

EFFICIENT TRANSACTION REDUCTION IN ACTIONABLE PATTERN MINING FOR HIGH VOLUMINOUS DATASETS BASED ON BITMAP AND CLASS LABELS

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Abstract – Frequent pattern mining in databases plays an indispensable role in many data mining tasks namely, classification, clustering, and association rules analysis. When a large number of item sets are processed by the database, it needs to be scanned multiple times. Consecutively, multiple scanning of the database increases the number of rules generation, which then consume more system resources. Existing CCARM (Combined and Composite Association Rule Mining) algorithm used minimum support in order to generate combined actionable association rules, which in turn suffer from the large number of generating rules. Explosion of a large number of rules is the major problem in frequent pattern mining that adds difficult to find the interesting frequent patterns. This paper presents an efficient transaction reduction technique named TR-BC to mine the frequent pattern based on bitmap and class labels. The proposed approach reduces the rule generation by counting the item support and class support instead of only item support. Moreover, the database storage is compressed by using bitmap that significantly reduces the number of database scan. The rules are reduced by horizontal and vertical transaction and then finally combined rules are generated by eliminating the redundancy. Experimental results validate the performance of the proposed approach and expose that proposed method is more effective and efficient than previously proposed algorithm.

Index terms – bitmap, item support, database scan, class support, class labels, database transaction, and combined rules.

I.INTRODUCTION

The more crucial and indispensable problem in numerous data mining applications are the frequent pattern mining, which is responsible for identifying the correlations, association rule analysis and many other substantial knowledge discovery tasks. Apriori is the most commonly used pattern mining algorithm that exploits breadth first search, bottom-up approach for each frequent item set. In general, the database transaction in Apriori is adopted by horizontal layout and the item set frequency is evaluated by counting its frequent appearance in each transaction. It gains good performance by reducing the size of candidate sets. Determining the most frequent patterns in a target database is the primary issue in frequent pattern mining, which is related to the threshold value specified by the user. Many of the traditional frequent pattern mining approaches identify the interesting frequent patterns by deploying a parameter named as minimum support. In this approach, the assumption is made by the users to define a suitable threshold value for the minimum support. This strategy makes the users difficult to specify which value is appropriate.

Another elementary issue faced during the mining is the processing of huge datasets, which produce high computational costs. Moreover, it requires multiple scanning of database to identify the support of a pattern. Consider an example, to determine the pattern support in database it requires the whole dataset to be scanned at once. When the transaction dataset contains $|I|$ items, the whole dataset is scanned by $(2^{|I|} - 1)$ times in order to identify the support of each pattern in the dataset. Multiple scanning of database leads to the explosion of large number of rules that negatively affect the efficiency and effectiveness of data mining processes. The eruption of large number of rules in frequent pattern mining makes it difficult to find the frequent patterns. Hence, it is crucial to develop new approach to overcome this shortcoming.

New era data mining application require decision making knowledge with reduced number of rules. The most substantial process of mining the frequent pattern is the specification of the database transaction that simplifies the task of counting support. To overcome the abovementioned shortcomings, an efficient transaction reduction algorithm TR-BC (Transaction Reduction based on Bitmap and Class labels) is presented in this paper. The proposed method addresses the multiple scanning of the database in terms of bitmap representation of database. Moreover, it

exploits horizontal and vertical transaction of the database to reduce the large number of generating rules. The rules are produced by considering the count from item support and class support. Finally, the generated rules are combined by eliminating redundancy.

The remaining part of this paper is organized as follows: Section 2 list out the various frequent pattern mining algorithms proposed in literature. In section3, the problems in existing frequent pattern mining methodology is described and elaborate the proposed work on transaction reduction technique. The experimental result and performance evaluation are illustrated in section 4. Section 5 contains conclusion along with future perspective.

II.RELATED WORKS

With the progressive explosion of huge volume of data, it is substantial to understand the features of data sets to enhance the performance of frequent pattern mining. Minimum support, one of the parameter used in frequent pattern mining algorithm that helps to extract more useful information for real world applications. Apriori is the frequent pattern mining algorithm that exhibits rare item problem due to high *minsup* value. The useful information is extracted only when the frequent patterns with low *minsup* is obtained. R. U. Kiran, *et al.* [9] proposed a frequent pattern mining approach named CFP-growth (Multiple Support Apriori and Conditional Frequent Pattern Growth), which consider multiple minsup framework and solve the rare item problem by mining both frequent and rare items. The frameworks include conditional minsup, least minsup, infrequent leaf node pruning and conditional closure property. One of the novel algorithm presented by J. Chen, *et al.* [4] is a BISC (Binary Item set Support Counting), which is responsible for efficient mining of frequent item set. According to this algorithm, support of all item sets in a database is derived with respect to direct supports. The context BISC transforms the database transaction into binary format. The memory consumption and the cost of support updating is minimized by integrating the two related techniques namely, one stage BISC (BISC1) and two stage BISC (BISC2). This technique is both time and space efficient because of BISC in conjunction with projection techniques that reduce the branching factor of database projection and maximum depth.

To produce frequent item sets with high speed processing of association rule mining, a conceit based on support approximation is used. With the problem of approximation error, accuracy is unstable in this concept. To address this shortcoming, support approximation in conjunction with clustering and CAC based mining method was proposed by K.-F. Jea, *et al.* [7]. The accuracy of the support approximation is enhanced by grouping the similar members. This technique enhances efficiency in mining the frequent patterns by less scanning of database. The interestingness of a pattern is measured by Apriori algorithm named Relative Support Apriori (RSA) that exhibit high computational cost and poor performance in pattern generation. These drawbacks can be addressed by R. U. Kiran, *et al.* [9] that discovers the frequent patterns using the measure relative support. To accomplish high performance, it is crucial that anti-monotonic property should be satisfied. The interestingness measure discovered using relative support satisfies the abovementioned property and leads to high performance with less computational cost. The properties of interestingness measure are analyzed by A. S. R. U. Kiran, *et al.* [8] [14] by discovering the interestingness of rare association rules. According to this analysis, the set of properties should be considered by the user at the time of selection of measure in order to discover the interestingness of associations.

Another frequent pattern mining technique proposed by K. Gouda, *et al.* [6] is based on backtrack search algorithm named Gen Max that mine the maximal frequent item sets. The search space is reduced by using a number of optimizations. The efficiency in mining the frequent item sets is accomplished by two techniques enclosed with this Gen Max i.e. diff set propagation to speed up the frequency checking and progressive focusing technique for the rejection of non maximal item sets. It is well known that building the candidate set of item set is the first step in the problem of frequent item set mining. Many of the Apriori based algorithm mainly focused only on reducing the number of database scan and the amount of candidate item sets. This in turn exhibit poor performance in terms of space and time. To overcome this shortcoming, BitTableF1 was proposed by J. Dong, *et al.* [5] that uses a special data structure to compress database in horizontally and vertically. This novel algorithm provides support count with quick candidate item set generation. Similarly, FPTree algorithm is used to discover the frequent item sets based on tree construction. This fails to meet the space and time requirements. So, a modified FPTree algorithm called Horizontal and vertical Compact Frequent Item set Pattern Mining Tree (HVCFPMINETREE) was proposed by A. Meenakshi, *et al.* [11] by which all the maximum occurrence of frequent item sets are combined before transforming into tree like structure.

To mine the sequential pattern in large database, an effective pruning mechanism called depth first strategy was introduced by J. Ayres, *et al.* [1]. This strategy defines the database in vertical bitmap format with effective support counting. For each item in the dataset, a vertical bitmap is constructed by which each data set transaction is represented as a bit. The value for items is set based on the item present in the transaction. The efficient support counting and candidate generation is obtained by partitioning the bitmap. An improved algorithm named LAPIN-SPAM (LAsT Position INduction Sequential PAttern Mining) was developed by Z. Yang, *et al.* [15] to mine the sequential pattern. The dissimilarity between previous algorithm and this strategy is that previous work scans the

database by using S-Matrix and SPADE is used to count the number whereas this framework performs the same task based on the current and last prefix position of an item.

S. K. Tanbeer, *et al.* [12] developed a new frequent pattern mining algorithm based on prefix tree that dramatically enhance the performance as compared to conventional Apriori based candidate generation. The tree structure called CP-tree (Compact Pattern Tree) that use single database scan in order to capture the dataset information. Moreover, it generates highly dynamic tree structure on descending frequency respectively. The branch sorting method used in conjunction with CP-tree reconstructs the prefix tree.

It is clear that generation of compact transaction database is substantial to mine the frequent pattern more effectively and efficiently. Q. Wan, *et al.* [13] proposed CT-Apriori based approach to produce transaction database compactly. The frequent pattern is generated by skipping the initial scanning of database thus reducing the search time and extracts the corresponding information. Many of the classical association rule mining encompass the capability of generating only simple rules. From a business perspective, it is often not useful, interesting and understandable at all times. Therefore further extraction of obtained learned rules is necessary in case of association rule mining. The concept of combined patterns was proposed that extract actionable knowledge and more helpful information from a voluminous amount of learned rules. The combined patterns involve combined rule clusters, combined association rules and combined rule pairs that contribute more interesting relation, knowledge and actionable result than the classical association rules [16] [3]. Technically, combined mining represents the combination of many data sources. It chooses the most important features from all sources and produce resultant patterns after combined them. The DDID-PD scheme for actionable pattern generation was proposed by M. S. R. Bhagwat, *et al.* [2] that exhibit good performance with decision making knowledge and reduced number of rules.

With the advancement in data mining applications, it is crucial to have reduced number of rules in pattern generation. The CCARM technique presented in [17] generate high number of rules that make difficult to find the frequent patterns. Hence, it is indispensable to develop an algorithm that overcomes the shortcoming in existing algorithm with reduced number of rules.

III. PROPOSED METHODOLOGY

Most of the preceding works on frequent pattern mining concentrate only on interestingness measures in order to find the items that occur frequently in the transaction of a database. This strategy leads to the generation of large number of rules that makes the user difficult to find the frequent patterns. The previously proposed algorithm CCARM (Combined and Composite Association Rule Mining) produces high number of rules and multiple database scans that negatively affect the mining performance by consuming more system resources. With that concern, an efficient transaction reduction technique termed TR-BC is proposed to address all the issues in existing pattern mining algorithm. This section defines the drawbacks exist in previously proposed CCARM technique and elaborates the newly proposed TR-BC with an illustrative example. The proposed transaction reduction algorithm is given below:

3.1 Bitmap representation of data set

The proposed framework incorporates vertical bitmap representation of the data to accomplish counting in an efficient manner. Consider the dataset, which is represented in Table 1. The training data set contains 8 transactions with 11 items and 3 class labels i.e. $T = \{1, 2, 3, 4, 5, 6, 7, 8\}$, $I = \{a, b, c, d, e, f, g, h, i, j, k\}$ and $C = \{A, B, C\}$. For each item in the data set, vertical bitmap is constructed. However, dataset transaction is corresponded by each bitmap that contains the bit. The vertical bitmap representation of the dataset given in Table 1 is exposed in Table 2. The major benefit of deploying vertical bitmap representation in the proposed method is that it provides convenience for efficient support counting.

Table 1: Training dataset with transaction

TID	Items	Class
1	a,c,f,i	A
2	a,d,f,j	B
3	b,e,g,k	A
4	a,d,h,k	C
5	a,d,f,k	C
6	a,k	B
7	f,g	A
8	h	C

The vertical bitmap representation maps an item that appears in transaction and set the bit 0 and 1 accordingly. Let us consider, we have a bitmap for item a and a bitmap for item b . These two bitmaps are helpful to create the bitmap for the item set $\{a,b\}$ based on performing bitwise AND operation.

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1. Algorithm: Transaction Reduction for TR-BC technique.
2. Input: Dataset D
3. Output: Reduced item set R
4. Begin
5.   Read D = {I, T, C}           // I→ items, T→Transaction id, C→class variable
6.   Transform D to Bitmap representation
7.   If I present T then
8.     Set  $I_p=1$  //  $I_p$ → items present in transaction
9.   Else
10.    Set  $I_p=0$ 
11.  End if
12.  For each transaction count F // frequent Items
13.    If  $I_p==1$ 
14.      Count F
15.      Increment the Transaction
16.    Else
17.      Move to next item in transaction
18.    End if
19.  Sort T in ascending order upon Count
20.  Database scan and record support for I
21.   $Min_{sup} = Min(F) + Max(F)/S$  //  $S$ → fixed support by user (E.g. 3 support)
22.  If  $F \leq Min_{sup}$ 
23.    Discard T
24.  Else
25.    Record F as  $I_r$  //Reduced Item set
26.  End if
27.  Vertical Bit map for  $I_r$  and class C
28.  Identify Items according to C
29.  If  $C \leq Min.Sup$ 
30.    discard item set  $I_r$ 
31.  Else
32.    Record  $I_r$  as R // Reduced Item set from  $I_r$ 
33.  Improved Vertical Bit map for R
34.  End if
35. End

```

Algorithm1: Proposed Transaction Reduction

Table 2: Bitmap representation of the dataset in table 1

TID	a	b	c	d	e	f	g	h	i	j	k
1	1	0	1	0	0	1	0	0	1	0	0
2	1	0	0	1	0	1	0	0	0	1	0
3	0	1	0	0	1	0	1	0	0	0	1
4	1	0	0	1	0	0	0	1	0	0	1
5	1	0	0	1	0	1	0	0	0	0	1
6	1	0	0	0	0	0	0	0	0	0	1
7	0	0	0	0	0	1	1	0	0	0	0
8	0	0	0	0	0	0	0	1	0	0	0

For instance, the data set information is converted into bitmap using 0 and 1. In the item set $\{a,b\}$, if the item a present in transaction b , then the bit relating to transaction b of the bitmap for item a is assigned as 1 or else the bit is assigned as 0.

3.2 Proposed Transaction reduction based on bitmap and class labels

The proposed methodology exploits horizontal and vertical transaction of the data set that automatically reduce the entire database scanning. In horizontal transaction, the number of 1's in each transaction is counted horizontally. Based on that count, the transactions are sorted in ascending order. Table 3 represents the horizontal transaction for the given data set.

Table 3: Horizontal transaction reduction

TID	a	b	c	d	e	f	g	h	i	j	k	Count
8	0	0	0	0	0	0	0	1	0	0	0	1
6	1	0	0	0	0	0	0	0	0	0	1	2
7	0	0	0	0	0	1	1	0	0	0	0	2
1	1	0	1	0	0	1	0	0	1	0	0	4
2	1	0	0	1	0	1	0	0	0	1	0	4
3	0	1	0	0	1	0	1	0	0	0	1	4
4	1	0	0	1	0	0	0	1	0	0	1	4
5	1	0	0	1	0	1	0	0	0	0	1	4

Now, the corresponding item set is extracted directly without moving for entire database scanning. If we need 3 item set means, it is not necessary to check the above 2 counts. It is sufficient to go for count = 3 transactions only. The database scan starts with 3rd count to the maximum. Hence, it is unessential to go 1 and 2 counts.

Table 4: Item set = 3 (so we start with 3rd count to max)

TID	a	b	c	d	e	f	g	h	i	j	k	Count
1	1	0	1	0	0	1	0	0	1	0	0	4
2	1	0	0	1	0	1	0	0	0	1	0	4
3	0	1	0	0	1	0	1	0	0	0	1	4
4	1	0	0	1	0	0	0	1	0	0	1	4
5	1	0	0	1	0	1	0	0	0	0	1	4

From table 4, it is clear that we can acquire 3 item sets directly from the training data set without go for 1 and 2 counts. Here, no counts for 3. So, we go directly to the 4th count (max) and extract item sets. By this way, the transaction is reduced horizontally.

Now, the data base is scanned at once and the support for each item given in table 3 is counted. The item support for {a = 4, b = 1, c = 1, d = 3, e = 1, f = 3, g = 1, h = 1, i = 1, j = 1, k = 3}. The minimum support value is 2, which is derived from the maximum and minimum frequency of item support i.e. $Min_{sup} = \frac{Min(F) + Max(F)}{3}$. The frequent item set are acquired based on item support that meets the minimum support threshold [17]. The frequent item set that is acquired after reduction is given as $Items = \{a, d, f, k\}$. For the obtained item sets {a, d, f, k}, the rules are generated as follows: {a, d}, {a, f}, {a, k}, {d, f}, {d, k}, {f, k}, {a, d, f}, {a, f, k}, {d, f, k} and the formulated combined rules without redundancy are furnished as follows: a->d, f; a->d, k; a, f->k; a, d->f, k.

Table 5: Vertical bitmap for data set

TId	a	d	f	k	A	B	C
1	1	0	1	0	1	0	0
2	1	1	1	0	0	1	0
3	0	0	0	1	1	0	0
4	1	1	0	1	0	0	1
5	1	1	1	1	0	0	1

The vertical bitmap for the acquired frequent item set along with the class variables are given in table 5. The database is scanned to count the support for both item and class variables. Existing algorithm record the support for item only. But, the proposed methodology records the support for both items and class labels to generate the result with reduced number of rules. The item support is counted based on number of 1's (frequent) for each item vertically. The class support is counted based on that item, which corresponds horizontally. The obtained item and class support are given as, a = 4 (A:1, B:1, C:2), d=3 (A:0, B:1, C:2), f=3 (A:1, B:1, C:1), k=3 (A:1, B:0, C:2). The transaction reduction is accomplished by identifying the items through the support of both item and corresponding class label whose values are greater than the value of computed minimum support.

Now, the reduced item set is $\{a, d, k\}$. Since, the class support for the item $f = 1$ which fails to meet the minimum support threshold.

Table 6: The enhanced vertical bitmap for data set

TId	a	d	k	A	B	C
1	1	0	0	1	0	0
2	1	1	0	0	1	0
3	0	0	1	1	0	0
4	1	1	1	0	0	1
5	1	1	1	0	0	1

The resultant vertical bitmap for the proposed methodology is shown in table 6. For the obtained item sets $\{a, d, k\}$, the rules are generated as follows: $\{a, d\}$, $\{a, k\}$, $\{d, k\}$ and $\{a, d, k\}$. The formulated combined rules after eliminating the redundancy is $a \rightarrow d, k$.

Notice the discrepancy between table 5 and table 6, the total rules for the item set $\{a, d, f, k\}$ is 9 and the combined rules is 4 whereas the total rules for the item set $\{a, d, k\}$ is only 4 and the combined rules is only 1. With this strategy, it is understandable that the number of rules generation can be reduced after accumulating the record of class variables. For instance, it reduces multiple scanning of database; enhance the efficiency of rule generation and save the storage space more effectively.

IV. EXPERIMENTAL ANALYSIS

To evaluate the effectiveness of proposed transaction reduction technique, a series of experiment is percolated thereby performance validation is carried out. The experimental data set are retrieved from UCI machine learning repository that contains items and class labels with a transaction limit of 40. The proposed approach is compared with the previously proposed CCARM technique in order to expose the superiority of the newly presented transaction reduction technique.

The frequent item set is determined based on minimum support value. If the support for the item is greater than the minimum support threshold then the item is said to be frequent item. The proposed framework compresses the data set into vertical bitmap format in order to accomplish efficient support counting.

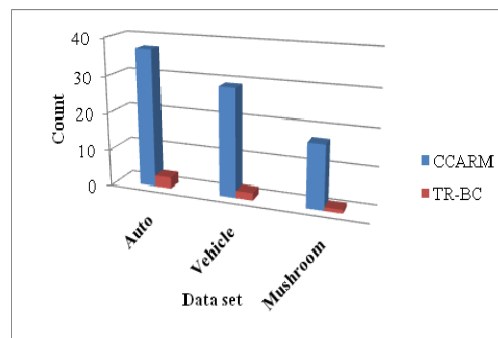


Fig 1: Rule comparison of CCARM with TR-BC

The previously proposed CCARM [17] generate combined rules by counting the item support only. This in turn generates large number of rules with multiple scanning of database. Fig 1 exhibits the rule comparison of existing CCARM with proposed TR-BC. Generation of large number of rules negatively affect the mining performance. From fig 1, it is clear that proposed transaction reduction technique significantly results reduced number of rules by using vertical bitmap and class variables.

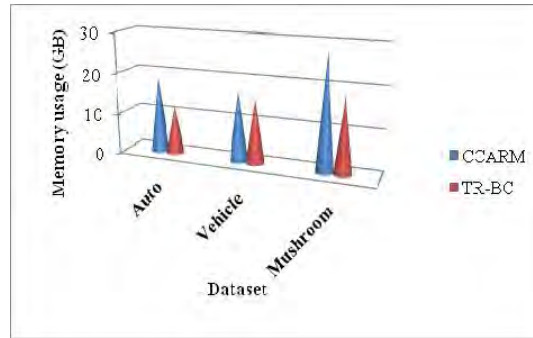


Fig 2: Memory usage comparison of CCARM with TR-BC

The previously proposed CCARM record the item support only whereas proposed transaction reduction technique accumulate the count of class labels in addition to item support. Hence, the proposed approach accomplishes reduced number of rules.

Next, the memory usage (GB) of proposed algorithm is tested, which reveals that it consume less memory than the existing technique due to reduced number of database scanning (Fig 2).

To gain better mining performance, it is indispensable to reduce the database transaction. Based on this motivation, proposed algorithm explores horizontal and vertical transaction reduction.

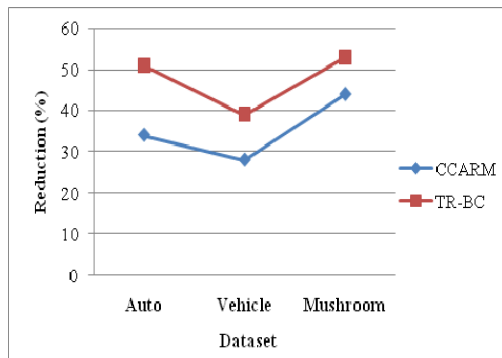


Fig 3: Transaction reduction comparison of CCARM with TR-BC

According to this approach, the item sets are acquired directly without go for entire database scanning. It is illustrated in section 3 in a detailed manner. From fig 3, it is obvious that proposed technique has high transaction reduction than the existing CCARM.

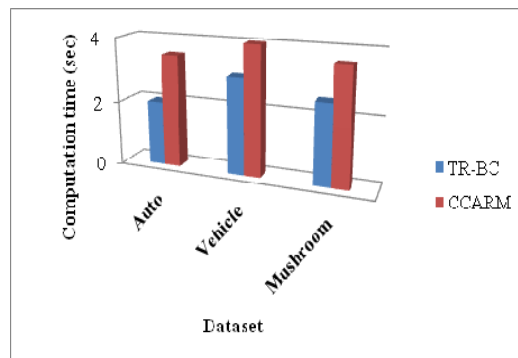


Fig 4: Computation time comparison of CCARM with TR-BC

The existing technique takes high computation time for minimum support and item support whereas proposed algorithm accommodate less computation time to create the bitmap and support count. The computation time taken by proposed algorithm is significantly lesser than the existing methodology as shown in fig 4.

From the experimental evaluation, it is reported that proposed algorithm yields higher performance in terms of reduced number of rules, low memory usage, high transaction reduction, less computational time and greater accuracy.

V. CONCLUSION

The most substantial field in data mining is the discovery of frequent objects like sequential pattern and item sets. It is a well known fact that it requires less number of database scanning, reduced number of rules, time and space efficiency. With that concern, an efficient transaction reduction approach named TR-BC is presented in this paper that compress the database storage by exploiting vertical bitmap thereby reducing the multiple scanning of database. The number of rules generation can be reduced by adding the count of class labels in addition to item support. The experimental evaluation compares the efficiency of the proposed approach with existing methodology in terms of rule count, memory usage, computing time and transaction reduction. Evidently, it is proven that proposed approach exhibits more feasibility and effectiveness in the rule generation of frequent pattern mining.

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