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# **Survey on Improvement of Apriori Algorithm**

Dixita Tandel<sup>#1</sup>, Prof. Neha Soni<sup>#2</sup>

M.E. Student, Dept. of Computer Engineering, Sardar Vallabhbhai Patel Institute of Technology, Vasad, Gujarat, India

Assistant Professor, Dept. of Computer Engineering, Sardar Vallabhbhai Patel Institute of Technology, Vasad, Gujarat,

India

**ABSTRACT:** Data mining is the process of analyzing the data from large database and summarizing that data into useful information. Association rule mining is one of the most important data mining's functionalities for finding frequent itemset or association between items or attribute. It can be consider as two step process, first it find frequent items and from that it generate association rule. Apriori algorithm is the most popular algorithm which is used to extract frequent itemsets from large data sets where these frequent itemsets can be used to generate association rules. These rules are used for discovering knowledge such as detecting unknown relationships, decision making, prediction, etc. It finds frequent itemset based on join and prune step. It's simple but having some disadvantages such as generate more candidate itemset, multiple scanning of database, etc. Large number of variations has been proposed in the literature to overcome the shortcomings of Apriori algorithm. So this paper presents a survey on Apriori algorithm of recent research work carried by different researchers with example.

KEYWORDS: Data mining, association rule, apriori, support, frequent itemset.

#### I. INTRODUCTION

Data mining is the process of examining large pre-existing databases in order to generate new information. Data mining also known as knowledge discovery is used to discover useful patterns from the huge database. Many techniques have been developed in data mining amongst which association rule mining is important for finding frequent itemset. Apriori is one of the best algorithms for the association rule mining. The Apriori algorithm generate frequent patterns from database whose support must satisfy the minimum support criteria where these frequent itemsets are used to generate association rule whose confidence must satisfy the minimum confidence criteria.

The main contribution of our work is to survey in the direction of optimized apriori algorithm. In all previous survey papers they simply give description about some improved algorithm. In our survey paper we are given summary of algorithm theory as well as an example. All examples are calculated using same sample transaction database. So, from that example we can easily understand the differences in different algorithm or difference in frequent itemset generation process. We can also get the idea about which algorithm produce more candidate itemsets than other.

#### II. RELATED WORK

This section includes literatures carried out on Improvement of apriori algorithm. Following are the improvement proposed over Apriori algorithm:

In [17] authors improved this algorithm, Pick a random sample S of the given data D, and then search for frequent itemsets in S instead of D. So, uses a lower support threshold than minimum support to find the frequent itemsets local to S. In [13] authors present the DHP algorithm which is hash-based. The candidate generated by this algorithm is much smaller than previous methods, especially generated candidate 2-itemsets. And the generation of smaller candidate sets enables us to effectively trim the transaction database size at a much earlier stage of the iterations. In [15] authors presented the partition-based algorithm, which scans the database only twice, reducing the I/O operation observably and thus improved the efficiency of the algorithm. Large capacity databases will be logically divided into several disjoint blocks which are used to generate locally frequent item sets, and then these local frequent item sets to get the final global frequent items sets through testing their support. In [8] authors presented filtration approach instead



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of pruning, in which frequent and infrequent itemsets are generated. They also improved the filtration approach [9] by checking only (k-1) infrequent itemset as filters. In [5] Authors proposed Improved DC\_Apriori algorithm, which restructured the storage structure of the database, improved connection of frequent item sets, improved join step, and greatly reduced the number of connections. In order to improve the efficiency of Apriori authors proposed, a novel algorithm, named BitApriori [6], for mining frequent itemsets. In BitApriori, the data structure binary string is used to describe the database. The support count can be implemented by performing the Bitwise "And" operation on the binary strings. Another technique presented in this paper is a special equal-support pruning. The Enhanced BitApriori algorithm [20] is same like a BitApriori algorithm, but the main difference is that in BitApriori used the Bitwise "And" operation on binary strings and in Enhanced BitApriori Bitwise "XOR" operation is used on binary strings. Ordering is not based on decreasing support count [20]. In [2] authors used adjacency matrix as optimized data structure. This algorithm reduces the size of candidate-K itemset in successive iteration. Pruning is also done at two stages which reduces the memory space. The algorithm works as follow: (Frequent item set generation: ) First select max item from sorted table as frequent Itemset name given as A. Items of adjacency matrix which are associated with A are consider as candidate itemsets. This procedure is continuing until no more itemsets are generated. In [7] the data mapping technique is optimized, so the database is scanned only once. After generating frequent 1-itemset following frequent item sets can be obtained by scanning  $C_k$  and  $L_k$ . Authors give the name of the algorithm as OApriori [7]. Algorithm [4] is based on transaction reduction in which the attribute SOT (size of transaction) is used. As compared to apriori algorithm authors [18] has improved join and pruned step. Join step: For two k-1 frequent itemset named  $l_x$  and  $l_y$ , if these two itemset can't be connected, then we can say that all the itemsets after  $l_x$  and  $l_y$  can't satisfy the connection condition. As a result, there is no need to determine whether the itemsets which are behind the itemset  $l_x$  and  $l_y$  satisfy the connection conditions or not. Prune step: The necessary condition for a k-dimensional becomes a frequent itemset is that all the (k-1) dimensional subsets are also frequent itemset. Let k-dimensional itemset {i1 i2,...,i<sub>k</sub>}, if  $|L_{k-1}(j)| < k-1$ is true then delete j from  $L_{k-1}$ . Here  $|L_{k-1}(j)|$  means the number of j in  $L_{k-1}(j)$ . In [14] Authors give the name of the algorithm as APRIORI-IMPROVE algorithm which generates L2 directly from one scan over the database without generating  $C_1$ ,  $L_1$  and  $C_2$ . And it replaces the hash tree by a hash table to reduce searching cost. The  $L_2$  is directly generated using a hash function. Hash function: H(x, y) = (P(x) - 1) \* (N - 1) + P(y) - P(x), Where x and y are the items in database, N is the number of transactions and P denotes the position. In [19] authors present an improved algorithm which is based on the classic Apriori algorithm, in which Pruned optimization strategy adapted to optimize the process of pruning in order to reduce the generation of frequent itemsets, and take Transaction Reduction strategy to reduce the size of the transaction database to be scanned.

#### III. METHODOLOGY

Apriori Algorithm is a traditional algorithm for frequent item generation, which is proposed by R.Agrawal and R.Srikant in 1994 [1].

The general block diagram of Apriori Algorithm is shown below:



Fig.1 Block diagram of Apriori Algorithm

The algorithm simply scans all of the transactions in order to count the number of occurrences of each itemset. The item which satisfies the minimum support criteria is taken as frequent k-itemset which is known as  $L_k$ .

Join step: To find  $L_k$  a set of candidate k-itemsets is generated by joining  $L_{k-1}$  with itself. This set of candidates is denoted  $C_k$ .



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Prune step: To reduce the size of  $C_k$ , the Apriori property is used as follows: if any (k-1)-subset of a candidate kitemset is not in  $L_{k-1}$ , then the candidate cannot be frequent either, so it can be removed from  $C_k$ .

#### IV. RESULT

This section includes the example of all improved algorithms using sample transaction database (Table.1). Table 1 is the sample transaction database which we used to solved the all Algorithms.

| TID        | List of item IDs |
|------------|------------------|
| Tl         | 11, 12, 15       |
| T2         | 12, 14           |
| T3         | 12, 13           |
| T4         | 11, 12, 14       |
| T5         | 11, 13           |
| T6         | 12, 13           |
| <b>T</b> 7 | 11, 13           |
| T8         | 11, 12, 13, 15   |
| T9         | 11, 12, 13       |

Table.1 Sample transaction database [21]

Fig. 2 is example of Apriori Algorithm which is solved (Table.1) based on Algorithm [1].



Fig.2 Example of Apriori Algorithm

Fig. 3 is example of research and improvement of apriori algorithm which based on Algorithm given in paper [5]. In this algorithm improved Join step is: The generation of k-frequent itemsets is only need to join the 1-frequent item sets with frequent k-1-itemsets ( $L_{k-1}$ ). For that it needs to compare last element of frequent k-1-itemset (l) with L1 items. If  $l<l_1$ , then join the itemset of  $L_{k-1}$  with  $L_1$ . Based on that frequent itemset generated is as Fig. 3:



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Fig. 4 is example of BitApriori based on Algorithm given in paper [6].

| r requent 2-itemset:          |     |              |             |         |         |         |         |          |          |  |  |  |
|-------------------------------|-----|--------------|-------------|---------|---------|---------|---------|----------|----------|--|--|--|
|                               | Tid | Items        | Ordered     | {I5,I1} | {I5,I2} | {I1,I2} | {I4,I2} | {I3, I2} | {I1, I3} |  |  |  |
| First scan of database we get | 1   | 11, 12, 15   | 15,11, 12   | 1       | 1       | 1       | 0       | 0        | 0        |  |  |  |
| I1=6, I2=7, I3=6, I4=2, I5=2. | 2   | I2, I4       | I4,I2       | 0       | 0       | 0       | 1       | 0        | 0        |  |  |  |
| Compare with min sup.         | 3   | 12, 13       | 13,12       | 0       | 0       | 0       | 0       | 1        | 0        |  |  |  |
| 1 _ 17                        | 4   | 11, 12, 14   | 14,11,12    | 0       | 0       | 1       | 1       | 0        | 0        |  |  |  |
| _                             | 5   | II, I3       | I1,I3       | 0       | 0       | 0       | 0       | 0        | 1        |  |  |  |
| Frequent items are:           | 6   | 12, 13       | 13,12       | 0       | 0       | 0       | 0       | 1        | 0        |  |  |  |
| Items I4 I5 I1 I3 I2          | 7   | II, I3       | 11,13       | 0       | 0       | 0       | 0       | 0        | 1        |  |  |  |
| Support 2 2 6 6 7             | 8   | 11, 12,13,15 | 15,11,13,12 | 1       | 1       | 1       | 0       | 1        | 1        |  |  |  |
|                               | 9   | 11, 12, 13   | 11,13,12    | 0       | 0       | 1       | 0       | 1        | 1        |  |  |  |
|                               |     | Suppo        | rt          | 2       | 2       | 4       | 2       | 4        | 4        |  |  |  |



Tree after generation (3) Fig. 4 Example of BitApriori



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Fig. 5 is example of Enhanced BitApriori Algorithm based on Algorithm given in paper [20].



Fig. 5 Example of Enhanced BitApriori Algorithm

Fig. 6 is example of Proposed algorithm for frequent itemset generation using Algorithm given in paper [2].

| Frequ<br>with s | ency of each ite<br>orted table: | em<br>Adjacency matrix R:                                   | Pruned adja | cency matrix: L <sub>1</sub> -<br>A= | ={I2} first item of sorted table<br>=L1={I2} |
|-----------------|----------------------------------|---|-------------|--------------------------------------|--|
| II              | 6                                | R(i,j) I2 I3 I4 I5  | R(i,j) 12 1 | 3 I4 I5 k=                           | $k+1=2; C_2=0$                               |
| I2              | 7                                | II 4 4 1 2  | II 4        | <u>4 - 2</u> II.                     | 13. 14. 15 associated with A                 |
| I3              | 6                                | I2 - 4 2 2  | I2 -        | 4 2 2 So                             | C <sub>2</sub> ∈{ 11.13.14.15}               |
| I4              | 2                                | <u>I3</u> 1   |             |                                      | , 02 0( 11,12,1,12)                          |
| I5              | 2                                | I4  |             |                                      |  |
| Candid          | ate 2-itemset:                   |   | Candid      | late 3-itemset:                      |  |
| Items           | Frequency                        | $\mathbf{L}_{2} \subseteq \mathbf{C}_{2} = \{\mathbf{II}\}$ | Items       | Frequency                            | ]  |
|                 | count with L <sub>1</sub>        | //items $\in C_2$ which has max freq                        | uency       | count with L <sub>2</sub>            | $L_3 \subseteq C_3 = \{I3\}$                 |
|                 | matrix                           | $A=A\cup L_2=\{I2,I1\}$                                     |             | m aujacency<br>matrix                | $A=A\cup L_3=\{I2,I1,I3\}$                   |
| 11              | R(I2,I1)=4                       | k=k+1=3; C <sub>3</sub> =Ø                                  | 13          | R(I3,I2)=4,                          | So frequent Itemset is {I2,I1,I3}.           |

Fig. 6 Example of Proposed algorithm for frequent itemset generation

15

13

**I**4

I5

R(I2,I3)=4

R(I2,I4)=2

R(12,15)=2

I3&I5 associated with A

So, C<sub>3</sub>∈{ I3,I5}

R(I3,I1)=4

R(I5,I2)=2,



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Fig. 7 is example of OApriori Algorithm based on Algorithm given in paper [7].

| Transactio | n ta | ble   | afte | er re | emapping: | Candio   | late       | 1- | iter | nse | et: |           |                                       |  |     | Freque    | nt  | 1-i  | ten          | ise  | t:   |     |   |   |      |       |       |                        |
|------------|------|-------|------|-------|-----------|----------|------------|----|------|-----|-----|-----------|---------------------------------------|--|-----|-----------|-----|------|--------------|------|------|-----|---|---|------|-------|-------|------------------------|
| Items      |      |       | Tie  | l's   |           | Items    |            |    | Ti   | d's | 5   |           |                                       | Support  |     | Items     |     |      | Т            | ïd'  | s    |     |   |   |      |       |       |                        |
| <u> </u>   | 1    | 4     | 5 1  | 7 8   | 89        | 11       | 1          | 4  | 5    | 7   | 8   | 9         |                                       | 6  |     | п         | 1   | 4    | 5            | 7    | 8    | 9   |   | For k=2, $L_1^{'}=L_1$<br>$J_1(I1)=1, L_1(I2)=1, L_1(I2)=1$ |      |       |       |                        |
| 12         | 1    | 2     | 3 4  | 4 (   | 589       | 12       | 1          | 2  | 3    | 4   | 6   | 8         | 9                                     | 7  |     | 12        | 1   | 2    | 3            | 4    | 6    | 8   | 9 |   |      |       |       | <sub>1</sub> (I3)=1,   |
| I3         | 3    | 5     | 6    | 7 8   | 89        | 13       | 3          | 5  | 6    | 7   | 8   | 9         |                                       | 6  |     | 13        | 3   | 5    | 6            | 7    | 8    | 9   |   | $L_1(14)=1, 1$  | 4(I  | 5)=.  | 1.    |                        |
| I4         | 2    | 4     |      |       |           | 14       | 2          | 4  | -    | 1   | -   | -         | _                                     | 2  |     | 14        | 2   | 4    | -            | -    | _    | -   |   | So, no item   | ı is | ren   | 10V6  | ed from L <sub>1</sub> |
| 15         | 1    | 8     |      |       |           | 15       | 1          | 8  | +    | +   | +   | +         | _                                     | 2  |     | 15        | 1   | 8    |              |      |      |     |   |   |      |       |       |                        |
| C2: cand   | idat | te 2- | -ite | mse   | ets       |          |            |    |      |     |     |           |                                       |  |     |           |     |      |              |      |      |     |   |   |      |       |       |                        |
| Itemset    |      | Tid   | l's  |       | Support   |          |            |    |      |     |     |           |                                       |  |     |           |     |      |              |      |      |     |   | C3: candid  | ate  | 3-i   | tem   | sets                   |
| 11,12      | 1    | 4     | 8    | 9     | 4         | L2: fi   | equ        | en | t 2- | ite | ms  | ets       | :                                     | For k=3.   | L   | a'= La    |     |      |              |      |      |     |   | Itemset   | 1    | Tid'  | s     | Support                |
| 11,13      | 5    | 7     | 8    | 9     | 4         | Iten     | nset       |    | ]    | Гid | l's |           |                                       | For each   | if  | em cou    | int | th   | e fr         | 'ea  | uer  | icv |   | 11,12,13  | 8    | 9     |       | 2                      |
| I1,I4      | 4    |       |      |       | 1         | п.       | 12         | +  | 1    | 4   | 8   | 9         |                                       | $L_2(11)=3$  | Ī   | o(12)=4   | 4.  |      |              | - 1  |      |     |   | 11,12,15  | 4    | 8     |       | 1                      |
| I1,I5      | 1    | 8     |      |       | 2         | <u> </u> | 13         | +  | 5    | 7   | 8   | 9         |                                       | $L_2(13)=2$  | ī   | a(14) = 1 | ï   |      |              |      |      |     |   | 12,13,15  | 8    |       |       | 1                      |
| 12,13      | 3    | 6     | 8    | 9     | 4         | п.       | 15         | +  | 1    | 8   | _   | F         |                                       | $L_2(15) = 2$                                      | , - | 2(14)     | ,   |      |              |      |      |     |   |   |      |       |       |                        |
| I2,I4      | 2    | 4     |      |       | 2         | 12.      | 13         | +  | 3    | 6   | 8   | 9         |                                       | L2(13)-2   |     | 0         |     |      |              |      |      |     |   | L3: fre   | que  | ent : | 3-it( | emsets                 |
| 12,15      | 1    | 8     |      |       | 2         | 12,      | <b>I</b> 4 |    | 2    | 4   |     | $\square$ |                                       | Here, L <sub>2</sub> (14) not satisfied condition. |     |           |     |      |              | Iten | iset | t   | 1 | 'id's   |      |       |       |                        |
| I3,I4      |      |       |      |       | 0         | 12,      | I5         | +  | 1    | 8   |     | $\square$ | So they are deleted from $L_2$ .      |  |     |           |     |      | I1,I2,13 8 9 |      |      |     | 9 |   |      |       |       |                        |
| 13,15      | 8    |       |      |       | 1         |          |            | _  |      |     |     |           | $L_2^{\prime} \in \{11, 12, 13, 15\}$ |  |     |           |     | I1,Ľ | 2,15         | 5    | 1    | 8   |   |   |      |       |       |                        |
| I4 I5      |      |       |      |       | 0         |          |            |    |      |     |     |           |                                       |  |     |           |     |      |              |      |      |     |   |   |      |       |       |                        |

Fig. 7 Example of OApriori

Fig. 8 is example of Improving Efficiency of Apriori Algorithm Using Transaction Reduction based on Algorithm given in paper [4] which is solved based on following steps:

Step 1: First convert database into the desired database that is with SOT column. In the first iteration of the algorithm, each item is a member of the set of candidate 1-itemsets,  $C_1$ . The algorithm simply scans all of the transactions in order to count the number of occurrences of each item. This algorithm will then generate number of items in each transaction (SOT). Based on the min\_sup the set of frequent 1-itemset,  $L_1$  can be determined.

Step 2: The deletion process of transaction in database will made according to the value of k. If value of k is match with value of SOT then delete those transactions from database.

Item

11

12

13

**T4** 

15

Support

б

6

7

2

2

Step 3:  $L_k$  is generated by join and prune operation.

Step 4: repeat step 2 and step 3 until  $C_{k+1} = \emptyset$ .

| Database(D) with attribute | SOT: C1: candidate 1-itemset | L1: frequent 1-itemset | $C_2 = L_2 C$ |
|----------------------------|------------------------------|------------------------|---------------|
|                            |                              | LI. II equent I-nember | C2 112        |

| Tid | Items          | SOT |
|-----|----------------|-----|
| 1   | 11, 12, 15     | 3   |
| 2   | 12, 14         | 2   |
| 3   | 12, 13         | 2   |
| 4   | 11, 12, 14     | 3   |
| 5   | II, I3         | 2   |
| 6   | 12, 13         | 2   |
| 7   | 11, 13         | 2   |
| 8   | 11, 12, 13, 15 | 4   |
| 9   | 11, 12, 13     | 3   |

 Item
 Support

 I1
 6

 I2
 6

 I3
 7

 I4
 2

 I5
 2

For k=2, delete those transactions Which are having SOT=k-1=1. Here D1 is same as D because there are no transactions which are having SOT=1.

| -2 - 12012 | <b>U</b> 2 |         |
|------------|------------|---------|
| Itemset8   | Itemset    | Support |
| 11,12      | 11,12      | 4       |
| 11,13      | 11,13      | 4       |
| I1,I4      | I1,I4      | 1       |
| 11,15      | 11,15      | 2       |
| 12,13      | 12,13      | 4       |
| 12,14      | I2,I4      | 2       |
| 12,15      | 12,15      | 2       |
| I3,I4      | 13,14      | 0       |
| 13,15      | 13,15      | 1       |
| 14 15      | 14 15      | 0       |

 $\mathbf{c}$ 

L<sub>2</sub>: frequent 2-itemset: For k=3, delete those transactions Itemset Support Which are having SOT= $k_1$ =2.

| itemset | Support | wme | n are naving 50 | /1-K-1-4. | Ca=LaOLa   |                             |         |                             |           |
|---------|---------|-----|-----------------|-----------|------------|-----------------------------|---------|-----------------------------|-----------|
| 11,12   | 4       | D2: |                 |           | Itemset    | ۱~.                         |         | <b>.</b>                    |           |
| 11,13   | 4       | Tid | Itoms           | SOT       | TI TO TO   | C <sub>3</sub> <sup>2</sup> |         | L <sub>3</sub> : frequent : | 5-itemset |
| 11 15   | 2       | 1   | TI TO TE        | 2         | 11, 12, 15 | Itemset                     | Support | Itemset                     | Support   |
| 70.70   | -       | 1   | 11, 12, 15      | 3         | 11, 12, 15 | 11 12 12                    |         | 11 12 13                    | 2         |
| 12,13   | 4       | 4   | I1, I2, I4      | 3         | 12 13 14   | 11, 12, 15                  | 4       | 11, 12, 13                  |           |
| 12.14   | 2       | 9   | 11 12 13 15     | 4         | 12, 13, 14 | 11, 12, 15                  | 2       | 11, 12, 15                  | 2         |
| 70.75   | -       | •   | 11, 12, 13, 13  | 4         | 12, 13, 15 |                             |         |                             |           |
| 12,15   | 2       | 9   | 11, 12, 13      | 3         | 12, 14, 15 | 1                           |         |                             |           |

Fig. 8 Example of Improving Efficiency of Apriori Algorithm Using Transaction Reduction



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Fig. 9 is example of Example of Mining Association Rules Based on an Improved Apriori Algorithm based on Algorithm given in paper [18].

| _    | l <sub>x</sub> =I1 | l,   | ,=I2     |                  | l <sub>x</sub> =I3 | 3    | l <sub>x</sub> =I4 | 1    | l <sub>x</sub> = | 15 | _       |
|------|--------------------|------|----------|------------------|--------------------|------|--------------------|------|------------------|----|---------|
| TLI  |                    | TL2  |          | $\downarrow$ TL2 |                    |      | 2                  | TL   | 2                | TI | ↓<br>L2 |
| Item | Г                  | Item | <u>ا</u> | Item             |                    | Iter | n                  | Iter | m                | It | em      |
| 11   |                    | 11   |          | I2               | 1                  | 13   |                    | 14   |                  |    | 15      |
| 12   |                    | 12   |          | 13               |                    | 14   |                    | 15   | ;                |    |         |
| 13   |                    | 13   |          | I4               |                    | 15   |                    |      |                  |    |         |
| I4   |                    | I4   | [        | 15               |                    |      |                    |      |                  |    |         |
| 15   |                    | 15   |          |                  | _                  |      |                    |      |                  |    |         |

Here the algorithm is same as 5<sup>th</sup> literature but it require less comparison time when joining (see in Fig. 9 for join procedure)

Fig. 9 Example of Mining Association Rules Based on an Improved Apriori Algorithm

Fig. 10 is example of APRIORI-IMPROVE algorithm based on Algorithm given in paper [14].

The first step is to read the database once and make a hash table which includes each itemset and its support. Before going to next step we will discard the items which does not satisfies the minimum support criteria. The next step is to make combination of 2-itemsets for each transaction (i.e.) if transaction 1 contains items like I1,I2,I3 then possible combination would be {I1,I2} {I1,I3} {I2,I3}. Now by using the Hash function we store the support of each combination. We get L2 after pruning the data we can get the 2 Itemset. Similarly for the further candidate set generation we use the same procedure. From the hash structure table we get  $L_2$  (after pruning the above table data we can get the 2 Item set). Similarly for the further candidate set generation we use the same procedure.

|                  |         |      | Hash table: | :  |      |       |        |      |               |                |               |               |               |               |
|------------------|---------|------|-------------|--|------|-------|--------|------|---------------|----------------|---------------|---------------|---------------|---------------|
| C <sub>1</sub> : |         |      | TID         | Item   |      |       |        |      |               |                |               |               |               |               |
| Item             | Support | P(X) | T1          | $\{11, 12\}, \{11, 15\}, \{12, 15\}$               |      |       |        |      |               |                |               |               |               |               |
| I                | 6       | 1    | T2          | {I2, I4}   | Has  | h Fun | ction: | H(x, | v) = (        | <b>P(x)</b> -1 | l)*(N-        | -1)+P(        | (v)-P(:       | x).           |
| 12               | 7       | 2    | T3          | {I2, I3}   |      |       | _      |      | · · ·         |                | <u> </u>      | <i></i>       | ~ `           | <u></u>       |
| 13               | 6       | 3    | T4          | $\{I1, I2\}, \{I1, I4\}, \{I2, I4\}$               | {II, | {II,  | {II,   | {II, | { <b>I</b> 2, | { <b>I</b> 2,  | { <b>I</b> 2, | { <b>I</b> 3, | { <b>I</b> 3, | { <b>I</b> 4, |
| 14               | 2       | 4    | T5          | {II, I3}   | L2}  | 13}   | I4}    | I5}  | I3}           | I4}            | I5}           | I4}           | I5}           | I5}           |
| 15               | 2       | 5    | T6          | {I2, I3}   | 4    | 4     | 1      | 2    | 4             | 2              | 2             | 0             | 1             | 0             |
| 10               | -       |      | T7          | {II, I3}   |      |       |        |      |               |                |               |               |               |               |
|                  |         |      | T8          | $\{\Pi, \Pi, \Pi, I2\}, \{\Pi, I3\}, \{\Pi, I5\},$ |      |       |        |      |               |                |               |               |               |               |
|                  |         |      |             | $\{12,13\},\{12,15\},\{13,15\}$                    |      |       |        |      |               |                |               |               |               |               |
|                  |         |      | T9          | $\{I1, I2\}, \{I1, I3\}, \{I2, I3\}$               |      |       |        |      |               |                |               |               |               |               |

Fig. 10 APRIORI-IMPROVE algorithm

Fig. 11 is example of An Improved Apriori Algorithm Based on Pruning Optimization and Transaction Reduction based on Algorithm given in paper [19] which is solved based on following steps:

Step 1: Generate  $L_1$  as same as classic Apriori.

Step 2: Generate k itemsets: if  $k \neq 2$ , count the frequency of  $|L_{k-1}(a)|$  of every item exists in  $L_{k-1}$ . If  $(|L_{k-1}(a)| < k-1)$  then delete those itemsets from  $L_{k-1}$  and update  $L_{k-1}$ .

Step 3:  $C_k = L_{k-1}\Theta L_{k-1}$ . For each transaction count the length of transaction, delete transaction whose length is less than k.

Step 4:  $L_k = \{c \in C_k | c.count \ge min\_sup\}$ 

Step 5: repeat step 2 to step 4 until  $L_{k-1} \neq \emptyset$ .



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Fig.11 Example of An Improved Apriori Algorithm Based on Pruning Optimization and Transaction Reduction

#### V. COMPARISON

A table given below summarizes the methods, advantages and limitations of improved apriori algorithm. Table.2 Comparative study of improvement of Apriori algorithms

| S.        |  |   |   |  |
|-----------|--|---|---|--|
| Sr.<br>No | Title  | Method  | Advantages  | Disadvantages  |
| 1         | Research and<br>Improvement of<br>Apriori<br>Algorithm[5]  | Database: Item-Tid form.<br>Storage structure is based on<br>dynamic array vector and map<br>set.<br>Join: $L_{k-1}$ with $L_1$ .<br>Support: use intersection. | Avoid repeated comparison<br>of (k-2) items.<br>Avoid scanning of db.<br>Only 1 traversal can get<br>the intersection because<br>Tid list is in ascending<br>order.                             | More candidate sets are generated.   |
| 2         | Enhanced<br>BitApriori<br>Algorithm: An<br>Intelligent<br>Approach for<br>Mining Frequent<br>Itemset[20] | BitApriori,<br>Equal Support Pruning (ESP),<br>Binary string, XOR operation   | Need to scan the db twice.<br>No candidate generated.<br>Reducing the height of the<br>tree because of ESP<br>Easy to calculate the<br>support count.<br>All frequent itemset are<br>generated. | When the database is<br>large, may suffer the<br>problem of memory<br>scarcity.<br>Traversing the tree<br>recursively (because of no<br>ordering). |
| 3         | Proposed<br>algorithm for<br>frequent item set<br>generation[2]  | Database: Adjacency matrix.<br>Pruning: Sorted table and<br>adjacency matrix are pruned.<br>Candidate: consist itemset which<br>have relation with $L_{k-1}$ .  | Reduced memory<br>utilization<br>Reduced number of item<br>to be scanned  | Not all frequent itemsets are generated.   |
| 4         | A Method to<br>Optimize Apriori<br>Algorithm for<br>Frequent Items<br>Mining[7]                          | Database: Item-Tid form.<br>Connection steps: delete the transaction from $L_k$ which not satisfies the min_sup.<br>Support: use intersection.                  | Scan database only once.<br>Avoid comparison of<br>checking (k-1) subset<br>frequent or not.  |  |
| 5         | An Efficient<br>Filtration<br>Approach for<br>Mining<br>Association                                      | Instead of pruning filtration<br>approach is used in which<br>frequent and infrequent itemsets<br>are generated.  | Optimum numbers of candidate k-frequent itemsets are generated.   | Extra space is required to store the all infrequent k-itemset.   |



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|    | Rules[8]  |   |  |  |
|----|---|---|--|--|
| 6  | Improved[9]<br>Filtration step for<br>Mining<br>AssociationRules  | Filtration steps: improved by checking only (k-1) infrequent itemset as filters.  | Optimum k-candidate<br>itemsets are generated.<br>Reduces the extra effort in<br>filtration process.   | Extra space is required to store the all infrequent k-itemset.   |
| 7  | Improving<br>Efficiency of<br>AprioriAlgorithm<br>UsingTransaction<br>Reduction[4]                          | Traction reduction strategy:<br>number of items in each<br>transaction <k delete="" those<br="">transaction.</k>  | Reduce the number of transaction scanning.   | Manage new db after every generation of $L_k$ .  |
| 8  | An efficient<br>algorithm for<br>frequent itemsets<br>in data mining[6]                                     | BitApriori, Equal support<br>pruning (ESP)<br>Binary string<br>Bitwise AND operator<br>Sorting of frequent 1-itemset<br>into non decreasing order of<br>support   | Need to scan the db twice.<br>No candidate generation.<br>Reducing the height of the<br>tree using ESP.<br>Easy to calculate the<br>support count.<br>All frequent itemset are<br>generated. | When the database is<br>large, the BitApriori may<br>suffer the problem of<br>memory scarcity.<br>Not all frequent itemsets<br>are generated.        |
| 9  | Mining<br>AssociationRules<br>Based on an<br>Improved Apriori<br>Algorithm[18]                              | Pruning: $ L_{k-1}(j)  < k-1$ then it if<br>not frequent.<br>Database: Delete transaction of<br>itemset which not contains the C <sub>k</sub><br>during the calculation of C <sub>k</sub> .   | Reduce the number of<br>candidate itemsets.<br>Optimize the database so<br>efficiency can be more<br>and more with the growth<br>of value k.   |  |
| 10 | An Improved<br>Apriori<br>Algorithm Based<br>on Pruning<br>Optimization and<br>Transaction<br>Reduction[19] | Prune step: temporary table used<br>to store the frequency of items of<br>$L_{k-1}$ , if freq(item) <k-1, all<br="" delete="">the frequent itemsets containing<br/>the item in <math>L_{k-1}</math>.<br/>Transaction Reduction Strategy:<br/>delete transaction whose length<br/>is less than k+1.</k-1,> | Avoid a lot of scanning<br>the database.<br>Eliminate non-frequent<br>candidate itemsets.  | Extra space is required to<br>temporary store table of<br>each items frequency<br>when generating k>2<br>itemset.                                    |
| 11 | An Effective<br>Hash-Based<br>Algorithm for<br>Mining<br>Association<br>Rules[13]                           | The proposed algorithm utilizes<br>a hash method for candidate<br>itemset generation during the<br>initial iterations and employs<br>pruning to reduce the transaction<br>database size.  | Effective reduction on<br>transaction db size.<br>Scans the full db for the<br>first 2 passes and then<br>scans D <sub>k</sub> thereafter.<br>Smaller transaction scan                       | The candidate itemsets<br>generation and support<br>count process is still the<br>time consuming.<br>Need extra time for<br>hashing the transaction. |
| 12 | Sampling Large<br>Database for<br>Association<br>Rule[17]   | Pick a random sample S of the<br>given data D.<br>Search frequent itemsets in S<br>instead of D.<br>Uses a lower support threshold.   | Scan only sample S, it<br>saves time.<br>Beneficial when<br>efficiency is of utmost<br>importance.   | Sacrifices some accuracy.<br>May lose some global<br>frequent items sets.  |
| 13 | An Efficient<br>Algorithm for<br>Mining<br>Association Rule<br>in Large<br>Database[15]                     | Partition: Database will be<br>logically divided into several<br>disjoint blocks.<br>Local frequent itemsets used to<br>get final global frequent items<br>sets for testing their support.  | Requires only two pass of<br>the db.<br>Improves the performance<br>of apriori algorithm as<br>partitioned data sets can<br>be executed parallel.  | Some items may get missed due to partitioning.   |



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#### VI. CONCLUSION

Association rule mining is one of the most important data mining techniques for finding association between items or attribute. Apriori is the classical and mostly used algorithm which is used to generate frequent itemsets from large data sets. Though it has been good algorithm, but have some disadvantage such as generate more candidate itemset, require multiple scanning of database. To overcome such issues number of algorithms has been proposed in the literature. After literature study it has been noted that the variations proposed may solve one or more issues of Apriori but results into some new problems or leaving the other issues untouched.

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#### BIOGRAPHY

**Dixita Pankajbhai Tandel** is a M.E. student in the Computer Engineering Department, SardarVallbhbhai Patel Institute of Technolgy, Vasad. Her research interest is Data Mining.