Efficient Association Rule Mining using Hybrid Techniques

Venu Mishra¹ and Dr. Meenu Dave²

¹M.Tech. Scholar, ²Assistant Professor,
Department of CSE, Jagan Nath University, Jaipur, India
Venu0110mishra@gmail.com, meenu.dave@jagannathuniversity.org

Abstract

As the information is increasing day by day, there is abundance of data but it is not very easy to draw the accurate or required knowledge. Improved and efficient mining techniques are needed to acquire the useful knowledge. In this paper, an algorithm is proposed that is based on count and record filtering techniques. Count based method is used for pruning of candidate itemset and record filtering technique is used to reduce data scan. Experiments show that this algorithm reduces the overall time of mining.

Keywords: ARM, AIS, SETM, Apriori, DIC, support, confidence

INTRODUCTION

With the betterment of technology and increase in the data generated, new data storage techniques like cloud computing and service oriented architecture are needed for integrating scattered data and finding interesting information out of that, and this is a new growing challenge. This information cannot be extracted by the traditional methods such as firing of queries or statistical analysis. It can be used in classification of the data and in prediction of future events etc. So far many techniques have been implemented that are used in data mining. Association rule mining is one of the techniques.

Classical algorithms for mining have two major problems first is the redundant candidate generation and the other is the number of database scans. In this paper some classical and improved mining algorithms are discussed but still there is a need to improve the quality of the mining algorithms by reducing the candidate generation and database scans. In section II, frequent pattern mining is discussed. Section III covers the proposed algorithm concepts. Section IV shows the experimental results of the proposed algorithm and the Apriori algorithm.
FREQUENT PATTERN MINING
Frequent pattern mining is to find the frequent and interesting patterns from the large databases. Frequent patterns are then used to create the association rules for further predictions, that is called association rule mining. We can define association rule mining problem as: Let DB be a database of transactions; each transaction consists of I, where I is \{i_1, i_2, i_3…i_n\} items. Association rules are in the form of

\[ A \rightarrow B, \text{ where } A \subset I, B \subset I \text{ and } A \cap B = \phi. \]

Each association rule has support and confidence that specifies the significance of the association rule. Support denotes the occurrence of item in the database DB. Confidence is the proportion of the data items containing B in all the items containing A also, in DB.

\[
Sup(A) = \frac{Count(A)}{Count(DB)} \\
Sup(A \rightarrow B) = \frac{Sup(A \cup B)}{Sup(A)} \\
Conf(A \rightarrow B) = \frac{Sup(A \cup B)}{Sup(A)}
\]

If the support and confidence of the rule is greater or equal to the threshold value minimum support and minimum confidence, then the rule is considered as a valid rule, otherwise it is discarded. The objective of the ARM is to find the set of the valid association rules [1, 2].

Many algorithms were proposed to perform ARM on transactional databases. Comparative analysis of some of them is described below:

Apriori Algorithm
Apriori algorithm states that itemset x containing subset itemset y is never frequent if y is not frequent. Based on this principle, Apriori generates new itemsets of length K+1 using k frequent itemsets. And eliminates rest of the elements, which have infrequent itemsets. So Apriori generates new itemsets by using frequent itemsets of previous itemset without considering transaction. But it considers transaction for counting of support of the new candidates. Problem with this algorithm is that, it is more time consuming because it generates redundant candidates itemsets, and it requires database scan at each pass for counting support of the itemset [3, 4].

AprioriTid & AprioriHybrid
This algorithm uses the concept of the Apriori, and is better than Apriori in terms of database scan. It makes TIDs at each pass. It just scans database in the first pass. After that, it uses Tid’s for counting, but the major downside of this algorithm is the generation of the Tid table at each pass.

Another algorithm, called Apriori Hybrid, introduced in [6], uses the combination of Apriori and aprioriTid. Idea behind this algorithm is to run the Apriori algorithm initially, when transactions are large and then switch to the AprioriTid algorithm when the generated database, i.e. large k itemset in the transaction with identifier TID, would fit in the memory [10].
Partition Algorithm
Partitioning algorithm[8], uses the concept of partitioning the database in parts. Algorithm consists of two phases. In the first phase, we partition the database in n partitions that are not overlapping and can fit into the memory; and start mining on the partitions. With every iteration, one partition is considered which finds frequent itemsets that are local to that partition. In second phase, these local frequent itemsets are combined to find global frequent itemsets[4, 10].

Dynamic Itemset Counting (DIC)
In DIC, candidate (k+1) itemsets are counted as soon as the algorithm discovers that all its subsets of size k have exceeded the support threshold and will be frequent. This is done by stopping at various points in the database to examine the possibility of including other itemsets in the counting procedure. It has been found that such techniques, with reasonable setting of the number of transactions passed before stopping for recalculation, can reduce the number of database passes dramatically while maintaining the number of candidate sets that need to be counted relatively less compared to other proposed techniques [5, 10].

Algorithms discussed so far are all mining algorithms but still all have some deficiencies and none is perfect on all type of datasets. Some of the shortcomings of the ARM algorithms are given in Table 1:

<table>
<thead>
<tr>
<th>S.No.</th>
<th>Algorithm</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AIS</td>
<td>AIS algorithm unnecessarily generates and counts too many candidate item sets. This algorithm requires too many passes over the whole database.</td>
</tr>
<tr>
<td>2</td>
<td>SETM</td>
<td>The problem with the SETM algorithm is that candidates are replicated for every transaction in which they occur, which results in huge sizes of intermediate results.</td>
</tr>
<tr>
<td>3</td>
<td>Apriori</td>
<td>Problem with this algorithm is that it is more time consuming because it generates redundant candidate itemsets and it requires database scan at each pass for counting support of the itemset.</td>
</tr>
<tr>
<td>4</td>
<td>AprioriTid &amp; AprioriHybrid</td>
<td>The size of database is limited to the main memory size. Second problem is the pruning of the database in the later stages of the algorithm. i.e., removing the part that will not be used further for mining process.</td>
</tr>
<tr>
<td>5</td>
<td>Dynamic itemset counting</td>
<td>Used only to find the frequent items; can’t used to generate association rules.</td>
</tr>
<tr>
<td>6</td>
<td>Partitioning algorithm</td>
<td>Sometimes, all frequent patterns are not found.</td>
</tr>
</tbody>
</table>
It requires several scans over the database for the construction of the FP-Tree. Whole mining process should be repeated whenever the support value is changed, as well when a new dataset is inserted into the database.

All frequent patterns are not found.

PROPOSED ALGORITHM (ICA)
Process of this algorithm can be divided in two steps after the generation of 1st candidate set. One step is the prune step and the other is count step. So we will use count based technique to improve the pruning process and e record filter technique improves the database scan to count occurrence of candidates. Details of these two methods are described below:

**Count based candidate pruning method**

Let $L_k$ denote the set of k-dimensional frequent itemsets and $C_k$ denote the set of frequent itemsets. $\overline{L_k}$ denotes the complement of $L_k$ set.

**Theorem1:** If any itemset X is frequent then every subset of X will also be frequent [1].

**Deduction 1:** If itemset X is infrequent then every superset of X is also infrequent.

To check if c is a frequent itemset or not, the apriori algorithm uses $L_{k-1}$, if $\exists s \notin L_{k-1}$, where s is subset of c, then c is not frequent itemset. In contrast to Apriori, HDO Apriori algorithm [9] uses $\overline{L_{k-1}}$ to remove infrequent itemsets. The pruning time of Apriori and HDO Apriori algorithm is based on the reference collection of $L_{k-1}$ and $\overline{L_{k-1}}$. Proposed algorithm uses a count based candidate prune operation.

**Deduction 2:** All k-dimensional frequent candidates are generated from (k-1)-dimensional frequent itemsets that have only one different itemset.

**Proof:** Let {L, a, b} and {L, d, c} be (k-1)-dimensional frequent itemsets with two different itemsets, so if k-dimensional itemsets {L, a, b, c} is frequent, using Theorem 1, {L, a, b} must also be frequent.

But {L, a, b, c} can be generated from {L, a, b} and {L, b, c}, so it concludes that generated set of {L, a, b} and {L, d, c} is redundant.

If k-dimensional itemset c is frequent, all its (k-1) dimensional itemsets are also frequent and two of these will generate c once. So if the total count is less than two, then it is sure that the item generated is not frequent itemset. Thus, it could be removed from further processing.
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**Figure 1:** counting based method for pruning

**Record Filter Approach**

Record Filter approach improves the efficiency of Apriori by memory management and removes the complexity of process. This uses a different approach in Apriori algorithm to count the support of candidate item set. In the classical Apriori algorithm, counting process covers all the transactions in each pass. But, record filter approach counts the support of candidate set only in the transaction record whose length is greater than or equal to the length of candidate set. As candidate set of length \( k \) cannot exist in the transaction record of length \( k-1 \), it may exist only in the transactions of length greater than or equal to \( k \).

**Figure 2:** Flow chart to show steps of the algorithm
**Improved counting based algorithm (ICA)**

Input: $DB_T, \text{Sup}_{\min}$ and $\text{Conf}_{\min}$

Output: association rules

Begin
   scan database get $L_1$ /* L1 list of 1-itemset $k := 2$; */

While ($L_{k-1} \neq \phi$) {
   //to perform pruning use count based method
   $C_k$ = count Based Pruning ($L_{k-1}$)

   For each $c \in C_k$ {
      for all $t \in DB_T$ where length of $t$ :length $\geq k$ {
         Increment the count of all candidates in $C_k$ that are contained in $t$
      }
   }
   Store $L_k$ = All candidates in $c \in C_k$ | $\text{Sup}_{\min} \geq \text{sup}_{\min}$:
   $k := k + 1$;
}

Use $L_k$ to generate association rules in $C \Rightarrow R$

Figure 3: Complete Proposed Algorithm

**EXPERIMENTAL RESULTS**
Analysis of this algorithm is done on 5.3GHz Intel® on window 7. Programs are coded on the platform of MATLAB 7.10.0(R2010a).

The experiment compares the runtime of the two algorithms Apriori and the proposed algorithm ICA.

First analysis is with the increasing transaction size and next one is with increasing the support count. Through given result we can see that there is Approximate 50% mining times is reduced by the ICA algorithm.

Next comparison is using the sampling technique that also shows the good results.
Measuring Performance With Increasing Database size

**Figure 4:** Comparative Analysis between Apriori and ICA with increasing number of transactions

**Table 2:** Comparative time for ICA and Apriori with increasing transactions

<table>
<thead>
<tr>
<th>Number of transactions</th>
<th>Apriori</th>
<th>ICA</th>
</tr>
</thead>
<tbody>
<tr>
<td>203</td>
<td>13.76</td>
<td>8.99</td>
</tr>
<tr>
<td>406</td>
<td>25.37</td>
<td>17.66</td>
</tr>
<tr>
<td>812</td>
<td>149.67</td>
<td>103.317</td>
</tr>
<tr>
<td>1200</td>
<td>188.55</td>
<td>118.691</td>
</tr>
<tr>
<td>1890</td>
<td>240.3</td>
<td>146.71</td>
</tr>
</tbody>
</table>

Measuring Performance With Increasing Support Count

**Figure 5:** Comparative analysis of Apriori and ICA with variant support count
Table 3: Comparative time for ICA and Apriori with variant support count

<table>
<thead>
<tr>
<th>Support count</th>
<th>Apriori (time in sec)</th>
<th>ICA (time in sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>179.644</td>
<td>122.359</td>
</tr>
<tr>
<td>3</td>
<td>180.319</td>
<td>122.376</td>
</tr>
<tr>
<td>5</td>
<td>186.35</td>
<td>123.049</td>
</tr>
<tr>
<td>8</td>
<td>55.4627</td>
<td>40.62</td>
</tr>
<tr>
<td>10</td>
<td>55.2617</td>
<td>40.53</td>
</tr>
</tbody>
</table>

Measuring Performance With Sampling

![Bar chart](image)

Figure 6: Comparative analysis of Apriori and ICA with sampling

Table 4: Comparative time for ICA and Apriori with sampling

<table>
<thead>
<tr>
<th>Number of transactions</th>
<th>Apriori with sampling (time in sec)</th>
<th>ICA with sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>1200</td>
<td>30.94</td>
<td>23.05</td>
</tr>
<tr>
<td>800</td>
<td>20.52</td>
<td>14.52</td>
</tr>
<tr>
<td>400</td>
<td>13.01</td>
<td>9.2</td>
</tr>
</tbody>
</table>

CONCLUSION

In this paper, an improved apriori algorithm is proposed that is based on counting based and record filter techniques. Pruning process of ARM is improved through count based technique and reduces the database scans through record filtering technique. This is notable using the experimental results and comparisons, where the proposed algorithm has improved the overall performance by reducing the time. This algorithm needs to be tested for incremental mining and constraint based mining and further research is required to implement this in the distributed environment.
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