Comparative Study of Various Sequential Pattern Mining Algorithms

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Abstract: In successive pattern mining represents a very important category of knowledge mining issues with big selection of applications. It's one in every of the terribly difficult issues as a result of it deals with the careful scanning of a combinatorial sizable amount of attainable subsequence patterns. Broadly speaking successive pattern Ming algorithms are often classified into 3 sorts specifically Apriori based mostly approaches, Pattern growth algorithms and early pruning algorithms. These algorithms have more classification and extensions. Elaborate rationalization of every formula alongside its necessary options, pseudo code, blessings and drawbacks is given within the future sections of the paper. At the top a comparative analysis of all the algorithms with their supporting options is given within the variety of a table. This paper tries to complement the information and understanding of varied approaches of sequential pattern mining.

Keywords: Basic Apriori, GSP, SPADE, PrefixSpan, FreeSpan, LAPIN, Early pruning.

1. Introduction

Sequential pattern mining is a significant topic of data mining with wide range of applications. It deals with extracting statistically useful patterns between data which occurs sequentially with a specific order. Sequential pattern mining is considered as a special case of structured data mining. It is considered to be a complex problem because in it a combinatorial explosive number of intermediate subsequences are generated. Sequential pattern mining is used in several domains [2] such as in business organizations to study customer behaviors, in web usage mining to mine several web logs distributed on multiple servers. The sequential pattern mining problem can be described as follows [1]: Consider a given a set of data-sequences, as the input wherein each data-sequence is a list of transactions such that each transaction contains a set of items. Given a user-specified minimum support threshold, then sequential pattern mining is applied to find out all frequently occurring subsequences whose ratios of occurrence exceed the minimum support threshold in the sequence database. Records are stored in a sequence database such that all the records are sequences of ordered events, with or without concrete notions of time [5]. An example sequence database is retail customer transactions showing the sequence or collection of products they purchased on weekly or monthly basis. A sequential pattern-mining algorithm can be

2. Literature Review

All As discussed earlier, sequential pattern is a set of itemsets arranged in sequence database occurring sequentially in a specific order [2]. A sequence database is a collection of ordered elements or events with or without a view of time. Each itemset contains a set of items which appear together in the same transaction and thus have the same session time value [2,1]. Whereas association rules indicate intra-transaction relationships, sequential patterns represents inter transaction relationships i.e. the relationship between transactions. Given two sequences α=<a1 a2…an> and β=<b1 b2…bm> where α is called a subsequence of β, denoted as α⊆β, if there exist integers 1≤j1<j2<…<jn ≤m such that a1⊆bj1, a2 ⊆bj2,…,an⊆bjn. Here if α and β have the following sequences α=<(xy), t> and β=< (xyz), (zt)>, β is denoted as a super sequence of α [2,6]. In addition to the discovery of recurrent itemsets, sequential pattern mining requires the arrangement of those itemsets in a sequence. Suppose Is denotes powerset of a set of items denoted by Cs. Let s represents minimum support threshold for mining the database and let m =|Cs|. Then aim of mining frequently occurring itemset is to discover recurrent itemsets among |Is| different possible itemsets as represented in equation (i) below [6]:

\[ I = \frac{-1}{s} = \frac{2}{-1} = \frac{1}{1} \] (i)

Now suppose that the database has sequences with at most p itemsets and each itemset has at most single item such that there are m^p possible different sequences the different variable length sequences are given by equation (ii) as below [6]:

\[ I = \frac{-1}{s} = \frac{2}{-1} = \frac{1}{1} \] (ii)
Now let $S_n$ be the possible frequent sequences with $n$ itemsets then value of $S_n$ is represented in equation (iii) as below [6]:

$$S_n = \frac{1}{n!} = \frac{2 - 1}{1} = 2 - 1$$

In general the existing $S_T$ sequences are given by the equation (iv) as shown below [6]:

$$S_T = \frac{2 + 1 - 2}{1 - 1} = 2 - 1 = \frac{2 - 1}{2 - 2}$$

Consider the example of a customer sequence [7] where each transaction made corresponding to a set of items is ordered by increasing transaction time. Table 1 shows the database corresponding to consumer transactions sorted by consumerID and Transaction time [7,1] as shown below:

Table 1: Table showing database for consumer transactions

<table>
<thead>
<tr>
<th>ConsumerID</th>
<th>TransactionTime</th>
<th>ItemsBought</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>November 25 '13</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>November 30 '13</td>
<td>90</td>
</tr>
<tr>
<td>2</td>
<td>November 10 '13</td>
<td>10,20</td>
</tr>
<tr>
<td></td>
<td>November 15 '13</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>November 20 '13</td>
<td>40,60,70</td>
</tr>
<tr>
<td>3</td>
<td>November 25 '13</td>
<td>30,50,70</td>
</tr>
<tr>
<td>4</td>
<td>November 25 '13</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>November 30 '13</td>
<td>40,70</td>
</tr>
<tr>
<td></td>
<td>December 25 '13</td>
<td>90</td>
</tr>
<tr>
<td>5</td>
<td>November 12 '13</td>
<td>90</td>
</tr>
</tbody>
</table>

Next, a customer sequence is created according to time duration as shown in Table 2 that contains consumerID and Consumer sequence for items bought [7,1]:

Table 2: Table showing customer sequence according to time duration

<table>
<thead>
<tr>
<th>ConsumerID</th>
<th>Consumer Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(30) (90)</td>
</tr>
<tr>
<td>2</td>
<td>(10 20) (30) (40 60 70)</td>
</tr>
<tr>
<td>3</td>
<td>(30 50 70)</td>
</tr>
<tr>
<td>4</td>
<td>(30) (40 70 ) (90)</td>
</tr>
<tr>
<td>5</td>
<td>(90)</td>
</tr>
</tbody>
</table>

The support for an itemset $i_t$ is defined as the fraction of customers who bought the items in $i_t$ in a single transaction. An itemset having minimum support is known as a large itemset or simply litemset [7]. It is required that each itemset in a large sequence must have minimum support. In this example of customer transaction sequence database is shown in Table 1, the large itemsets so found are (30), (40), (70), (40 70) and (90). A possible mapping for this set is shown in Table 4 in order to treat litemsets as single entities. Thus two litemsets can be compared for equality in constant time and it also decreases the time needed for checking whether a sequence is contained in a customer sequence or not [7].

Table 3. Table showing mapping of large item sets

<table>
<thead>
<tr>
<th>Large Itemsets</th>
<th>Mapping To</th>
</tr>
</thead>
<tbody>
<tr>
<td>(30)</td>
<td>1</td>
</tr>
<tr>
<td>(40)</td>
<td>2</td>
</tr>
<tr>
<td>(70)</td>
<td>3</td>
</tr>
<tr>
<td>(40 70)</td>
<td>4</td>
</tr>
<tr>
<td>(90)</td>
<td>5</td>
</tr>
</tbody>
</table>

3. Classification Of Sequential Pattern Mining Algorithms

The three main categories of Sequential pattern mining algorithms that have been proposed are discussed as follows [1, 5]:

1. Apriori Based algorithms such as GSP, SPADE, SPAM algorithms
2. Pattern Growth algorithms such as FreeSpan and PrefixSpan
3. Early Pruning algorithms such as LAPIN-SPAM. Some other algorithms are hybrids of these techniques.

3.1 Apriori Based algorithms

3.1.1 Basic Apriori Algorithm

Apriori algorithm is classically used over transactional databases for mining frequently occurring itemsets and association rule generation. It is a difficult task to develop efficient and scalable methods for mining frequent itemsets in a large transaction database because normally there are a large number of distinct single items in a
The pseudocode of Apriori algorithm is given as follows [8]:

\[ \text{Lk: frequent itemset of size k} \]

\[ L_k = \{ \text{Large } k\text{-itemsets}; \} \quad // \text{Outcome of itemset} \]

\[ \text{phase for}(k = 2; \ L_{k-1} = \emptyset; \ k++) \text{ do begin} \]

\[ C_k = \text{New candidates generated from } L_{k-1}; \]

\[ \text{foreach transaction } t \text{ in database do} \]

\[ \text{Increment the count of all candidates in } C_k \text{ that are contained in } t \]

\[ \text{end} \]

\[ L_k = \text{candidates in } C_k \text{ with minimum support} \]

end

return ;

Various methods have been proposed for improving the efficiency of Apriori algorithm. Some of the proposed work includes sampling approach, dynamic itemset counting, incremental mining, parallel and distributed mining [2]. A point of concern in Apriori algorithm is that in some cases, the size of candidate sets using the Apriori principle is significantly reduced and lead to two main problems [2, 5]:

a. **Generate-and-test:** This is the feature of early sequential pattern mining algorithms. It proposes use of exhaustive join operators such that the pattern simply grows one item at a time and tested for the minimum support. This leads to an inefficient pruning and generates an explosive number of candidate sequences and thus taking up a lot of memory [5].

b. **Scanning database repeatedly:** This feature suggests multiple scanning of the original database to determine if the list of generated candidate sequences is frequent or not. It is a very detrimental characteristic as it requires a lot of processing time and I/O cost. To overcome this drawback database should be scanned only once or twice to generate a temporary data structure containing necessary information used in mining [5].

### 3.1.2 GSP Mining Algorithm

Generalized Sequential Patterns (GSP) also follows Apriori-based approach of sequential pattern mining. Algorithm uses the downward-closure property of sequential patterns as discussed in previous section and follows a multiple pass generate-and-test approach [3]. GSP follows the principle of candidate generation and test. The algorithm starts by detecting the frequent 1-sequences and then generating the collection of frequent \((k+1)\)-sequences derived from the set of frequent \(k\)-sequences usually known as candidates [6]. The frequent \(k\)-sequences \((k\) candidates) so generated use the frequent \((k-1)\)-sequences and this reduces the number of sequences to consider at each moment [6]. GSP also includes time constraints, a sliding time window, and user-defined taxonomies [3]. The features of GSP algorithm are as follows [2]:

a. The algorithm allows inserting bounds on the time separation between contiguous elements in a pattern.

b. It allows the items present in the pattern element to span a transaction set within a time window specified by user.

c. It allows discovery of frequent patterns in different levels as desired by user.

d. It also enables for discovering generalized sequential patterns.

The GSP algorithm makes multiple passes over sequence database as per the following procedure [2, 6]:

1. In the first pass, from a given set of frequent \(n\)-1 patterns, the candidate set for next generation are generated and based on the thresholds it finds the
The SPADE algorithm can be described as follows [4, 2]:

1. The algorithm proposes the usage of vertical id-list database format with the help of which each sequence can be associated with a list of objects in which it occurs in conjunction with the related timestamps [11].
2. On implementing simple temporal joins on id-lists frequent sequences are enumerated [11].
3. A lattice-theoretic approach is used to divide the original lattice into smaller sub-lattices such that each one is processed independently in main-memory.
4. In order to minimize the I/O costs the algorithm requires up to three database scans or alternatively one scan with some pre-processed information [11].
5. The problem decomposition task is separated from pattern search process.
6. Two different search strategies have been defined in order to find and list frequent sequences in each sublattice, namely breadth-first search (BFS) and depth-first search (DFS) [11].

The SPADE algorithm can be described as follows [4, 2]:

Let D denote ID-List of sequences
Let ms denote Minimum Support
Let F_S denote set of sequences

**SPADE (ms, D)**

1. Let F_1 = Frequent 1-Sequences
2. Let F_2 = Frequent 2-Sequences
3. Determine E as set of Equivalence classes for all 1-Sequences [Q]_0
4. For each Q ∈ E do

Find frequent sequences F_S

**Advantages of SPADE algorithm can be enumerated as follows [2, 4]:**

a) SPADE outperforms GSP since it is about twice as fast as GSP because it uses a support counting method based on the id list structure which is more efficient method.
b) SPADE scales linearly with respect to the database size, number of sequences and other database parameters.
c) SPADE decreases I/O costs by reducing database scans.
d) SPADE reduces computational costs by using efficient search schemes.
e) The vertical id-list based approach that SPADE follows is not sensitive to data-skewing.

### 3.2 Pattern Growth Algorithms

Please The Pattern-growth methods represent a new approach for handling problems related to sequential pattern mining by providing solution to the problem of generate-and-test. The search space partitioning is an important feature of pattern-growth algorithms [5]. The algorithm avoids repeatedly scanning the entire database for generating and testing large sets of candidate sequences. Instead it proposes to recursively project a sequence database into a set of smaller databases and locally mining frequent patterns in each projected database [11]. The idea is to avoid the candidate generation step concentrate the search on a smaller and limited portion of the database [6, 5]. The initial pattern growth algorithms used projected databases and two types of database projections can be used either Level-by-level projection or Alternative-level projection. The two popular projection-based sequential pattern mining methods are: FreeSpan [12] and an improved method PrefixSpan [13]. Both methods generate projected databases with difference in the database projection criteria. While FreeSpan uses current set of frequent patterns not in particular growth direction (ordering), to create projected databases, PrefixSpan projects databases by growing frequent prefixes [6]. PrefixSpan is a better pattern-growth method that focuses on constructing patterns recursively and limiting the search to projected databases.

#### 3.2.1 FreeSpan Algorithm

FreeSpan algorithm has been proposed with the intend to reduce the generation of candidate subsequences by using projected databases for mining frequent patterns. In order to generate subsequence fragments in each projected database
FreeSpan uses frequent items to project sequence databases into a set of smaller projected databases recursively using the currently mined frequent sets [2]. In FreeSpan database is scanned three times regardless of maximal length of the sequence. FreeSpan is efficient and faster than the GSP algorithm but the major issue of FreeSpan is to deal with projected databases [2]. The major steps in the FreeSpan algorithm can be explained as follows [12]:

Let sequence database be denoted by $S_T$.

Let minimum supported threshold as $ms$ then

1. Scan $S_T$ to find set of frequent items in $S_T$.
2. Sort frequent items in above step in $Freq\_list$ in the decreasing order of frequency.
3. Execute alternative level projection mining in the following steps:
   a. Scan the database once to create a frequent item matrix.
   b. Generate length-2 sequential patterns on item-repeating patterns and projected databases.
   c. Scan database to generate item repeating patterns and projected databases.
   d. If still longer candidate patterns exist then recursively execute matrix projection mining on projected databases.

### 3.2.2 PrefixSpan Algorithm

PrefixSpan algorithm represents a new pattern-growth approach for mining sequential patterns. The algorithm proposes that the projection of sequence databases is based only on occurrences of frequent subsequences and not by considering all the possible occurrences of frequent subsequences since any frequent subsequence can be found by growing its frequent prefix [13]. The PrefixSpan algorithm scans only the prefix subsequences and projects their corresponding postfix subsequences into the databases. Thus, sequential patterns in each projected database grow by exploration [5]. The steps of PrefixSpan algorithm are given as follows [13]:

Let sequence database be denoted by $S$.

Let minimum supported threshold as $ms$ then

Let $p$ denotes sequential pattern and $len$ denotes the length of $p$.

Let $S[p]$ denotes the $p$ projected database if $p<>$, otherwise the sequence database $S$.

1. Scan $S[p]$ to find the set of frequent items $k$ such that either of below two steps can take place:
   a. $k$ can be assembled to the last element of $p$ for forming a sequential pattern or,
   b. $<k>$ can be appended to $p$ to form sequential pattern.
2. For each frequent item $k$ append it to $p$ to generate sequential pattern $p_k$ and show $p_k$ as output.
3. For each $p_k$ construct $p_k$-projected database $S[p_k]$ and repeat the steps.

The features of PrefixSpan can be summarized as follows:

- No candidate sequence needs to be generated by PrefixSpan.
- A projected database is smaller than the original database since in it only the postfix subsequences of a frequent prefix are projected. Thus, the projected databases keep on shrinking.

In the worst case, PrefixSpan constructs a projected database for every sequential pattern.

### 3.3 Early Pruning Algorithms

The Early-Pruning approaches are emerging as a new class of algorithms for sequential pattern mining. These algorithms use a type of position induction concept to prune candidate sequences at early stage in the mining and the remaining algorithm represents a simple pattern growth process [5]. The concept of position induction is as follows: During mining process if an item’s last position is smaller than the current prefix position then the item cannot appear behind the current prefix in the same customer sequence [5]. These algorithms use a table to record the last positions of each item in the sequence and later use this information for early candidate sequence pruning because the last position of an item can be effectively used to decide whether the item can be appended to a given prefix k-sequence or not, thus avoiding support counting and generation of candidate infrequent sequences [5]. LAPIN is an example of early-pruning algorithms. The following table shows the comparative features of the different sequential pattern mining algorithms [1, 2, 5].

<table>
<thead>
<tr>
<th>Algorithm Characteristics</th>
<th>Apriori All</th>
<th>GSP</th>
<th>SPADE</th>
<th>FreeSpan</th>
<th>PrefixSpan</th>
<th>LAPIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generate and Test</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MultiScan of Database</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Candidate Sequence Pruning</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sampling and/or compression</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DFS based approach</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BFS based approach</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td>Support</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Table 4. Table showing comparative features of different sequential pattern mining algorithms

<table>
<thead>
<tr>
<th>Algorithm Characteristics</th>
<th>Top-down search</th>
<th>Support</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generate and Test</td>
<td>Support</td>
<td>Support</td>
<td></td>
</tr>
<tr>
<td>MultiScan of Database</td>
<td>Support</td>
<td>Support</td>
<td></td>
</tr>
<tr>
<td>Candidate Sequence Pruning</td>
<td>Support</td>
<td>Support</td>
<td></td>
</tr>
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<td>Sampling and/or compression</td>
<td>Support</td>
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</tr>
<tr>
<td>DFS based approach</td>
<td>Support</td>
<td>Support</td>
<td></td>
</tr>
<tr>
<td>BFS based approach</td>
<td>Support</td>
<td>Support</td>
<td></td>
</tr>
</tbody>
</table>

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4. Conclusion

In this paper a very important and complex data mining problem known as Sequential pattern mining has been analyzed in details. This paper gives a brief description of the latest and popular sequential pattern mining algorithms as classified under three broad categories namely: apriori-based algorithms, pattern growth methods and early-pruning based algorithms and their subtypes and extensions. Under the Apriori based algorithms category: Basic apriori algorithm, GSP and SPADE algorithms have been described; under pattern growth approaches FreeSpan and PrefixSpan algorithms have been explained; basics of early pruning methods and its popular algorithm LAPIN have also been defined further. The paper presents a detailed explanation of their features, respective advantages and disadvantages. At the end comparative analysis of these algorithms based on their characteristic features is presented. In depth research work needs to be conducted for extending the capabilities of existing sequential mining approaches. Various considerations in this direction include distributed mining of sequences, object oriented view of sequential pattern mining, sequence regeneration and future items predictions in a given sequence using mathematical models of sequences etc.

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