An Efficient Real-Time Frequent Pattern Mining Technique Using Diff-Sets

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Abstract. Frequent pattern mining in real-time is of increasing thrust in many business applications such as e-commerce, recommender systems, and supply-chain management and group decision support systems, to name a few. A plethora of efficient algorithms have been proposed till date. However, with dense datasets, the performances of these algorithms significantly degrade. Moreover, these algorithms are not suited to respond to the real-time need. In this paper, we describe BDFS(b)-diff-sets, an algorithm to perform real-time frequent pattern mining using diff-sets. Empirical evaluations show that our algorithm can make a fair estimation of the probable frequent patterns and reaches some of the longest frequent patterns much faster than the existing algorithms.

1 Introduction

In recent years, business intelligence systems are playing pivotal roles in fine-tuning business goals such as improving customer retention, market penetration, profitability and efficiency. In most cases, these insights are driven by analyses of historic data. Now the issue is, if the historic data can help us make better decisions, how real-time data can improve the decision making process [1].

Frequent pattern mining for large databases of business data, such as transaction records, is of great interest in data mining and knowledge discovery [2], since its inception in 1993, by Agrawal et al. Researchers have generally focused on the frequent pattern mining, as it is complex and the search space needed for finding all frequent itemsets is huge [2]. A number of efficient algorithms have been proposed in the last few years to make this search fast and accurate. Among these, a number of effective vertical mining algorithms have been recently proposed, that usually outperforms horizontal approaches. Despite many advantages of the vertical format, the methods tend to suffer, when the tid-list cardinality gets very large as in the case of dense datasets [3]. Again, these algorithms have limited themselves to either breadth first or depth first search techniques. Hence, most of the algorithms stop only after finding the exhaustive (optimal) set of frequent itemsets and do not promise to run under user defined real-time constraints and produce some satisficing (interesting sub-optimal) solutions due to their limiting characteristics[4, 5].

2 Business Issues of Real-Time Frequent Pattern Mining

Using up-to-date information, getting rid of delays, and using speed for competitive advantage is what the real-time enterprise is about. There are numerous areas where real-time decision making plays a crucial role. These include areas like real-time customer relationship management, real-time supply chain management systems real-time enterprise risk and vulnerability management, real-time stock management and vendor inventory, real-time recommender systems, real-time operational management with special applications in mission critical real-time information as is used in the airlines industry, real-time intrusion and real-time fraud detection, real-time negotiations and other areas like real-time dynamic pricing and discount offering to customers in real-time. More than that, real-time data mining will have tremendous importance in areas where a real-time decision can make the difference between life and death – mining patterns in medical systems.

3 BDFS(b)-Diff-Sets: An Efficient Technique of Frequent Pattern Mining in Real-Time Using Diff-Sets

Algorithm BDFS(b)-diff-sets:

Initialize the allowable execution time τ

Let the initial search frontier contain all 3-length candidate patterns. Let this search frontier be stored as a global pool of candidate patterns. Initialize a set called Border Set to null.

Order the candidate patterns of the global pool according to their decreasing length (resolve ties arbitrarily). Take a group of most promising candidate patterns and put them in a block b of predefined size.

▪ *Expand (b)*

Expand (b): block of candidate patterns)

If not last_level

then

begin

Expand₁(b)

end.

Expand₁(b):

1. *Count support for each candidate pattern in the block b by intersecting the diff-set list of the items in the database.*
2. *When a pattern becomes frequent, remove it from the block b and put it in the list of frequent patterns along with its support value. If the pattern is present in the Border Set increase its subitemset counter. If the subitemset counter of the pattern in Border Set is equal to its length move it to the global pool of candidate patterns.*
3. *Prune all patterns whose support values $<$ given minimum support. Remove all supersets of these patterns from Border Set.*
4. *Generate all patterns of next higher length from the newly obtained frequent patterns at step 3. If all immediate subsets of the newly generated pattern are frequent then put the pattern in the global pool of candidate patterns else put it in the Border Set if the pattern length is > 3 .*
5. *Take a block of most promising b candidate patterns from the global pool.*
6. *If block b is empty and no more candidate patterns left, output frequent patterns and exit.*
7. *Call Expand (b) if enough time is left in τ to expand a new block of patterns, else output frequent patterns and exit.*

Fig. 1. Algorithm BDFS(b)-diff-sets

4 Empirical Evaluation

The following figures shows the empirical evaluation of BDFS(b)-diff-sets. We have found that BDFS(b)-diff-sets compares well with the existing best performing algorithms in time of completion and scalability. Real-time performance of BDFS(b)-diff-sets (in Fig. 9 and 10) show that it is always ahead of time while providing outputs. We have made detailed performance evaluation based on empirical analysis using commonly used synthetic and real-life dense datasets. Thus, we have demonstrated that real-time frequent pattern mining can be done successfully using BDFS(b)-diff-sets. We believe this study will encourage use of AI heuristic search techniques in real-time frequent pattern mining.

Fig. 2. Time comparison of FP-Growth, Eclat and dEclat with BDFS(b)-diffsets (b= 20880) on PUMSB, N=2113, T=74, D=49046

Fig. 3. Time comparison of FP-Growth with BDFS(b)-diffsets for T10I8D100K, b=100K

Fig. 4. Time comparison of Eclat and dEclat with BDFS(b)-diffsets for T10I8D100K, b=100K

Fig. 5. Time comparison of FP-Growth, Eclat and dEclat with BDFS(b)-diffsets (b=2088K) for PUMSB*, N=2088 T= 50.5, D = 49046

Fig. 6. Scalability evaluation of BDFS(b)-diffsets with Eclat and dEclat supp=0.5%, $b = 100K$ for T10I8D1K, 10K and 100K

Fig. 7. Number of patterns checked by Apriori and BDFS(b)-diffsets ($b=208800$) for Pumsb, $N=2113, T=74, D=49046$, with varying support

Fig. 8. Time-Patterns % of BDFS(b) for $b=75K$ and 65% supp for Chess ($N=75, T=37, D=3196$)

Fig. 9. Time-Patterns % for $b=75K$ and 65% supp for T10I8D100K

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