5(b) and (c), and the finding of frequent itemsets is preceded on the basis of the relation table which has been preprocessed. We suppose the **minimum support threshold is 2**, figure (d) shows the process of searching for frequent itemsets in detail. In the figure, we eliminate the candidates generated in each step. For each generated frequent itemsets, we find that it meet the character of the frequent itemsets which are generated by means of hybrid-dimension association rules mining algorithm. Thus, we can easily generate corresponding hybrid-dimension association rules from the generated frequent itemsets.

Table1: Multidimensional Transaction Database

Product Order

Id	Age	Area	OrderId
1	33----39	Beijing	I1,I2,I5
2	33----39	Beijing	I2,I4
3	33----39	Shanghai	I2,I3
4	40----48	Shanghai	I1,I2,I4
5	40----48	Shanghai	I1,I3
6	33----39	Beijing	I2,I3
7	40----48	Shanghai	I1,I3

(A)

Mapping Age

Interval	Variable
33----39	A
40----48	B

(B)

Mapping Area

Area	Integer
Beijing	1
Shanghai	2

(c)

Product Order after Mapping

Id	Age	Area	OrderId
1	A	1	I1,I2,I5
2	A	1	I2,I4
3	A	2	I2,I3
4	B	2	I1,I2,I4
5	B	2	I1,I3
6	A	1	I2,I3
7	B	2	I1,I3

(D)

Figure (D):-A multi dimensional Transaction Database

Process of Searching for frequent itemsets

L1

Itemsets Support Count
{a:4},{b:3},{1:3},{2:4},{1:4},{I2:5},{I3:4}{I4:2}

↓

L2

Itemsets Support Count
{a,1:3},{a,I2:4},{a,I3:2},{b,2:3},{b,I1:3},{b,I3:2},{1,I2:3},{2,I1:3},{2,I2:2},{2,I3:2}, {I1,I2:2},{I2,I4:2},{a,I1:3},{I1,I3:2},{I2,I3:2}

↓

L3

Itemsets Support Count
{b,2,I1:3},{b,2,I3:2},{b,I1,I3:2},{2,I1,I3:2},{a,1,I2:3},{a,I2,I3:2}

↓

L4

Itemsets Support Count
{b,2,I1,I3:2}

Process of Searching for frequent itemsets

After processing we get, {b, 2, II, I3} is a frequent itemsets. We can generate such a hybrid-dimension association rule :{ b, 2, I1, I3:2} or **b ∧ 2 ∧ I1→I3**

Now, Hybrid Dimensional association rule is obtaining i.e.

Age (X,"40 . . . 48") ∧Area (X,"shanghai") ∧OrderID (X,"11") →OrderID (X,"I3")

IX EVALUATING THE INTERESTINGNESS OF HYBRID DIMENSIONAL ASSOCIATION RULE BY CLASSICAL METHODS.

Let us consider a new transaction database with having quantitative attribute of Age Predicate.

Id	Age	Area	OrderId
1	36	Beijing	I1,I2,I5
2	34	Beijing	I2,I4
3	39	Shanghai	I2,I3
4	45	Shanghai	I1,I2,I4
5	40	Shanghai	I1,I3
6	35	Beijing	I2,I3
7	47	Shanghai	I1,I3

Computation of support and confidence by Classical Method:

Support: The support of the rule $X \rightarrow Y$ is the percentage of transactions in T that contain $X \cap Y$. It determines how frequent the rule is applicable to the transaction set T. The support of a rule is represented by the formula

Supp (x→y) = $|x \cap y| / n$

Where $|X \cap Y|$ is the number of transactions that contain all the items of the rule and n is the total number of transactions. The support is a useful measure to determine whether a set of items occurs frequently in a database or not. Rules covering only a few transactions might not be valuable to the business. The above presented formula computes the relative support value, but there also exists an absolute support. It works similarly but simply counts the number of transactions where the tested item set occurs without dividing it through the number of tuple.

Confidence: The confidence of a rule describes the percentage of transactions containing *X* which also contain *Y*.

Conf (x→y) = $|x \cap y| / |x|$

This is a very important measure to determine whether a rule is interesting or not. It looks at all transactions which contain a certain item sets or the transactions also including all the items contained in the consequent.

Applying this method we get support and confidence of **Hybrid dimensional association rule** i.e.

RULE 1:-

Age (X,"40 . . . 48") ˄Area (X,"shanghai") ˄OrderID (X,"I1") →OrderID (X,"I3")

Result

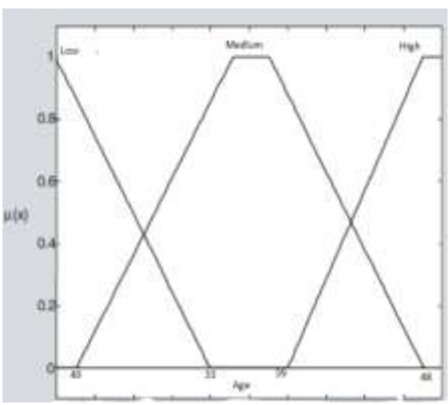
Support =28.6%

Confidence=66.7%

X CALCULATING ACCURATE VALUE BY FUZZY LOGICAL APPROACH

10.1 Calculation of membership values

Let us consider Fuzzy domain for Age is (Low, Medium, and High)



Trapezoidal curves depend on four Parameters and are given by

$$F(x,a,b,c,d) = \begin{cases} 0 & for\ x < a \\ \frac{x-a}{b-a} & \text{for } a \le x < b \\ 1 & \text{for } b \le x < c \\ \frac{c-x}{c-b} & \text{for } c \le x < d \\ 0 & \text{for } d \le x \end{cases}$$

We may consider A and B as sets of fuzzy labels. Simply, A and B are called fuzzy datasets. We may consider A and B as sets of fuzzy labels. Simply, A and B are called fuzzy datasets.

$A = \{A_j | A_j \varepsilon\ F(D_j)$,for some j Nn$\}$,

Where $F(D_j)$ is a fuzzy power set of D_j, or in other words, A_j is a fuzzy set on D_j.Support of A is then defined by:

$$\text{support}(A) = \frac{\sum_{i=1}^{r} \inf_{A_j \in A} \{\mu_{A_j}(d_{ij})\}}{|QD(D_A)|}$$

$$\text{support}(A \Rightarrow B) = \text{support}(A \cup B) = \frac{\sum_{i=1}^{r} \inf_{C_j \in A \cup B} \{\mu_{C_j}(d_{ij})\}}{|QD(D_A \cup D_B)|}$$

Confidence$(A \Rightarrow B)$ is defined by

$$\text{confidence}(A \Rightarrow B) = \frac{\sum_{i=1}^{r} \inf_{C_j \in A \cup B} \{\mu_{C_j}(d_{ij})\}}{\sum_{i=1}^{r} \inf_{A_j \in A} \{\mu_{A_j}(d_{ij})\}}$$

Finally, correlation$(A \Rightarrow B)$ is defined by

$$\text{correlation}(A \Rightarrow B) = \frac{\sum_{i=1}^{r} \inf_{C_j \in A \cup B} (\mu_{C_j}(d_{ij}))}{\sum_{i=1}^{r} \inf_{A_j \in A} (\mu_{A_j}(d_{ij})) \times \inf_{B_k \in B} (\mu_{B_k}(d_{ik}))}$$

After applying Trapezoidal curves parameters, we obtain membership values as soon in table2.

Id	**μ_{age}(ά)**	**$\mu_{area}(\beta)$**	**$\mu_{orderid\text{-}I1}(\gamma)$**	**$\mu_{orderid\text{-}I3}(\delta)$**	**∑min value**
1	**.5**	**0**	**1**	**0**	**0**
2	**.166**	**0**	**0**	**0**	**0**
3	**1**	**1**	**0**	**1**	**0**

4	**1**	**1**	**1**	**0**	**0**
5	**1**	**1**	**1**	**1**	**1**
6	**.33**	**0**	**0**	**1**	**0**
7	**1**	**1**	**1**	**1**	**1**
∑	**4.996**	**4**	**4**	**4**	**2**

Table 2

Therefore,

$$\text{Support(Rule1)} = \frac{1+1}{\{t1\ldots\ldots t2\}} = .285$$

$$\text{Confidence (Rule1)} = \frac{1+1}{0+1+1} = 1$$

Support=28.5%

Confidence=100%

XI RESULT ANALYSIS

Experimental result of data set to show improvement in result by fuzzy concept. With the present work we improve accuracy of hybrid dimensional rule by calculating accurate value of support and confidence.

XII CONCLUSION

This paper presenting an algorithm for generating hybrid dimensional association rules mining as a generalization of inter-dimension and Intradimensional rule. The algorithm is based on the concept that the larger number of values/categories in a dimension/attribute means the lower degree of association among the items in the transaction. Moreover, to generalize inter-dimension association and intra-dimensional rules, the concept of fuzzy itemsets is discussed, in order to calculate the support and confidence by using fuzzy multidimensional association rules. Two generalized formulas were also proposed in the relation to the fuzzy association rules. Finally, an illustrated example is given to clearly demonstrate and understand steps of the algorithm.

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