Recurrent Item sets Mining by GAP Seclusion over Large-Scale Data

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***Abstract:*- Common item sets mining with differential privacy refers to the trouble of mining all common item sets whose helps are above a given threshold in a given transactional dataset, with the constraint that the mined consequences ought to no longer wreck the privacy of any unmarried transaction. Contemporary solutions for this trouble cannot nicely balance efficiency, privateness and information application over large scaled data. Towards this case, we endorse an efficient, differential private frequent item sets mining set of rules over huge scale data. Based at the ideas of sampling and transaction truncation using duration constraints, our algorithm reduces the computation intensity, reduces mining sensitivity, and thus improves data application given a hard and fast privacy finances. Experimental effects show that our set of rules achieves better performance than previous approaches on more than one datasets.**

Index Terms:* *Frequent Item sets mining; Differential Privacy; Sampling; Transaction Truncation; String Matching

I. INTRODUCTION

In recent years, with the explosive boom of information and the fast improvement of records era, diverse industries have accumulated big amounts of information thru diverse channels. To discover beneficial expertise from big amounts of facts for top-layer programs (e.g. enterprise selections, potential client evaluation, and so on.), facts mining [1]– [9] has been advanced rapidly. it has produced a effective impact in many regions together with enterprise and medical care. Together with the first-rate benefits of those advances, the big quantity of records additionally carries privateness sensitive records, which can be leaked if now not well controlled. For instance, smart cell phone packages are recording the whereabouts of users via GPS sensors and are transferring the statistics to their servers. Clinical records are also storing ability relationships between sicknesses and a spread of information. Mining on user vicinity facts or clinical file information each provide precious information; however, they will additionally leak person privacy.

Consequently mining expertise below assured privacy ensures is tremendously expected. This paper investigates how to mine common item sets with privateness guarantee for big statistics. We recollect the subsequent software scenario. A company (consisting of facts consulting company) has a huge-scale dataset. The corporation would really like to make the dataset public and therefore allow the public to execute frequent item sets mining for purchasing cooperation or profits. But because of privacy issues, the employer can't provide the unique dataset at once. Consequently, privateness mechanisms are hard to method the data, which is the focus of this paper.

To ensure privateness of statistics mining, conventional methods are primarily based on ok-anonymity and its prolonged models [10]–[16]. These strategies require sure assumptions; it's miles hard to shield privateness when the assumptions are violated. The insufficiency of ok-anonymity and its prolonged models is that there is no strict definition of the attack model, and that the information of the attacker cannot be quantitatively described. To pursue strict privacy evaluation, work proposed a strong privacy safety version called differential privateness [17]. This privacy definition features independence of heritage knowledge of the attacker and proves very useful.

Frequent sample mining with privacy protection has additionally acquired widespread attention. as initial methods [18]– [24], these works have supplied a number of contributions in this region. However with the improvement of research, those privacy methods have no longer been able to provide effective privateness. So as to conquer those problems, researches started out to recognition on the differential privateness safety framework [25]–[31]. Despite the fact that making certain privacy transient, but, the stability between privateness and software of frequent item sets mining consequences desires to be similarly pursued.

on this paper, we recommend a unique differential private frequent item sets mining set of rules for large information by merging the thoughts of [27], [30], which has better performance due to the brand new sampling and better truncation techniques. We build our algorithm on Fp-tree for common item sets mining. on the way to clear up the hassle of constructing Fp-tree with huge-scale facts, we first use the sampling concept to reap consultant information to mine ability closed frequent item sets, which can be later used to discover the final common items inside the big-scale records. Further, we appoint the length constraint strategy to resolve the trouble of excessive worldwide sensitivity. Particularly, we use string matching thoughts to find out the most similar string inside the supply dataset, and enforce transaction truncation for reaching the bottom statistics loss. We ultimately upload the place noise for frequent item sets to make certain privateness guarantees.

A few demanding situations exist: first, the way to layout a sampling technique to control the sampling errors? We use the important restriction theorem to calculate an affordable sample length to govern the mistake variety. After obtaining the pattern length, the dataset is randomly sampled using a data analysis toolkit. The second one undertaking is the way to layout an amazing string matching method to truncate the transaction without dropping statistics as a long way as feasible? we healthy the capacity item sets in the sample records to locate the most comparable gadgets after which merge them with the most common objects until the most duration constraint is reached.

As a result, our set of rules reduces the computation intensity and addresses excessive sensitivity of frequent item sets mining. The overall performance is also guaranteed. Through the analysis of privacy, our set of rules achieves -differential privacy. Experiment outcomes the usage of a couple of datasets confirmed that our set of rules achieves better performance than previous strategies.

To summarize, we make the subsequent contributions:

- We endorse a differentially private big information common item sets mining algorithm with excessive software and occasional computational depth. the algorithm guarantees the change-off between information application and privateness.
- We obtain excessive data application by using the large-scale statistics sampling and duration constraint approach, decreasing the variety of candidate sets of common item sets and the global sensitivity. Experimental outcomes verified the facts utility.
- We conduct formal privacy evaluation. The proposed set of rules achieves -differential privacy.

The relaxation of this paper is prepared as follows: section ii discusses related works. Segment iii introduces history know-how about differential privateness and primary tools that for use. Phase iv affords the proposed set of rules to mine pinnacle k frequent item sets with differential privacy. Phase v gives the evaluation. Section vi suggests the performance evaluation on multiple datasets. Section vii subsequently concludes our paintings.

II. RELATED WORK

The privateness trouble of frequent item sets mining is a primary cognizance of studies efforts. We categorize applicable work based totally on the underlying techniques - from anonymity to differential privateness.

Anonymity approaches. For distributed datasets, clifton et al. proposed a comfy multi-birthday celebration privateness-protecting association rule mining set of rules [18]. the idea is to transform the hassle into a comfy multi-birthday party computation problem under horizontal distribution. vaidya et al. proposed a privacy preserving affiliation rule set of rules that makes use of secure scalar calculation method to discover all frequent item sets beneath vertical distribution [19]. In [20], z teng et al. proposed a hybrid privateness-maintaining algorithm underneath vertical distribution. For centralized datasets, wonget al. proposed to hire 1-to-n encryption method to trade unique item sets so that it will guard records privacy while outsourcing common item sets mining [21]. Ling et al. proposed an algorithm that transforms commercial enterprise records into very long binary vector and a series of random mapping capabilities primarily based on bloom filters. Later, Tai et al. proposed a okay-guide anonymity based totally common item sets mining algorithm [23]. These kinds of techniques above sacrifice the precision of mining result.

Differential privacy methods. Because traditional strategies are based totally on heuristics, a strong privateness assure is missing. Consequently, researchers started out to investigate common item sets mining with differential privateness. Bhanu et al. provided mining algorithms [25], which are representatives of common item sets mining with differential privacy. Later, that allows you to solve the excessive dimensional undertaking of dataset, li et al. proposed the privacies set of a rule that mixes θ-foundation and mapping approach to attain top-okay frequent item sets mining [26]. zeng et al. proposed a greedy method of transaction truncation technique by proscribing the most period of transactions of dataset [27].

Besides researches in the interactive framework, differentially private common item sets mining is also studied within the non-interactive framework [28]–[30]. han et al. focused on the problem of pinnacle-okay query privateness in Map reduce [28]. chen et al. proposed a method that employs a context-loose type tree and combines a pinnacle-down tree partitioning technique to put up a dataset [29]. lee et al. proposed a method of the use of the prefix tree to privately publish frequent item sets [30]. su et al. proposed a cryptographic algorithm that divides the dataset based at the high global sensitivity [31]. Regardless of some of these works, there are nevertheless rooms for balancing utility and privateness, that's our paintings here.

Similarly to the above fashionable researches, domain-particular common item sets mining with differential privacy is also studied. chen et al. proposed the pinnacle-down prefix tree to submit the trajectory dataset [32]. chen et al. additionally proposed a way for publishing collection dataset based on variable length n-gram models [33]. bonomi et al. analyzed the each above algorithms and proposed a two-section set of rules [34] to improve performance. For fixing the hassle of huge common sequence candidate units, xu et al. offered to shrink and convert dataset, which reduces the quantity of candidate sets to improve statistics utility [35]. shen et al. focused on the problem of publishing map dataset [36]. xu et al. studied mining frequent sub graphs with differential privateness in a complex massive graph primarily based on constructing directed lattices [37].

III. PRELIMINARIES

A. Differential Privacy

Differential privacy as a new type of privacy definition is proposed for the privacy of statistical databases by Dwork [17]. It defines a very strict attack model, and gives a rigorous, quantitative representation and proof for the risk of privacy disclosure.

The smaller the is, the higher the degree of privacy is preserved. The differential privacy protection is achieved by adding quantitative noise; the amount of required noise depends on the sensitivity. Intuitively, the sensitivity quantifies the change of the query results caused by deleting any transaction in the dataset.

Definition 1. **(ϵ-Differential Privacy).** *Let D and D' denote any databases which differ by at most one record, $Range(K)$ represent the range of a random function K. If a random function K satisfies ϵ-differential privacy, for any $S \subseteq Range(K)$, we have*

$$\Pr\left[K\left(D\right) \in \ S\right] \leq \exp\left(\epsilon\right) \Pr\left[K\left(D'\right) \in \ S\right] \qquad (1)$$

where ϵ is a real number denoting the privacy budget parameter.

Definition 2. **(Sensitivity).** *Given any function: $D^n \rightarrow \mathbb{R}^k$, denote $\triangle f$ as the sensitivity of f; it is defined as follows: for all neighboring databases (i.e., differs only in one row) D and D'*

$$\triangle f = \max_{D,D'} ||f\left(D\right) - f(D')||_1 \qquad (2)$$

The sensitivity importance of the function is determined by the function itself; distinctive functions have one-of-a-kind sensitivities. For maximum question features f, the value of 4f is notably small. The sensitivity is then used to manipulate the noise degree in differential privateness. Whilst the noise is simply too big, it impacts records utility. It's far well worth noting that sensitivity is impartial of the dataset.

B. Noise Mechanism

The main technique of accomplishing differential privateness protection is to feature noise. dwork proposed the laplace mechanism to attain differential privacy. for specific conditions, the exponent mechanism, geometric mechanism and Gaussian mechanism had been also proposed. the normally used noisy addition mechanisms are the Laplace mechanism and the exponential mechanism. The Laplace mechanism is normally for mining algorithms that output numeric end result; the exponential mechanism is specially implemented to algorithms that output nonnumeric results.The quantity of noise is affected by the sensitivity and the privateness budget. Commonly, the privacy budget is set earlier, and then the noise is decided by means of the sensitivity.

Definition 3. **(Laplace Distribution).** *The probability density function of the Laplace distribution with scale parameter λ is defined as:*

$$\Pr\left(x|\lambda\right) = \frac{1}{2\lambda} e^{-|x|/\lambda} \qquad (3)$$

Theorem 1. **(Laplace Mechanism).** *Let $f : D^n \rightarrow \mathbb{R}$ be a function with image over real number values. The following mechanism K satisfies ϵ-differential privacy.*

$$K\left(D\right) = f\left(D\right) + \mathrm{Lap}\left(\frac{\triangle f}{\epsilon}\right) \qquad (4)$$

where $\mathrm{Lap}\left(\frac{\triangle f}{\epsilon}\right)$ *is a noise with the Laplace distribution.*

The noise size is proportional to $\triangle f$ and is inversely proportional to ϵ.

Comparability theorems: In popular, a complicated privacy preserving algorithm requires a couple of software of various differential privacy mechanisms. in this example, a good way to make sure that the complete system satisfies -differential privacy, it is vital to allocate the privateness finances fairly. The computability theorems of differential privateness guarantee the overall privateness.

Theorem 2. (Sequential Composition). Given a fixed dataset, let {A_1,A_2,...,A_n} be n mechanisms where each A_i provides -differential privacy. A sequential application of each mechanism provides$\sum_{i=1}^{n} \epsilon_i -$ differential privacy.

Theorem 3. (Parallel Composition). Given disjoint datasets, let {A_1,A_2,...,A_n} be n mechanisms where each A_i provides -differential privacy. A parallel application of each mechanism provides $\max\left(\epsilon_i\right)-$differential privacy.

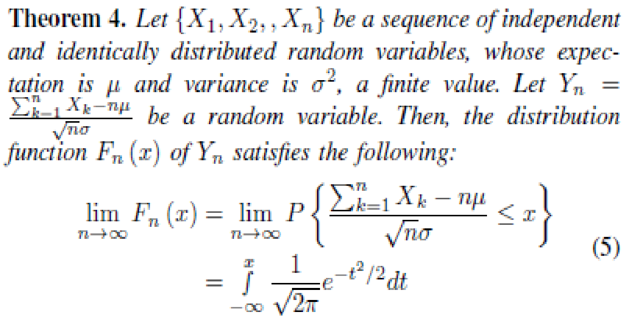
C .Frequent Item Sets Mining

We now in brief introduce frequent item sets mining. allow ti = t1,t2,...,tn be a transactional dataset along with n transactions, i = i1,i2,...,in be a fixed of different objects, and x be a subset of i such that x ⊆ i. if x is contained in a transaction and x has ok items, x is called a k-item set. The support of an item set is described as the entire wide variety of transactions that contains the item set. The undertaking of frequent item sets mining is to find all item sets that have guide extra than a given threshold. Common item sets is hired for locating affiliation regulations for a set of statistics items. Association policies show correlation members of the family of various items, that have several sensible software [38], [39]. Affiliation rule technology is typically split up into separate steps: 1) a minimal help threshold is applied to locate all frequent item sets in a database; 2) a minimum self-assurance constraint is implemented to those frequent item sets in an effort to form guidelines. At the same time as the second step is straightforward, the first step desires more attention. Locating all common item sets in a database is difficult because it involves searching all feasible item sets. The representative algorithms for mining frequent item sets include the apriori set of rules [38] and the fp-growth Algorithm [39].

We describe the basics of the fp-growth set of rules [39] which underlies our proposed privateness-keeping algorithm. the fp-increase set of rules functions small database scanning operations: it handiest has two-bypass database scanning. in the first bypass, the set of rules counts incidence of each object (attributevalue pairs), and shops them to a header desk in descending order. It additionally builds the null Fp-tree. Within the 2nd skip, it inserts the Fp-tree with statistics items and stores their frequency. Items in every example that do not meet minimal aid threshold are discarded. the final core records structure "Fp-tree" stores all of the information for frequent item sets. Eventually, all common item sets may be mined from the fp-tree.

D. Crucial Restrict Theorem

In our scheme, we use the central limit theorem for reasonable sampling.



Theorem 4. *Let $\{X_1, X_2, , X_n\}$ be a sequence of independent and identically distributed random variables, whose expectation is μ and variance is σ^2, a finite value. Let $Y_n = \frac{\sum_{k-1}^{n} X_k - n\mu}{\sqrt{n}\sigma}$ be a random variable. Then, the distribution function $F_n(x)$ of Y_n satisfies the following:*

$$\lim_{n\to\infty} F_n(x) = \lim_{n\to\infty} P\left\{\frac{\sum_{k=1}^{n} X_k - n\mu}{\sqrt{n}\sigma} \leq x\right\} = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt \tag{5}$$

That is, when *n* is sufficiently large, the distribution approximately follows the normal distribution. For random sampling, with the increasing of sample size, the distribution of the sampling average also tends to be the normal distribution. In our proposed algorithm, we employ this theorem to determine our sampling strategy.

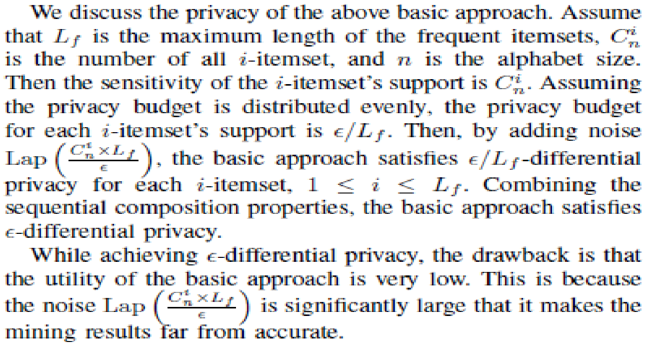
E. PROBLEM STATEMENT

Subsequently, we nation our trouble explicitly. given a large-scale dataset, a privateness price range , and a minimal threshold σ, the task is to design a privacy-preserving set of rules that mines top k frequent item sets whose helps are not much less than the threshold σ, where ok is an arbitrary given range. The algorithm must have minimum computational price and excessive mining result utility, besides gratifying -differential privacy.

IV. PROPOSED ALGORITHM

A.A Straw man Approach

In order to better understand the challenges posed by differential privacy, we first discuss a basic approach. Thatis, first generate all the candidate item sets, and then add noise to the support of all candidate item sets directly, and finally select the top *k* frequent item sets above a given threshold.

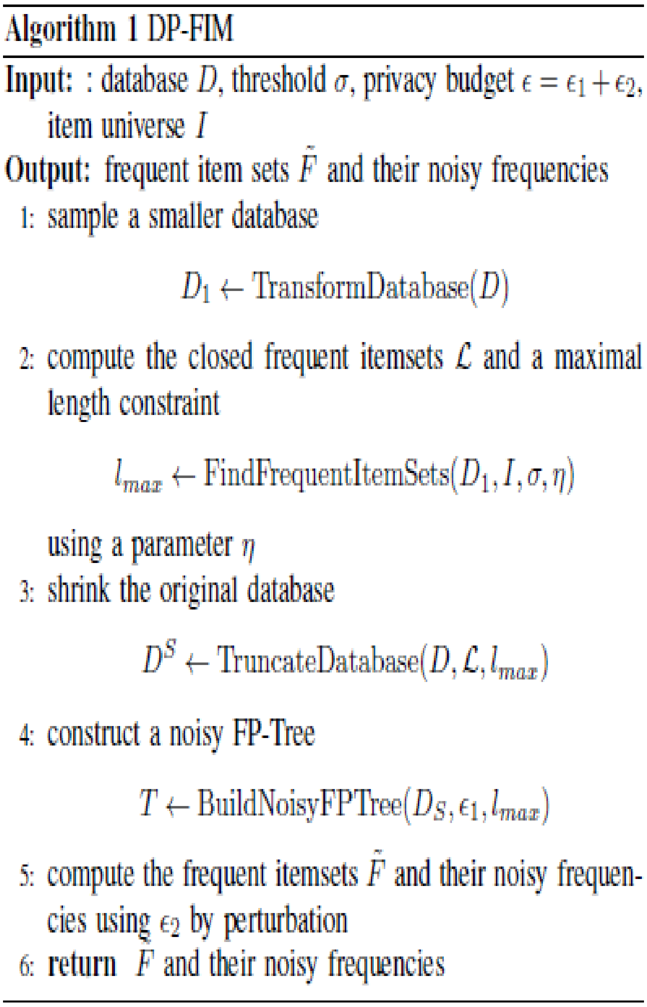


We discuss the privacy of the above basic approach. Assume that L_f is the maximum length of the frequent itemsets, C_n^i is the number of all i-itemset, and n is the alphabet size. Then the sensitivity of the i-itemset's support is C_n^i. Assuming the privacy budget is distributed evenly, the privacy budget for each i-itemset's support is ϵ/L_f. Then, by adding noise Lap $\left(\frac{C_n^i \times L_f}{\epsilon}\right)$, the basic approach satisfies ϵ/L_f-differential privacy for each i-itemset, $1 \leq i \leq L_f$. Combining the sequential composition properties, the basic approach satisfies ϵ-differential privacy.

While achieving ϵ-differential privacy, the drawback is that the utility of the basic approach is very low. This is because the noise Lap $\left(\frac{C_n^i \times L_f}{\epsilon}\right)$ is significantly large that it makes the mining results far from accurate.

B. Overview

We now describe our newly proposed algorithm, called dpfim, which merges the ideas of [27], [30], however employs a specific (better) truncation scheme and boosts computation efficiency the usage of both sampling and truncation. as compared with preceding work the use of random truncation, our new string similarity-matching-primarily based truncation mechanism has higher performance than previous work [27], [30], that's because string-similarity-matching-primarily based truncation preserves greater useful common item set applicants. The experimental consequences in section vi-b also confirm the higher performance. the algorithm is differentially non-public; it takes a threshold value σ and outputs the frequent item sets with aid as a minimum σ. the fundamental concept is as follows: first, compute a noisy support for the edge σ˜ = σ + lap(•), then truncate the authentic database noisily, in the end assemble a noisy fp-tree for mining common item sets.



Algorithm 1 DP-FIM

Input: : database D, threshold σ, privacy budget $\epsilon = \epsilon_1 + \epsilon_2$, item universe I

Output: frequent item sets $\tilde{F}$ and their noisy frequencies

```
1: sample a smaller database
       $D_1 \leftarrow \text{TransformDatabase}(D)$
2: compute the closed frequent itemsets $\mathcal{L}$ and a maximal length constraint
       $l_{max} \leftarrow \text{FindFrequentItemSets}(D_1, I, \sigma, \eta)$
   using a parameter $\eta$
3: shrink the original database
       $D^S \leftarrow \text{TruncateDatabase}(D, \mathcal{L}, l_{max})$
4: construct a noisy FP-Tree
       $T \leftarrow \text{BuildNoisyFPTree}(D_S, \epsilon_1, l_{max})$
5: compute the frequent itemsets $\tilde{F}$ and their noisy frequencies using $\epsilon_2$ by perturbation
6: return $F$ and their noisy frequencies
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Set of rules 1 describes the high-level technique of our proposed algorithm. it includes three levels: the preprocessing section, the mining section, and the perturbing phase.

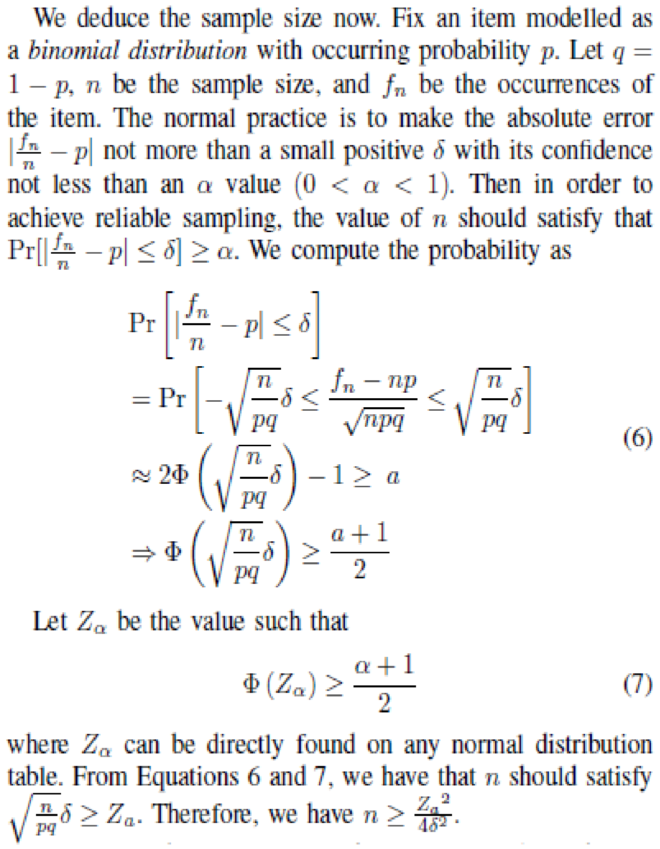
A. *Preprocessing Section*

Given the large-scale dataset, we first sample the dataset and then compute the closed frequent item sets within the smaller sample using a conventional common item sets mining algorithm. We later estimate the duration distribution of the sampled dataset and achieve the most length constraint, which is later used to shrink the dataset. Some factors out of the closed frequent item sets are removed from the supply dataset if their supports are beneath the aid threshold. We then employ string matching ideas to cut off the transactions inside the dataset; in this step, the purpose of changing the dataset is to decrease the facts size and concurrently keep the potential common items. Mining segment. We then construct a noisy Fp-tree over the shrunken dataset. We distribute the privacy calmly; we also upload noise to the real count outcomes. Perturbing section. Upload Laplace noise in the candidate common item sets and output them. We provide an explanation for some intuitions behind the proposed set of rules. To enhance mined result software, it's far important to lessen the amount of noise brought. The amount of noise depends at the privateness price range and the sensitivity of the underlying additives of the mining characteristic. Given that the privacy price range is ready earlier, it is key to reduce the sensitivity. In line with the definition of sensitivity, the sensitivity of kitemset’s aid relates to , wherein ckl is the set of all kitem sets in all transactions with l-length. Accordingly, we are able to lessen the sensitivity by using constraining the duration of each transaction. Particularly, we use the string matching and the longest commonplace subsequence idea to perform transaction truncation. That is, we discover the maximum comparable capability item sets within the source dataset, and on the same time attain the lowest lack of records, which improves statistics application. in this paper, the privateness finances is particularly allocated to the mining phase and the perturbing section. Let. The cost of µ influences the overall performance of our proposed algorithm. Unique privateness budget undertaking approach may additionally affect the accuracy of the algorithm outcomes’. Preprocessing phase at this segment, we first pattern the dataset to have a hard estimation of the dataset the usage of the imperative limit theorem. We first compute the pattern length and then use as statistics evaluation software program for random sampling. The samples can reduce the computational intensity of the built Fp-tree and discover the potential frequent item sets of the source dataset. Much like [27], we acquire a most period constraint max to decrease the transactions in the dataset.

Set of guidelines 1 describes the excessive-degree method of our proposed set of rules. It includes 3 degrees: the preprocessing phase, the mining phase, and the perturbing section. Preprocessing phase. Given the large-scale dataset, we first pattern the dataset after which compute the closed frequent item sets inside the smaller sample the usage of a traditional commonplace item sets mining set of rules. We later estimate the period distribution of the sampled dataset and acquire the maximum duration constraint that is later used to decrease the dataset. Some elements out of the closed frequent item sets are removed from the deliver dataset if their supports are below the resource threshold. We then employ string matching ideas to reduce off the transactions inside the dataset; on this step, the cause of converting the dataset is to decrease the records size and simultaneously hold the potential common items. Mining phase. We then construct a loud fp-tree over the shrunken dataset. We distribute the privacy frivolously; we additionally upload noise to the real depend consequences.

B. *Perturbing section*

Upload Laplace noise inside the candidate common item sets and output them. We offer an explanation for a few intuitions behind the proposed set of rules. to decorate mined result software, it's far essential to lessen the quantity of noise delivered. the quantity of noise relies upon on the privacy price variety and the sensitivity of the underlying additives of the mining feature. given that the privacy fee range is ready in advance, it is key to lessen the sensitivity. Consistent with the definition of sensitivity, the sensitivity of kitemset’s aid relates to , wherein ckl is the set of all kitem sets in all transactions with l-length. as a consequence, we're able to lessen the sensitivity via the usage of constraining the length of each transaction. especially, we use the string matching and the longest common subsequence idea to carry out transaction truncation. that is, we find out the maximum comparable capability item sets within the source dataset, and at the same time reap the lowest lack of information, which improves records application.



We deduce the sample size now. Fix an item modelled as a *binomial distribution* with occurring probability p. Let $q = 1 - p$, n be the sample size, and f_n be the occurrences of the item. The normal practice is to make the absolute error $|\frac{f_n}{n} - p|$ not more than a small positive δ with its confidence not less than an α value $(0 < \alpha < 1)$. Then in order to achieve reliable sampling, the value of n should satisfy that $\Pr[|\frac{f_n}{n} - p| \le \delta] \ge \alpha$. We compute the probability as

$$\begin{aligned} & \Pr\left[|\frac{f_n}{n} - p| \le \delta\right] \\ & = \Pr\left[-\sqrt{\frac{n}{pq}}\delta \le \frac{f_n - np}{\sqrt{npq}} \le \sqrt{\frac{n}{pq}}\delta\right] \\ & \approx 2\Phi\left(\sqrt{\frac{n}{pq}}\delta\right) - 1 \ge a \\ & \Rightarrow \Phi\left(\sqrt{\frac{n}{pq}}\delta\right) \ge \frac{a+1}{2} \end{aligned} \tag{6}$$

Let Z_α be the value such that

$$\Phi\left(Z_\alpha\right) \ge \frac{\alpha + 1}{2} \tag{7}$$

where Z_α can be directly found on any normal distribution table. From Equations 6 and 7, we have that n should satisfy $\sqrt{\frac{n}{pq}}\delta \ge Z_a$. Therefore, we have $n \ge \frac{{Z_a}^2}{4\delta^2}$.

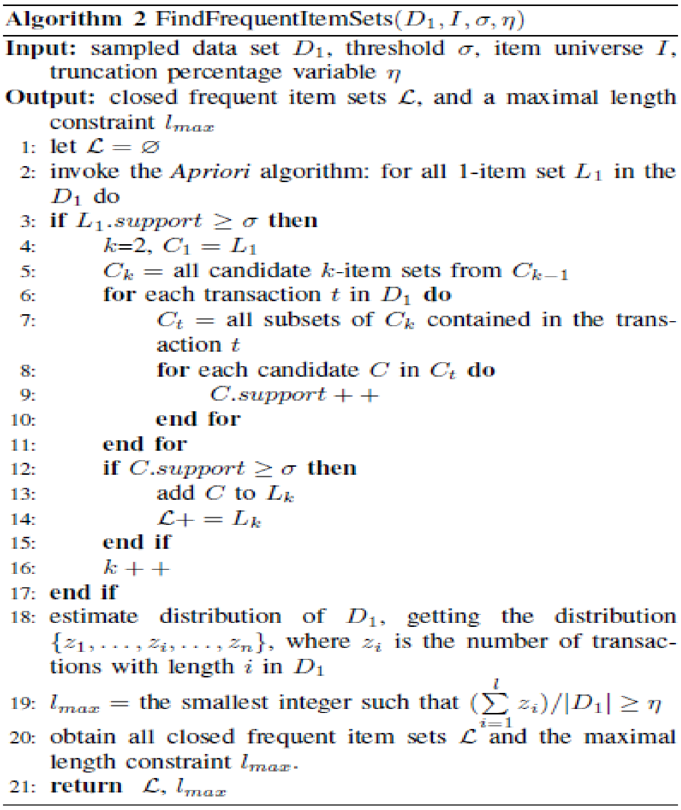
In this paper, the privateness finances are mainly allotted to the mining phase and the perturbing phase. Allow the value of µ impacts the overall performance of our proposed algorithm. Unique privateness finances venture method may also additionally have an effect on the accuracy of the algorithm outcomes.

C. *Preprocessing section*

At this section, we first pattern the dataset to have a hard estimation of the dataset using the vital restrict theorem. we first compute the sample duration after which use sas records evaluation software program software for random sampling. The samples can reduce the computational depth of the constructed Fp-tree and discover the potential common item sets of the supply dataset. Just like [27], we accumulate a most length constraint max to lower the transactions inside the dataset. Set of guidelines 1 describes the excessive-degree method of our proposed set of rules. it includes 3 degrees: the preprocessing phase, the mining phase, and the perturbing section.

D. *.Preprocessing phase:*

Given the large-scale dataset, we first pattern the dataset after which compute the closed frequent item sets inside the smaller sample the usage of a traditional commonplace item sets mining set of rules. we later estimate the period distribution of the sampled dataset and acquire the maximum duration constraint, that is later used to decrease the dataset. Some elements out of the closed frequent item sets are removed from the deliver dataset if their supports are below the resource threshold. We then employ string matching ideas to reduce off the transactions inside the dataset; on this step, the cause of converting the dataset is to decrease the records size and simultaneously hold the potential common items.



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Algorithm 2 FindFrequentItemSets($(D_1, I, \sigma, \eta)$)
Input: sampled data set $D_1$, threshold $\sigma$, item universe $I$,
    truncation percentage variable $\eta$
Output: closed frequent item sets $\mathcal{L}$, and a maximal length
    constraint $l_{max}$
let $\mathcal{L} = \varnothing$
invoke the Apriori algorithm: for all 1-item set $L_1$ in the
    $D_1$ do
if $L_1.support \geq \sigma$ then
    $k$=2, $C_1 = L_1$
    $C_k =$ all candidate $k$-item sets from $C_{k-1}$
    for each transaction $t$ in $D_1$ do
        $C_t =$ all subsets of $C_k$ contained in the trans-
        action $t$
        for each candidate $C$ in $C_t$ do
            $C.support + +$
        end for
    end for
    if $C.support \geq \sigma$ then
        add $C$ to $L_k$
        $\mathcal{L} + = L_k$
    end if
    $k + +$
end if
estimate distribution of $D_1$, getting the distribution
    $\{z_1, \dots, z_i, \dots, z_n\}$, where $z_i$ is the number of transac-
    tions with length $i$ in $D_1$
$l_{max} =$ the smallest integer such that $(\sum_{i=1}^{l} z_i)/|D_1| \geq \eta$
obtain all closed frequent item sets $\mathcal{L}$ and the maximal
    length constraint $l_{max}$.
return $\mathcal{L}$, $l_{max}$
```

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b.perturbing section:

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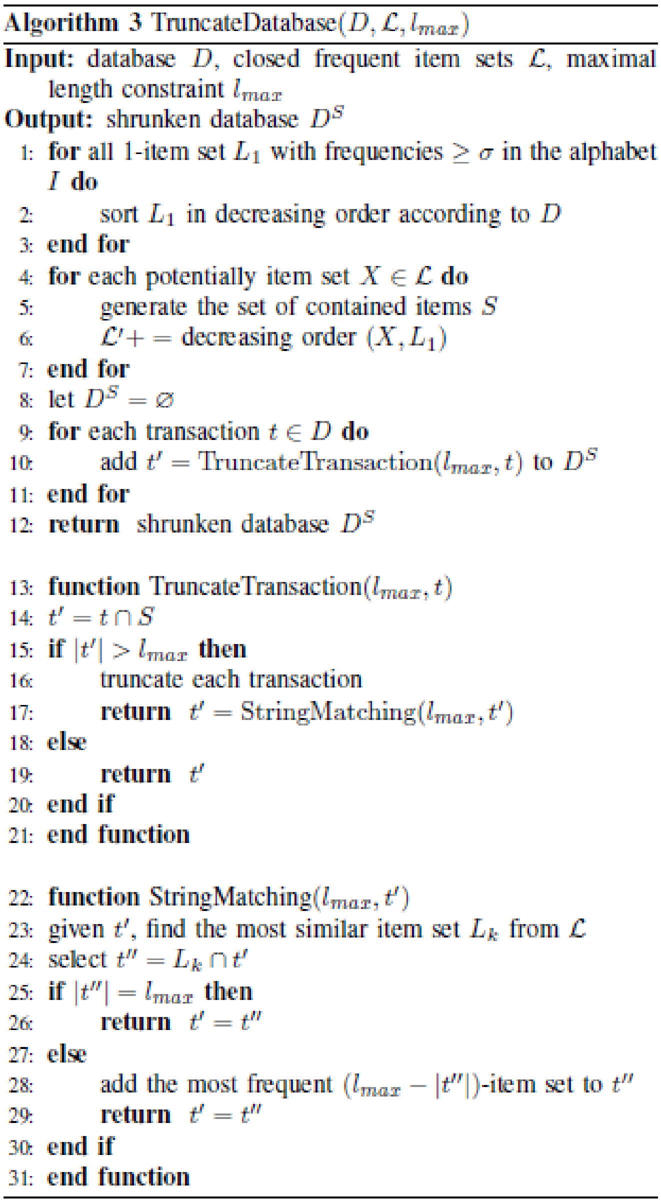

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Algorithm 3 TruncateDatabase($D, \mathcal{L}, l_{max}$)
Input: database $D$, closed frequent item sets $\mathcal{L}$, maximal
    length constraint $l_{max}$
Output: shrunken database $D^S$
for all 1-item set $L_1$ with frequencies $\geq \sigma$ in the alphabet
  $I$ do
    sort $L_1$ in decreasing order according to $D$
end for
for each potentially item set $X \in \mathcal{L}$ do
    generate the set of contained items $S$
    $\mathcal{L}' + =$ decreasing order $(X, L_1)$
end for
let $D^S = \varnothing$
for each transaction $t \in D$ do
    add $t' =$ TruncateTransaction$(l_{max}, t)$ to $D^S$
end for
return shrunken database $D^S$

function TruncateTransaction$(l_{max}, t)$
$t' = t \cap S$
if $|t'| > l_{max}$ then
    truncate each transaction
    return $t' =$ StringMatching$(l_{max}, t')$
else
    return $t'$
end if
end function

function StringMatching$(l_{max}, t')$
given $t'$, find the most similar item set $L_k$ from $\mathcal{L}$
select $t'' = L_k \cap t'$
if $|t''| = l_{max}$ then
    return $t' = t''$
else
    add the most frequent $(l_{max} - |t''|)$-item set to $t''$
    return $t' = t''$
end if
end function
```

D. Mining Phase

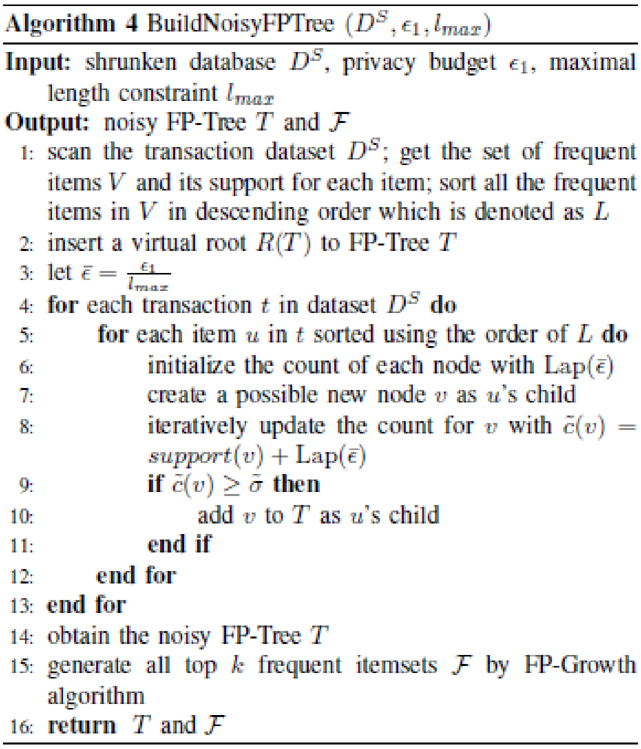
Set of tips 1 describes the excessive-degree approach of our proposed set of policies. it consists of 3 tiers: the preprocessing section, the mining segment, and the perturbing section.

Preprocessing phase. Given the large-scale dataset, we first sample the dataset after which compute the closed common item sets inside the smaller sample using a traditional common item sets mining set of policies. We later estimate the period distribution of the sampled dataset and gather the most period constraint, this is later used to decrease the dataset. Some factors out of the closed common item sets are eliminated from the supply dataset if their helps are underneath the aid threshold. We then employ string matching ideas to lessen off the transactions within the dataset; in this step, the reason of changing the dataset is to lower the statistics length and simultaneously hold the capacity common items mining segment. We then assemble a loud Fp-tree over the shrunken dataset. We distribute the privateness flippantly; we additionally add noise to the real depend results. Perturbing phase. Add Laplace noise inside the candidate not unusual item sets and output them. we provide an explanation for some intuitions in the back of the proposed set of policies. to beautify mined end result software program, it's miles critical to reduce the quantity of noise introduced. the quantity of noise is predicated upon at the privateness price range and the sensitivity of the underlying additives of the mining feature. For the reason that the privateness rate variety is prepared in advance, it's miles key to reduce the sensitivity. Consistent with the definition of sensitivity, the sensitivity of k-item set’s useful resource pertains to, wherein ckl is the set of all k-item sets in all transactions with l-duration. As a result, we are capable of lessen the sensitivity thru the usage of constraining the duration of every transaction. Mainly, we use the string matching and the longest commonplace subsequence concept to carry out transaction truncation. That is, we find out the most comparable capability item sets inside the supply dataset, and at the equal time reap the lowest loss of information, which improves data application. in this paper, the privateness finances is specially allocated to the mining segment and the perturbing section. Permit. The cost of µ impacts the general performance of our proposed set of rules. Specific privateness finances mission method may additionally have an impact on the accuracy of the set of rules outcomes.

E. Preprocessing Phase

at this segment, we first pattern the dataset to have a tough estimation of the dataset the usage of the important restrict theorem. we first compute the pattern duration after which use sas facts assessment software program program software program for random sampling. the samples can lessen the computational depth of the built fp-tree and discover the ability commonplace item sets of the deliver dataset. similar to [27], we acquire a most length constraint lmax to decrease the transactions inside the dataset.

$$\triangle f = \max_{D,D'} ||f(D) - f(D')||_1 = 1 \qquad (8)$$



```
Algorithm 4 BuildNoisyFPTree ($D^S, \epsilon_1, l_{max}$)
Input: shrunken database $D^S$, privacy budget $\epsilon_1$, maximal
    length constraint $l_{max}$
Output: noisy FP-Tree $T$ and $\mathcal{F}$
  scan the transaction dataset $D^S$; get the set of frequent
    items $V$ and its support for each item; sort all the frequent
    items in $V$ in descending order which is denoted as $L$
  insert a virtual root $R(T)$ to FP-Tree $T$
  let $\bar{\epsilon} = \frac{\epsilon_1}{l_{max}}$
  for each transaction $t$ in dataset $D^S$ do
      for each item $u$ in $t$ sorted using the order of $L$ do
          initialize the count of each node with Lap($\bar{\epsilon}$)
          create a possible new node $v$ as $u$'s child
          iteratively update the count for $v$ with $\tilde{c}(v) =$
            $support(v) + \text{Lap}(\bar{\epsilon})$
          if $\tilde{c}(v) \geq \bar{\sigma}$ then
              add $v$ to $T$ as $u$'s child
          end if
      end for
  end for
  obtain the noisy FP-Tree $T$
  generate all top $k$ frequent itemsets $\mathcal{F}$ by FP-Growth
    algorithm
  return $T$ and $\mathcal{F}$
```

F. *Perturbing Phase*

This phase is simple, relatively. Based on the noisy FP-Tree, mine all the frequent item sets that satisfy the threshold σ˜, select all the top *k* frequent item sets, add the noise Lap $\left(\frac{|C|}{\epsilon_2 n}\right)$where C contains the final candidates sets and *n* represents the size of the dataset. Finally, output the result.

V. ANALYSIS

Set of guidelines 1 describes the immoderate-degree approach of our proposed set of policies. it includes three degrees: the preprocessing section, the mining segment, and the perturbing segment. Preprocessing section. given the big-scale dataset, we first sample the dataset and then compute the closed commonplace item sets inside the smaller sample the use of a traditional common item sets mining set of policies. we later estimate the length distribution of the sampled dataset and collect the maximum duration constraint, that is later used to lower the dataset. some factors out of the closed common item sets are removed from the supply dataset if their facilitates are under the aid threshold. we then employ string matching ideas to reduce off the transactions in the dataset; in this step, the motive of converting the dataset is to lower the information duration and concurrently hold the potential common items.

A. *Mining phase.*

We then assemble a noisy fp-tree over the shrunken dataset. We distribute the privateness evenly; we additionally add noise to the real depend effects. perturbing section. Upload Laplace noise in the candidate not unusual item sets and output them. We provide an reason for some intuitions within the returned of the proposed set of rules. to beautify mined end result software program software, it's far essential to reduce the quantity of noise introduced. the amount of noise relies upon at the privateness fee variety and the sensitivity of the underlying additives of the mining feature. for the reason that the privacy charge variety is prepared in advance, it is key to lessen the sensitivity. Regular with the definition of sensitivity, the sensitivity of k-item set's useful aid relates to , in which ckl is the set of all k-item sets in all transactions with l-period. as a end result, we are capable of lessen the sensitivity through the usage of constraining the length of every transaction. Particularly, we use the string matching and the longest commonplace subsequence idea to perform transaction truncation. This is, we discover the most comparable functionality item sets inside the supply dataset, and at the equal time obtain the bottom loss of records, which improves records software. in this paper, the privateness finances is specifically allotted to the mining segment and the perturbing section. Allow. The fee of µ impacts the general overall performance of our proposed set of policies. specific privacy price range undertaking method may also additionally have an impact at the accuracy of the set of regulations effects.

B. *Preprocessing Phase*

At this phase, we first pattern the dataset to have a hard estimation of the dataset the usage of the essential limit theorem. We first compute the sample period after which use as information evaluation software program software program software for random sampling. The samples can lessen the computational depth of the built Fp-tree and discover the capacity common item sets of the deliver dataset. Similar to [27], we collect a maximum length constraint max to lower the transactions in the dataset.

Theorem 5. *The proposed scheme achieves -differential privacy.*

Proof. set of guidelines 1 describes the immoderate-degree technique of our proposed set of regulations. it includes three degrees: the preprocessing phase, the mining phase, and the perturbing segment.

Preprocessing phase. given the huge-scale dataset, we first pattern the dataset and then compute the closed not unusual item sets inside the smaller pattern the usage of a conventional common item sets mining set of policies. we later estimate the period distribution of the sampled dataset and collect the maximum duration constraint, this is later used to decrease the dataset. a few elements out of the closed commonplace item sets are eliminated from the deliver dataset if their enables are below the resource threshold. we then hire string matching ideas to lessen off the transactions within the dataset; on this step, the purpose of converting the dataset is to lower the statistics duration and concurrently hold the ability not unusual objects.

Mining segment. We then collect a loud fp-tree over the shrunken dataset. We distribute the privacy frivolously; we moreover upload noise to the real rely results. perturbing section. Add Laplace noise within the candidate common item sets and output them.

we provide an purpose for a few intuitions in the lower back of the proposed set of regulations. to beautify mined end end result software program software program, it's miles critical to lessen the quantity of noise brought. The quantity of noise is based upon on the privateness charge variety and the sensitivity of the underlying additives of the mining feature. for the reason that the privacy rate range is prepared earlier, it is key to lessen the sensitivity. Ordinary with the definition of sensitivity, the sensitivity of k-item set's useful aid pertains to , in which ckl is the set of all k-item sets in all transactions with l-length. As a cease end result, we are capable of lessen the sensitivity through using constraining the duration of each transaction. Especially, we use the string matching and the longest commonplace subsequence concept to perform transaction truncation. This is, we discover the maximum comparable capability item sets within the supply dataset, and at the identical time acquire the bottom lack of information, which improves records software.

In this paper, the privacy budget is in particular allotted to the mining phase and the perturbing section. Permit. The charge of µ impacts the overall performance of our proposed set of rules. Particular privacy fee range undertaking technique may additionally moreover has an effect on the accuracy of the set of rules effects.

preprocessing section

At this section, we first sample the dataset to have a hard estimation of the dataset the use of the vital limit theorem. we first compute the sample length after which use sas facts evaluation software program software program software application software for random sampling. The samples can lessen the computational intensity of the constructed fp-tree and discover the potential common item sets of the deliver dataset. Similar to [27], we gather a maximum length constraint max to decrease the transactions within the dataset.

VI. EXPERIMENTS

In this section, we evaluate the performance of our algorithm. To illustrate the effectiveness of the our algorithm, we also compare it with two state-of-art algorithms *Smart Truncation (ST)* [27] and *PrivBasis(PB)* [26] in the same conditions. One algorithm is the basis of our algorithm while the other is totally different; this arrangement is to have a broader comparison.

A. *Experiment Setup*

Implementation: We implement our algorithm using C++ on a PC with CPU Intel Core i7-4790k, processor base frequency 4.00GHz, RAM 8G. In the experiments, we specifically take $\epsilon = 0.1, 0.25, 0.5, 0.75, 1.0$, $\eta =$ 0.75,0.8,0.85,0.9,0.95, and k = 50,100 to parameterize our experiments. We run our algorithm 10 times and report the average values as stable performance indicators.

Datasets: set of hints 1 describes the excessive-degree method of our proposed set of regulations. It consists of 3 degrees: the preprocessing section, the mining phase, and the perturbing segment. Preprocessing section. Given the big-scale dataset, we first sample the dataset after which compute the closed commonplace item sets inside the smaller sample the use of a conventional common item sets mining set of rules. We later estimate the length distribution of the sampled dataset and acquire the maximum length constraint that is later used to lower the dataset. Some elements out of the closed common item sets are removed from the deliver dataset if their permits are below the useful resource threshold. We then lease string matching ideas to lessen off the transactions within the dataset; on this step, the cause of converting the dataset is to decrease the data duration and simultaneously keep the capacity not unusual gadgets.

TABLE I
DATASET CHARACTERISTICS

Dataset	$\|D\|$	$\|I\|$	$\max\|t\|$	$\text{avg}\|t\|$
Kosarak(KOS)	990002	41270	2498	8.1
BMS-POS(POS)	515597	1657	164	6.5
Accidents(ACC)	340183	468	51	33.8
Retail(RET)	88162	16470	76	10.3
mushroom(MUS)	8124	119	23	23

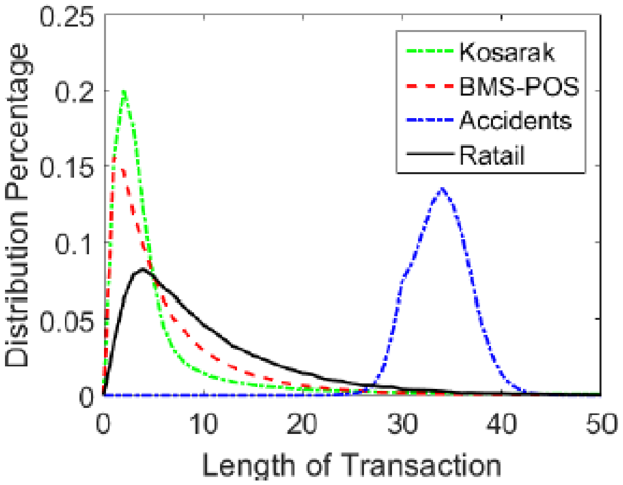


Fig. 1. Transaction Length Distribution

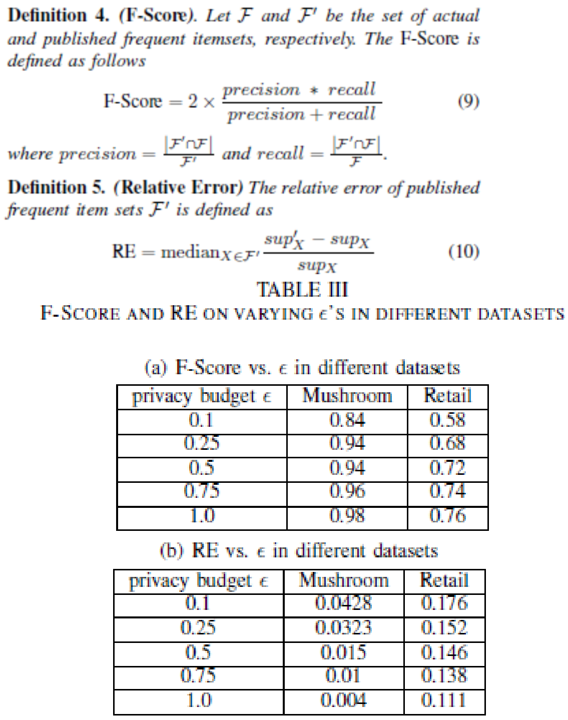
Mining segment. We then acquire a noisy Fp-tree over the shrunken dataset. We distribute the privateness calmly; we moreover upload noise to the real depend results.

Perturbing section. Add Laplace noise in the candidate commonplace item sets and output them. We offer an motive for a few intuitions within the lower back of the proposed set of policies. To decorate mined cease quit result software program application software application, it's far vital to reduce the amount of noise delivered. The quantity of noise is based upon on the privateness price variety and the sensitivity of the underlying components of the mining feature. For the purpose that the privateness charge variety is prepared in advance, it is key to reduce the sensitivity. Every day with the definition of sensitivity, the sensitivity of k-item set's useful resource relates to; in which ckl is the set of all k-item sets in all transactions with l-period. As a quit give up end result, we are capable of reduce the sensitivity thru the usage of constraining the length of every transaction. Especially, we use the string matching and the longest commonplace subsequence concept to perform transaction truncation. That is, we find out the most comparable functionality item sets within the supply dataset, and at the equal time accumulate the bottom lack of facts, which improves information software program.

In this paper, the privacy price range is specifically allotted to the mining section and the perturbing phase. Allow. The rate of µ affects the overall universal ordinary overall performance of our proposed set of policies. Unique privateness fee range task technique may moreover additionally furthermore has an impact on the accuracy of the set of regulations results.

B. *Preprocessing Phase*

At this phase, we first pattern the dataset to have a difficult estimation of the dataset the usage of the essential restriction theorem. We first compute the sample duration and then use as records evaluation software program software program software application software for random sampling. The samples can lessen the computational depth of the constructed Fp-tree and discover the capacity commonplace item sets of the deliver dataset. Similar to [27], we collect a maximum length constraint max to lower the transactions inside the dataset.



Definition 4. (F-Score). *Let $\mathcal{F}$ and $\mathcal{F}'$ be the set of actual and published frequent itemsets, respectively. The* F-Score *is defined as follows*

$$\text{F-Score} = 2 \times \frac{precision * recall}{precision + recall} \quad (9)$$

where $precision = \frac{|\mathcal{F}' \cap \mathcal{F}|}{\mathcal{F}'}$ *and* $recall = \frac{|\mathcal{F}' \cap \mathcal{F}|}{\mathcal{F}}$.

Definition 5. (Relative Error) *The relative error of published frequent item sets $\mathcal{F}'$ is defined as*

$$\text{RE} = \text{median}_{X \in \mathcal{F}'} \frac{sup'_X - sup_X}{sup_X} \quad (10)$$

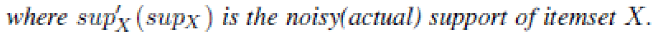
TABLE III
F-SCORE AND RE ON VARYING ϵ'S IN DIFFERENT DATASETS

(a) F-Score vs. ϵ in different datasets

privacy budget ϵ	Mushroom	Retail
0.1	0.84	0.58
0.25	0.94	0.68
0.5	0.94	0.72
0.75	0.96	0.74
1.0	0.98	0.76

(b) RE vs. ϵ in different datasets

privacy budget ϵ	Mushroom	Retail
0.1	0.0428	0.176
0.25	0.0323	0.152
0.5	0.015	0.146
0.75	0.01	0.138
1.0	0.004	0.111



where sup'_X (sup_X) is the noisy(actual) support of itemset X.

Where $sup^0{}_X(sup_X)$ is the noisy(actual) support of item set X.

Set of guidelines 1 describes the excessive-degree method of our proposed set of policies. it consists of 3 tiers: the preprocessing segment, the mining segment, and the perturbing phase.

Preprocessing section. given the huge-scale dataset, we first sample the dataset and then compute the closed commonplace item sets in the smaller sample the use of a traditional not unusual item sets mining set of regulations. We later estimate the length distribution of the sampled dataset and acquire the maximum length constraint that is later used to decrease the dataset. A few factors out of the closed commonplace item sets are eliminated from the supply dataset if their permits are under the beneficial useful resource threshold. We then rent string matching thoughts to reduce off the transactions within the dataset; on this step, the purpose of changing the dataset is to decrease the statistics period and concurrently hold the capability commonplace devices.

Mining phase. We then acquire a noisy fp-tree over the shrunken dataset. We distribute the privateness lightly; we moreover upload noise to the real depend consequences.

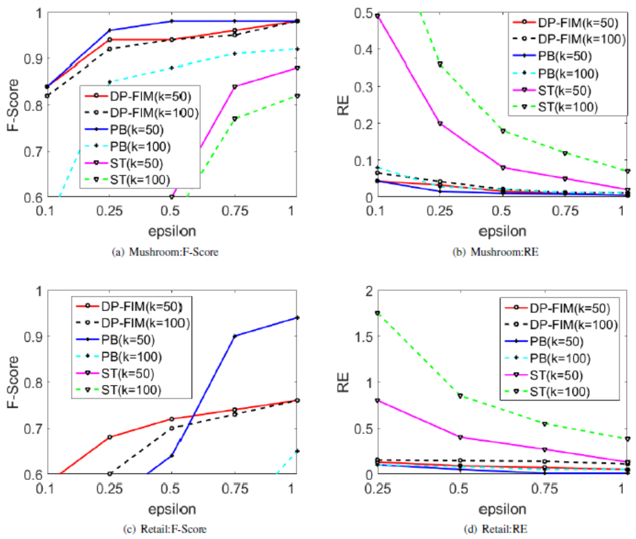
Perturbing segment. Upload Laplace noise inside the candidate not unusual item sets and output them.

We provide a purpose for a few intuitions within the decrease again of the proposed set of rules. To enhance mined cease give up end result software application software program software, it's miles vital to reduce the quantity of noise delivered. The amount of noise is based totally upon at the privateness charge variety and the sensitivity of the underlying components of the mining characteristic. For the cause that the privateness price range is ready earlier, it is key to reduce the sensitivity. Ordinary with the definition of sensitivity, the sensitivity of k-item set's useful resource pertains to; in which ckl is the set of all k-item sets in all transactions with l-length. As an end give up cease result, we're capable of reduce the sensitivity through the usage of constraining the period of every transaction. In particular, we use the string matching and the longest commonplace subsequence idea to perform transaction truncation. this is, we discover the most similar functionality item sets inside the deliver dataset, and on the identical time acquire the bottom lack of facts, which improves records software program software.

on this paper, the privacy price variety is mainly allotted to the mining section and the perturbing phase. Permit . the price of µ influences the overall ordinary normal overall performance of our proposed set of policies. Particular privacy charge variety venture technique might also moreover furthermore have an impact at the accuracy of the set of rules results.

C. *Preprocessing Segment*

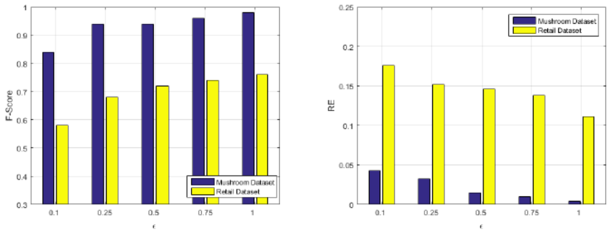
At this section, we first pattern the dataset to have a hard estimation of the dataset the usage of the critical limit theorem. We first compute the pattern period after which use as records evaluation software program software program software program application software for random sampling. The samples can reduce the computational depth of the built Fp-tree and find out the ability commonplace item sets of the supply dataset. Similar to [27], we gather a maximum duration constraint max to decrease the transactions inside the dataset.



(a) Mushroom:F-Score (b) Mushroom:RE

(c) Retail:F-Score (d) Retail:RE

2. Performance vs. Privacy Budget



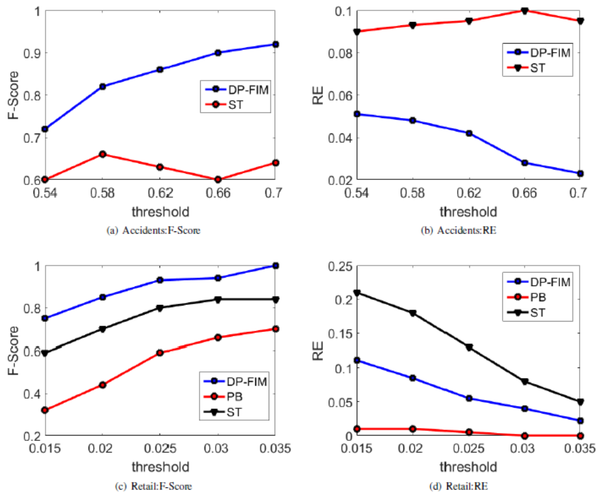
(a) F-Score vs. ϵ in different datasets (b) RE vs. ϵ in different datasets

Fig. 3. F-Score and RE on varying ϵ's in different datasets

TABLE II
EXPERIMENT PARAMETERS

Parameters	Description	Default values
ϵ	privacy budget	1.0
k	top-k values	50
η	maximum length constraint parameter	0.85
μ	allocated privacy budget parameter	1/3

Set of hints 1 describes the immoderate-degree technique of our proposed set of regulations. It includes 3 stages: the preprocessing section, the mining section, and the perturbing segment. Preprocessing section. Given the big-scale dataset, we first sample the dataset after which compute the closed commonplace item sets in the smaller sample the use of a conventional commonplace item sets mining set of guidelines. We later estimate the period distribution of the sampled dataset and accumulate the maximum length constraint; this is later used to decrease the dataset. Some factors out of the closed not unusual item sets are eliminated from the deliver dataset if their allows are below the beneficial resource threshold.



(a) Accidents:F-Score (b) Accidents:RE

(c) Retail:F-Score (d) Retail:RE

Fig. 4. Performance vs. Threshold

We then lease string matching thoughts to lessen off the transactions inside the dataset; in this step, the cause of converting the dataset is to lower the facts duration and concurrently preserve the functionality commonplace gadgets.

Mining segment. We then collect a noisy Fp-tree over the shrunken dataset. We distribute the privacy lightly; we furthermore upload noise to the actual depend effects.

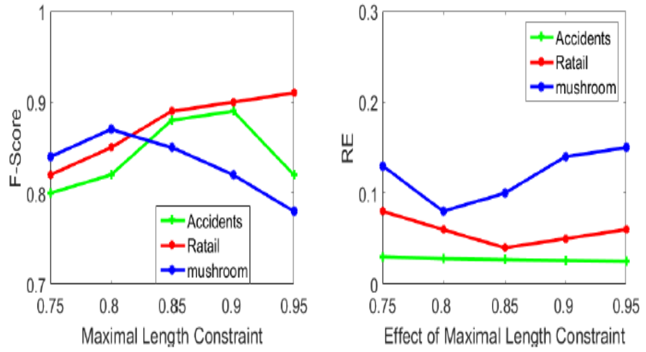
Perturbing section. Add Laplace noise within the candidate common item sets and output them.

We provide a purpose for a few intuitions within the decrease once more of the proposed set of policies. To decorate mined give up give up end result software application software program software, it's far important to reduce the quantity of noise added. The quantity of noise is based totally absolutely upon at the privateness fee range and the sensitivity of the underlying additives of the mining feature. for the reason that the privateness charge range is ready earlier, it's far key to lessen the sensitivity. Regular with the definition of sensitivity, the sensitivity of k-item set's beneficial useful resource pertains to, wherein ckl is the set of all k-item sets in all transactions with l-period. As a stop give up quit end result, we're able to lessen the sensitivity via using constraining the duration of every transaction. Particularly, we use the string matching and the longest common subsequence idea to perform transaction truncation. that is, we find out the maximum comparable functionality item sets inside the deliver dataset, and on the identical time accumulate the lowest lack of information, which improves information software.

In this paper, the privateness charge variety is specially allocated to the mining section and the perturbing segment. Permit. The charge of μ impacts the overall normal ordinary normal universal overall performance of our proposed set of policies. specific privateness price range mission technique can also moreover furthermore have an effect on the accuracy of the set of regulations outcomes.

D. Preprocessing Phase

At this phase, we first pattern the dataset to have a hard estimation of the dataset using the crucial limit theorem. We first compute the pattern duration after which use as facts evaluation software program software application software for random sampling. The samples can reduce the computational depth of the built Fp-tree and find out the ability common item sets of the supply dataset. Similar to [27], we gather a maximum period constraint max to lower the transactions within the dataset.



(a) F-Score

(b) RE

5. Performance vs. Maximal Length Constraint

TABLE IV
F-SCORE AND RE ON VARYING k IN DIFFERENT DATASETS

(a) F-Score vs. k in different datasets

k	Mushroom	Retail	Accidents
25	0.98	0.90	0.94
50	0.98	0.76	0.94
100	0.98	0.76	0.93
150	0.93	0.73	0.92
200	0.92	0.68	0.90

(b) RE vs. k in different datasets

k	Mushroom	Retail	Accidents
25	0.005	0.055	0.019
50	0.004	0.05	0.017
100	0.011	0.111	0.018
150	0.015	0.136	0.023
200	0.023	0.158	0.028

and low relative error indicate that our algorithm has high utility.

VII. CONCLUSIONS

In this paper, we propose a unique differentially non-public algorithm for frequent item sets mining. The set of rules features better data utility and better computation efficiency. Numerous experimental evaluations validate that the proposed algorithm has high f-rating and occasional relative errors. a lesson found out is that quality tuned parameters result in higher differentially non-public frequent item sets mining algorithms with regard to records application.

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