Differentially Private Linear Sketches: Efficient Implementations and Applications

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Abstract

Linear sketches have been widely adopted to process fast data streams, and they can be used to accurately answer frequency estimation, approximate top K items, and summarize data distributions. When data are sensitive, it is desirable to provide privacy guarantees for linear sketches to preserve private information while delivering useful results with theoretical bounds. We show that linear sketches can ensure privacy and maintain their unique properties with a small amount of noise added at initialization. From the differentially private linear sketches, we showcase that the state-of-the-art quantile sketch in the turnstile model can also be private and maintain high performance. Experiments further demonstrate that our proposed differentially private sketches are quantitatively and qualitatively similar to noise-free sketches with high utilization on synthetic and real datasets.

1 Introduction

Data sketches are fundamental tools for data analysis, statistics, and machine learning [Cormode and Yi, 2020]. Two of the most widely studied problems in data summaries are frequency estimation and quantile approximation. Many real world applications need to estimate the frequency of each item in the database and understand the overall distribution of the database. These applications include stream processing [Das et al., 2009, Bailis et al., 2017], database management [Misra and Gries, 1982, Metwally et al., 2005, Zhao et al., 2021a], caching [Zakhary et al., 2020], network monitoring [Gupta et al., 2016, Ivkin et al., 2019], federated learning [Rothchild et al., 2020], among others.

On one hand, the motivation for data sketch algorithms is to efficiently process a large database and extract useful knowledge, since computing the exact information for a large amount of data is both time and memory intensive. For instance, Munro and Paterson [1980] proved that to find the true median of a database with n items using p sequential passes requires at least $\Omega(n^{1/p})$ memory. On the other hand, to protect user-level privacy, privacy-preserving algorithms limit the disclosure of private information in the database so that an observer cannot infer much about an individual. Recent works have shown that data sketches can be integrated with privacy-enhancing technologies to provide insightful information and preserve individual privacy at the same time [Cormode, 2022].

Differential privacy [Dwork et al., 2006] is a widely-accepted definition of privacy. Recently, researchers have observed that some data sketches are inherently differentially private [Blocki et al., 2012, Smith et al., 2020], while many other data sketches need modifications to the algorithm to be differentially private. In particular, a substantial amount of literature has focused on differentially private data sketches for tasks such as linear algebra [Upadhyay, 2014, Arora et al., 2018], cardi-

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nality estimation [Mir et al., 2011, Pagh and Stausholm, 2020, Dickens et al., 2022] and quantile approximation [Tzamos et al., 2020, Gillenwater et al., 2021, Alabi et al., 2022].

In this paper, we introduce new differentially private algorithms that support both insertions and deletions for frequency and top k estimation and quantile approximation. While many data sketches assume an insertion-only model [Greenwald and Khanna, 2001, Shrivastava et al., 2004, Karnin et al., 2016] or a bounded-deletion model [Jayaram and Woodruff, 2018, Zhao et al., 2021a,b], our algorithms build on top of linear sketches [Charikar et al., 2002, Cormode and Muthukrishnan, 2005] and operate in the most general turnstile model, which allows an arbitrary number of insertions and deletions into the database. Earlier, researchers attempted to prove Count-Median [Charikar et al., 2002] itself preserves differential privacy, but the authors acknowledged that there are issues in the proof [Li et al., 2019]. Instead of proving that linear sketches, i.e., both Count-Median and Count-Min, are inherently differentially private, we add a small amount of Gaussian noise at their initialization to provide a privacy guarantee while maintaining linear sketches' original properties, providing high utility for frequency and top K estimations, and keeping update and query algorithms unchanged. In addition, we propose the first differentially private quantile sketch in the turnstile model by leveraging the differentially private linear sketch. Our differentially private sketches can be queried an arbitrary number of times without affecting privacy guarantees based on the post-processing immunity. Moreover, in our work, we removed the assumption on the existence of secret uniform random hash functions to provide randomness in the algorithm. Following prior works [Choi et al., 2020, Smith et al., 2020], we assume ideal random hash functions exist, and this assumption can be replaced in practice by cryptographic hash functions [Dickens et al., 2022].

2 Preliminaries

Consider a database $X = \{i_t\}_{t\in[N]}$ of N items that are drawn from a large $universe$ of size U, such as IPv4 address of size 2^{32}, and for each insert or delete operations, one item can be inserted into or deleted from the database X. To support ordered statistic such as quantile, we assume that the $universe$ is some finite totally ordered data universe.

Definition 2.1. *Given a database X, the frequency of an item x is $f(x) = \sum_{t=1}^{N} \pi(i_t = x)$ where π returns 1 if i_t is x, and 0 otherwise.*

Definition 2.2. *Given a database X of items drawn from an ordered universe, the rank of an item x is $R(x) = \sum_{t=1}^{N} \pi(i_t \leq x)$ where π returns 1 if i_t is less or equal to x and 0 otherwise.*

Given the large size of N, calculating the actual statistics, such as frequency and quantile, is often hard, and hence most applications are satisfied with an *approximation*. The *randomized frequency estimation problem* takes an accuracy parameter γ and a failure probability β such that, for any item x, $|\widehat{f}(x) - f(x)| \leq \gamma \cdot N$ with high probability $1-\beta$, where $\widehat{f}(x)$ is the estimated frequency and $f(x)$ is the true frequency [Cormode and Hadjieleftheriou, 2008]. In addition, the *randomized quantile approximation problem* also takes an accuracy parameter γ and a failure probability β such that, for any item x, $|\widehat{R}(x) - R(x)| \leq \gamma \cdot N$ with high probability $1-\beta$ where $\widehat{R}(x)$ is the estimated rank and $R(x)$ is the actual rank [Karnin et al., 2016].

2.1 Differential Privacy

Definition 2.3. *Databases X and X' are neighbors ($X \sim X'$), if they differ in at most one element.*

Through this paper, we assume the $update/replace$ definition of differential privacy instead of $add/remove$ definition of differential privacy, in which one item in X is updated or replaced by another item in X' [Vadhan, 2017].

Definition 2.4 (Differential Privacy [Dwork et al., 2006])**.** *A randomized algorithm M satisfies (ϵ, δ)-differential privacy ((ϵ, δ)-DP) if for all neighboring databases X, X' and for all possible events E in the output range of M, we have*

$$\mathbb{P}(M(X) \in E) \leq e^{\epsilon} \cdot \mathbb{P}(M(X') \in E) + \delta.$$

When $\delta = 0$, ϵ-DP is known as pure DP, and when $\delta > 0$, (ϵ, δ)-DP is known as approximate DP.

Definition 2.5 (Gaussian Mechanism [Dwork et al., 2006])**.** *Define the ℓ_2 sensitivity of a function $f : \mathbb{N}^{\mathcal{X}} \mapsto \mathbb{R}^d$ as*

$$\Delta_2(f) = \sup_{\textit{neighboring } X, X'} \|f(X) - f(X')\|_2.$$

The Gaussian mechanism $\mathcal{M}$ with noise level σ is then given by

$$\mathcal{M}(X) = f(X) + \mathcal{N}(0, \sigma^2 I_d).$$

Specifically, the Gaussian mechanism is known to satisfy a stronger notion of privacy known as zero-concentrated differential privacy (zCDP, defined below); zCDP lies between pure and approximate DP and can be translated into standard DP notations, as shown in Lemma 2.9. Moreover, zCDP satisfies cleaner composition theorems, as shown in Lemma 2.7.

Definition 2.6 (zCDP [Dwork and Rothblum, 2016, Bun and Steinke, 2016])**.** *A randomized mechanism M satisfies ρ-Zero-Concentrated Differential Privacy (ρ-zCDP), if for all neighboring databases X, X' and all $\alpha \in (1, \infty)$,*

$$D_\alpha(M(X) \| M(X')) \leq \rho\alpha,$$

where D_α is the Renyi divergence [Van Erven and Harremos, 2014].

Lemma 2.7 (Adaptive composition and Post Processing of zCDP [Bun and Steinke, 2016])**.** *Let $M : \mathcal{X}^n \to \mathcal{Y}$ and $M' : \mathcal{X}^n \times \mathcal{Y} \to \mathcal{Z}$. Suppose M satisfies ρ-zCDP and M' satisfies ρ'-zCDP (as a function of its first argument). Define $M'' : \mathcal{X}^n \to \mathcal{Z}$ by $M''(x) = M'(x, M(x))$. Then M'' satisfies $(\rho + \rho')$-zCDP.*

Lemma 2.8 (Privacy Guarantee of Gaussian mechanism [Dwork et al., 2014, Bun and Steinke, 2016])**.** *Let $f : \mathbb{N}^{\mathcal{X}} \mapsto \mathbb{R}^d$ be an arbitrary d-dimensional function with ℓ_2 sensitivity $\Delta_2 = \sup_{\textit{neighboring } X, X'} \|f(X) - f(X')\|_2$. Then for any $\rho > 0$, Gaussian Mechanism with parameter $\sigma^2 = \frac{\Delta_2^2}{2\rho}$ satisfies ρ-zCDP.*

Lemma 2.9 (Converting zCDP to DP [Bun and Steinke, 2016])**.** *If M satisfies ρ-zCDP then M satisfies $(\rho + 2\sqrt{\rho \log(1/\delta)}, \delta)$-DP.*

As we use exclusively Gaussian mechanisms and their composition in our proposed algorithms, our method actually satisfies the stronger (ϵ, δ)-DP guarantees than what is implied by zCDP via techniques from [Balle and Wang, 2018, Dong et al., 2019], which reduces the ϵ parameter by a sizable fraction in typical parameter regimes. We stick to zCDP for clarity and generality, because all our results would apply without changes if we modify the noise into other mechanisms satisfying zCDP, e.g., the Discrete Gaussian Mechanism [Canonne et al., 2020].

2.2 Revisiting Linear Sketches

Charikar et al. [2002] proposed the **Count-Median** sketch, a randomized algorithm that summarizes a database and solves the frequency estimation problem. The Count-Median sketch uses a $d \times w$ array of counters, i.e, C[d, w], where all the counters are initialized to **zero**, and has two sets of independent hash functions h and g. For each row r, the hash function h_r maps input items uniformly onto $\{1, \ldots, w\}$ and the hash function g_r maps input items uniformly onto $\{-1, +1\}$. For item x with value $v \in \{-1, +1\}$, Count-Median sketch updates d counters, one per each row, based on the hash values such that for a particular row r, $g_r(x)$ will be added or subtracted to the counter at the $h_r(x)^{th}$ index depending on whether x is being inserted or deleted respectively, as shown in Algorithm 1. Hence, the update time is $O(d)$. To estimate the frequency of item x, Count-Median sketch will output the $\text{median}_{1 \leq r \leq d}\ g_r(x) \cdot C[r, h_r(x)]$, as shown in Algorithm 2. By updating each row's counter based on the hashed value of either 1 or -1 and reporting the median for query, Count-Median sketch provides an unbiased estimate. To reduce the failure probability of bad estimations, d is set to $O(\log(1/\beta))$ and it uses $O(\frac{1}{\gamma}\log(\frac{1}{\beta}))$ space to solve the frequency estimation problem.

Algorithm 1 Linear Sketch Update(x, v)

Input: Item x with value $v \in \{-1, +1\}$, counter arrays C, and two sets of hash functions $\{h_1, \ldots, h_{C.rows}\}$ and $\{g_1, \ldots, g_{C.rows}\}$.
for $r \leftarrow 1, 2, \ldots, C.rows$ **do**
  $C[r, h_r(x)] \leftarrow C[r, h_r(x)] + v \cdot g_r(x)$
end for
Output: C.

Cormode and Muthukrishnan [2005] proposed the **Count-Min** sketch that shares the same initialization, update, and data structure as Count-Median sketch. Count-Min sketch also uses $O(\frac{1}{\gamma}\log(\frac{1}{\beta}))$ space to solve the frequency estimation problem. A major difference is that Count-Min sketch makes all hash functions in set g return positive 1. As a result, to estimate the frequency of item x, Count-Min sketch returns $\min_{1 \le r \le d} C[r, h_r(x)]$ instead of the median, as shown in Algorithm 2. In addition, it has the nice property of never underestimating item's frequency. Since linear sketches can approximate an item's frequency accurately, they also solves the top K approximation problem by returning the K items associated with the highest estimated frequency.

Algorithm 2 Linear Sketch Query(x)

Input: Item x, counter arrays C, and two sets of hash functions $\{h_1, \ldots, h_{C.rows}\}$ and $\{g_1, \ldots, g_{C.rows}\}$.
arr $\leftarrow [\,]$
for $r \leftarrow 1, 2, \ldots, C.rows$ **do**
  arr.append$(g_r(x) \cdot C[r, h_r(x)])$
end for
Output: $\min(\text{arr})$ **for Count-Min or** $\text{median}(\text{arr})$ **for Count-Median.**

Moreover, Gilbert et al. [2002] made the connection between frequency and quantiles to propose the first universe based RSS quantile sketch in the turnstile model. The observation is that the quantile range, from 0 to the item, can be decomposed into at most $\log U$ dyadic intervals [Cormode et al., 2019] and the sum over the estimated frequencies for these intervals gives the estimated rank. Cormode and Muthukrishnan [2005] proposed the Dyadic Count-Min sketch (DCM) which uses Count-Min sketches for estimating the frequencies of each dyadic interval with space complexity $O(\frac{1}{\gamma}\log^2 U \log\frac{\log U}{\gamma})$ and update time $O(\log U \log\frac{\log U}{\gamma})$. Later, Wang et al. [2013] leveraged the unbiased property of Count-Median sketches and proposed the Dyadic Count-Median sketch (DCS) which replaces the Count-Min sketch with the Count-Median Sketch [Charikar et al., 2002] to further improve the space complexity to $O(\frac{1}{\gamma}\log^{1.5} U \log^{1.5}(\frac{\log U}{\gamma}))$ while maintaining the same update time. DCS and DCM share the same update and query algorithms as shown in Appendix B. DCM uses $O(\frac{1}{\gamma}\log U \log\frac{\log U}{\gamma})$ space for each Count-Min sketch and DCS uses $O(\frac{1}{\gamma}\log^{0.5} U \log^{1.5}(\frac{\log U}{\gamma}))$ space for each Count-Median sketch, where both of them use $O(\log\frac{\log U}{\gamma})$ rows. For more specific details, [Cormode and Yi, 2020] provide a comprehensive analysis of linear and quantile sketches.

3 Private Linear Sketches

In this section, we present new algorithms for differentially private linear sketches. We highlight that our Private Count Min/Median only require a different initialization while they share the same update (Algorithm 1) and query (Algorithm 2) with the original Count Min/Median. Therefore, the implementation of our algorithms is efficient. Below we show our private initialization.

Algorithm 3 DP Linear Sketch Initialization with Gaussian Noise

Input: Desired accuracy parameter γ, failure probability β, and budget for zCDP ρ.
Initialize Counter Arrays
$\sigma \leftarrow \sqrt{\log(2/\beta)/\rho}$
$E \leftarrow \sqrt{\frac{2\log\frac{2}{\beta}}{\rho}} \cdot \sqrt{\log\frac{\frac{4}{\gamma}\log(\frac{2}{\beta})}{\beta}}$
for $r \leftarrow 1, 2, \ldots, \log(2/\beta)$ **do**
  for $c \leftarrow 1, 2, \ldots, 1/\gamma$ **do**
    $C[r, c] \leftarrow \mathcal{N}(0, \sigma^2)$ if Private Count-Median
    $C[r, c] \leftarrow E + \mathcal{N}(0, \sigma^2)$ if Private Count-Min
  end for
end for
Output: C.

In Algorithm 3, the set of arrays we use is C which consists of $\log(2/\beta)$ arrays with length $1/\gamma$, which has the same space complexity as original Count Min/Median. Recall that two neighboring databases X and X' differ by at most one item. Therefore, after updating all the items respectively, for each corresponding array in $C(X)$ and $C(X')$, they differ by at most two elements and the difference is at most 1. Then the ℓ_2-sensitivity of the set of arrays C is bounded by

$$\Delta_2 = \sqrt{2\log(2/\beta)}. \tag{1}$$

By applying the Gaussian Mechanism (Definition 2.5), we can add *independent* Gaussian noises $\mathcal{N}(0, \sigma^2)$ to each counter in C, where $\sigma = \sqrt{\frac{\log(2/\beta)}{\rho}}$. Due to the privacy guarantee of Gaussian Mechanism (Lemma 2.8), it satisfies $\frac{\Delta_2^2}{2\sigma^2} = \rho$-zCDP.

Define $E(\beta, \gamma, \rho) = \sqrt{\frac{2\log\frac{2}{\beta}}{\rho}} \cdot \sqrt{\log\frac{\frac{4}{\gamma}\log(\frac{2}{\beta})}{\beta}}$, for simplicity, we will use E in Algorithm 3 and the proof in Appendix A. The private version of Count Min can be derived by adding *independent* Gaussian noises $\mathcal{N}(E, \sigma^2)$ to each counter of C, while the private version of Count Median can be derived by adding *independent* Gaussian noises $\mathcal{N}(0, \sigma^2)$ to each counter of C. The private version of Count Min/Median is derived by combining Algorithm 3, Algorithm 1, and Algorithm 2.

Some explanations. Note that here the difference in the noises we add to Private Count Min/Median is because we want to retain the nice properties of Count Min (never underestimating) and Count Median (unbiased estimate).

3.1 Main results about Private Count Min/Median

We present the privacy guarantee and utility analysis of our Private Count Min/Median below. Recall that for each item x, we perform update as in Algorithm 1 and query as in Algorithm 2. In addition, $\widehat{f}(x)$ is the output estimated frequency and $f(x)$ is the actual frequency. We begin with the properties of Private Count Min. Note that all the proofs are deferred to Appendix A.

Theorem 3.1. *Private Count Min satisfies ρ-zCDP regardless of the number of queries. Furthermore, for each item x, with probability $1-\beta$, the output $\widehat{f}(x)$ satisfies that*

$$0 \le \widehat{f}(x) - f(x) \le \gamma \cdot N + 2E = \gamma \cdot N + 2\sqrt{\frac{2\log\frac{2}{\beta}}{\rho}} \cdot \sqrt{\log\frac{\frac{4}{\gamma}\log(\frac{2}{\beta})}{\beta}}. \tag{2}$$

Comparison to Count Min. Comparing our Theorem 3.1 with the conclusion in [Cormode and Muthukrishnan, 2005], our Private Count Min preserves the nice property that the output will not underestimate the frequency with high probability. Furthermore, within the most popular regime where the privacy budget ρ is a constant, the additional error bound due to differential privacy is independent of the size of database N, therefore it will become negligible as N goes large.

Justification of our Gaussian noise. Note that with high probability, all the noises we add ($E + \sigma_{i,j}$, $\sigma_{i,j} \sim \mathcal{N}(0, \sigma^2)$) will be non-negative. Therefore, the noise we add and the original error induced by

Count Min will directly sum up and lead to larger error in evaluation. However, we claim that the additional E ensures that with high probability, for all item x, the output will not underestimate the actual frequency. This nice property enables the good performance of our Private Count Min when used in approximate top k task, as shown in Section 5.

Next, Theorem 3.2 shows the properties of Private Count Median.

Theorem 3.2. *Private Count Median satisfies ρ-zCDP regardless of the number of queries. Furthermore, for each item x, the output $\widehat{f}(x)$ satisfies that $\mathbb{E}\widehat{f}(x) = f(x)$ and with probability $1-\beta$,*

$$|\widehat{f}(x) - f(x)| \leq \gamma \cdot N + E = \gamma \cdot N + \sqrt{\frac{2\log\frac{2}{\beta}}{\rho}} \cdot \sqrt{\log\frac{\frac{4}{\gamma}\log(\frac{2}{\beta})}{\beta}}. \tag{3}$$

Comparison to Count Median. Comparing our Theorem 3.2 with the conclusion in [Charikar et al., 2002], our Private Count Median preserves the nice property that the output will be an unbiased estimate of the frequency. This property enables our use of Private Count Median in quantile estimation below (Section 4). Furthermore, within the most popular regime where the privacy budget ρ is a constant, the additional error bound due to differential privacy is independent of the size of database N, thus it will become negligible as N goes large.

Better performance in evaluation. Since the noise we add is independent to the error of Count Median, these two errors may cancel each other out. In addition, the scale of the whole error is smaller than a direct summation of the scale of these two errors, which will lead to a much better performance in evaluation (Section 5) compared to the worst case bound.

4 Private Quantile Sketches

In this section, we apply our Private Count Median to state of the art quantile sketches in the turnstile model. Our private Dyadic Count-Median sketch can estimate all the quantiles accurately at the same time while ensuring differential privacy.

4.1 Revisiting DCS

In [Wang et al., 2013], it is shown that DCS can return all γ-approximate quantiles with constant probability using space $O\left(\frac{1}{\gamma}\log^{1.5}U\log^{1.5}(\frac{\log U}{\gamma})\right)$. More specifically, the sketch structure here consists of $\log U$ Count Medians, each Count Median uses a counter arrays C, which is $d \times w$ counters. The choice of d, w follows $d = \Theta\left(\log(\frac{\log U}{\gamma})\right)$ and $w = O\left(\sqrt{\log U\log(\frac{\log U}{\gamma})}/\gamma\right)$.

4.2 Private DCS

In this work, we aim to estimate the quantiles accurately while preserving privacy. We do this by replacing Count Median with Private Count Median, which bases on the same structure as Count Median discussed above. Given the privacy budget ρ, the privacy budget of each Private Count Median is thus $\rho_0 = \frac{\rho}{\log U}$, due to composition of zCDP (Lemma 2.7). The ℓ_2-sensitivity of each Private Count Median is

$$\Delta_2 = O(\sqrt{2d}) = O\left(\sqrt{\log\left(\frac{\log U}{\gamma}\right)}\right).$$

To keep the whole algorithm ρ-zCDP, it suffices to keep each Count Median ρ_0-zCDP (Lemma 2.7). Therefore, Gaussian Mechanism (Definition 2.5) with $\sigma^2 = O\left(\log U\log\left(\frac{\log U}{\gamma}\right)/\rho\right)$ ensures ρ-zCDP (Lemma 2.8). Similar to Lemma A.1, define $E(\gamma, U) = O\left(\sqrt{\frac{\log U\log(\frac{\log U}{\gamma})}{\rho}} \cdot \sqrt{\log\frac{\log U\log(\frac{\log U}{\gamma})}{\gamma}}\right)$, we can prove that with constant probability, all the

Gaussian noises we add to all $\log U$ Count Medians are bounded by E (for simplicity, we use E to represent $E(\gamma, U)$).

Conditioned on the high probability event above, we prove that for a fixed quantile, the estimated quantile will be accurate with high probability. As has been proven in Theorem 3.2, the output estimated frequency is unbiased for any item. Therefore, similar to [Wang et al., 2013], for any item x (corresponding to a fixed Count Median), we have the output $\widehat{f}(x)$ of that Count Median satisfies

$$\mathbb{P}\left[\left|\widehat{f}(x) - f(x)\right| > \frac{1}{w} \cdot N + E\right] < \exp\left(-O(d)\right) = O\left(\frac{\gamma}{\log U}\right).$$

By a union bound, with probability $1 - \log U \times O\left(\frac{\gamma}{\log U}\right) = 1 - O(\gamma)$, for any item corresponding to this fixed quantile, the error of Count Median is bounded by $\frac{1}{w} \cdot N + E$. Conditioned upon this event, by Hoeffding's inequality, with probability $1 - O\left(\frac{\gamma}{\log U}\right)$, the sum of $\log U$ such independent errors is bounded by

$$\sqrt{\log U \log\left(\frac{\log U}{\gamma}\right)} \cdot \left(\frac{N}{w} + E\right) = \gamma \cdot N + E', \tag{4}$$

where $E' = O\left(\frac{\log U \log\left(\frac{\log U}{\gamma}\right)}{\sqrt{\rho}} \cdot \sqrt{\log \frac{\log U \log\left(\frac{\log U}{\gamma}\right)}{\gamma}}\right)$. To sum up, for a fixed quantile, with probability $1 - O(\gamma)$, the estimating error is bounded by $\gamma \cdot N + E'$.

Finally, apply another union bound on the $\frac{1}{\gamma}$ different quantiles, with constant probability, all the quantiles are estimated accurately (within the error bound (4)). Note that similar to [Wang et al., 2013], the failure probability here is a constant. For any failure probability β, we can further increase d by a factor of $\log \frac{1}{\beta}$ to reduce this failure probability to β.

Take-away of Private DCS. First, our Private DCS has a same space complexity as the original DCS. In addition, according to (4), the additional error bound is proportional to $\frac{\log U \log \frac{1}{\gamma}}{\sqrt{\rho}}$ (ignoring $\log\log$ terms), and independent to the size of database N. In the most popular regime where the privacy budget ρ is a constant, the additional error bound only appears as lower order terms, which will become negligible as N goes large.

5 Evaluation

5.1 Data Sets

The experimental evaluation is conducted using both synthetic and real world data sets. We consider the synthetic Zipf dataset Zipf [2016] and the real CAIDA Anonymized Internet Trace 2015 dataset pas. For each independent run in the experiments, we use an input database size $N = 10^5$.

- **Zipf Dataset**: Items are drawn from a bounded universe of size 2^{16} and items' frequencies follow the Zipf Law Zipf [2016].
- **2015 CAIDA Dataset**: The CAIDA dataset is collected from the Chicago high-speed monitor. Items are the source IP addresses with bounded universe size of 2^{32}.

5.2 Metrics

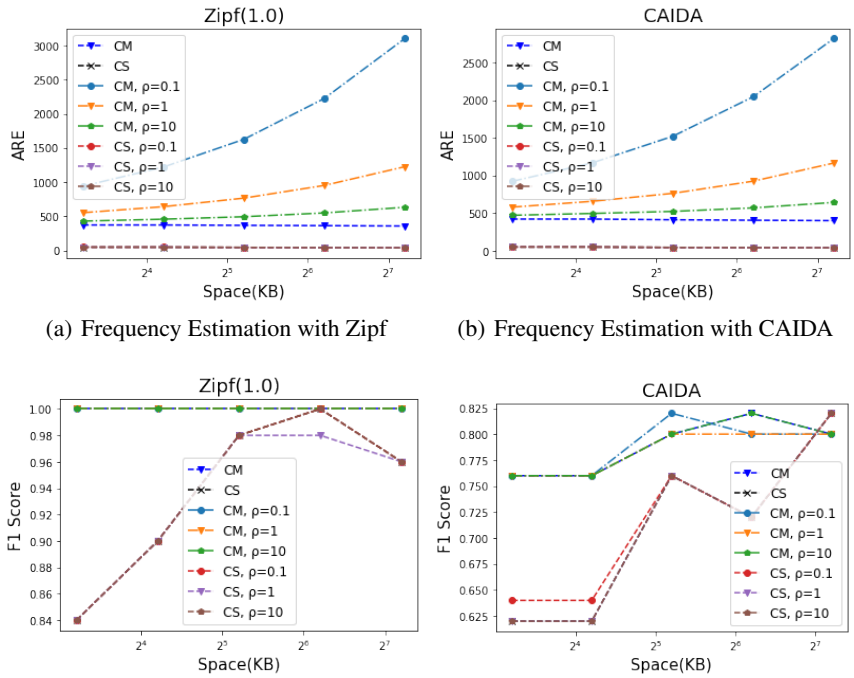
In all experiments, we average the various metrics over 5 independent runs to minimize the measurement variance as all data sketches have randomness depending on the hash function. The metrics used in the experiments are:

- **Average Relative Error**: Let the set Ψ denotes all unique items in the database. The average relative error (ARE) is computed based on Ψ in which $\frac{1}{\Psi}\sum_{e\in\Psi}\frac{|f(e)-\widehat{f}(e)|}{f(e)}$.

- **F1 Score**: F1 score is the harmonic mean of the precision and recall ($2 \cdot \frac{precision \cdot recall}{precision + recall}$).
- **Average Rank Error**: For each evenly spaced quantile and its associated item, we average the distance between the true rank and estimated rank.

We use ARE to evaluate sketch performance on frequency estimation and F1 score to evaluate the sketch's performance in identifying the top 10 items. For quantile approximation, we consider the m evenly spaced quantiles and items. For instance, if $m = 1$, we consider the rank error for the median item; if $m = 2$, we consider then average rank error for the 33rd and 67th percentile items. Lower ARE and average rank error, and higher F1 score indicate better approximation.

5.3 Private Linear Sketches Experiments



(a) Frequency Estimation with Zipf (b) Frequency Estimation with CAIDA

(c) Top 10 with Zipf (d) Top 10 with CAIDA dataset

Figure 1: Comparison of non-private linear sketches and DP linear sketches with various privacy budget under synthetic and real world datasets. The experiments assume $\beta = 1\%$ and $N = 10^5$.

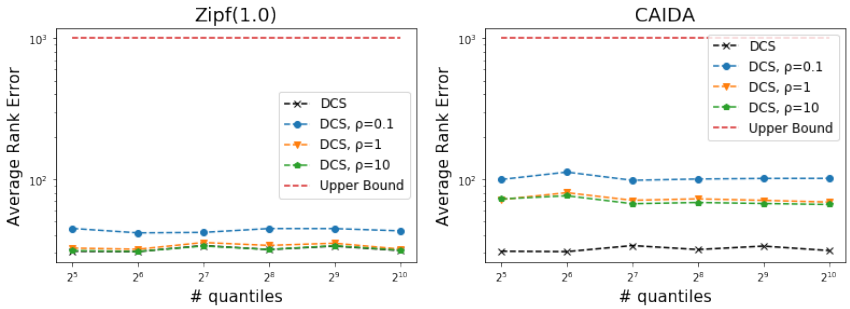
To evaluate the utility of DP linear sketches, we compare the average relative error (ARE) and F1 score for frequency estimation and identify the top 10 items, respectively. As shown in Figure 1, the x-axis represents the space budget for each sketch (from 9.2 KB to 147.3 KB), and the y-axis denotes ARE or F1 score. The DP linear sketches use $\rho \in \{0.1, 1, 10\}$ in which lower ρ value indicates more noise need to be added, and all sketches assume $\beta = 1\%$.

For frequency estimation, the performance of private Count-Median sketches with various privacy budgets is basically equivalent to the performance of the non-private Count-Median sketch. Under different space and privacy budgets, they have minimal difference in ARE for both Zipf and CAIDA datasets, meaning that, while providing strong privacy guarantee, the estimated frequencies are still very accurate. The accurate estimation of private Count-Median is primarily due to the unbiased nature of Count-Median in which, by adding Gaussian noise, the private Count-Median still provides unbiased estimation for an item's frequency as proved in Theorem 3.2. As shown in both Figure 1(a) and Figure 1(b), the performance of private Count-Min degrades when the space budget increases or the privacy budget decreases. This behavior is expected as the upper bound on the frequency

error in Theorem 3.1 has a dependency on both γ and ρ. In order to preserve the property of not underestimating an item's frequency, the private Count-Min sketch needs to add larger noise to each counter when the number of counters increases. As a result, the estimated frequencies for low-frequency items become inflated and this in turn decreases the overall accuracy.

For approximate top 10 items, private Count-Median has similar performance to Count-Median. Since non-private and private Count-Median are unbiased, they may underestimate the frequency of true top K items and decrease the recall. On the other hand, the property of no underestimation is desirable for approximate top K items. In particular, non-private and private Count-Min sketch score high F1 scores for all datasets. While providing privacy guarantees, private Count-Min achieve 1.0 F1 scores for all space and all privacy budgets in Zipf dataset, as shown in Figure 1(c).

5.4 Private Quantile Sketch Experiments



(a) Quantile Approximation with Zipf (b) Quantile Approximation with CAIDA

Figure 2: Compare DCS and DP DCS with various privacy budget under synthetic and real world datasets. The experiments assume $\gamma = 1\%$, $N = 10^5$, and the desired error upper bound is 10^3 (γN).

To evaluate the utility of DP DCS, we compare the average rank error. As shown in Figure 2, the x-axis represents the number of evenly spaced quantiles, and the y-axis denotes the average rank error. The DP DCS use privacy budget $\rho \in \{0.1, 1, 10\}$ and all sketches assume $\gamma = 1\%$.

For the quantile approximation, we observe that the increase in the number of evenly spaced quantiles does not impact the average rank error, as shown in both Figure 2(a) and Figure 2(b). Since the CAIDA dataset universe size (2^{32}) is larger than Zipf dataset universe size (2^{16}), the average rank error in the CAIDA dataset is larger than the average rank error in the Zipf dataset. As shown in Equation (4), the error bound has a term depending on the universe size in which a large universe size leads to more error. When the privacy budget decreases, the average rank error increases as more noise needs to be added. Comparing DP DCS with strong privacy ($\rho = 0.1$) to DCS, the increase in rank error is relatively small compared to the database size of 10^5. In addition, the desired rank error upper bound is $\gamma \cdot N = 10^3$ and all the rank errors are one order of magnitude lower.

6 Conclusion

In this work, we demonstrate that linear sketches can be made differentially private and provide useful information while maintaining their original properties by adding a small amount of Gaussian noise at initialization. In addition, leveraging the private Count-Median sketch, we propose the DP DCS for quantile approximation in the turnstile model, and the DP DCS achieves low rank error even for a large data universe. Moreover, for all proposed algorithms, when the privacy budget is constant, the additional error due to privacy is independent of the database size and the error will become negligible when the database grows larger. As a result, we believe our proposed algorithms are efficient and practical for real-world systems and enable these systems to perform data analysis and machine learning tasks privately.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] Claims in abstract and introduction reflect our contributions.
   (b) Did you describe the limitations of your work? [Yes] In Theorem 3.1, the private Count-Min frequency estimation's additional error has a dependency of $\sqrt{\log \frac{1}{\gamma}}$ in order to keep the property of not underestimating item's frequency. Assume database size is fixed, decreasing gamma will increase the average error. Note the error is independent from the database size, and when database size grows, the error will become negligible.
   (c) Did you discuss any potential negative societal impacts of your work? [N/A] Apply our proposed algorithms to current systems will protect user privacy.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes] We put some proves in Appendix A due to space limits

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We will provide an url to our Github Repo once the paper is accepted.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] We provide the parameters used for the experiments.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [N/A] We didn't use random seed
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [N/A] we didn't use any external resources beside a macbook pro.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [N/A] We did not use existing assets.
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [N/A]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] We did not use crowdsourcing or conducted research with human subjects.
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]