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Exploration of Novel Algorithm for Reduced Computational Time by Using Fuzzy Classification Technique in Data Mining

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Abstract*— we will work on reduction of unwanted data sets from large data sets. We apply fuzzy logic , classification and data mining techniques to do the same. The size of data items is very large, so it is difficult to reduce its operational time. This research paper tries to eliminate those item sets which are not important for finding any association rule. We also try to eliminate more than 60% of item sets which is not important by using fuzzy classification technique.
***Keywords*— Fuzzy Logic, Data Mining, Classification, Data sets, TRApriori**

I. INTRODUCTION

Now a day's fuzzy logic and data mining are the two most important techniques on the field of research area. Fuzzy logic uses linguistic variable to provide the answer that human being are not able to give. Whereas data mining is used to find out the essential things from large data sets ,then apply some association data mining algorithm to find the relationships among the item sets. This research paper find out the range of linguistic variable by using standard deviation and mean in place of assuming its values. Secondly on fuzzy logic contains the distinct values by applying membership function. When we apply data mining association algorithm on it, it is difficult to find out the essential things from large data sets because of distinct fuzzy values will not get the minimum frequency of item sets. So it will be better to define different classes for fuzzy values. i.e. Class A contains the fuzzy values between the ranges .01 to 0.1. Similarly Class B contains the fuzzy values between the ranges .11 to .20 and so on. From this we will get the appropriate frequency of different item sets. Our research paper aim is to reduce the large data set to small data set before applying data mining algorithm. Imagine how wonder the research will be if it reduces more than 60% of large data sets. We will only apply data mining algorithm to less than 40% of large data sets. How easy and fast our data mining association algorithm will be.

Advantages of this Research are as follows:-

A. EASY TO FIND THE RANGE OF FUZZY LINGUISTIC VARIABLES.
B. REDUCING MORE THAN 60% OF LARGE DATA SET WITHOUT AFFECTING THE OUTCOMES OF FUZZY MINING ASSOCIATION ALGORITHM.
C. REDUCING THE OPERATIONAL TIME OF ITEM SET UP TO 30%.
D. MORE FRUITFUL FOR ANY BUSINESS PREDICTION PROCESS.
E. THIS ALSO MAKES DATA MINING RULES WITH MORE PERSUASIVENESS.

II. LITERATURE REVIEW

Mohammed Al-Maoleg1[1] et al chooses those item sets that are frequently present in particular transaction id. Its algorithm works on low support .3 and reduces the time complexity of the program very easily. Zhiyong ma [4] et al converts all the item sets into Boolean matrix by using CP tree method and reduces the time for the task.ArpnaShrivastava [5] et al , in this paper the authors have used the codes for all the items and remove the duplication by using data cleansing technique. This is also most efficient as compared to simple Apriori algorithm. K. Sathesh Kumar and M. Hemalatha [3] , this paper reduces the operational time carried out by Apriori algorithm by using artificial Bee colony optimization method (FABCO).Mehmet Kaya et al [38] , in this paper the author find the efficient algorithm by carried out mining fuzzy clustering algorithm (CURE). They found out the centroid by CURE for triangular membership function.so that they can range the fuzzy membership method correctly and also reduces the computational time. As we know we need some kind of association rule to perform data mining algorithm. Getting this Agrawal and his co-worker carried out some mining algorithm based on the large data sets, which is difficult to find association mining rule [9-18]. These break the mining steps into two phases. In the first phase candidate of item sets are obtained and counted by scanning the transactions. The number of item set must support the minimum pre-defined threshold value called minimum support. Then later we make the pair of item sets and apply the association rule for getting the required

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output. Srikant and Agrawal also proposed partitioned based mining association algorithm. The fuzzy set was first carried out by Zadah in 1965 [37]. Fuzzy set are used to provide the answer, when human being are unable to provide the answer of some complicated questions. Hong et al, proposed a fuzzy mining algorithm to mine fuzzy rules from quantitative data [31]. They required each quantitative data into a fuzzy set and fuzzy steps to find fuzzy rule.Cai at al proposed weighted mining rule of data sets [22]. Yue et al, extended the fuzzy concept based on vectors [36].Most of them are find out the range of triangular fuzzy membership function directly , means they assumed the range of linguistic variable. But on Our paper we have find out the range of linguistic variable by using mean and standard deviation. Relevant attribute and membership function is carried out by Hong [29]. He also combines Fuzzy Logic and Data Mining techniques to improve the operational time. The aim of his research is to remove unwanted data sets from very large data items. Chang [24] et al Fuzzy decision tree is carried out by using the cluster technique. Mining association rule was also performed by Hang [32]. The aim of his research is digging out the essential or useful item from very large data set. He also wants to improve the data mining algorithm in terms of time complexity. I used [9],[15] for comparison with Our algorithm. They have done on fuzzy mining association rule to reduce the computational time. They all used the simple mining association rule for doing the task, the TRApriori mining association technique is used from the the paper [16] .

The first step is to take an exemplary data set of 10 students with having their grades of different five subjects. i.e.
First Subject: DBMS (Database Management System)
Second Subject: JAVA
Third Subject: TOC (Theory Of Computation)
Fourth Subject:MPI (Microprocessor and Interface)l
Fifth Subject: ADA (Analysis and Design of Algorithm)
Shown in table no 1.1

S. N	**DBMS**	**JAVA**	**TOC**	**MPI**	**ADA**
1	87	78	73	86	69
2	62	80	91	78	81
3	85	90	66	73	90
4	74	87	81	85	63
5	71	92	85	80	80
6	64	76	84	60	86
7	66	86	88	70	79
8	85	82	67	83	85
9	74	64	76	72	87
10	78	60	84	84	86

Table No 1.1. The set of students' course scores

STEP 1: Partition the continuous attributes by standard deviation and mean. The standard deviation and mean is used to find the universe of discourse. Find out the minimum, maximum and mean of each element that is shown in table No 1.2.
STEP 2: The domain of the linguistic variable low middle and High.

S. N	**Attribute**	**low**	**Middle**	**High**
1	DBMS	**(53,62,72.6)**	**(66.6,74.6, 83.6)**	**(77.6,87,96)**
2	JAVA	**(53, 62,73.5)**	**(65.7,77.5,89.3)**	**(81.5,90,100)**
3	TOC	**(57,66,76.6)**	**(70.9,79.5,88)**	**(82,91,100)**
4	MPI	**(52,60,74)**	**(68.7,77,85.3)**	**(80,86,95)**
5	ADA	**(54,63,77.6)**	**(72,80.6,89)**	**(83,90,99)**

Table No 1.2 Range of Linguistic Variable

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Low (Minimum –SD , Minimum, I + 2/3SD)
Middle (I=Mean-SD, Mean, II=Mean + SD)
High (II-2/3SD, maximum, maximum + SD)

STEP: 3 Find out the membership function.
The membership function is carry out by using triangular fuzzy logic number model .Shown in Figure No 1.1

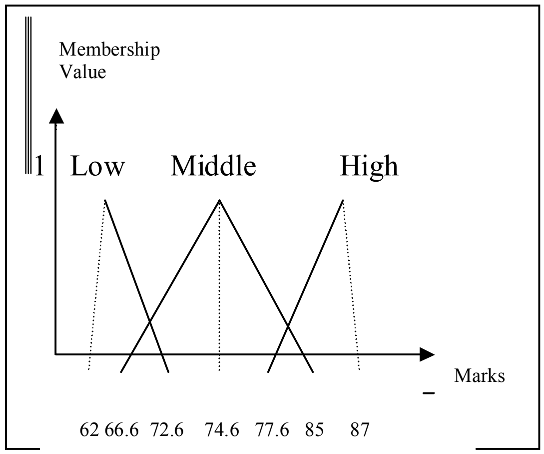

Fig.No1.1 Triangular Membership Function of DBMS

STEP 4: Find the fuzzy values of continues data sets.
According to our membership function of step2, the degree of membership for each data set is calculated. The table no 1.4 shows the degree of membership function.
In this, we have used triangular membership function because of its easiness and computational efficiency. We can also use Gaussian membership function.We can categories it's as Low, Middle and high. Thus we have used three fuzzy membership values produced for each attributes. According to the predefined membership functions for this transaction data in table 1, the proposed classified based fuzzy TRApriori data mining algorithm proceed as follows. Transform the actual values of each attribute into fuzzy sets. Take DBMS marks in case 1 as an example. The marks 87 is replaced by a fuzzy set (.0/low + 0.0/middle + 1 / high) Using the given membership functions. This step is repeated for all the data sets. At last the result obtained is as follow:-

SN	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
DB	.0	1	.0	.0	.0	.84	.68	.0	.0	.0
L	.0	.0	.0	.9	.5	.0	.0	.0	.9	.6
M M S H	1	.0	.76	.0	.0	.0	.0	.76	.0	.1
JA	.0	.0	.0	.0	.0	.0	.0	1	.7	.1
L	.9	.77	.0	.2	.0	.9	.39	.0	.0	.0
V M A H	.0	.0	.9	.66	1	.0	.33	.0	.0	.0
T	.22	.0	.9	.0	.0	.0	.0	.8	.1	.0
L	.24	.0	.0	.8	.3	.4	.0	.0	.66	.4
O M	.0	1	.0	.0	.31	.28	.7	.0	.0	.28

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CH										
MLPMIH	.0	.0	.1	.0	.0	.1	.3	.0	.18	.0
	.0	.9	.1	.0	.6	.0	.09	.3	.2	.1
	1	.0	.0	.82	.0	.0	.0	.44	.0	.79
ALDMAH	.6	.0	.0	1	.0	.0	.0	.0	.0	.0
	.0	.92	.0	.0	.9	.3	.7	.5	.2	.3
	.0	.0	1	.0	.0	.5	.0	.6	.7	.5

Table No 1.3: The fuzzy set transformation Table.

STEP: 5 Define various classes for the fuzzy values

We know that when we find the fuzzy values, we will get more distinct values. So it is difficult to find the minimum frequency of item sets. So we use the classification of the above fuzzy values data sets. the fuzzy values in the range of .01 to .10 belongs to class A, similarly the fuzzy values fall under the range of .11 to .20 is came under the class B item set and So on up to the class J. this is depicted on table no 1.4.

S.N	**Classes**	**Range**
1	A	0.01-0.10
2	B	0.11-.20
3	C	0.21-0.30
4	D	0.31-0.40
5	E	0.41-0.50
6	F	0.51-0.60
7	G	0.61-0.70
8	H	0.71-0.80
9	I	0.81-0.90
10	J	0.91-1

Table 1.4 The fuzzy classification table for fuzzy values

STEP: 6 Classificationtable for Given Data sets. Place the item set to their respective class. That is shown Table No 1.5

N	**TName**	**Classes**
1	DBMS(L)	G, I ,J
2	DBMS(M)	E , F ,I
3	DBMS(H)	A , H ,J
4	JAVA(L)	A , G ,J
5	JAVA(M)	B, D, H, I, I
6	JAVA(H)	D, G, I, J
7	TOC(L)	A, C, H, I
8	TOC(M)	C, C, D, G, H, D
9	TOC(H)	C, C, D, G, J

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10	MPI(L)	A, A, B, C
11	MPI(M)	A, A, A, B, F, I
12	MPI(H)	E, H, I , J
13	ADA(L)	F,J
14	ADA(M)	B, C, C, E, G, I, J
15	ADA(H)	E, E, F, G, J

Table No 1.5 Classification Table for Data Items

STEP:7 Point out the item set which contains maximum number of classes with having duplication of classes. ADA (M) contains maximum of 7 classes.
STEP: 8 select any those item set which has having more than 60% of the classes as compared to item sets which contains the maximum no of classes.
60/100 * 7=4.2
It means we select that item set which contains at least 5 classes.
STEP: 9 Duplication of class is not more than 50% of the total no of classes exist for the particular item set.
Maximum Number of classes is 7, so duplication of classes is not more than 3.
STEP: 10 The actual data set is shown is table no 1.6. This is the important data sets where we apply the fuzzy mining association rule .we eliminate the unimportant data set with the help of fuzzy classification technique.

S.N	Tname	Classes
1	JAVA(M)	B,D,H,I,I
2	TOC(M)	C,C,D,G,H,D
3	TOC(H)	C,C,D,G,J
4	MPI(M)	A,A,A,B,F,I
5	ADA(M)	B,C,C,E,G,I,J
6	ADA(H)	E,E,F,G,J

Table No 1.6 The actual Data Set

STEP 11 Now we apply any fast data mining association rule for extracting the important fact.Assume the minimum support value and confidence value for the data sets.
Minimum Support Value =2.0
Confidence threshold =.70
STEP: 12 Find out the large Item set L1

L1		
S.N	**Item set**	**Frequency**
1	A	3
2	B	3
3	C	6
4	D	4
5	E	3
6	F	2
7	G	4
8	H	2
9	I	4
10	J	3

Table 1.7.L1 Item sets

STEP 13: find out the candidate item set C1.
Find the C1 according to their classified based value on the data set in Table No 1.6.

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C1		
S.N	**TName**	**Classes Or Item sets**
1	JAVA(M)	{B},{ D}, {H} , {I}
2	TOC(M)	{C},{ D}, { G}, {H}
3	TOC(H)	{C},{ D}, { G}, {J}
4	MPI(M)	{A},{ B}, {F} ,{I}
5	ADA(M)	{B},{ C}, {E} ,{ G}, {I} ,{J}
6	ADA(H)	{E},{F} ,{ G}, {J}

Table No 1.8 .C1 Item sets

STEP: 14find the large item set L2

L2		
SN	**Classes**	**Frequency**
1	{B , I}	2
2	{C , D}	2
3	{C , G}	3
4	{C , J}	2
5	{D , G}	2
6	{E , G}	2
7	{G , J}	3

Table No 1.9 .L2 Item sets

STEP: 15 Find the candidate item set C2

C2		
S.N	**TName**	**Classes Or Item sets**
1	JAVA(M)	{B},{ D} , {I}
2	TOC(M)	{C},{ D}, { G}
3	TOC(H)	{C},{ D}, { G}, {J}
4	ADA(M)	{B},{ C}, {E} ,{ G}, {I} ,{J}
5	ADA(H)	{E} ,{ G}, {J}

Table No 1. 10 .C2 Item sets

STEP: 16 Find the Large Item set L3

L3		
SN	**Item set**	**Frequency**
1	{C , D ,G}	2
2	{C , G ,J}	2
3	{E , G , J}	2

Table No 1.11 .L3 Item sets

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STEP: 17 Find the candidate item set C3

C3		
SN	TNAME	CLASSES
1	TOC(H)	{C},{ D}, { G}, {J}
2	ADA(M)	{B},{ C}, {E} ,{ G}, {I} ,{J}

Table No 1.12 C2 Item sets

STEP: 18 Take the data sets that are participated in C3 candidate item set. Ignore the remaining data set.

S.N	TOC(H)	ADA(M)
1	.0	.0
2	1	.92
3	.0	.0
4	.0	.0
5	.31	.9
6	.28	.3
7	.7	.7
8	.0	5
9	.0	.2
10	.28	.3
sum	2.57	3.82

Table No 1.13 Useful fuzzy set

STEP 19: Find the L1 large item set.
Table No 1.14 frequency Table
The value of L1 >= minimum support value

STEP 20: Now check the fuzzy values satisfies data mining association rule or not. Find the candidate item set C1from actual fuzzy set.
→Take the linguistic value TOC (H) as above example, the scalar cardinality is (.1+.3+.28+7+.28) = 2.57.The the *remaining value of candidate C1 for the data set.*
{(TOC(H),2.57), (ADA(M),3.82)}

STEP: 21 Find the candidate item set C2 from l1 we will take the lesser membership value when we compare the two item sets

S.N	TOC(H)	ADA(M)	TOC(H),ADA(M)
1	.0	.0	.0
2	1	.92	.92
3	.0	.0	.0
4	.0	.0	.0
5	.31	.9	.31
6	.28	.3	.28
7	.7	.7	.7
8	.0	.5	.0
9	.0	.2	.0
10	.28	.3	.28
sum	2.57	3.82	2.49

Table 1.15: The C2 candidate item set

STEP: 22 Find the L2 Large item set

The linguistic value (TOC(H)), ADA(M)) has the scalar cardinality of 1+.31+.28+.7+.28 =2.49. The Large item set L2 shown below. **The L2 large item set rides on the count value, which is greater than the minimum support.**

{ (TOC(H), ADA(M) **2.49)**}

S.N	**Item set**	**Frequency**
1	TOC (H)	2.57
2	ADA(M)	3.82

STEP 23: (a) Construct the association rules for all the large item set .there are three possible association rules.

TOC(H) , ADA(M)/ TOC(H) = 2.49 /2.57

CMC_M , PPC_M / CMC_M = 2.49 /3.82

The fuzzy association rules are listed on table 1.16

S.N	Fuzzy Association Rule	Confidence Value
1	TOC(H)→ADA(M)	96.88%
2	ADA(M)→ TOC(H)	65.18%

Table No: 1.16 Summary of Association rule

(b)We can also find the confidence of the entire rule. Suppose our minimum threshold is .50 for confidence. Its confidence value is calculated as:

The confidence values of the other two rule are shown below.

"If TOC = HIGH, then ADA = Middle" has a confidence value of 0.968;

"If ADA = Middle, then TOC = HIGH" has a confidence value of 0.6518;

STEP 1: Partition the continuous attributes by standard deviation and mean. The standard deviation and mean is used to find the universe of discourse. Find out the minimum, maximum and mean of each element that is shown in table No 1.2.

STEP 2: The domain of the linguistic variable low middle and High.

III.CONCLUSIONS

It will reduce the unimportant data sets from large or quantitates data sets. We can also predict the relationship between the data sets that appears frequently. This will also reduce the computational time for the data sets.

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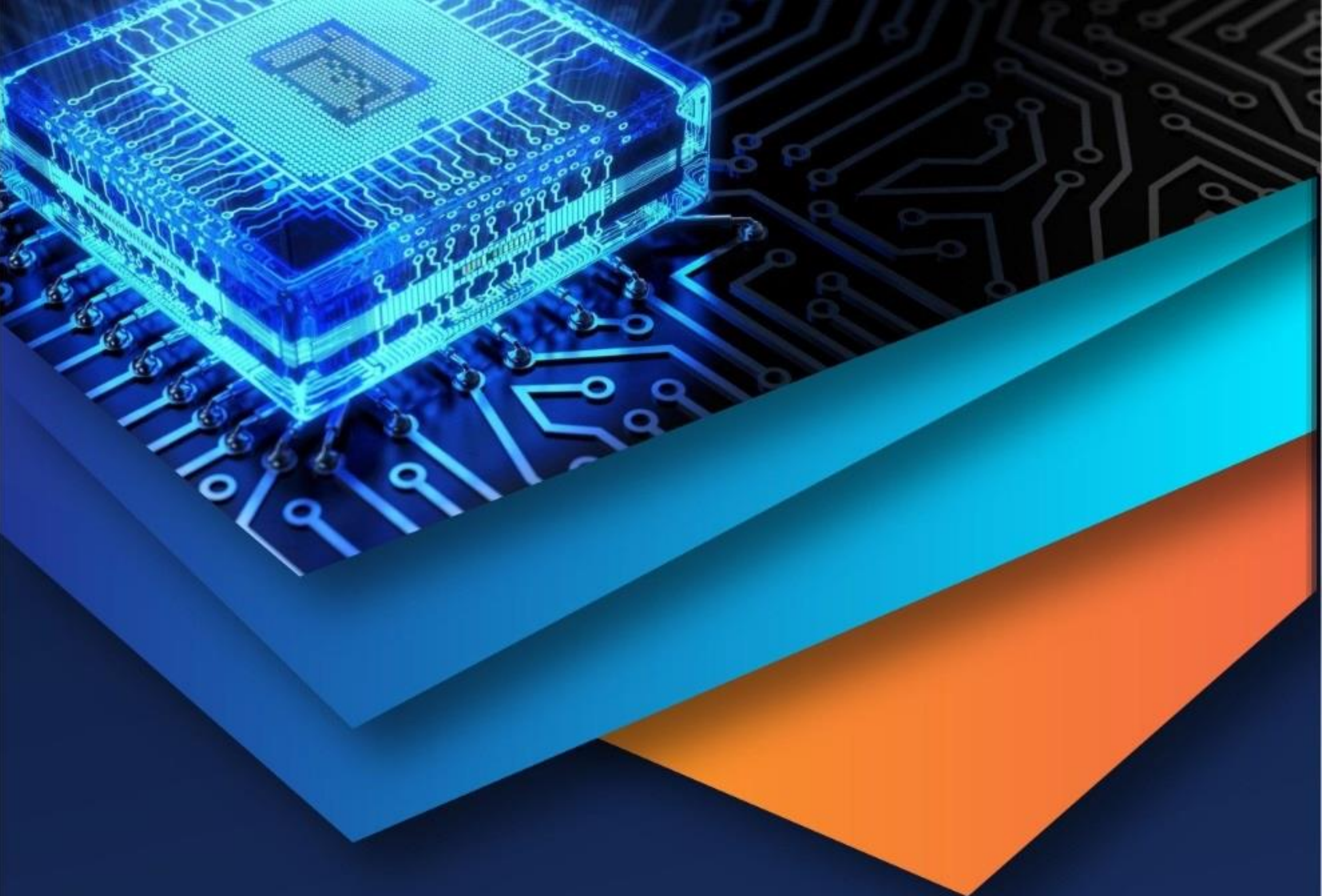

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