Survey on Frequent Item set Mining Algorithms

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ABSTRACT

Many researchers invented ideas to generate the frequent itemsets. The time required for generating frequent itemsets plays an important role. Some algorithms are designed, considering only the time factor. Our study includes depth analysis of algorithms and discusses some problems of generating frequent itemsets from the algorithm. We have explored the unifying feature among the internal working of various mining algorithms. Some implementations were done with KDD cup Dataset to explore the relative merits of each algorithm. The work yields a detailed analysis of the algorithms to elucidate the performance with standard dataset like Adult, Mushroom etc. The comparative study of algorithms includes aspects like different support values, size of transactions and different datasets.

Keywords

Frequent Itemset, Mining, KDD cup, Mashroom, Adult.

1. INTRODUCTION

In recent years the size of database has increased rapidly. This has led to a growing interest in the development of tools capable in the automatic extraction of knowledge from data. The term data mining or knowledge discovery in database has been adopted for a field of research dealing with the automatic discovery of implicit information or knowledge within the databases. The implicit information within databases, mainly the interesting association relationships among sets of objects that lead to association rules may disclose useful patterns for decision support, financial forecast, marketing policies, even medical diagnosis and many other applications.

The problem of mining frequent itemsets arose first as a sub-problem of mining association rules [9]. Frequent itemsets play an essential role in many data mining tasks that try to find interesting patterns from databases such as association rules, correlations, sequences, classifiers, clusters and many more of which the mining of association rules is one of the most popular problems. The original motivation for searching association rules came from the need to analyze so called supermarket transaction data, that is, to examine customer behavior in terms of the purchased products. Association rules describe how often items are purchased together. For example, an association rule "beer, chips (80%)" states that four out of five customers that bought beer also bought chips. Such rules can be useful for decisions concerning product pricing, promotions, store layout and many others.

2. PROBLEM STUDY

2.1. Need of Frequent Itemset Mining

Studies of Frequent Itemset (or pattern) 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 major 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.

3. RELATED WORK

3.1. FP-Growth Algorithm

The most popular frequent itemset mining called the FP-Growth algorithm was introduced by [5]. The main aim of this algorithm was to remove the bottlenecks of the Apriori-Algorithm in generating and testing candidate set. The problem of Apriori algorithm was dealt with, by introducing a novel, compact data structure, called *frequent pattern tree*, or FP-tree then based on this structure an FP-tree-based pattern fragment growth method was developed. FP-growth uses a combination of the vertical and horizontal database layout to store the database in main memory. Instead of storing the cover for every item in the database, it stores the actual transactions from the database in a tree structure and every item has a linked list going through all transactions that contain that item. This new data structure is denoted by FP-tree (Frequent-Pattern tree) [4]. Essentially, all transactions are stored in a tree data structure. The definition, according to [5] is as follows:

Definition (FP-tree): A frequent pattern tree is a tree structure defined as

1.It consists of one root labeled as "root", a set of item prefix sub-trees as the children of the root, and a frequent-item header table.
2.Each node in the item prefix sub-tree consists of three fields: item-name, count and node-link, where item-name registers which item this node represents, count registers the number of transactions represented by the portion of the path reaching this node, and node-link links to the next node in the FP-tree carrying

the same item-name, or null if there is none. 3.Each entry in the frequent-item header table consists of two fields, I. item-name and II. head of node-link, which points to the first node in the FP-tree carrying the item-name.The algorithm FP-tree[5] is as below:

Algorithm 1 (FP-tree construction**):**

Input: A transactional database *DB* and a minimum support threshold.

Output: Its frequent pattern tree, FP-tree

Method: The FP-tree is constructed in the following steps:

1.Scan the transaction database *DB* once. Collect the set of frequent items *F* and their supports. Sort *F* in support descending order as *L*, the *list* of frequent items.
2.Create the root of an FP-tree, *T*, and label it as "root".

For each transaction *Trans* in *DB* do the following:

1.Select and sort the frequent items in *Trans* according to the order of *L*. Let the sorted frequent item list in *Trans* be [*p* | *P*], where *p* is the first element and *P* is the remaining list. Call *insert_tree*([*p* | *P*], *T*). 2.The function *insert_tree*([*p* | *P*], *T*) is performed as follows. If *T* has a child *N* such that *N.item-name* = *p.item-name*, then increment *N*'s count by 1; else create a new node *N*, and let its count be 1, its parent link be linked to *T*, and its node-link be linked to the nodes with the same *item-name* via the node-link structure. If *P* is nonempty, call *insert_tree*(*P*, *N*) recursively.

3.2. Broglet's FP-Growth

Broglet implemented an efficient FP-Growth[1] algorithm using C Language. The FP-growth in his implementation preprocesses the transaction database according to [1] is as follows:

1.In an initial scan the frequencies of the items (support of single element item sets) are determined. 2. All infrequent items, that is, all items that appear in fewer transactions than a user-specified minimum number are discarded from the transactions, since, obviously, they can never be part of a frequent item set. 3. The items in each transaction are sorted, so that they are in descending order with respect to their frequency in the database.

3.3. Goethals FP-Growth

Goethal also implemented the FP-Growth algorithm. This implementation is based on the Fp-growth algorithm [5]. Consider a transaction database and a minimal support threshold of 2. First, the supports of all items is computed, all infrequent items are removed from the database and all transactions are reordered according to the support descending order resulting in the example transaction database in Table 1. The FP-tree for this database is shown in Figure 1.

Table 1: An example preprocessed transaction database.

Tid	X
100	{a, b, c, d, e, f}
200	{a, b, c, d, e}
300	{a, d}
400	{b, d, f}
500	{a, b, c, e, f}

The FP-Growth tree will be constructed as below figure 1.

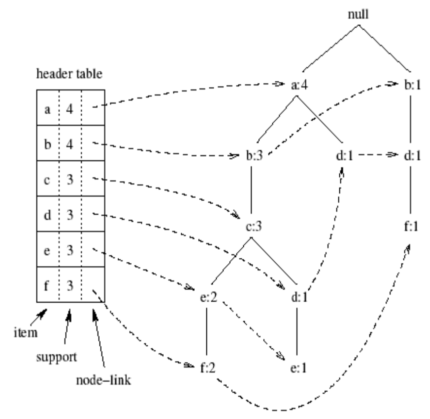


Figure 1: An example of a FP-tree.

3.4 Eclat

Eclat [11, 8, 3] algorithm is basically a depth-first search algorithm using set intersection. It uses a vertical database layout i.e. instead of explicitly listing all transactions; each item is stored together with its cover (also called tidlist) and uses the intersection based approach to compute the support of an itemset. In this way, the support of an itemset X can be easily computed by simply intersecting the covers of any two subsets Y, Z ⊆ X, such that Y U Z = X. It states that, when the database is stored in the vertical layout, the support of a set can be counted much easier by simply intersecting the covers of two of its subsets that together give the set itself.

The Eclat algorithm is as given below.

```
Input: D, σ, i ⊆ I
Output: F[I](D, σ)
1: F[I] :={}
2: for all I Є I occurring in D do
3: F[I] := F[I] ∪ {I ∪ {i}}
4: // Create D^i
5: D^i: = {}
6: for all j Є I occurring in D such that j>I do
7: C := cover({i}) ∩ cover({j})
8: if |C| >= σ then
```

```
9: $D^i$: = $D^i \cup \{(j, C)\}$
10: end if
11: end for
12: //Depth-first recursion
13: Compute $F[I \cup \{i\}](D^i, \sigma)$
14: $F[I] := F[I] \cup F[I \cup \{i\}]$
15: end for
```

In this algorithm each frequent item is added in the output set. After that, for every such frequent item i, the i-projected database Di is created. This is done by first finding every item j that frequently occurs together with i. The support of this set {i, j} is computed by intersecting the covers of both items. If {i, j} is frequent, then j is inserted into D^i together with its cover. The reordering is performed at every recursion step of the algorithm between line 10 and line 11. Then the algorithm is called recursively to find all frequent itemsets in the new database Di.

It essentially generates the candidate itemsets using only the join step from Apriori. Again all the items in the database is reordered in ascending order of support to reduce the number of candidate itemsets that is generated, and hence, reduce the number of intersections that need to be computed and the total size of the covers of all generated itemsets. Since the algorithm doesn't fully exploit the monotonicity property, but generates a candidate itemset based on only two of its subsets, the number of candidate itemsets that are generated is much larger as compared to a breadth-first approach such as Apriori. As a comparison, Eclat essentially generates candidate itemsets using only the join step from Apriori [6], since the itemsets necessary for the prune step are not available.

A technique that is regularly used is to reorder the items in support ascending order to reduce the number of candidate itemsets that is generated. In Eclat, such reordering can be performed at every recursion step in the algorithm. Also that at a certain depth d, the covers of at most all k-itemsets with the same $k - 1$-prefix are stored in main memory, with $k \leq d$. Because of the item reordering, this number is kept small.

3.5 SaM Algorithm

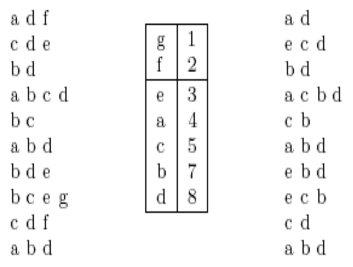
The SaM (Split and Merge) algorithm established by [10] is a simplification of the already fairly simple RElim (Recursive Elimination) algorithm. While RElim represents a (conditional) database by storing one transaction list for each item (partially vertical representation), the split and merge algorithm employs only a single transaction list (purely horizontal representation), stored as an array.

This array is processed with a simple split and merge scheme, which computes a conditional database, processes this conditional database recursively, and finally eliminates the split item from the original (conditional) database.

SaM preprocesses a given transaction following the steps below:

1. The transaction database is taken in its original form. 2. The frequencies of individual items are determined from this input in order to be able to discard infrequent items immediately. 3. The (frequent) items in each transaction are sorted according to their frequency in the transaction database, since it is well known that processing the items in the order of increasing frequency usually leads to the shortest execution times. 4. The transactions are sorted lexicographically into descending order, with item comparisons again being decided by the item frequencies; here the item with the higher frequency precedes the item with the lower frequency. 5. The data structure on which SaM operates is built by combining equal transactions and setting up an array, in which each element consists of two fields:

An occurrence counter and a pointer to the sorted transaction (array of contained items). This data structure is then processed recursively to find the frequent item sets. The basic operations of the recursive processing are based on depth-first/divide-and-conquer scheme. In the split step the given array is split with respect to the leading item of the first transaction. All array elements referring to transactions starting with this item are transferred to a new array. The new array created in the split step and the rest of the original arrays are combined with a procedure that is almost identical to one phase of the well-known merge sort algorithm.The main reason for the merge operation in SaM is to keep the list sorted, so that: 1.All transactions with the same leading item are grouped together and 2.Equal transactions (or transaction suffixes) can be combined, thus reducing the number of objects to process.



a d f			a d
c d e	g	1	e c d
b d	f	2	b d
a b c d	e	3	a c b d
b c	a	4	c b
a b d	c	5	a b d
b d e	b	7	e b d
b c e g	d	8	e c b
c d f			c d
a b d			a b d

Figure 2: Transaction database (left), item frequencies (middle), and reduced transaction database with items in transactions sorted accordingly with respect to their frequency (right).

Each transaction is represented as a simple array of item identifiers (which are integer numbers). The transaction list is prepared which are stored in a simple array, each element of which contains a support counter and a pointer to the head of the list. The list elements themselves consist only of a successor pointer and a pointer to the transaction. The transactions are inserted one by one into this structure by simply using their leading item as an index.

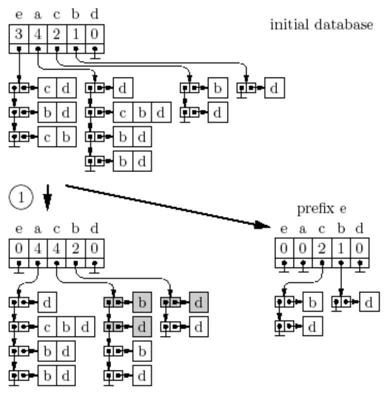


Figure 3: Procedure of the recursive elimination with the modification of the transaction lists (left) as well as the transaction lists for the recursion (right).

4. Data Set Requirements

For the experiment we have used datasets of different application. These datasets was obtained from the UCI repository of machine learning databases [7]. The Table 2 below portraits the characteristics of the datasets selected for the experiment.

Table 2: Details of Datasets used in the comparison

File name	Divisions	Dist./ Rand.	Records	I/P Columns
adult.D97. N48842.C2.num	5	Yes	48842	15
Census	0	No	48842	14
letRecog.D106. N20000.C26. num	5	Yes	20000	17
Mushroom. D90.N8124. C2.num	5	Yes	8124	23

5.Performance Comparisons

We have conducted a detailed study to assess the performance of FP-Growth with respect to the other FIM algorithms. The performance metrics in the experiments is the total execution time taken and the number of Itemsets Generated for different data sets. For this comparison also same data sets were selected as for the above experiment with 30% to 70% of minimum support threshold.

The table 3 below shows the execution time for all the algorithms with different support threshold for adult data set. The time of execution is decreased with the increase support threshold.

Table 3: Adult data set execution time.

Support	Total Time in Seconds			
	BROGLET			
	FP-Growth	Eclat	Relim	SaM
30	0.56	0.54	0.49	0.47
40	0.5	0.49	0.44	0.44
50	0.49	0.45	0.42	0.41
60	0.48	0.44	0.4	0.4
70	0.42	0.4	0.39	0.37

Figure 4 shows that the execution time for the FP-growth algorithm decreases with the increase in support threshold form 30% to 70% for adult dataset. We observed that FP-growth and Eclat takes more time as that compared to RElim and SaM.

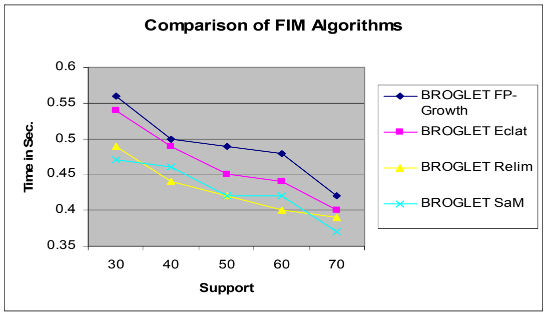


Figure 4: Execution Time for adult data set.

The table 4 shows the execution time for all the algorithms with different support threshold for census data set. The time of execution is decreased with the increase support threshold.

Table 4: Census data set execution time.

Support	Total Time in Seconds			
	BROGLET			
	FP-Growth	Eclat	Relim	SaM
30	1.21	0.76	0.74	0.74
40	1.16	0.75	0.72	0.71
50	0.86	0.72	0.7	0.69
60	0.73	0.69	0.67	0.67
70	0.68	0.65	0.65	0.64

Figure 5 shows that the execution time for the FP-growth algorithm is high with the small support threshold and it decreases with the decrease in support using census data set. It is also analyzed that the execution time for other FIM algorithms is less as compared to FP-growth algorithm.

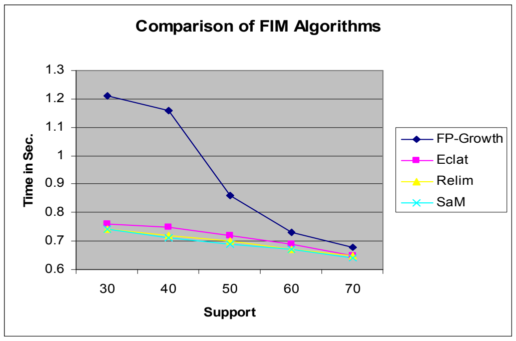


Figure 5: Execution Time for census data set.

The table 5 below show the execution time for all the algorithms with different support threshold for Letter Recognition data set. The time of execution is decreased with the increase support threshold.

Table 5: Letter Recognition data set execution time

Support	Total Time in Seconds			
	BROGLET			
	FP-Growth	Eclat	Relim	SaM
30	0.21	0.21	0.2	0.19
40	0.2	0.21	0.19	0.18
50	0.18	0.2	0.19	0.17
60	0.17	0.19	0.18	0.16
70	0.15	0.17	0.16	0.14

Figure 6 shows that the execution time of the FP-growth algorithm is near by the execution time of Eclat and RElim with the decrease in support threshold for Letter Recognition data set. It is also analyzed that the execution time for other SaM algorithm is less as compared to other FIM algorithms.

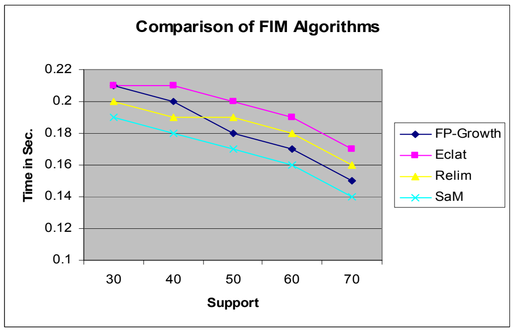


Figure 6: Execution Time for Letter Recognition data set.

The table 7 below shows the execution time for all the algorithms with different support threshold for mushroom data set. The time of execution is decreased with the increase support threshold.

Table 7: Mashroom data set execution time.

Support	Total Time in Seconds			
	BROGLET			
	FP-Growth	Eclat	Relim	SaM
30	0.13	0.11	0.11	0.11
40	0.11	0.11	0.09	0.1
50	0.09	0.09	0.09	0.08
60	0.08	0.09	0.08	0.07
70	0.08	0.08	0.07	0.06

Figure 7 shows that the execution time of the all FIM algorithm is nearby but it can also be analyzed that the execution time of SaM is comparatively less for higher support threshold.

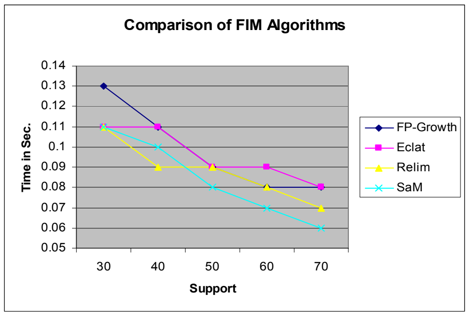


Figure 7: Execution Time for Mushroom data set.

6.Findings and Analysis

The first interesting behavior can be observed in the Experiment 1 for the adult, census and letter recognition data set. Indeed, Broglet's FP performs better for adult and letter data set, as it takes much less time to generate frequent itemsets in comparison of Goethal's FP. Whereas for letter recognition data set Goethal's FP takes much less time of execution then the other, but it can also be studied that it generates constant number of frequent itemsets even with the increase in the minimum support threshold.

Another remarkable result is that the frequent itemsets generated by Goethal's is enormous then that generated by the Broglet's FP of which numerous itemsets may not be useful from the point of mining purpose. Future no. of transaction of adult and census data set are same, even then Goethal's FP behave inappropriate for census data set.By these consequences we consider Broglet's FP to be better performer than that of Goethal's FP and accordingly we performed the second experiment to compare the Broglet's FP with the classical frequent itemset mining algorithms (like Apriori and Eclat) along with the newly implemented algorithms (RElim and SaM).

In the later experiment it can be observed that for adult and census data set FP-Growth takes more time than that of other FIM algorithms. Along that RElim performs in close proximity to that of SaM. For letter recognition and mushroom dataset all the FIM algorithms performs close to each other. Nevertheless, SaM can be considered as an improved performer from the overall dataset analysis.

7.CONCLUSION

A comparison framework has developed to allow the flexible comparison of existing and new frequent itemset mining algorithms that conform to the defined algorithm interface. Using this framework this paper presented the comparative performance study of three iterative algorithms for FIM algorithms with FP-Growth algorithms.

In this work, an in-depth analysis of few algorithms is done which made a significant contribution to the search of improving the efficiency of frequent itemset mining. By comparing them to classical frequent item set mining algorithms like FP-growth and Eclat the strength and weaknesses of these algorithms were analyzed.

The developed framework can be used for comparing the other algorithms, which does not use candidate set generation to discover frequent patterns. And can also lead to several ideas for optimizations, which could improve the performance of other algorithms.

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