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An Improved Algorithm for Fuzzy Association Rule Mining (IAFARM) Using Grouped Transaction Items

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Abstract: Association rule mining is an important and widely used research field in data mining. This paper proposes a new algorithm named as An Improved Algorithm for Fuzzy Association Rule Mining (IAFARM). As a routine process, before finding minimum support the following preprocessing steps are performed on the raw transaction data set. First, the text information are converted into numeric sequence with assigned value for each attribute of transaction dataset and removed noise and missing values. Second, the converted data are grouped and sorted for mining Association rules. After this preprocessing, it finds minimum support for frequent item sets with multiple frequent using encryption catalog code. This proposed algorithm in this paper demonstrates the top down procedural approach and show cast the sharpening of boundary intervals. The main target of this proposed algorithm is to reduce the scanning time of the transaction datasets.

Keywords: Data Mining, Association rule mining, Fuzzy, encryption catalog code, IAFARM.

I. INTRODUCTION

Data mining is a widely used important research field, connecting the three worlds of databases, artificial Intelligence and statistics [1]. For the activities of discovery knowledge, prediction market dataset, and decision making from a database is very important for providing necessary information to a business [2]. Association Rule Mining (ARM) is one of the well-established data mining techniques. The objective of ARM is to identify patterns expressed in the form of Association Rules in transaction data sets[3,4,5,6]. For example, if A is a set of item occurs in a sales transaction, then B is a another set of items will likely also occur in the same transaction, that kind of associations called association rule. The most challenging in database mining is developing fast and efficient algorithms that can deal with large volume of data because several data mining algorithm computation is used to solve diverse data mining problem.

A. Association Rule

Mining association rule is a recent important research topic in the data mining field, It is generate association rules from huge amount of databases [18, 7], of the form A =>B, that will produce strong association rules which satisfy both minimum support degree (min_sup) and the minimum confidence degree (min_conf) greater than the user defined minimum support and minimum confidence [17, 19, 20].

Definition 1: let A = {a1 , a2 ….. an} be a set of items, then $D = \{< T_{id}, T > | T \subseteq A\}$ is a transaction database, where T_{id} is an identifier which be associated with each transaction.

Definition 2: Let $X \subseteq A, Y \subseteq A, and X \cap Y = \phi,$, we call this $X \Rightarrow Y$ as association rule.

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Generally most of the algorithms are executed in two steps. First, finding support above the given minimum of item sets. and then generating the desired rules from these item sets. The apriori algorithm is do the same job, to find all frequent itemsets., second is to pruning strong association rules from frequent itemsets [21].

B. Apriori Algorithm

The apriori algorithm is based on [22,7] association rule mining algorithm and it is a fast algorithm for mining association rules, the problem of this algorithm is number of data scans n, where n is the size of large nonempty itemset and number of discovering rules is huge while most of the rules are not interesting. Therefore several improved algorithms were proposed after apriori for efficiency and scalability.

C. Multiple level Association Rule

Multiple level association rules mining are different minimum support threshold used at different concept level. To find frequent itemsets and strong association rules at the top most concept level[9,10].

D. Fuzzy Association Rules

A Fuzzy Association Rules is an implication of the form:

If $\langle X, A\rangle then \langle Y, B\rangle$

Where X and Y are disjoint intemsets and A and B are fuzzy sets. In this case the itemsets are made up of property attributes and the fuzzy sets are identified by linguistic lables.

A Raw Dataset DB consists of a set of transactions $TS = \{ts_1, ts_2 \cdots ts_n\}$, a set of composite items $I = \{i_1, i_2 \cdots i_I\}$ and a set of properties $P = \{p_1, p_2 \cdots p_m\}$. The "$k^{th}$" property value for the "j^{th}" item in the "i^{th}" transaction is given by $t_i[[i_j]v_k]$.

This paper introduces an algorithm MMLFAR, which is basically different from previous algorithms; the remaining paper is organized as follows: related work is presented in Section 2, Section 3 gives the details of MMLFAR algorithm with example and finally the conclusion is given in Section 4.

II. LITERATURE REVIEW OF ASSOCIATION RULE AND FUZZY APRIORI

Sunita Soni and O.P.Vyas had proposed a theoretical model to introduce new associative classifier that takes advantage of Fuzzy Weighted Association rule mining, this Classifier is generates classification rules using Fuzzy Weighted Support and Confidence framework. The domains partitioning is using in fuzzy logic. The problem of Invalidation of Downward Closure property is solved and the concept of Fuzzy Weighted Support and Fuzzy Weighted Confidence frame work for Boolean and quantitative item with weighted setting is generalized[14].

Mehmet Kaya, Reda Alhajj, Faruk Polat and Ahmet Arslan had proposed an autonomous mining for automated method of both fuzzy association rules and fuzzy sets. This method first using clustering algorithm to find fuzzy sets, and then determine their membership functions. Finally, extract on interesting fuzzy association rules[15].

S.Veeramalai and A.Kannan had proposed Fuzzy-T ARM to categorize the dataset. ARM is used for Multidimensional dataset and Fuzzy logic is used for intelligent classification. The FTA has applied to the Wisconsin breast cancer dataset to evaluate the overall system performance[16].

Many association rules algorithms are effective implementations than producing effective rules [12, 13]. Apriori algorithm ignores the number of items and determining relationship of the items [11].

Fuzzy Apriori and its different variations are the only popular fuzzy association rule mining algorithms available today. Like the crisp version of Apriori, fuzzy Apriori is a very slow and inefficient for millions of transactions and very large datasets.

The proposal method MMLFAR is a consequence to overcome the above said drawbacks

III. PROPOSED METHODOLOGY

The proposed algorithm discovers all the largest itemsets for the given transactions by comparing the fuzzy count of each candidate itemset with its support threshold. The process of building the Grouped transaction datasets are converted a sequence number and symbol using encryption catalog table, furthermore, some pruning strategies are used to reduce the number of frequent itemsets generated.

The proposed algorithm is given in below:

Step 1:

The given transaction datasets are converted a sequence numbers and the symbol"*" using encryption catalog table, the levels of item representing number "n".

Step 2:

The converted items are sorted and each transaction TS have group

i – items threshold

$$i \in \{2,3,....\}$$

i.e, i is a maximum number of item threshold in a transaction, each transaction may or may not be considered in the process of generating rules mining.

Each $TS \leq i$

Step 3:

DB is a set of universal transactions. A is a qualified subset of DB transactions for generating rules. The number of items in its transactions is not greater than i, defined by:

$$A = \{TS / TS^1 \leq i, TS \in DB\} \qquad (1)$$

$\therefore TS^1$ is the number of items in transaction TS .

Step 4:

$p \in \{1,2,3,4,5\}$

$for\, p = 1; p \leq 5;$

Here, p is used to store the level number.

Step 5:

$q \in \{1,2,3,4,5\}$

$for\, q = 1; q \leq 5;$

Here, q is an index variable, to determine the number of frequent items in itemsets.

The frequent itemsets consider upto 5- itemsets.

Step 6:

Determine minimum support for frequent q-itemsets at level p

$\gamma_q^p \in (0,|A|)$

The whole qualified transactions appearing from minimum threshold of a combination items,

$|A|$ is a qualified subset transactions.

γ_q^p may have same value for every q at value p.

Step 7:

Group the similar item first p digits in transaction TS_k, and add the occurrence of the items in the same groups in TS_j.

The amount of the k^{th} group I_k^q for TS_j as v_{jk}^q.

Step 8:

I^q as a fuzzy set on set of qualified transactions, A built every candidate q itemset. A Fuzzy membership function μ is a mapping:

$\mu_{I^q} : A \rightarrow [0,1]$ as defined by:

$$\mu_{I^q}(TS) = v_{jk}^q \cdot \inf_{i \in I^q} \left\{ \frac{\eta,(j)}{TS^1} \right\}, \forall TS \in A \qquad (2)$$

TS is a qualified transaction $TS \subseteq DB$.

ie, TS is a subset of DB items.

A Boolean membership function, η is a mapping

$\eta_{TS} : DB \rightarrow \{0,1\}$

as defined by:

$$\eta_{TS}(j) = \begin{cases} 1, j \in TS \\ 0, otherwise \end{cases} \qquad (3)$$

j is an item, is an element of TS then $\eta_{TS}(I) = 1,$ otherwise .

Step 9:

Using the following equations to calculate q itemset support.

$$Support(I^q)^p = \sum_{TS \in A} v_{jk}^q \cdot \mu_{I^q}^p \qquad (4)$$

A is the subset of qualified transactions, the equation (4) satisfied the following property:

$$\sum_{j \in DB} Support(j) = |A| \qquad (5)$$

if $q = 1$ then

considered as a single item;

else if $q > 1$ then

generate candidate set C_2^p , that means newly generate frequent 2-itemsets to following steps.

Step 10:

I^q sorted in the set of frequent q -itemsets, M_q^p if and only if $Support(I_j^q) > \gamma_q^p$.

Step 11:

Set $q = q + 1$, for level p also same

if $q > 5$ then

goto step 13

Step 12:

for possible frequnent q - itemsets from $M_q - 1$ by the following rules

if I^q satisfied then

considered as a possible frequent q - itemset.

$$\forall F \subset I^q |F| = p - 1 \Rightarrow F \in M_{q-1}$$

(no possible itemset goto step13)

else

the process goto step 4.

end if

Step 13:

This operation similar in aprior algorithm,

Confidence is defined as the measure of certainty or trustworthiness associated with each discovered pattern $X \Rightarrow Y$, formula $(Y \setminus X)$.

Conf $X \Rightarrow Y = P(Y \setminus X) = \dfrac{Support(X \cup Y)}{Support(X)}$ (6)

Where $X, Y \in DB$

The above equation expressed in following way using equation (5)

$$conf(X \Rightarrow Y) = \frac{\sum_{TS \in A} \inf_{j \in X \cup Y} \left(v_{jk}^q \cdot \mu_j(TS)\right)}{\sum_{TS \in A} \inf_{j \in X} \left(v_{jk}^q \cdot \mu_j(TS)\right)} \quad (7)$$

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TABLE I
An example of transaction database

ID	Age	work class	marital-status	native-country	P_task
1	39	State-gov	Never-married	United-States	<=50K
2	50	Self-emp-not-inc	Married-civ-spouse	United-States	<=50K
3	38	Private	Divorced	United-States	<=50K
4	53	Private	Married-civ-spouse	United-States	<=50K
5	28	Private	Married-civ-spouse	Cuba	<=50K
6	37	Private	Married-civ-spouse	United-States	<=50K
7	49	Private	Married-spouse-absent	Jamaica	<=50K
8	52	Self-emp-not-inc	Married-civ-spouse	United-States	>50K
9	31	Private	Never-married	United-States	>50K
10	42	Private	Married-civ-spouse	United-States	>50K
11	37	Private	Married-civ-spouse	United-States	>50K
12	30	State-gov	Married-civ-spouse	India	>50K
13	23	Private	Never-married	United-States	<=50K
14	54	Private	Separated	United-States	<=50K
15	35	Federal-gov	Married-civ-spouse	United-States	<=50K
16	43	Private	Married-civ-spouse	United-States	<=50K
17	59	Private	Divorced	United-States	<=50K
18	56	Local-gov	Married-civ-spouse	United-States	<=50K
19	19	Private	Never-married	United-States	>50K
20	23	Local-gov	Never-married	United-States	<=50K

Therefore, an itemset of support as given by(4) can be expressed as followed

$$Supp(I^q)^p = \sum_{TS \in A} \inf_{j \in I^q} (\mu_j(TS)) \qquad (8)$$

Step 14:

Set $p = p + 1$ and goto step 6 (do the process for next level)

The performance of proposed algorithm fuzzy association rule mining step by step process example is given to understand well the concept.

The following adult data set is got from Data Mining and Visualization, silicon Graphics(UCI), the dataset contains Age, work class, fnlwgt, education, education-num, marital-status, occupation, relationship, race, sex, capital-gain, capital-loss, hours-per-week, native-country and Prediction task is to determine whether a person makes over 50K a year. An example of transaction database is shown in Table I..

The given transaction datasets Table 1 are converted a sequence numbers shown in Table II.

TABLE II
Dataset are converted a sequence numbers

ID	ITEMs	ID	ITEMS	ID	ITEMS
1	16311	8	22112	15	14111
2	22111	9	11312	16	21111
3	11111	10	21112	17	21211
4	21111	11	11112	18	25111
5	11171	12	16132	19	11312
6	11111	13	11311	20	15311
7	21681	14	21411		

TABLE III Dataset are converted a sequence numbers

TID	ITEMS
T1	11111,11111,11112,11171,11311
T2	11312,11312,14111,15311,16132
T3	16311,21111,21111,21112,21211
T4	21411,21681,22111,22112,25111

The converted items are sorted and each transaction TS have group, i – items threshold equals to 5, that means the twenty itemsets are converted qualified transaction with less than or equal to five items in the transactions. The qualified transactions are show in Table III, where $A = \{T_1, T_2, T_3, T_4\}$.

TABLE IV
Encryption catalog table

ITEM NAME	CODE	ITEM NAME	CODE
40 >=	1 * * * *	Separated	* * 4 * *
40 <	2 * * * *	Widowed	* * 5 * *
Private	* 1 * * *	Married spouse absent	* * 6 * *
Self emp-not inc	* 2 * * *	Married AF spouse	* * 7 * *
Sel emp inc	* 3 * * *	US	* * * 1 *
Federal-gov	* 4 * * *	England	* * * 2 *
Local-gov	* 5 * * *	India	* * * 3 *
State-gov	* 6 * * *	Japan	* * * 4 *
Without-pay	* 7 * * *	China	* * * 5 *
Never worked	* 8 * * *	Italy	* * * 6 *
Married-civ-spouse	* * 1 * *	Cuba	* * * 7 *
Divorced	* * 2 * *	<= 50K	* * * * 1
Never married	* * 3 * *	> 50K	* * * * 2

The encryption catalog Table IV. has sequence numbers and the symbol"*". For example , the items age = 38,work-class=private, marital-status=Divorced, native-country=United-state, P_task=<=50k is encrypted as catalog code 11111in which the first digit 1 represent the age greater than or equal to 40 at level 1, second digit 1 represent the work-class at level 2, third digit 1 represent the marital-status at level 3, fourth digit 1 represent the native-country at level 4 and fifth digit 1 represent the P_task at level 5.

TABLE V
Grouped 1 - itemsets

TID	ITEMS
T1	(*1***,5)
T2	(*1***,2) (*4***,1) (*5***,1) (*6***,1)
T3	(*6***,1) (*1***,4)
T4	(*1***,2) (*2***,2) (*5***,1)

Next $p \in \{1,2,3,4,5\}$ is used to store the level number. $q = 1$, it support of frequent items in 1- itemsets, for level p=1.

The minimum support for frequent q-itemsets is determine as follows:

For p=1, γ_q^1 =0.4(if $\gamma_q^1 \geq$ 0.4)

For p=2, γ_q^2 =0.2(if $\gamma_q^2 \geq$ 0.2)

For p=3, γ_q^3 =0.2(if $\gamma_q^3 \geq$ 0.2)

For p=4, γ_q^4 =0.2(if $\gamma_q^4 \geq$ 0.2)

For p=5, γ_q^5 =0.2(if $\gamma_q^5 \geq$ 0.2)

I^q as a fuzzy set on set of qualified transactions, A built every candidate q -itemset, as given by the following results:

Level p=1

Min_Sup (γ_q^1) = 0.4

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1 – Itemset	**Support of 1 – Itemsets**
{*1***} = (1 / T1, 0.4 / T2, 0.8 / T3, 0.4 / T4)	{*1***} =2.6
{*2***} = (0.4 / T4)	{*2***} =0.4
{*4***} = (0.2 / T2)	{*4***} =0.2
{*5***} = (0.2 / T2, 0.2 / T4)	{*5***} =0.4
{*6***} = (0.2 / T2, 0.2 / T3)	{*6***} =0..2

TABLE VI

M_1^1

1 – Itemset	Min-Sup
{*1***}	2.6
{*2***}	0.4
{*5***}	0.4

The {*4***},{*6***} cannot be consider for further process because their $Support \geq \gamma_1^1$.Table VI. shows the further process Itemset.

2 – Itemset	**Support of 2 – Itemsets:**
{*1***}{*2***} = {0.4 /T4 ^ 0.4 / T4}={0.4 / T4}	{*1***}{*2***} = 0.4
{*1***}{*5***} = {0.4 / T2 ^ 0.2 / T2, 0.4 / T4 ^ 0.2 / T4} = {0.2 / T2, 0.2 / T4}	{*1***}{*5***} = 0.4
{*2***}{*5***} = {0.4 / T4 ^ 0.2 / T4} = {0.2 / T4}	{*2***}{*5***} = 0.2

TABLE VII

M_2^1

2 – Itemset	Min-Sup
{*1***}{*2***}	0.4
{*1***}{*5***}	0.4

All 2- itemsets are considered for further process because their $Support \geq \gamma_2^1$. Table VII. shows the further process Itemset.

3 – Itemset

{*1***}{*2***}{*5***} = {0.4 / T4 ^0.4 / T4 ^ 0.2 / T4} = {0.2 / T4}

Support of 3 - itemsets

{*1***}{*2***}{*5***} = 0.2

TABLE VIII

M_3^1

3 – Itemset	Min-Sup
{*1***}{*2***}{*5***}	0.4

Table VIII. shows the further process Itemset.

Level p=2

1 – itemset

Min_Sup (γ_q^2) = 0.2

TABLE IX
Grouped 2 - itemsets

TID	ITEMS
T1	(11***,5)
T2	(11***,2) (14***,1) (15***,1) (16***,1)
T3	(16***,1) (21***,4)
T4	(21***,2) (22***,2) (25***,1)

Table IX. shows the Grouped two itemsets in further process.

Support of 1- itemset

TABLE X

M_1^2

1 – Itemset	Min-Sup
{11***}	1.4
{14***}	0.2
{15***}	0.2
{16***}	0.4
{21***}	1.2
{22***}	0.4
{25***}	0.2

All 1- itemsets are considered for further process because their $Support \geq \gamma_1^2$, Shown in Table X.

Support of 2- itemset

{11***}{14***}=0.2
{11***}{15***}=0.2
{11***}{16***}= 0.2
{14***}{15***}=0.2
{14***}{16***}=0.2
{15***}{16***}= 0.2
{16***}{21***}=0.2
{21***}{22***}=0.4
{21***}{25***}= 0.2
{22***}{25***}= 0.2

TABLE XI

M_2^2

2 – Itemset	Min-Sup
{11***}{14***}	0.2
{11***}{15***}	0.2
{11***}{16***}	0.2
{14***}{15***}	0.2
{14***}{16***}	0.2
{15***}{16***}	0.2
{16***}{21***}	0.2
{21***}{22***}	0.4
{21***}{25***}	0.2
{22***}{25***}	0.2

The{11***}{21***},{11***}{22***},{11***}{25***},{14***}{21***},{14***}{22***},{14***}{25***},{15***}{21***},{15***}{22***},{15***}{25***}, {16***}{22***}, {16***}{25***} cannot be considered for further process because their $Support \geq \gamma_2^2$, Shown in Table XI.

Support of 3 – itemset

{11***}{14***}{15***}=0.2/T2

{11***}{14***}{16***}=0.2/t2

{11***}{15***}{16***}=0.2/T2

{14***}{15***}{16***}=0.2/T2

{21***}{22***}{25***}=0.2/T4

TABLE XII

M_3^2

3 – Itemset	Min-Sup
{11***}{14***}{15***}	0.2
{11***}{14***}{16***}	0.2
{11***}{15***}{16***}	0.2
{14***}{15***}{16***}	0.2
{21***}{22***}{25***}	0.2

The{11***}{14***}{21***},{11***}{14***}{22***},{11***}{14***}{25***},{11***}{15***}{21***},{11***}{15***}{22***},{11***}{15***}{25***},{14***}{15***}{21***},{14***}{15***}{22***},{14***}{15***}{25***}cannot be considered for further process because their $Support \geq \gamma_3^2$, Shown in Table XII.

TABLE XIII

M_4^2

4 – Itemset	Min-Sup
{11***}{14***}{15***}{16***}	0.2

The{11***}{15***}{16***}{21***},{11***}{15***}{16***}{22***}, {11***}{15***}{16***}{25***}cannot be considered for further process because their $Support \geq \gamma_4^2$, Shown in Table XIII.

5 - itemset

Level p=5

TABLE XIV

M_5^2

5 – Itemset	Min-Sup
{11***}{11***}{14***}{15***}{16***}	0.2

All 5- items are considered for further process because their $Support \geq \gamma_5^2$, shown in Table XIV.

Min_Sup (γ_q^5) = 0.2

1-Itemset

TABLE XV

M_1^5

1 – Itemset	Min-Sup	1 – Itemset	Min-Sup
{11111}	0.4	{21111}	0.4
{11112}	0.2	{21112}	0.2
{11171}	0.2	{21211}	0.2
{11311}	0.2	{21411}	0.2
{11312}	0.4	{21681}	0.2
{14111}	0.2	{22111}	0.2
{15311}	0.2	{22112}	0.2
{16132}	0.2	{25111}	0.2
{16311}	0.2		

All 1- items are considered for further process because their $Support \geq \gamma_1^5$, shown in table XV.

TABLE XVI

M_2^5

2 – Itemset	Min-Sup	2 – Itemset	Min-Sup	2 – Itemset	Min-Sup
{11111}{11112}	0.2	{14111}{16132}	0.2	{21411}{22112}	0.2
{11111}{11171}	0.2	{15311}{16132}	0.2	{21411}{25111}	0.2
{11111}{11311}	0.2	{16311}{21111}	0.2	{21681}{22111}	0.2
{11112}{11171}	0.2	{16311}{21112}	0.2	{21681}{22112}	0.2
{11112}{11311}	0.2	{16311}{21211}	0.2	{21681}{25111}	0.2
{11171}{11311}	0.2	{21111}{21112}	0.2	{22111}{22112}	0.2
{11312}{14111}	0.2	{21111}{21211}	0.2	{22111}{25111}	0.2
{11312}{15311}	0.2	{21112}{21211}	0.2	{22112}{25111}	0.2
{11312}{16132}	0.2	{21411}{21681}	0.2		
{14111}{15311}	0.2	{21411}{22111}	0.2		

The content of Table XVI. (2- items) are considered for further process because their $Support \geq \gamma_2^5$.

TABLE XVII

M_3^5

3 – Itemset	Min-Sup	3 – Itemset	Min-Sup
{11111}{11112}{11171}	0.2	{21111}{21112}{21211}	0.2
{11111}{11171}{11311}	0.2	{21411}{21681}{22111}	0.2
{11112}{11171}{11311}	0.2	{21411}{22111}{22112}	0.2
{11312}{14111}{15311}	0.2	{21411}{22112}{25111}	0.2
{11312}{15311}{16132}	0.2	{21681}{22111}{22112}	0.2
{14111}{15311}{16132}	0.2	{21681}{22112}{25111}	0.2
{16311}{21111}{21112}	0.2	{22111}{22112}{25111}	0.2
{16311}{21112}{21211}	0.2		

The content of Table XVII. (3- items) are considered for further process because their $Support \geq \gamma_3^5$

TABLE XVIII

M_4^5

4 – Itemset	Min-Sup
{11111}{11112}{11171}{11311}	0.2
{11312}{14111}{15311}{16132}	0.2
{16311}{21111}{21112}{21211}	0.2
{21411}{21681}{22111}{22112}	0.2
{21681}{22111}{22112}{25111}	0.2
{21681}{22111}{22112}{25111}	0.2

The content of Table XVIII. (4- items) are considered for further process because their $Support \geq \gamma_4^5$

TABLE XIX

M_5^5

5 – Itemset	Min-Sup
{21411}{21681}{22111}{22112}{25111}	0.2

All 5- items are considered for further process because their $Support \geq \gamma_5^5$ satisfied, shown in Table XIX.

Minimum Support of each q-itemset is calculated as given in the following results. The set of frequent 1- itemsets, 2-itemsets, 3 - itemsets, 4 - itemsets and 5 - itemsets at multiple levels are given in Table 5. to Table XIX, respectively.

The last step is to calculate confidence of each possible association rules as follows.

LEVEL P=1

$$Conf(*1*** \Rightarrow *5***) = \frac{Support(*1***, *5***)}{*1***}$$

$$= \frac{0.4}{2.6} = 0.154$$

$$Conf(\{*1***\} \wedge \{*2***\} \Rightarrow \{*5***\})$$

$$= \frac{Support(\{*1***\}\{*2***\}\{*5***\})}{\{*1***\}\{*2***\}\{*5***\}} = \frac{0.4}{0.4} = 1$$

LEVEL P=2

$$Conf(\{14***\} \wedge \{15***\} \Rightarrow \{16***\})$$

$$= \frac{Support(\{14***\},\{15***\},\{16***\})}{\{14***\},\{15***\}} = \frac{0.2}{0.2} = 1$$

LEVEL P=3

$$Conf(\{\{111**\} \Rightarrow 113**\})$$

$$= \frac{Support(\{111**\},\{113**\})}{\{111**\}} = \frac{0.2}{0.8} = 0.25$$

LEVEL P=4

$$Conf(\{1111*\} \Rightarrow \{1131*\})$$

$$= \frac{Support(\{1111*\},\{1131*\})}{\{1111*\}} = \frac{0.2}{0.6} = 0.333$$

LEVEL P=5

$$Conf(\{22111\} \wedge \{22112\} \Rightarrow \{25111\}) =$$

$$\frac{Support(\{22111\},\{22112\},\{25111\})}{\{22111\},\{22112\}} = \frac{0.2}{0.2} = 1$$

$$Conf(\{21411\} \wedge \{21681\} \wedge \{22111\} \wedge \{22112\} \Rightarrow \{25111\})$$

$$= \frac{Support(\{21411\},\{21681\},\{22111\},\{22112\},\{25111\})}{\{21411\},\{21681\},\{22111\},\{22112\}}$$

$$= \frac{0.2}{0.2} = 1$$

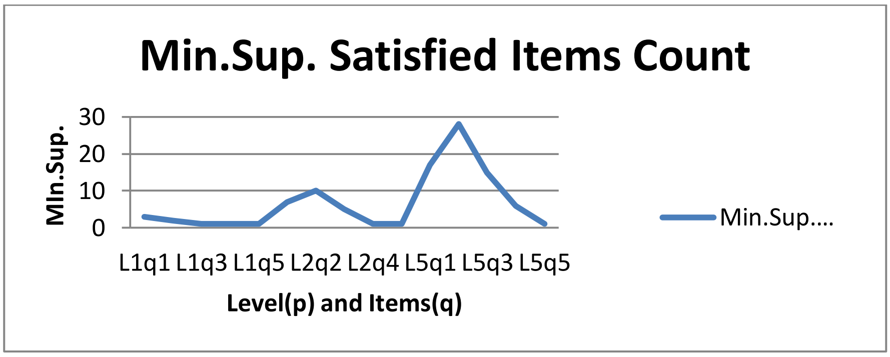

Fig. 1 Minimum Support satisfied Items count

The Minimum Support of each q-itemset and confidence of each possible association rules is calculated as given in the above results; fig.1 is show Minimum Support Satisfied items count. This proposed algorithm IAFARM demonstrated the top down procedural approach and show cast the sharpening of boundary intervals and reduces the scanning time of the transaction datasets.

IV. Conclusion

The rule quality can be viewed in terms of its accuracy and comprehensibility. Multiple level encryption catalog transaction table and different minimum support to discover the fuzzy multiple level frequent item association rules, it's extracted from a given grouped transaction dataset. Fuzzy set concepts solved and work well in the hesitancy relationship data. The new algorithm stem Fuzzy Association Rule and generated frequent itemsets, an example of adult censes data set took and explain clearly for understand the step by step concept of Proposed Algorithm.

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