Efficient Analysis of Closed Frequent Pattern Set Mining Approach

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Abstract: Many researchers’ unreal ideas to get the frequent item sets/pattern sets. Some frequent pattern mining often produces a large number of frequent patterns, which imposes a great challenge on visualizing, understanding and further analysis of the generated patterns. This emerges the need for finding small number frequent occurring patterns. The time needed for generating frequent pattern sets plays important role. Some algorithms are designed, considering solely the time issue. Our study includes analysis of algorithms that are used to find frequent pattern sets by using the technique of closed pattern sets.

Keywords: frequent pattern, closed pattern, analysis, frequent items, pattern mining

1. Introduction

Data mining is the process of finding new patterns from large amount of data. Data mining is a process of extraction of useful information and patterns from huge data. It is also called as knowledge discovery process, knowledge mining from data, knowledge extraction or data/pattern analysis. The goal of this technique is to find patterns that were previously unknown. Once these patterns are found they can further be used to make certain decisions for development of their businesses. Data mining aims to discover implicit, previously unknown, and potentially useful information that is embedded in data. As a common data mining task, frequent itemset mining [1–3] looks for itemsets (i.e., sets of items) that are frequently co-occurring together. It has been well recognized that frequent pattern mining plays an essential role in many important data mining tasks, e.g., associations, sequential patterns, episodes, partial periodicity, etc. However, it is also well known that frequent pattern mining often generates a very large number of frequent itemsets and rules, which reduces not only efficiency but also effectiveness of mining since users have to sift through a large number of mined rules. There is an interesting alternative, proposed recently by Pasquier et al. [4]: instead of mining the complete set of frequent itemsets and their associations, association mining only needs to find frequent closed itemsets and their corresponding rules. An itemset X is a closed frequent itemset in set S if X is both closed and frequent in S. An important implication is that mining frequent closed itemsets has the same power as mining the complete set of frequent itemsets, but it will substantially reduce redundant rules to be generated and increase both efficiency and effectiveness of mining.

Let’s examine a simple example. Suppose a database contains only two transactions, “{(a1, a2, …, a100), (a1; a2; … ; a50)}”, the minimum support threshold is 1 (i.e., every occurrence is frequent), and the minimum confidence threshold is 50%. The traditional association mining method will generate 2¹⁰⁰ – 1 ≈ 10⁶⁰ frequent itemsets, which are (a1), …, (a100), (a1; a2), …, (a99; a100), …, (a1; a2; … ; a100), and a tremendous number of association rules, whereas a frequent closed itemset mining will only generate two frequent closed itemsets: [(a1; a2; … ; a50), (a1; a2; … ; a100)], and one association rule, “(a1; a2; … ; a50) \rightarrow (a51; a52; … ; a100)”, since all the others can be derived from this one easily. Pasquier et al. [5] propose an Apriori-based mining algorithm, called A-close. Zaki and Hsiao [10] propose another mining algorithm, CHARM, which improves mining efficiency by exploring an item-based data structure. According to our analysis, A-close and CHARM are still costly when mining long patterns or with low minimum support thresholds in large databases. As a continued study on frequent pattern mining without candidate generation [10], we propose an efficient method for mining closed itemsets. Three techniques are developed for this purpose: (1) the framework of a recently developed efficient frequent pattern mining method, FP-growth [10], is extended, (2) strategies are devised to reduce the search space dramatically and identify the frequent closed itemsets quickly, and (3) a projection-based projection mechanism is established to make the mining efficient and scalable for large databases. Our performance study shows that CLOSET is efficient and scalable over large databases, and is faster than the previously proposed methods.

2. Literature Review

Mining frequent closed itemsets with projected database: An example

Let’s examine how to mine frequent closed itemsets using the following example. Example (CLOSET) For the same transaction database TDB in Table 1 with min_sup = 2, we introduce a divide-and-conquer method for mining frequent closed itemset. The method explores the concepts of projected database [5,6], 1. Find frequent items. Scan TDB to find the set of frequent itemsets, called f_list, and f_list = {c : 4, e : 4, f : 4, a : 3, d : 2}, where the items are sorted in support descending order, and the number after “:” indicates the support of the item. Foreasier understanding, the frequent items in each transaction are listed in Figure 1 according to the order of list and any infrequent item, such as b, is omitted. For example, abe is listed as ea.

2. Divide search space. All the frequent closed itemsets can be divided into 5 non-overlap subsets based on the f_list: (1) the ones containing item d, (2) the ones containing item a but no d, (3) the ones containing item f but no a nor d, (4)
the ones containing e but no f, a nor d, and (5) the one containing only c. Once all frequent closed itemsets are found, the complete set of frequent closed itemsets is done.

3. Find subsets of frequent closed itemsets. The subsets of frequent closed itemsets can be mined by constructing corresponding conditional databases and mine each recursively.

(a) Find frequent closed itemsets containing d. Only transactions containing d are needed. The d-conditional database, denoted as TDB|d, contains all the transactions having d, which is \{cefa, cfa\}. Notice that item d is omitted in each transaction since it appears in every transaction in the d-conditional database. The support of d is 2. Items c, f, and a appear twice respectively in TDB|d. That is, every transaction containing d also contains c, f, and a. Moreover, e is infrequent since it appears only once in TDB|d. Therefore, cfd : 2 is a frequent closed itemset. Since this itemset covers every frequent item in TDB|d, the mining of TDB|d finishes.

(b) Find frequent closed itemsets containing a but no d. Similarly, the a-conditional database, TDB|a = \{ce, ef, cf\}. Item d in such transactions are omitted, since all frequent closed itemsets containing d have been found in TDB|d. Since sup(a) = 3 and there is no item appearing in every transactions in the a-conditional database, a : 3 is a frequent closed itemset. To find the remaining frequent closed itemsets containing a but no d, we need to further project the conditional database. First, the set of frequent items in the a-conditional database forms a local frequent item list, f_list = \{e : 2, c : 2, f : 2s^3\}. Local infrequent item is ignored even if it is in global f_list. According to f_list, the frequent closed itemsets containing a but no d can be further partitioned into three subsets: (1) the ones containing afbuto d, (2) the ones containing aebut not d or f, and (3) the ones containing ac but not d, e or f. They can be mined by constructing conditional databases recursively. Support of fa equals to that of cfa, which is a super set of fa and also a frequent closed itemset already found. That means every transaction containing famust also contain cfa. Therefore, there is no frequent closed itemset containing fa but no d. Similarly, there is no frequent closed itemset containing cabut not d, e or f, since ca is a subset of cfa and sup(ca) = sup(cfa). The ea-conditional database, TDB|a = \{e\}, cannot generate any frequent items. Thus, ea : 2 should be a frequent closed itemset. (c) Find frequent closed itemsets containing f but no a nor d. The f-conditional database, TDB|f = \{ce : 3, c\}, where ce : 3 indicates that ce happens three times. Since c happens in every transaction in the f-conditional database, and cf is not a subset of any frequent closed itemset with the same support, cf : 4 is a frequent closed itemset. Since the support of fc also equals to those of f and c, f and c always happen together, so there is no frequent closed itemsets containing c but not f. Also, that cef : 3 is not a subset of any itemset found, so it is a frequent closed itemset. (d) Find frequent closed itemsets containing e but no f, a nor d. Similarly, the e-conditional database, TDB|e = \{ce : 3\}. But ce is not a closed itemset since it is a proper subset of cef and sup(ce) = sup(ce). However, e : 4 is a frequent closed itemsets. (e) Find frequent closed itemsets containing only c. In Step 3c, we know that there is no frequent closed itemsets containing c but not f, so there is no frequent closed itemsets containing only c. 4. In summary, the set of frequent closed itemsets found is \{acdf : 2, a : 3, ae : 2, cf : 4, cef : 3, e : 4\}.

### Algorithm 1 (CLOSET): Mining frequent closed itemsets by the FP-tree method.

**Input:** Transaction database TDB and support threshold min_sup;

**Output:** The complete set of frequent closed itemsets;

**Method:**

1. Initialization. Let FCI be the set of frequent closed itemset. Initialize FCI = \{\};

2. Find frequent items. Scan transaction database TDB, compute frequent itemlist f_list;


### 3. Problem Study

#### 3.1. Need of Frequent Itemset Mining

Studies of Frequent Itemset (or pattern set) Mining is acknowledged in the data mining field because of its broad applications in mining association rules, correlations, and graph pattern constraint based on frequent patterns, sequential patterns, and many other data mining tasks. Efficient algorithms for mining frequent itemsets are crucial for mining association rules as well as for many other data mining tasks. The main challenge found in frequent pattern mining is a large number of result patterns. As the minimum threshold becomes lower, an exponentially large number of itemsets are generated. Therefore, pruning unimportant patterns can be done effectively in mining process and that becomes one of the main topics in frequent pattern mining. Consequently, the main aim is to optimize the process of finding patterns which should be efficient, scalable and can detect the important patterns which can be used in various ways clusters and lots of additional of which the mining of association rules is one amongst the foremost widespread problems. The first motivation for looking out association rules came from the necessity to investigate thus referred to as grocery store dealing data, that is, to look at client behavior in terms of the chips (80%)" states that four out of 5 customers that bought beer conjointly bought chips. Such rules are often helpful for selections

#### 3.2 Problem Definition

Let I = \{i_1, i_2, ..., i_m\} be a set of items. AnitemsetX is a nonempty subset of I. For brevity, itemsetX = \{i_{j_1}, i_{j_2}, ..., i_{j_n}\} can also be denoted as X = i_{j_1} i_{j_2} ... i_{j_n}. An itemset with m items is called an m-itemset. Duple <tid,X> is called a transaction if tid is a transaction identifier and X is an itemset. A transaction database TDB is a set of transactions.

**Table 1:** The transaction database TDB

<table>
<thead>
<tr>
<th>Transaction ID</th>
<th>Items in transaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>a; c; d; e; f</td>
</tr>
<tr>
<td>20</td>
<td>a; be</td>
</tr>
<tr>
<td>30</td>
<td>c; ef</td>
</tr>
<tr>
<td>40</td>
<td>a; cd; f</td>
</tr>
<tr>
<td>50</td>
<td>c; ef</td>
</tr>
</tbody>
</table>


An itemset X is contained in transaction (tid, Y) if X \subseteq Y. A pattern is closed if it is more frequent than all of its supersets. A pattern is closed frequent if its support is no less than \text{min} \_ \text{sup}. If a set of patterns R \subseteq \text{supp}(X)\cup\text{supp}(X'), then R \subseteq \text{supp}(X)\cup\text{supp}(X').

Lemma 1. Given two patterns X1 and X2 such that X1 \subseteq X2 and \text{supp}(X1) = \text{supp}(X2), if X2 is \epsilon\text{-covered by a pattern X}, then X1 must be \epsilon\text{-covered by X too.}

Lemma 2. Let F be the set of frequent patterns in a dataset D with respect to a threshold \text{min} \_ \text{sup}. If a set of patterns R \epsilon\text{-covers all the frequent closed patterns in F}, then R \epsilon\text{-covers all the frequent patterns in F.}

Lemma 3. Given two patterns X1 and X2 such that X1 \subseteq X2 and \text{supp}(X1) = \text{supp}(X2), if a pattern X is \epsilon\text{-covered by X1}, then X must be \epsilon\text{-covered by X2 too.}

This lemma also directly follows from Definition 2. It suggests that we can use closed patterns only to cover all frequent patterns. The number of frequent closed patterns can be orders of magnitude smaller than the total number of frequent patterns. Consider only closed patterns improves the efficiency of the MinRPset algorithm in two aspects. On one hand, it reduces the size of individual C(X) since now they contain only frequent closed patterns. On the other hand, it reduces the number of patterns whose C(X) needs to be generated as now we need to generate C(X) for closed patterns only.

Algorithm MinRPset Algorithm

\text{Description:}
1: Mine patterns with support \geq \text{min} \_ \text{sup} \cdot (1-\epsilon) and store them in a CFP-tree;
2: DFS\_Search\_CXs(root);
3: Remove non-closed entries from C(X)s;
4: Apply the greedy set cover algorithm on C(X)s to find representative patterns and output them;

When \epsilon=0, the representative patterns are closed frequent patterns[14].

5. Result and Discussion

The proposed technique generates fewer number of closed frequent patterns than the previous algorithms. MinRPsetadditional benefits besides producing fewer representative patterns:

Users may not know what value should be used for \text{min} \_ \text{sup} at the beginning. The post-processing strategy allows users to try different \text{min} \_ \text{sup} values without missing frequent patterns multiple times. This is especially beneficial on very large datasets as number of dataset increases, time also increases Graph shows as the size of dataset doubles, times approximately doubles.

6. Conclusion

Mining complete set of itemsets often suffers from generating a very large number of itemsets and association rules. However, the proposed method reduces the number of patterns to be generated and uses a CFP-tree to efficiently generate representative patterns. As the number of dataset increases, time also increases Graph shows as the size of dataset doubles, times approximately doubles.
rules. Mining frequent closed itemsets provides an interesting alternative since it inherits the same analytical power as mining the whole set of frequent itemsets but generates a much smaller set of frequent itemsets and leads to less and more interesting association rules than the former. In this paper, we proposed MinRPSet algorithm for locating minimum frequent pattern sets is introduced. It mines frequent patterns, and then finds closed frequent patterns during a post-processing step. As a result of the utilization of the post-processing strategy, MinRP set have the extra benefits besides giving fewer representative patterns.

References


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