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TRApriori Classification Based Algorithm by Fuzzy Techniques to Reduced Time Complexity

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***Abstract*—. Our simple classification technique on this approach is also able to remove the unwanted data sets that are not useful for making the decision system. We can also combined the fuzzy techniques, TRApriori Algorithm and classification technique to provide the close output. Our classification based fuzzy mining association algorithm can also work on low support values. Due to online notes (Video based and Web based) for education also plays an important role for enhancement of their result. Students of this generation are smart due to internet. Also the cost of internet goes down , a low income family student can also used web based learning.Video from NPTEL can also be downloaded from you tube free of cost. Once downloaded the video is distributed amongst the students.**

***Keywords*—TRApriori, Classified data sets, fuzzy approach, quantitative data**

I.INTRODUCTION

In data mining technique, association rules plays an important role in knowledge discovery technique. Data mining is a technique digging out the essential thing and leaving unimportant item. Similarly if there is a huge amount of data or quantitatively data then we need a suitable algorithm or technique to remove or hide unimportant data. If someone is suffering from any diseases then he/she will ensure from many different ways of health checkup, it means it will check its diseases from two or more doctor or two or more blood testing. Similarly I am using fuzzy logic, classification technique, TRApriori mining algorithm to get the close output. Here our classification based fuzzy mining algorithm help in reduced time complexity in later steps of this algorithm. So we can remove the quantitavely data that are not important for making knowledge discovery. Our classification based fuzzy mining association algorithm can also work on low support values.

The remaining parts of this paper are organized as follows. Related research is reviewed in Section 2. The proposed fuzzy TRApriori data-mining algorithm is described in Section 3. An example is given to illustrate the proposed algorithm in Section 4. Experiments to demonstrate the performance of the proposed data-mining algorithm are stated in Section 5. Conclusions and future work are finally given in Section 6.

Fuzzy logic are used for intelligent system like human similarity[25]. Several fuzzy system are used for the set of data with some domain [14,16-17,18,20,22-24,29]. Fuzzy approach with data mining approach has been used in [15,25,29]

II. RELATED WORK

As we know , the aim of data mining is to apply some kind of association rule on data sets. Getting this agrawal and his co-worker proposed some mining algorithm based on the large data sets to find association rule[1-10]. These break the mining steps into two phases. In the first phase candidate of itemsets are obtained and counted by scanning the transactions. The number of itemset 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 output.

Srikant and agrawal also proposed mine association rule that are partitioned based[27].The fuzzy set was first introduced by zadah in 1965 [29]. Fuzzy set is used to define the exact answer of data set when human being is unable to provide answer. Hong et al, proposed a fuzzy mining algorithm to mine fuzzy rules from quantitative data[22]. 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[15]. Yue et al, then extended the fuzzy concept based an vectors[28].

III. THE PROPOSED FUZZY DATA-MINING CLASSIFIED BASED ALGORITHM

I read all the references[1-29] for classification based techniques. They have used the fuzzy based mining techniques using TRApriori algorithm. I added the extra classified techniques. This technique will not require to fuzzifies every itemsets. On later steps of mining algorithm. This will reduces some complexity to theprior work. The TRApriori algorithm also works on low support and low confidence. Our proposed methodology is based on two part. First part mostly deal with classification based TRApriori algorithm set. Then later we will also apply the Apriri algorithm dor important fuzzy values for finding the association rule.

IV. AN EXAMPLE

In this section, an example is given to illustrate the proposed Classification based TRA data-mining algorithm by fuzzy techniques. This is a simple example to our proposed model where I am taking the percentage of under graduate (Polytechnic) , graduate (Bachelor of Engineering)and post graduate (Master of technology) marks for their first and final year of each course.. The data set includes 12 transactions, as shown in Table 1.I have taken the first 12 passed student from the course result.

S.N	Polytechnic		Engineering Graduate		Engineering Post Graduate	
	PFY	PFiY	BFY	BFiY	MFY	MFiY
1	60	65	68	76	66	75
2	61	68	78	67	67	77
3	58	67	62	76	70	70
4	67	65	64	80	80	88
5	62	76	74	83	78	85
6	63	72	73	81	74	87
7	72	65	66	75	77	88
8	57	70	61	88	78	85
9	59	80	62	86	82	90
10	61	64	73	72	76	82
11	66	66	70	85	74	85
12	64	64	73	83	71	78

Table 1. The set of students' course scores

The data sets include 12 transaction with having three courses i. e undergraduate (Polytechnic) , Graduate (B.E) , Post Graduate (M.Tech) . Each course contain data sets of first year and final year grade marks. Each denotes as polytechnic first year (PPY) , Polytechnic final year (PFiY). B.E First Year (BFY), B.E Final Year (BFiY) , M.Tech First Year (MFY), Mtech Final Year (MFiY). The fuzzy membership function of above courses are shown in fig 1.

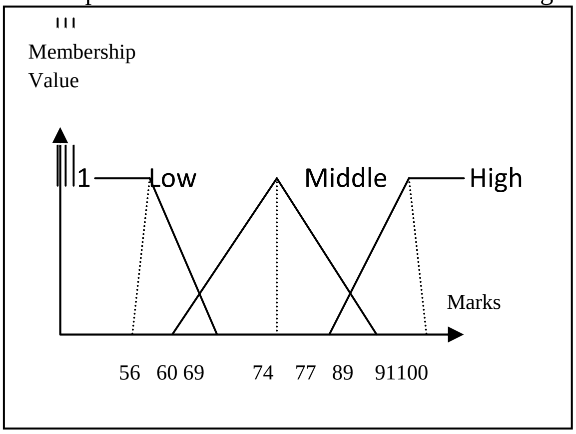

Fig. 1 Triangular Membership Function

In this, we have used triangular membership function because of its suppleness and computational efficiency. We can also derived its value from automatic adjustment [12]. 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 are 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.

Step 1:Transform the actual values of each attribute into fuzzy sets. Take PFY marks in case 1 as an example. The marks 60 is replaced by a fuzzy set (.6/low + 0.0/middle + 0.0 / 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	11	12
P	L	.6	.0	.8	.1	.1	.2	.0	.8	.7	.0	.2	.3
F	M	.0	.0	.2	.1	.1	.9	.0	.0	.0	.0	.3	.2
Y	H	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
P	L	.3	.0	.1	.3	.0	.0	.3	.0	.0	.3	.2	.3
Fi	M	.3	.0	.2	.3	.9	.9	.3	.7	.0	.3	.3	.3
Y	H	.0	.0	.0	.0	.0	.0	.0	.0	.1	.0	.0	.0
B	L	.0	.0	.1	.3	.0	.0	.3	.0	.1	.0	.0	.0
F	M	.0	.6	.1	.3	1	.9	.3	.0	.1	.9	.6	.9
Y	H	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
B	L	.0	.1	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
Fi	M	.9	.2	.9	.0	.2	.1	.9	.1	.2	.9	.3	.2
Y	H	.0	.0	.0	.0	.3	.1	.0	.1	.3	.0	.3	.0
M	L	.3	.2	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
F	M	.2	.2	.7	.0	.7	1	.8	.7	.2	.9	1	.7
Y	H	.0	.0	.0	.0	.0	.0	.0	.0	.1	.0	.0	.0
M	L	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
Fi	M	.9	.8	.7	.1	.3	.2	.1	.3	.0	.2	.3	.7
Y	H	.0	.0	.0	.1	.3	.2	.1	.3	.0	.2	.3	.0

Table 2: The fuzzy set transformation Table.

Step 2: Create a Classification of fuzzy values.The fuzzy values falls under the range of 0.01 to 0.10 is belong to category of 'a' item set. Similarly the fuzzy values fall under the range of 11 to .20 is belong to category of b item sets and so on upto item set 'j'. These are is depicted on table 3 .

S.N	Item	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 3. The fuzzy classification table

Step: 3 Take the proposed Database

Provide the proposed data set to its classified based value. for an example, it is shown below in table 4

S.N	TName	Items
1	PFY(L)	f, h, a, a, b, h, g, b, c
2	PFY(M)	b, a, a, i, c, b
3	PFY(H)	nil
4	PFiY(L)	c, a, c, c, c, b, c
5	PFiY(M)	c, b, a, c, i, i, c, g, c, c, c
6	PFiY(H)	a
7	BFY(L)	a, c, c, a
8	BFY(M)	a, a, c, j, i, c, a, i, f, i
9	BFY(H)	nil
10	BFiY(L)	a
11	BFiY(M)	i, b, i, b, a, i, a, b, i, c, b
12	BFiY(H)	c, a, a, c, c, b
13	MFY(L)	c, b
14	MFY(M)	b, b, g, g, j, h, g, b, i, j, g
15	MFY(H)	a
16	MFiY(L)	nil
17	MFiY(M)	i, h, g, a, c, b, a, c, b, c, g
18	MFiY(H)	a, c, b, a, c, b, c

Table 4. Classification values of data sets

Step:4 Find out the large itemset L1

L1		
S.N	**Itemset**	**Frequency**
1	a	21
2	b	19
3	c	28
4	g	8
5	i	12

Table 5. L1 Item sets

Step 5: Now we will define the minimum support as .4 and the minimum confidence threshold as .5.

Step 6: find out the candidate itemset C1.

Find the C1 according to their classified based value on the data set in Table 6..

C1		
S.N	**TName**	**Items**
1	PFY(L)	{a},{ a}, {b} ,{ b}, {c}, {g},
2	PFY(M)	{a},{ a}, {b} ,{ b}, {c}, {i}
3	PFiY(L)	{a}, {b} ,{ c}, {c}, {c}, {c}, {c}
4	PFiY(M)	{a},{ b}, {c} ,{ c}, {c}, {c}, {c}, {c},{g}.{i},{i}
5	PFiY(H)	{a}
6	BFY(L)	{a},{ a}, {c} ,{ c}
7	BFY(M)	{a},{ a}, {c} ,{ c},{i},{i},{i}
8	BFiY(M)	{a}
9	BFiY(M)	{a},{ a}, {b} ,{ b}, {b}, {b}, {c}, {i},{i},{i},{i}
10	BFiY(H)	{a},{ a}, {c} ,{ c}, {c}, {b}
11	MFY(L)	{b},{ c}
12	MFY(M)	{b},{ b}, {b} ,{ g}, {g}, {g}, {i}
13	MFY(H)	{a}
14	MFiY(M)	{a},{ a}, {b},{ b}, {c} , {c}, {c}, {g},{i}
15	MFiY(H)	{a},{ a}, {b},{ b}, {c} , {c}, {c}

Table 6.C1 Item sets

Step:7 Find the large itemset L2

L2		
SN	**Itemset**	**Frequency**
1	{a,b}	13
2	{b,c}	11
3	{a,c}	14
4	{a, i}	7
5	{b,g}	7
6	{b,i}	8
7	{c,i}	7
8	{c,g}	4

Table 7 .L2 Item sets

Step:8 Find the candidate itemset C2.

C2		
S.N	**TName**	**Items**
1	PFY(L)	{a},{ a}, {b} ,{ b}, {c}, {g}
2	PFY(M)	{a},{ a}, {b} ,{ b}, {c}, {i}
3	PFiY(L)	{a}, {b} ,{ c}, {c}, {c}, {c}, {c}
4	PFiY(M)	{a},{ b}, {c} ,{ c}, {c}, {c}, {c}, {c},{g}.{i},{i}
5	BFY(M)	{a},{ a}, {c} ,{ c},{i},{i},{i}
6	BFiY(M)	{a},{ a}, {b} ,{ b}, {b}, {b}, {c}, {i},{i},{i},{i}
7	BFiY(H)	{a},{ a}, {c} ,{ c}, {c}, {b}
8	MFY(M)	{b},{ b}, {b} ,{ g}, {g}, {g}, {i}
9	MFiY(M)	{a},{ a}, {b},{ b}, {c} , {c}, {c}, {g},{i}
10	MFiY(H)	{a},{ a}, {b},{ b}, {c} , {c}, {c}

Table 8 .C2 Item sets

Step:9 Find The Large Itemset L3

Table 9 .L3 Item sets

L3		
SN	**Itemset**	**Frequency**
1	{a, b, c}	10
2	{a , c, i }	6

Step:10 Find the candidate itemset C3 in Table 10.

C3		
S.N	**Tname**	**Items**
1	PFY(M)	{a},{ a}, {b} ,{ b}, {c}, {i}
2	PFiY(M)	{a},{ b}, {c} ,{ c}, {c}, {c}, {c}, {c},{g}.{i},{i}
3	BFiY(M)	{a},{ a}, {c} ,{ c}, {c}, {b}
4	MFiY(M)	{a},{ a}, {b},{ b}, {c} , {c}, {c}, {g},{i}

Table 10 .C3 Item sets

Step:11 Find The Large Itemset L4 in Table 11

L4		
SN	**Itemset**	**Frequency**
1	{a, b , c, i}	4

Table 11 .L4 Item sets

STEP:12 Create the Actual fuzzy value table according to C3 candidate itemsets. This datasets are important datasets where we are able to make any fruitful decision.

Take only those data sets that are present or found in generating C3 candidate itemsets and ignore the remaining datasets. This datasets are important dataset where we are able to make any fruitful decision. Now this is our actual table where we will get the exact output.

S.N	PFY(M)	PFiY(M)	BFiY(M)	MFiY(M)
1	.0	.3	.9	.9
2	.0	.0	.2	.8
3	.0	.2	.9	.7
4	.2	.3	.0	.1
5	.1	.9	.2	.3
6	.1	.9	.1	.2
7	.9	.3	.9	.1
8	.0	.7	.1	.3
9	.0	.0	.2	.0
10	.0	.3	.9	.2
11	.3	.3	.3	.3
12	.2	.3	.2	.7

Table 12 . useful Item sets

Step 13: Find the candidate itemset C1 fromactual fuzzy set.

→Take the linguistic value PFY(M) as above example, the scalar cardinality is (.2 + .1 +. 1 + .9 +. 3 + .2) = 1.8.The *C1* candidate itemset for this example is shown as follows: {(PF1Y(M),4.5), (BFiY(M),5.0), (MFiY(M),,4.6)}

S.N	PFY(M)	PFiY(M)	BFiY(M)	MFiY(M)
1	.0	.3	.9	.9
2	.0	.0	.2	.8
3	.0	.2	.9	.7
4	.2	.3	.0	.1
5	.1	.9	.2	.3
6	.1	.9	.1	.2
7	.9	.3	.9	.1
8	.0	.7	.1	.3
9	.0	.0	.2	.0
10	.0	.3	.9	.2
11	.3	.3	.3	.3
12	.2	.3	.2	.7
	1.8	4.5	5.0	4.6

Table 13 . C1 Value

Step 14: Find the L1 large itemset.

→The large itemset rides on the count value, which is greater than the minimum support value.In this exemplary dataset, L2 can be denoting as follows:
{(PFiY(M),(MFiY(M),2.30),(BFiY(M),(MFiY(M),3.00) }

Step:15 Find the candidate itemset C2 from l1 we will take the lesser membership value when we compare the two itemsets

S.N	PFiY(M)	BFiY(M)	PFiY(M), MFiY(M)
1	.3	.9	.3
2	.0	.2	.0
3	.2	.9	.2
4	.3	.0	.0
5	.9	.2	.2
6	.9	.1	.1
7	.3	.9	.3
8	.7	.1	.1
9	.0	.2	.0
10	.3	.9	.3
11	.3	.3	.3
12	.3	.2	.2

Table 14: C2 values

Step:16 find the L2 Large itemset

The linguistic value (PFiY(M), MFiY(M)) has the scalar cardinality of .3+.2+.2+.1+.3 +.1+.3+.1 +3+ .3+2=2.00. The Large itemset L2 shown as

S.N	itemset	Frequency
1	PFiY(M),(BFiY(M))	2.00
2	BFiY(M),(MFiY(M))	3.00
3	PFiY(M),(MFiY(M))	2.30

The l2 large item set rides on the count value, which is greater than the minimum support.
{ (PFiY(M),(BFiY(M)),(PFiY(M),MFiY(M),2.30) (BFiY(M),MFiY(M) 3.00)}

STEP:17 Find the C3 candidate itemset

S.N	PFY(M)	BFiY(M)	MFiY(M)	PFiY(M),BFiY(M) MFiY(M)
1	.0	.9	.9	.3
2	.0	.2	.8	.0
3	.0	.9	.7	.2
4	.2	.0	.1	.0
5	.1	.2	.3	.2
6	.1	.1	.2	.1
7	.9	.9	.1	.1
8	.0	.1	.3	.1
9	.0	.2	.0	.0
10	.0	.9	.2	.2
11	.3	.3	.3	.3
12	.2	.2	.7	.2

Step 18.Construct the association rules for all the largeset .there are three possible association rules.
If BFiY = middle, then MFiY = Middle;
If PFiY = Middle, then MFiY = Middle;
(b)We can also find the confidence of all the 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 BFiY = Middle, then MFiY = Middle" has a confidence value of 0.60;
"If PFiY = Middle, then MFiY = Middle" has a confidence value of 0.51;
The final resulting rules are thus obtained:
"If BFiY = Middle, then MFiY = Middle" has a confidence value of 0.60;
"If PFiY = Middle, then MFiY = Middle" has a confidence value of 0.51;

V. Conclusion

We can reduce the time complexity of large data set by using fuzzy data mining TRApriori classified based algorithm.
We can remove our quantitatively data set in to the qualitatively data set that are used to perform association of itemset.
Our classification based TRApriori fuzzy based mining association algorithm will also work on low support value and provide the fruitful result.
Our simple classification technique on this approach is also able to remove the unwanted data sets that are not useful for making the decision system.
We can also combine the fuzzy techniques, TRApriori Algorithm and classification technique to provide the close output.

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References

[1] Tzung-Pei Honga,Chan-Sheng Kuob,Shyue-Liang Wangc "A fuzzy AprioriTid mining algorithm with reduced computational time" Volume 5, Issue 1, December 2004, Pages 1–1

[2] Tiberiu Ban , Fuzzy computing for complexity level of evaluation tests. Studia Univ, Babes-Bolai, Informatica, Volume LVIII number 1, 2013

[3] Tzung-pei-Hang, Guo-Cheng lan, Yi-Hsin lin and Shing-tai pan. An effective gradual data reduction strategy for fuzzy item set mining international journal of fuzzy systems , vol 15 no2 june 2013.

[4]Usha Rani, R Vijaya Prakkash, Dr A. Gavardhan,Mining Multi-level association Rules using fuzzy logic, International journal of emerging technology and advanced engineering. Volume 3, issue 8, August 2013.

[5] Ruchi Bhargava , Shrikant lade , Effective positive negative association rule mining using improved frequent pattern tree. International journal of advanced research in computer science and software engineering . Volume 3 , issue 4 April 2013 .

[6] Dharmendra Kumar , Deepak Bhardwaj rise of data mining: Current and Future application areas. IJCSI international journal of computer science issue vol 8 issue 5 No1 September 2011.

[7] Kanu Patel , Vatsal shal , jitendra patel , jayna donga comparision of various association rule mining algorithm on frequent itemsets. International journal of advanced research in computer Science and software engineering Vol-3 issue II nov 2013 .

[8] Jr Shian chen hung lieh chou, Ching Hsue Cheng, jen-ya Wang CPDA Based Fuzzy association rules for learning achievement mining, 2009 international conference on machine learning and computing IPCSIT vol3 (2011) IACSIT PRESS SINGAPUR.

[9]E Ramaraj, K Rameshkumar, N Venkatesan"A better performed transaction Reduction algorithm for mining frequent item set from large voluminous database"Volume 5, Issue 1, December 2004, Pages 1–10

[10] R. Agrawal, T. Imielinksi and A. Swami, "Mining association rules between sets Submitted manuscript 24 of items in large database," The 1993 ACM SIGMOD Conference, Washington DC,USA, 1993.

[11] R. Agrawal, T. Imielinksi and A. Swami, "Database mining: a performance perspective," IEEE Transactions on Knowledge and Data Engineering, Vol. 5, No.6, 1993, pp. 914-925.

[12] R. Agrawal, R. Srikant and Q. Vu, "Mining association rules with item constraints," The Third International Conference on Knowledge Discovery in Databases and Data Mining, Newport Beach, California, August 1997.

[13] R. Agrawal and R. Srikant, "Fast algorithm for mining association rules," The International Conference on Very Large Data Bases, 1994, pp. 487-499.

[14] A. F. Blishun, "Fuzzy learning models in expert systems," Fuzzy Sets and Systems, Vol. 22, 1987, pp 57-70.

[15] C. H. Cai, W. C. Fu, C. H. Cheng and W. W. Kwong, "Mining association rules with weighted items," The International Database Engineering and Applications Symposium, 1998, pp. 68-77.

[16] L. M. de Campos and S. Moral, "Learning rules for a fuzzy inference model," Fuzzy Sets and Systems, Vol. 59, 1993, pp.247-257.

[17] R. L. P. Chang and T. Pavliddis, "Fuzzy decision tree algorithms," IEEE Transactions on Systems, Man and Cybernetics, Vol. 7, 1977, pp. 28-35. Submitted manuscript 25

[18] M. Delgado and A. Gonzalez, "An inductive learning procedure to identify fuzzy systems," Fuzzy Sets and Systems, Vol. 55, 1993, pp. 121-132.

[19] W. J. Frawley, G. Piatetsky-Shapiro and C. J. Matheus, "Knowledge discovery in databases: an overview," The AAAI Workshop on Knowledge Discovery in Databases, 1991, pp. 1-27.

[20] A.Gonzalez, "A learning methodology in uncertain and imprecise environments," International Journal of Intelligent Systems, Vol. 10, 1995, pp. 57-371.

[21] T. P. Hong, C. H. Chen, Y. L. Wu and Y. C. Lee, "Using divide-and-conquer GA strategy in fuzzy data mining", The Ninth IEEE Symposium on Computers and Communications, 2004.

[22] T. P. Hong and J. B. Chen, "Finding relevant attributes and membership functions," Fuzzy Sets and Systems, Vol. 103, No. 3, 1999, pp.389-404.

[23] T. P. Hong and J. B. Chen, "Processing individual fuzzy attributes for fuzzy rule induction," Fuzzy Sets and Systems, Vol. 112, No. 1, 2000, pp. 127-140.

[24] T. P. Hong and C. Y. Lee, "Induction of fuzzy rules and membership functions from training examples," Fuzzy Sets and Systems, Vol. 84, 1996, pp. 33-47.

[25] T. P. Hong, C. S. Kuo, and S. C. Chi, "Mining association rules from quantitative data," Intelligent Data Analysis, Vol. 3, No. 5, 1999, pp. 363-376. A. Kandel, Fuzzy Expert Systems, CRC Press, Boca Raton, 1992, pp.8-19. Submitted manuscript 26

[26] H. Mannila, "Methods and problems in data mining," The International Conference on Database Theory, 1997.

[27] R. Srikant and R. Agrawal, "Mining quantitative association rules in large relational tables," The 1996 ACM SIGMOD International Conference on Management of Data, Monreal, Canada, June 1996, pp. 1-12. [20] C. H. Wang, J. F. Liu, T. P. Hong and S. S. Tseng, "A fuzzy inductive learning strategy for modular rules," Fuzzy Sets and Systems, Vol.103, No. 1, 1999, pp.91-105.

[28] S. Yue, E. Tsang, D. Yeung and D. Shi, "Mining fuzzy association rules with weighted items," The IEEE International Conference on Systems, Man and Cybernetics, 2000, pp. 1906-1911.

[29] L. A. Zadeh, "Fuzzy sets," Information and Control, Vol. 8, No. 3, 1965, pp. 338-353.

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