A Study of Differentially Private Frequent Itemset Mining

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Abstract: Frequent sets play an important role in many Data Mining tasks that try to search interesting patterns from databases, such as association rules, sequences, correlations, episodes, classifiers and clusters. Frequent Itemsets Mining (FIM) is the most well-known techniques to extract knowledge from dataset. In this paper differential privacy aims to get means to increase the accuracy of queries from statistical databases while minimizing the chances of identifying its records and itemset. We studied algorithm consists of a preprocessing phase as well as a mining phase. We under seek the applicability of FIM techniques on the MapReduce platform, transaction splitting. We analyzed how differentially private frequent itemset mining of existing system as well.

Keywords: Frequent itemset mining, Differential Privacy, Transaction Splitting.

1. Introduction

Frequent sets play an essential role in many Data Mining tasks that try to find interesting patterns from databases, such as association rules, correlations, sequences, episodes, classifiers and clusters. The identification of sets of items, products, symptoms and characteristics, which often occur together in the given database, can be seen as one of the most basic tasks in Data Mining. The original motivation for searching frequent sets came from the need to analyze so called supermarket transaction data, that is, to examine customer behavior in terms of the purchased products. Frequent sets of products describe how often items are purchased together.

The existing system has problem of tradeoff between utility and privacy in designing a differentially private FIM algorithm. The existing system does not deal with the high utility transactional itemsets. Existing methods has large time complexity. Existing system gives comparatively large size output combination. To solve this problem, this project develops a time efficient differentially private FIM algorithm. With communication, data storage technology, a huge amount of information is being collected and stored in the Internet. Data mining, with its promise to efficiently find valuable, non-obvious information from huge databases, is particularly vulnerable to misuse. The situation may become worse when the database contains lots of long transactions or long high utility itemsets. To solve this, we propose an algorithm for the top-k item set mining. In general it is impossible to devise a run-time finding method to find the actual support of itemsets in the original database. Here, we search the applicability of FIM techniques on the MapReduce platform. It is a parallel distributed programming framework introduced in [4, 6], which can process large amounts of data in a massively parallel way using simple commodity machines. We use MapReduce to implement the parallelization of algorithm, thereby improving the overall performance of frequent itemsets mining.

2. Existing System

- C. Dwork [5] The author give a general impossibility result showing that a formalization of Dalenius” goal along the lines of semantic security cannot be achieved. Contrary to intuition, a variant of the result threatens the privacy even of someone not in the database. This state of affairs suggests a new measure, differential privacy, which, intuitively, captures the increased risk to one’s privacy incurred by participating in a database. The techniques developed in a sequence of papers, culminating in those described in, can achieve any desired level of privacy under this measure. In many cases, extremely accurate information about the database can be provided while simultaneously ensuring very high levels of privacy.
- C. Zeng, J. F. Naughton, and J.-Y. Cai,[22],In this author elaborates difficulties of finding good utilities and privacy and also they have proposed differentially private algorithm for the top-k item set mining. In general it is
difficulties occur during processing of long transaction so they had investigated an approach that begins by truncating transactions that contains more items, trading off errors introduced by the truncation with those introduced by the noise added to guarantee privacy. Their algorithm solves the frequent item set mining problem in which they find all item sets whose support exceeds a threshold. The advantage of this algorithm is it achieves better F-score unless k is small.

- N. Li, W. Qardaji, D. Su, and J. Cao [8]. In this paper, they searched the problem of how to perform frequent itemset mining on transaction databases while satisfying no of privacy. They propose an approach, called PrivBasis, which leverages a novel notion called basis sets. A 0-basis set has the property that any itemset with frequency higher than θ is a subset of some basis. They represented algorithms for privately constructing all basis set and then using it to find the most frequent itemsets. Experiments show that our approach greatly outperforms the state of the art.

- Maurizio Atzori, F. Bonchi, F. Giannotti [18]. In this paper, authors show that this belief is ill-founded. By concept of k-anonymity from the source data to the extracted patterns, they formally characterize the notion of a threat to anonymity in the context of pattern, and gives a methodology to efficiently and effectively show all such possible threats that arise from the disclosure of the set of patterns. On this basis, they gain a formal notion of privacy protection that allows the disclosure of the extracted knowledge while protecting the anonymity of the individuals in the source database. Rather in order to handle the cases where the threats to anonymity cannot be avoided, they study how to eliminate such threats by means of pattern distortion performed in a dataset.

- Evfimievski, R. Srikan, R. Agrawal, and J. Gehrke [19]. Author present a work for mining association rules from transaction consisting of categorical items where the data has been randomized to maintain privacy of individual transactions. While it is possible to recover association rules and preserve privacy using a forward uniformization, the searched rules can unfortunately be exploited to gain privacy. They analyze the nature of privacy and propose a class of operators that are much more effective than uniform randomization in limiting the breaches. They prove formulae for an unbiased support estimator and its variance, which allow us to get backitem set supports from randomized database, and show how to incorporate these formulae into mining algorithms. At last, they present experimental analysis that validates the algorithm by applying it on real datasets.

- W. K. Wong, D.W. Cheung, E. Hung, B. Kao, and N. Mamoulis [16]. They found frequent item sets is the most costly task in association rule mining. This task to a service provider brings several benefits to the data owner such as cost relief and a less obligation to storage and computational resources. Mining results, can be loss if the service provider (i) is honest but makes error in the mining process, or (ii) is lazy and reduces costly computation, returning incomplete results, or (iii) is malicious and infected the mining results. They show the integrity issue in the outsourcing process, i.e., how the data owner verified the accuracy of the mining results. For this purpose, we propose and develop an audit environment, which consists of a dataset transformation method and a result verification method. The main component of its audit environment is an artificial itemset planting (AIP) technique. They provide a theoretical base on our method by showing its appropriateness and showing probabilistic guarantees about the correctness of the verification process. Through analytical and experimental studies, they represented that their technique is both effective and efficient.

- E. Shen and T. Yu [23]. Author discovered frequent graph patterns in a graph database. If graph database contains sensitive data of individuals, liberating discovered frequent patterns may present a threat to privacy of individuals. So they proposed the first differentially private algorithm for mining frequent graph patterns. Their proposed solution incorporates the process of graph mining and privacy protection into an MCMC(Markov Chain Monte Carlo) sampling framework.

SheelaGole and Bharat Tidke [24], implement FIM sampling framework. They introduced ClustBigFIM algorithm that works on large datasets with increased execution efficiency using preprocessing. Their Result of ClustBigFIM shows that it works on BigData very efficiently and with higher speed.

3. Related Work

In differentially private frequent mining it uses different algorithm to find itemset as follows:

- **UP-Growth**: The basic method to generate high utility item sets is the FP-Growth [3] algorithm. However, it produces huge number of item sets. In order to reduce the number of item sets and produce only high utility item sets UP-Growth algorithm [21] is used. Utility pattern growth algorithm for mining high utility item set.

- **FP-Growth**: The FP-Growth algorithm skips the candidate itemset generation process by using a compact tree structure to store itemset frequency information. FP-Growth works in a divide and conquers way. It requires two scans on the database. FP-Growth first computes a list of frequent items sorted by frequency in descending order (F-List) during its first database scan [15].

- **Frequent itemset mining**: A frequent itemset mining algorithm takes as input a dataset consisting of the transactions by a group of individuals, and produces as output the frequent itemsets [22]. This immediately creates a privacy concern how can we be confident that publishing the frequent itemsets in the dataset does not reveal private information about the individuals whose data is being studied.

- **PFP-growth**: We devise partitioning strategies at different stages of the mining process to achieve balance between processors and adapt some data structure to reduce the information transportation between processors. The experiments on national high performance parallel computer show that the PFP-growth is an efficient parallel algorithm for mining frequent itemset.

- **Apriori**: Finding all frequent itemsets in a database is difficult since it involves searching all possible itemsets that exist in the database.
(item combinations). The set of possible itemsets is the power set over $I$ and has size $2^n - 1$ (excluding the empty set which is not a valid itemset). Although the size of the power set grows exponentially in the number of items $n$ in $I$, efficient search is possible using the downward-closure property of support (also called anti-monotonicity).

The below table shows comparison between each algorithm used in frequent itemset mining.

<table>
<thead>
<tr>
<th>Algorithm/ Parameter</th>
<th>FP-growth</th>
<th>PFP-growth</th>
<th>UP-growth</th>
<th>Apriori</th>
<th>FIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Based on</td>
<td>Bottom up approach</td>
<td>Breadth-first search</td>
<td>Tree structure</td>
<td>Tree structure</td>
<td>transaction splitting</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Low</td>
<td>Average</td>
<td>Average, High for dataset</td>
<td>Average</td>
<td>High</td>
</tr>
<tr>
<td>Time Complexity</td>
<td>High</td>
<td>High</td>
<td>Average</td>
<td>Average</td>
<td>low</td>
</tr>
<tr>
<td>Performance</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>average</td>
<td>high</td>
</tr>
</tbody>
</table>

### 4. System Model

![System Diagram](image-url)

Figure 1 shows system model Frequent Itemset Mining. It takes data from raw data store then by using user transformation it apply data processing and algorithm on data table. It uses Map reduce to find frequent itemset and gives result. Main aim of using map reduce is to handle big data. As we know transaction file may contain sensitive and huge data. We are proposing private frequent itemset mining based on mapreduce so that long dataset will get splits into multiple parts and these files will be parallel handle, which in turns reduce space and time complexity. It was proposed which is used to obtain frequent itemsets from the dataset.

MINimal Infrequent Itemsets (MINIT) is the algorithm designed specifically for mining minimal infrequent itemsets [9]. MINIT computes both minimal (weighted) and non-minimal (unweighted) infrequent itemset mining from unweighted data which is based on algorithm and also proved that the minimal infrequent itemset problem is NP-complete problem. Different from [10], Clifton and Kantarcioglu [11] consider the dataset is horizontally partitioned and model the problem as a secure multi-party computation. Evtimievski et al. [12] present a set of randomization operators the privacy breaches in FIM. Based on k-anonymity [13], Atzorietal. The most relevant work from the statistical database literature is the work by Warner [4], where he represented the “randomized response” method for survey results. Through formal privacy analysis, he shows how our PFP-growth algorithm is differentially private. Extensive experiments on real database illustrate that our PFP-growth algorithm and its outperforms the state-of-the-art techniques. The problem of outsourcing the task of data mining with accurate result was introduced in our previous work [16]. Frequent itemsets, as name suggest, are the sets of items often occurring frequently in transactional dataset. It leads to discovery of the association rules from the datasets. Frequent itemsets are appearing with frequency more than a user-specified threshold. This task to a service provider brings several bents to the data owner such as cost relief and a less commitment to storage and computational resources. The following section shows algorithm and mining long patterns.

#### 4.1 Algorithm

Construct data Set: Construct a Basis Set Using Frequent Items and Pairs
Input: F, frequent items, and P, frequent pairs.
Output: B, a basis set covering all maximal cliques in the graph (F, P).
1: function Construct Basis Set(F, P)
2: B1 ← all maximal cliques of size at least 2 in the graph given by P
3: B2 ← items in F but not in P, divided into the smallest number of itemsets such that each contains at most 3 items
4: Repeatedly find Bi, Bj ∈ B1 such that merging Bi and Bj results in the huge reduction of average-case error variance (EV) when using B = B1 ∪ B2 to obtain no. of itemsets in F
and P; and update B1 by merging Bi, Bj; stop when no merging reduces EV
5: Again find Bi ∈ B2 such that deleting Bi and moving items in Bi to bases in B1 ∪ B2 with smallest sizes results in the largest EV-reduction; update B when Bi is found; stop when no such Bi can be found
6: return B = B1 ∪ B2
7: end.

5. Conclusion and Future Work

In this paper, we investigate the problem of designing a differentially private FIM algorithm. We use differential privacy to stop the potential information exposure about individual recordset during the data mining process. Here we studied system model of Frequent Itemset Mining using MapReduce. We put forward algorithm and mining long patterns. It minimizes time required for large dataset. As we are using map reduce here, can also handle huge size dataset without any problem. We represented comparative table between different algorithms used in FIM. As our future work we plan to design more effective differentially private FIM on big data.

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