Fast top-k frequent itemset mining under Local Differential Privacy*

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***Abstract*—This is the abstract.**

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I. Introduction

Differential privacy (DP) [7] is the state-of-the-art approach that is used to protect individual privacy in the process of data collection, which has been named one of the world's top 10 breakthrough technologies in 2020 by the MIT technology review. It is a means in cryptography that aims to provide a way to maximize the accuracy of data queries when querying from statistical databases while minimizing the chances of identifying their records. Meanwhile, as a mathematical technique, it can add noise to the data while quantifying the extent of the increase in privacy, thus making the process of adding "noise" more rigorous.

Due to its unique advantages, DP has been widely studied by the academia and industry. For example, Google, Microsoft, apple and other companies use this technology to protect users' privacy, and at the same time, mobile phones aggregate data, so as to improve service quality. And the U.S. government is to complete a census of 330 million U.S. residents by 2020, keeping their identities secret, in what would be the largest application of DP ever.

There are two types of differential privacy - Centralized differential privacy (CDP) and Local differential privacy (LDP). Compared with CDP, the LDP does not require the assumptions of a trusted third party and provides stronger privacy guarantees. DP's research has involved many aspects, in recent years, the work in mining frequent itemsets has attracted the attention, which is one of the most important techniques because of its ability to locate the repeating relationships between different items in a data set and plays an essential role in mining association rules [9]. Formally, let $\mathcal{X} = \{x_1, x_2, ..., x_d\}$ be the global domain of items with size is d and $\mathcal{T} = \langle T_1, T_2, ..., T_n \rangle$ denote a transaction database for n users, where $T_i(i \in [1...n])$ denotes a transaction that is a subset of $\mathcal{X}$. For example, a sample of transational data is shown in Table I. The support of an itemset X, where $X \subseteq \mathcal{X}$ is a set of items, is the number of transactions containing X in $\mathcal{T}$. Then, given a minimum support threshold δ, the problem of finding the complete set of frequent itemsets that supports no less than δ is called the frequent itemset mining (FIM) problem.

A lot of work [3]–[6] has been done to solve DM problems in CDP. However, since the analyst holds the user's raw data in CDP setting, its main job is to add noise to the results to satisfy the DP definition.

In this paper, we consider the $top-k$ FIM problem in transaction databases under LDP. Although LDP is similar to CDP, the LDP has no reliance on third party. The data analyst wants to find k itemsets with highest support while while users are sensitive and unwilling to answer their real infomation. The main challenge is that the analyst does not hold the user's original sensitive information, which makes it quite difficult to mine useful information with sanitized data. Qin et al. [1] point out that if utlize directly existing FIM algorithm (e.g. Apriori [9], [10], FP-growth [8], Eclat [13]) would result in accumulation of dramatic noise because of multi-iteration between users and analyst.

Specifically for FIM in the local setting, Qin et al. [1] leave it as a future work but there is no clear solution. Wang et al. [2] solves the $top-k$ frequent itemset mining (FIM) task for the first time with **padding-and-sampling-based frequency oracle** (PSFO). In [2], the Set-Value Item Mining (SVIM) protocol is proposed to handles set values under the LDP setting, with the purpose of finding the k most frequent items and their frequencies. To mine frequent itemsets , a core technique is "Guessing Frequency (GF)". That is, the analyst

TABLE I
Sample of transactional data.

TID	List of items
T01	a, f, c, g, p
T02	a, b, c, f, l, o
T03	b, f, h, o
T04	b, c, p
T05	f, a, c, l, p, n

Identify applicable funding agency here. If none, delete this.

first calculated the frequency of a given itemset X for all candidate itemsets by (1),

$$\varphi(X) = \prod_{x \in X} \mu(x), \mu(x) = \frac{0.9 \times \tilde{\theta}(x)}{\max\limits_{x \in S'} \tilde{\theta}(x)} \quad (1)$$

where $\varphi(X)$ represents the speculative frequency of itemset X, S' and $\tilde{\theta}(x)$ are denoted separately the $top-k$ frequent items set and the frequency of a given item x. Then $2k$ itemsets with highest guessing frequencies are selected to construct candidate set IS. Finally, it utilizes SVIM protocol again with the domain IS to mine $top-k$ itemsets. We observe that, the size of candidate set to construct IS increase significantly with k. As a result, it is computationally expensive when k is large (e.g., $k = 100$).

Inspiringly, we propose minefp protocol, which aims at finding $top-k$ itemsets under the LDP setting and provides similar accuracy while providing lower overhead than existing SVSM protocol within the same privacy constraints. First, the SVIM protocol is used to estimate the k most frequent items and their frequencies. Second, users report the number of frequent items they have; the analyst estimates the distribution user reported and figure out the right M as the maximum iteration of the tree. Third, users interact with the analyst to build effectively the FP-tree [8]. Fourth, the analyst optimizes and mines the FP-tree. Fifth, the analyst publishes $top-k$ itemsets.Experimental results how that minefp outperforms SVSM in that it identifies quickly frequent itemsets as well as estimates the frequencies more accurately.

To summarize, the main contributions of this paper are:

- We study the application of FP-growth algorithm and design the FP-tree-based-mine (minefp) protocol to find frequent itemsets as well as their frequencies in the LDP setting. Experimental results on real-world datasets show the significant improvement over previous techniques.
- We investigate GF to construct candidate set and point out that it is beneficial to build hierarchically FP-tree.

Roadmap.

II. Preliminaries

A. Local Differential Privacy (LDP)

In the local setting, there is no trusted third party and an aggregator wants to gather information from users, where each user possesses an input v. The privacy of the data contributor is protected by perturbing her/his original data at the data contributor's side; thus, the agregator cannot access the original data, but is still able to obtain population statistics.

Formally, let $\mathcal{T}$ denote the whole transaction databases. ϵ-local differential privacy (or ϵ-LDP) is defined on an algorithm $\mathcal{A}$ and a privacy budget $\epsilon \geq 0$ as follows.

Definition 1: ($\epsilon - LDP$). A randomized algorithm $\mathcal{A}$ satisfies ϵ-local differential privacy (ϵ-LDP), if and only if for (1) all pairs of input $t_i, t_j \in \mathcal{T}$, and (2) any possible output $\mathcal{O}$ of $\mathcal{A}$, we have:

$$\frac{\mathbf{Pr}[\mathcal{A}(t_i) = \mathcal{O}]}{\mathbf{Pr}[\mathcal{A}(t_j) = \mathcal{O}]} \leq e^{\epsilon}$$

Sequential composability [12] and *post−processing* [14] are vitally important properties of differential privacy. The former allows each user to divide privacy budget into multiple portions and use each portion to execute independent LDP protocols on the same input while the sequential executions provide $\sum \epsilon_i$-LDP; the latter guarantees that any processing of the noisy data do not disclose the privacy.

Theorem 2.1: ($sequential\ composability$). Given m randomized algorithms $\mathcal{A}_i (1 \leq i \leq m)$, each of which satisfies ϵ_i-local differential privacy. Then the sequence of $\mathcal{A}_i$ collectively provides $(\sum_{i=1}^{m} \epsilon_i)$-local differential privacy.

Theorem 2.2: ($post - processing$). For any method ϕ which works on the output of a ϵ-LDP algorithm $\mathcal{A}$ without accessing the raw data, the procedure $\phi(\mathcal{A}(\cdot))$ remains ϵ-LDP.

B. Frequency Oracle in the LDP setting

A frequency oracle (FO) protocol under LDP enables aggregator to estimate the frequency of any given value $v \in \mathcal{X}$ from all sanitized data recived from the users. A fundamental FO protocol is Randomized Response (RR) [15], which is a traditional technique for estimating unbiasedly a population proprotion. It is the building block of many sophisticated LDP protocols, such as RAPPOR [16], GRR and OLH [11]. Suppose the respondents were asked to answer a sensitive Boolean question (e.g. have you ever cheated on your partner?) in a survey, then RR makes provisions for each person to be interviewed. That is, each respondent gives the raw answer with probability p and gives the opposite answer with probabilit $q = 1 - p$. Specially, to satisfy ϵ-LDP, the probability p is set to $\frac{e^{\epsilon}}{1+e^{\epsilon}}$.

Then, the agregator calculates the estimated percentage of "Yes" (denote as $\tilde{\theta}$) as example from all sanitized answers, which is unbiased, as follows:

$$\tilde{\theta}_{RR}(Yes) = \frac{\mathcal{C}(answer = Yes) - nq}{p - q}$$

where n is the total number of respondents and $\mathcal{C}(answer = Yes)$ denotes the number of occurrences respondents answered "Yes". Accordingly, the variance of it is

$$Var\big[\tilde{\theta}_{RR}(Yes)\big] =$$

However, the RR protocol only applies to binary Boolean problems, which greatlt limits its application. Therefore, in [11], two effective protocols, Generalized Random Response (GRR) and Optimized Local Hash (OLH), are proposed for the purpose of solving problems with large domain size $d = |\mathcal{X}|$.

Generalized Random Response (GRR) [11]: GRR extends the RR protocol in case of $d \neq 2$ by setting probability $p = \frac{e^{\epsilon}}{e^{\epsilon}+d-1}$ to give the raw answer $y = v$ and probability $q = \frac{1-p}{d-1}$ (i.e. $q = \frac{1}{e^{\epsilon}+d-1}$) to give the perturbed answer $y \neq v$. Specially, it has been shown that RR is the special case while $d = 2$. The shortage of GRR is that its estimated variance is linear with d, which makes poor perform when d is large:

$$Var\big[\tilde{\theta}_{GRR}(v)\big] = n \cdot \frac{d - 2 + e^{\epsilon}}{(e^{\epsilon} - 1)^2} \quad (2)$$

Optimized Local Hashing (*OLH*) [11]: In order to deal with a large domain size d as well as reduce the communication cost, OLH protocol applies a hash function to map each input value into a value in $[g]$, where $g \geq 2$ and $g \ll d$. Then randomized response is used to the hashed value in the smaller domain. In [11], the optimal choice of the parameter g is $\lceil e^{\epsilon} + 1 \rceil$ which meets the minimal variance.

Let H is randomly chosen from a family of hash functions that outputs a value in $[g]$ and $x = H(v)$. The perturbing protocol in OLH is $Perturb_{OLH}(\langle H, x \rangle) = \langle H, y \rangle$, where

$$\forall_{i \in [g]} \mathbf{Pr}[y = i] = \begin{cases} p = \frac{e^{\epsilon}}{e^{\epsilon}+g-1}, & \text{if } x = i \\ q = \frac{1}{e^{\epsilon}+g-1}, & \text{if } x \neq i \end{cases}$$

Accordingly, the aggregator first calculates the number of perturbed values that "supports" that the input is v (denote as $\mathcal{C}(v)$), then transforms $\mathcal{C}(v)$ to its unbiased estimation

$$\tilde{\theta}_{OLH}(v) := \frac{\mathcal{C}(v) - n/g}{p - 1/g} \tag{3}$$

The variance of this estimation is

$$Var\left[\tilde{\theta}_{OLH}(v)\right] = n \cdot \frac{4e^{\epsilon}}{(e^{\epsilon} - 1)^2} \tag{4}$$

Intuitively, OLH has a variance that does not depend on d. In [11], it suggests that when domain size $d < 3e^{\epsilon} + 2$, GRR is the best among all approaches; but for large d, OLH meets high accuracy as well as low communication cost

— — — — — — — — — — — — — In [11], the two best performing FO protocols are Generalized Random Response (GRR) and Optimized Local Hash (OLH). The former extends the randomized response (RR) technique [15], which is an old technique developed for the interviewees in a survey to give random answer to a sensitive boolean question so that they can achieve plausible deniability; the latter deals with a large domain size $|I|$ by hashing a large domain size $|I|$ to a smaller size g and applying RR to the hashed value. It was found that GRR offers the best accuracy than OLH when $|I| < 3e^{\epsilon} + 2$, where $|I|$ is the size of the domain of items under consideration. Therefore, in [2], an adaptive FO protocol can be proposed from the known I as well as ϵ.

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C. FP-growth algorithm

Frequent pattern growth (FP-growth) [8] is an algorithm that mines the complete set of frequent patterns without a costly candidate generation process, which based on the frequent pattern tree (FP-tree) structure that is an extended prefix-tree structure for storing compressed, crucial information about frequent patterns. The FP-Tree is further divided into a set of Conditional FP-Trees for each frequent item so that they can be mined separately. An example of the FP-Tree that represents the frequent items is shown in Fig. 1, where the minimum support threshold is set to 3.

The FP-growth algorithm solves the problem of identifying long frequent itemsets by searching through smaller conditional FP-tree repeatedly. The conditional pattern base is a "sub-database" which consists of every prefix path in the FP-Tree that co-occurs with every frequent length-1 itemset. It is used to construct the conditional FP-tree and generate all the frequent patterns related to the length-1 items. In this way, the cost of searching for the frequent patterns is substantially reduced.

TABLE II
NOTATIONS.

Symbol	Description
n	the number of users
X	the itemset
$\lvert X \rvert$	the cardinality of itemset X
$\mathcal{T}$	the transaction database
T_i	the transaction of user i
$\mathcal{X}$	the set of items
d	the number of items, $d = \lvert \mathcal{X} \rvert$

Definition 2: (*length* $-$ α *itemset*). is this necessary?

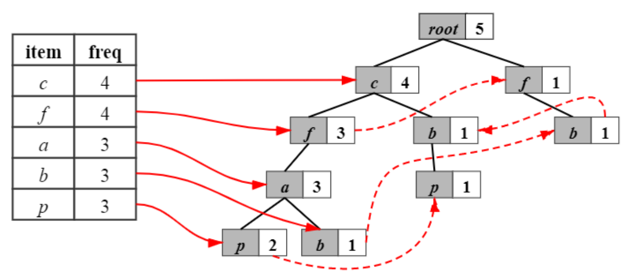

Fig. 1. Frequrnt pattern tree(FP-tree).

III. Problem Overview

A. Problem Definition

In this paper, we study the FIM problem while fully considering users' personal privacy. Or rather, we look at privacy preserving frequent itemset mining under the LDP setting. In general, let $\mathcal{X} = \{x_1, x_2, ..., x_d\}$ denote the whole domain of items, X is a length-$|X|$ itemset where $X \subseteq \mathcal{X}$ is a subset of $\mathcal{X}$ and $|X|$ denote the cardinality of it.

There are n users, and each user has a sensitive transaction, which is a subset of $\mathcal{X}$. Formally, the transaction of i-th user is $T_i (i \in [1, n])$ and $\mathcal{T} = \langle T_1, T_2, ..., T_n \rangle$ denote the whole transaction database. An untrusted data analyst (or aggregator) is going to mining $top - k$ most tfrequent itemsets and their frquencies among all users under ϵ-LDP. More specifically, we aim to mine k length-α itemset with highest frequencies, where $\alpha \geq 2$.

Table II lists the notations used in this paper

B. Existing Approaches to FIM under LDP

Since Qin et al. [1] first introduces set-valued data to differential privacy in the local setting for the purpose of discovering heavy hitters as well as their frequencies, it has been a challenge that mining frequent itemsets from all sanitized data. To the best of our konwledge, only SVSM [2] protocol that implements effectively FIM task in context of

LDP. Particularly, it focuses on mining $top-k$ most frequent length-α ($\alpha > 1$) itemsets while utilizing SVIM [2] protocol that obtains the frequent items (or length-1 itemsets) as initial condition to construct candidate set. Details as follows.

$Set-Value\ Item\ Mining\ (SVIM)$: SVIM is a PSFO protocol with the same problem setting as LDPMiner [1], which aimming at discovering the k frequent items with highest frequencies. It has four steps and splits the privacy budget ϵ into three parts.

1. Prune the Domain. The goal is to identify a candidate set for items so that it can reduce the domian size into $2k$, which is greatly less than the domain d. In this step, each user uses FO to perturb a randomly sampled item from his raw data. Then, the analyst estimates the frequency of each value in the domain and selects the $2k$ frequent items with highest frequencies. The analyst broadcasts the domain set S pruned to all users.

2. Size Estimation. In order to further estimate the frequency of the set S. It is necessary to approximate the distribution of the number of frequent items that users hold. Thus, the perturbing data of each user is the size of the raw of intersected with the set S. After the perturbing of users finishes, the alalyst estimates the length distribution and calculates the $\beta = 90\%$ length L by

$$\frac{\sum_{i=1}^{L}\tilde{\theta}(i)}{\sum_{i=1}^{2k}\tilde{\theta}(i)} > \beta \tag{5}$$

IV. A Simple FP-tree-Based Approach

V. Ease of Use

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References

[1] Qin, Zhan, et al. "Heavy Hitter Estimation over Set-Valued Data with Local Differential Privacy." computer and communications security (2016): 192-203.

[2] Wang, Tianhao, Ninghui Li, and Somesh Jha. "Locally Differentially Private Frequent Itemset Mining." ieee symposium on security and privacy (2018): 127-143.

[3] Bhaskar, Raghav, et al. "Discovering frequent patterns in sensitive data." knowledge discovery and data mining (2010): 503-512.

[4] Li, Ninghui, et al. "PrivBasis: frequent itemset mining with differential privacy." very large data bases (2012): 1340-1351.

[5] Lee, Jaewoo, and Chris Clifton. "Top-k frequent itemsets via differentially private FP-trees." knowledge discovery and data mining (2014): 931-940.

[6] Zeng, Chen, Jeffrey F. Naughton, and Jinyi Cai. "On differentially private frequent itemset mining." very large data bases (2012): 25-36.

[7] C. Dwork. Differential privacy. In ICALP, pages 1–12, 2006.

[8] Han J, Pei J, Yin Y, et al. Mining frequent patterns without candidate generation[C]. international conference on management of data, 2000, 29(2): 1-12.

[9] Agrawal R, Imielinski T, Swami A N, et al. Mining association rules between sets of items in large databases[C]. international conference on management of data, 1993, 22(2): 207-216.

[10] Agrawal R, Srikant R. Fast Algorithms for Mining Association Rules in Large Databases[C]. very large data bases, 1994: 487-499.

[11] Wang T, Blocki J, Li N, et al. Locally Differentially Private Protocols for Frequency Estimation[C]. usenix security symposium, 2017: 729-745.

[12] F. D. McSherry. Privacy integrated queries: an extensible platform for privacy-preserving data analysis. In SIGMOD, pages 19–30, 2009.

[13] Zaki M J. Scalable algorithms for association mining[J]. IEEE Transactions on Knowledge and Data Engineering, 2000, 12(3): 372-390.

[14] C. Dwork, F. McSherry, K. Nissim, and A. Smith, "Calibrating noise to sensitivity in private data analysis," in Theory of Cryptography Conference. Springer, 2006, pp. 265–284.

[15] S. L. Warner. Randomized response: A survey technique for eliminating evasive answer bias. Journal of the American Statistical Association, 60(309):63–69, 1965.

[16] U. Erlingsson, V. Pihur, and A. Korolova. Rappor: Randomized aggregatable privacy-preserving ordinal response. In CCS, pages 1054–1067. ACM, 2014.

[17] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[18] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[19] I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[20] K. Elissa, "Title of paper if known," unpublished.

[21] R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[22] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, "Electron spectroscopy studies on magneto-optical media and plastic substrate interface," IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[23] M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

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