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Research Article

A STUDY ON INCREMENTAL MINING OF FREQUENT PATTERNS

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ABSTRACT

Data generated from both the offline and online sources are incremental in nature. Changes in the underlying database occur due to the incremental data. Mining frequent patterns are costly in changing databases, since it requires scanning the database from the start. Thus, mining of growing databases has been a great concern. To mine the growing databases, a new Data Mining technique called Incremental Mining has emerged. The Incremental Mining uses previous mining result to get the desired knowledge by reducing mining costs in terms of time and space. This state of the art paper focuses on Incremental Mining approaches and identifies suitable approaches which are the need of real world problem.

Keywords: Data Mining, Frequent Pattern, Incremental Mining, Frequent Pattern Minung, High Utility Mining, Constraint Mining.

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1. INTRODUCTION

For every organization to be in the right place at right times are the crucial factors to ensure right decision from large amount of data [1]. To deal with the large amount of data stored in the database, Data Mining (DM) has been introduced. A widely accepted definition of DM is: "*It is the process of discovering interesting knowledge from large amounts of data stored in* *databases, data warehouses, or other information repositories* [2]". Various DM techniques such as Frequent Pattern Mining, Incremental Mining of Frequent Patterns**,** Association Rule Mining, Classification, Prediction, Clustering, and Neural Networks etc. are discussed in various literatures.

Frequent Pattern Mining (FPM) is an important research topic in the field of DM to discover interesting patterns in databases. A pattern is said to be *interesting pattern* if it appears at least as frequently as a predetermined minimum support threshold. Mining frequent patterns is costly during changes of the underlying database. Most of the traditional approaches need repetitive scanning of the database as well as generating huge number of candidate sets [3].

The **Incremental Mining (IM)** is an important research topic in the field of DM, uses previous mining result to get the desired information by reducing mining costs in terms of time and space [4]. Incremental Mining is broadly defined as the way of extracting knowledge from dynamic dataset, where new instances of transactions keep adding and the obsolete instances keep deleting from the mining process (Refer Figure 1 (a) & (b)).

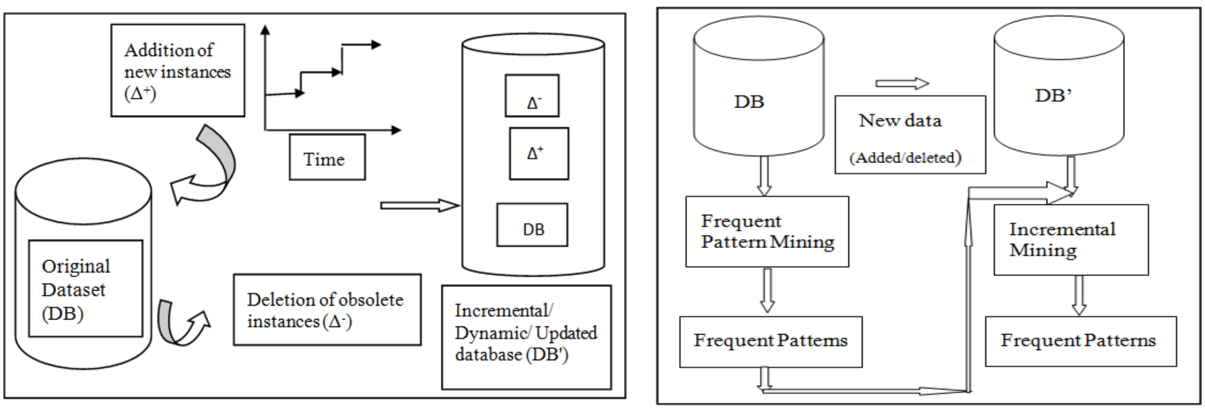

Fig.1. (a) Incremenmtal Database (b) Incremental Mining of Frequent Patterns

The important issue is that how to utilize the mining result to efficiently reflect these changes. The motivation of this work is to find research trends of Incremental Mining of frequent patterns with respect to Research Questions (RQs) listed below.

- **RQ#1:** What is the need for Incremental Mining?
- **RQ#2:** What are the published literature/approaches for Incremental mining of frequent patterns?

- **RQ#3:** Can they be classified according to functionality?
- **RQ#4:** Are they able to measure the semantic significance of an item as per user requirements?
- **RQ#5:** Does they satisfy users' constraints?

The rest of the paper is organized into 6 sections: The next section, Section 2 Review of Incremental Mining approaches are discussed, in Section 3 Key Resarch Findings are presented, Section 4 discusses the Goal-realted issues, Section-5 presented Application of Incremental Approaches, Section 6 we summarize the overall reviewed approaches as Conclusion and in Section 7 References we have included in this work are presented.

2. REVIEW OF INCREMENTAL MINING APPROACHES

Incremental data can be defined as dynamic data that changes with time. In real world applications, underlying database consists of Incremental data that keeps changing and requires continual updating. Mining frequent patterns from such type of changing/growing databases is costly, as most of the approaches need repetitive scanning of the databases as well as generating huge number of candidate sets [3].

Frequent pattern mining is an important data mining technique that can be utilized to discover the frequent patterns from changing/growing database [5]. It is important to take into account the functionality (what kind of patterns) and performance (how to mine frequent patterns). On the basis of this concept, the research works are divided into the following three categories chronologically:

- Apriori based Incremental Mining
- Partition based Incremental Mining and
- Pattern Growth based Incremental Mining
- High Utility based Incremental Mining
- Constraint based Incremental Mining

2.1. Apriori based Incremental Mining

This section describes a candidate set generation process based on Apriori based Incremental Mining approach. We have considered those approaches that are widely used by the research community as listed below.

Fast UPdate (FUP) (1996) [6]**,** is the first Apriori based Incremental Mining algorithm is proposed for the efficient maintenance of discovering association rules in large databases when new transaction data are added to a transaction database. It generates less number of candidate keys as compared to Apriori, but deletion operation is not incorporated in this algorithm.

Fast UPdate2 (FUP2) (1997) [7] is an extended version of FUP, which handles the association rules in both Insertion and Deletion operation. This algorithm assumes that the large itemsets and their Support Count in the database came from the results of previously stored mining activities. It is more desirable to store counts rather than the association rules as the association rules can be calculated from these counts efficiently. The focus of this algorithm is that, the transaction to be deleted is a small part of the database activity.

Update With Early Pruning (UWEP) (1999) [8]**,** is another Apriori based algorithm that updates association rules with early pruning. It uses a dynamic look ahead strategy in updating the existing large itemsets. This algorithm detects and removes those items that will no longer remain large after the contribution of the new set of transactions. The limitation is that it does not allow changes in minimum support value.

PELICAN (2001) [9] algorithm is similar to FUP2 algorithm which is based on a lattice decomposition strategy to find out the maximum frequent/ large itemset when the database is updated. Apart from that it allows changes in minimum support value and the generation of candidate sets is less, compared to FUP algorithm. Limitation of the algorithm is that, it considers only maximum frequent itemset in mining process.

2.2. Partition based Incremental Mining

The limitation of the Apriori based Incremental Mining Algorithms are that they require multiple numbers of scans as well as generate large candidate sets. To cope up with this problem **[10]** developed a partition-based algorithm known as **Sliding Window Filtering (SWF)** algorithm. In this algorithm, a transaction database, ‘D’ is divided into ‘n’ number of partitions i.e. {P1, P2---Pn} and it employs filtering threshold in each partition to deal with the candidate itemset generation. The Cumulative Filter (CF) produced in processing each partition constitutes the key component to realize the incremental mining. If ‘L’ is a frequent itemset in

'D', then 'L' must be frequent at least in one of the 'n' number of partitions.

An extended version of SWF is proposed by [11]**.** Two algorithms have been proposed by reusing previous mining task for generating frequent patterns, namely SWF with Frequent Itemset (FI SWF) and SWF with Candidate Itemset (CI SWF).

This approach is faster and generates fewer candidates as compared to SWF and Apriori based algorithms. The limitation of this algorithm is that it does not take into consideration the situation that the dataset to be Inserted or Deleted is either too large or too small.

2.3. Tree/Pattern Growth based Incremental Mining

The limitations of the Apriori based Incremental Mining Algorithms and Partition based Incremental Mining Algorithms are:

- Multiple no. of scans required
- Do not allow changes in minimum support value
- Large candidate sets
- Assumption that data resides only on primary memory is not possible in most of the real-world applications

Taking into account of the above mentioned four limitations, Tree/Pattern Growth based Incremental Mining Algorithms has been introduced by the researchers.

Compressed and Arranged Transaction Sequences Tree (CATS Tree) (2003) [12] is an extension of FP tree which improves storage compression and allow frequent pattern mining without generation of candidate itemsets. The procedure of tree construction of CATS tree is as follows:

- Initialize CATS tree as Empty tree
- Calculate its itemset frequency. Frequency of Parent node always greater than sum of children node.
- The all itemset appears in the first transaction added to the initial tree. During the addition of next transactions, common items are extracted and merge with the existing tree if Parent node frequency > sum of Children node frequency. Similar procedure applicable for rest descendent. Remaining transactions are inserted as a new branch at the parent node.

Another variation of CATS is **FELINE** (Frequent/Large pattern mining with CATS tree) that generates frequent patterns without generating candidate set. It follows divide and conquer strategy. It partitions the dataset according to the transactions it has.

Canonical order Tree (CanTree) (2007) [13] is a tree where the nodes are arranged according to Canonical order. It is suitable as compared to CATS is that no adjustment of nodes is required in case of modification of the tree.

Fast updated Frequent Pattern Tree (FUFP) (2006) [14] is similar to FP-Tree except that the links between parent nodes and their child nodes are bi directional which helps fasten the process of deletion in the maintenance process.

Incremenatl Mining Binary Tree (IMBT) (**2009)** [15] approach does not require predetermining the minimum support threshold. This algorithm efficiently enumerates the support of each item set.

Pre-Frequent Pattern(**Pre-FP)** algorithm **(2010)** [16] based on the theory of pre-large itemsets, predefined support threshold named as "upper" and "lower". When the new transaction is added the frequent item do not transform into infrequent ones or vise versa, but the items are put into prelarge itemset first.

Item-Itemset (**I-Is) (2012)** [17] is based on IMBT. The item is placed in the tree depending upon its frequency. Original dataset is scanned only scans and frequency of each item and itemset is calculated and I-Is tree is constructed. When incremental data arrives, the I-Is tree is updated.

Tree for Incremental Mining of Frequent Pattern (TIMFP) (2016) [18] is a binary search-based tree structure where building the tree is unaffected by changes in item frequency as it uses binary search tree property to build the tree. This work is suitable for both interactive and incremental mining.

2.4. High Utility Frequent Pattern Incremental Mining

The approaches discussed in the above section was well defined on binary domain with equal measure of interestingness of items. In real world scienerio it is not always possible to have equal measures. Interestingness measures of items can be calculated in context of Unit cost, Profit, Priority, Distance, Credit e.g. Cost of items in a transactional database, importance of the traversing different web pages as per the priority basis etc.

Several algorithms have been proposed by researchers to reflect the Interestingness measures of items. Few are listed below:

Weighted Frequent Itemset Mining (WFIM) (2005) [19]is the first FP tree-based algorithm that reflects the relative importance (weight) of an item. Items are assigned with fixed weight in ascending order in the tree.

Weighted Interesting Patterns (WIP) (2006) [20] is a remarkable algorithm which introduces a new measure, weight-confidence to mine correlated patterns with weight affinity. Researcher have pointed out that weighted frequency of an item does not have the downward closure property.

Weighted Itemsets (WIT) (2013) [21] is used to fast mining of Frequent Weighted Itemsets (FWI) from transaction databases. In such framework, two tree structures i.e. Incremental Weighted Frequent Pattern Tree based on Weight Ascending order (IWFPTWA) & Incremental Weighted Frequent Pattern Tree based on Frequency Descending order (IWFPTFD) and two algorithms IWFPWA & IWFPFD are proposed by [22].

Some of the remarkable research in high utility incremental mining includes Utility Pattern Growth+ (UP-Growth+) and Utility Pattern Tree (UP tree) [23], Fast High-Utility Miner (FHM) [24], Maximum Utility Growth (MU-Growth, MU-Strategy1, MU-Strategy2) and Maximum Item Quantity Tree (MIQ-Tree) [25].

High Utility Mining (HUM) (2017) [26]**:** This approach is utility is profit and quantiuty and applied in education domain dataset. This is suitable to calculate the incremental semester wise performance of the students.

Mine High Average-Utility Patterns with Multiple Minimum Average-Utility Thresholds (HAUIM-MMAU) (2018) [27]**:** This approach uses average-utility list structure with multiple utility threshold that reduces mining time instead of coverarging the maximum ulility pattern. This approach works on the build once and mine property.

2.5. Constraint based Incremental Mining

Constraint based Incmemental Mining deals with the mining of patterns what exactly a user wants to extract instead of generating all the patterns. Following are some constraint based incremental mining algorithm.

Gap with Index Apriori (GwI-Apriori) (2009) [28]: uses gap constraint and level-wise approach to mine the frequent patterns. The limitation of this approach is that it spends much time in disk I/O hence not suitable for mine large amount of data.

RegularMine (2010) [29] uses an extension of itemsets called regular to investigate subset, superset or proper subset of items present or not. This approach produces user required frequent patterns from a large amount of closed itemsets.

Maximum Constraint Rare Pattern Tree (MCRP-Tree) (2015) [30] is FP tree-based approach to mine rare itemset and genereate association among them. Rare items are the item that occurs uncommonly in the dataset.

Constraint based Incremental Frequent Pattern Mining (CIFMine) (2015) [31]is an incremental constraint mining approach where dataset filtering techniques are used to reduce the size of the dataset. The main constraints discussed in this work are pattern, pattern length user defined minimum support threshold. This work is suitable for buid once and mine many constraint patterns from dynamic dataset.

NegI-NSP (Negative Sequential Patterns) (2017) [32]is a recent work which introduces strict constraints to solve a series of consequent problems. This approach starts with calculating negative sequnces then algorithm **NegI-NSP** applied to mine the useful patterns.

NOSEP (Nonoverlapping Sequence Pattern Mining With Gap Constraints) (2018) [33] is a most recent work focuses on maximally utilised pattern discovery using gap constraint. This research uses Nettree data structure to build and mine the pattern tree.

3. KEY RESEARCH FINDINGS

3.1 Apriori based Incremental Mining Algorithm

- These algorithms are mostly suitable for transactional databases
- Iteration based algorithm
- Huge number of Candidate set generation both in original as well as incremental portion which is undesirable in Incremental Mining process
- There is no concept of pruning particularly in FastUPdate based algorithms so generates a large number of candidate sets. But UWEP and PELICAN work with the concept of

early pruning

- In data base updatation, rescans are required both in the original and incremental databases
- Minimum Support value is fixed in both FastUPdate based and UWEP algorithms where as PELICAN allows changes in minimum support
- Overall assumption is that computation of all data takes place main memory only
- Does not consider the situation that transaction dataset to be inserted or be deleted too large or too small.

3.2. Partition based Incremental Mining Algorithms

- These algorithms are suitable for transactions as well as temporal databases. Particularly time –variant transaction databases.
- Partition based algorithm and employs filtering threshold in each partition to deal with the candidate itemset generation.
- Reduces the number of scans by using previous resultant candidate sets. Only one scan is required in incremenatal portion.
- Faster mining and less space required as compared to fast update-based algorithms because no need to keep all large itemsets in the main memory. Only one has to keep the resultant candidate set for further incremental mining process.
- Does not consider the situation that transaction dataset to be inserted or deleted is too large or too small.

3.3. Tree/Pattern Growth based Incremental Mining

- The tree is built without generating candidate sets
- Cope up of different support value without rebuilding the tree
- Apriori based incremental mining algorithm need multiple passes for an incremental mining process where as most of pattern growth algorithm need only single pass.
- Concurrent deletion is possible
- Faster mining and less space required as because uses the concept “build once and mine many”.
- The common assumption is, each item in a database is equal in weight

3.4. High Utility Incremental Frequent Pattern Mining

- The tree captures items along with weight in transaction database and arranges tree nodes according to normalized weight in ascending order.
- It is easily manageable when performed Insertion, Deletion and Update and mining operations.
- It fulfills "Build once and Mine many" which is suitable for incremental as well as interactive mining.

3.5. Constraint based Incremental Mining

- Focuses on the constraints and to specify the desired properties of the patterns to be mined that are likely to be of interest to the end user
- Identifies different constraints
- Suitable for semi structured/unstructured data

4. GOAL-REALATED ISSUES

This state-of art work presents a systematic way to address the frequent pattern mining problem using incremental frequent pattern mining. The following table shows goal related issues with respect to the RQs listed in the introduction section.

Table 1. Goal related issues of Imcremental Mining w.r.to RQS

	RQs	**Goal-related issues addresses w.r.to RQs**
1	What is the need for Incremental Mining?	Cost of Frequent Pattern Mining
2	What are the published literature/ approaches for Incremental mining of frequent patterns?	Review of Incremental Mining Approaches
3	Can they be classified according to functionality?	Problems in terms of Computational and Algorithmic Development
4	Are they able to measure the semantic significance of an item as per user requirements?	Importance of Semantic Significance
5	Do they satisfy users' constraints?	Importance of Constraints

The following goal-related issues have been addressed:

- **Cost of Frequent Pattern Mining**: Mining frequent patterns are costly during changes of the underlying database. Most of the traditional approaches need repetitive scanning of the database as well as generating huge number of candidate sets. In such type of situation, the important issue is how to utilize the mining result efficiently to reflect these changes. Thus, mining of growing databases is an interesting area of research in Data Mining.
- **Problems in terms of Computational and Algorithmic Development**: This causes Creation of duplicate node, Greater computation time required for Searching common itemsets, Merging and finding a suitable path, Consumption of large amounts of memory to construct the tree and greater mining time etc. It is important to develop efficient approaches to enhance the performance of mining.
- **Importance of Semantic Significance**: In Frequent pattern Mining, the common assumption is that each item in a database is equal in weight. As a matter of fact, in real life applications, it is not always possible to treat all patterns in an equal or binary way. Utility/weight associated with items is important in real life applications and it provides Semantic Significance of items presents in a database.
- **Importance of Constraints**: It is not always suitable for end users that all generated patterns are equally important. Constrains are important in cases where end user wishes to mine patterns that are interesting and specific to their application point of view. This experimental section can be divided into subsections, the contents of which vary according to the subject matter of the article. It must contain all the information about the experimental procedure and materials used to carry out experiments.

5. APPLICATION OF INCREMENTAL MINING OF FREQUENT PATTERNS

- **Business:** Pattern and trend analysis of customers. e.g.: Shopping patterns of customers which can help the retailer to know the need of customers and as a future action stores layout may change accordingly. The customer data keeps growing with time. This growing data can be mined incrementally using our research; Stock analysis by investors. e.g.: Investors can find out stocks with good performance etc.

- **Education:** Behavior analysis of students both in offline and online environment; Identification of the risk level of students; Enrollment Management (branch of study, courses, and programs in which they can enrol) and Curriculum Development which can help planners design a curriculum focused on the demands of the future workforce etc. so that successful, goal-oriented and quality education can be obtained.
- **Banking and Finance:** Patterns and association analysis specially loan payment and credit analysis of customers; unusual pattern analysis etc.

6. CONCLUSION

To address the issues arising from real time increasing data, the research need to focus on incremental mining that helps in the decision-making process. This state of the art paper reviews methods of Incremental Mining of frequent patterns and highlights the possible advantages and limitation of each method. Incremental Mining of frequent patterns approaches discussed here is Apriori based Incremental Mining Algorithm, Partition based Incremental Mining Algorithms, Tree/Pattern Growth based Incremental Mining, High Utility Incremental Frequent Pattern Mining and Constraint based Incremental Mining. This is a state-of-art paper, where have discussed five Research Questions, Goal-related issues and Application of Incremental Mining of Frequent Patterns in real world scenario. This work will help researchers to find out related advances, limitations of each approach and suitable methods as per their research requiremetnts.

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