Incorporating Item Frequency for Differentially Private Set Union

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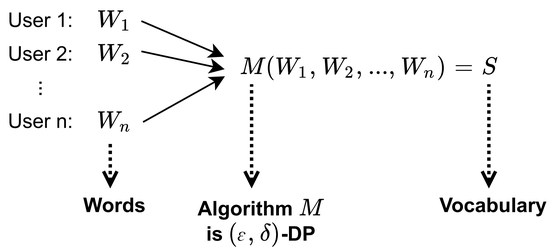
Summary

We propose greedy differentially private set union mechanisms that incorporate item frequency. Our contributions are the following:

- We incorporate the item frequency, which is typically available in set union problems, to boost the utility of private mechanisms.
- The sampling step to limit the number of items each user contributes to is eliminated: users keep all of their items for the set union.
- Novel DP greedy mechanisms with smaller output threshold compared to previous work.
- A mechanism variation with knowledge transfer, with improved utility on experiments.

Introduction

Motivating example: Set union mechanism to build a vocabulary while satisfying user privacy.



Differential Privacy (DP)

$\mathcal{M}$ is (ε, δ)-DP, if for all neighboring datasets D and D' that differ in the addition or removal of one user's data, and all sets S of possible outputs, we have:

$$\Pr[\mathcal{M}(D) \in S] \leq e^{\varepsilon} \Pr[\mathcal{M}(D') \in S] + \delta$$

Differentially Private Set Union

The problem of DPSU was formalized by [1].

Let U be some unbounded universe of items. Each user i has a set of items $W_i \subseteq U$, we want an (ε, δ)-DP mechanism $\mathcal{M}$ that outputs a subset $S \subseteq \cup_i W_i$ such that the size of S is as large as possible.

Previous DPSU Mechanisms

The previous mechanisms used for DPSU are the:

- COUNT mechanisms [2, 3]
- WEIGHTED mechanisms [1]
- POLICY mechanisms [1]

Overview: Iterations over users and items.

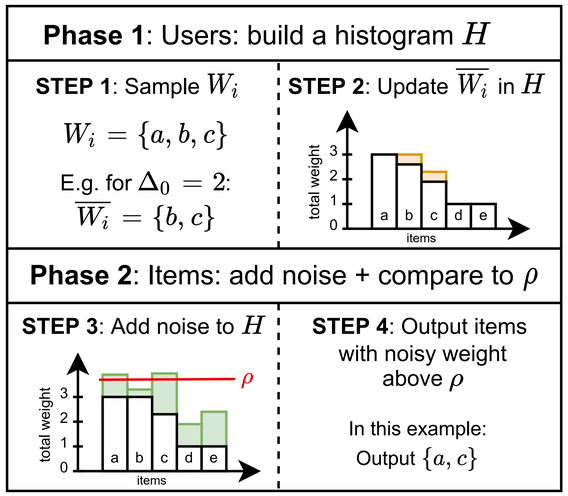


Table: Differences between our work and previous.

Mechanism	Sampling	User View	Updates	KT
COUNT	Yes	Independent	$1/\Delta_0$	No
WEIGHTED	Yes	Independent	$1/\lvert W_i \rvert$	No
POLICY	Yes	Dependent	Gap to Γ	No
This work	**No**	**Dependent**	**Greedy**	**Yes**

Our Main Mechanism: GW

GW: **G**reedy updates **W**ithout sampling: (ε, δ)-DP

Phase 1: Iterate over users to build histogram H:

- Each user keeps all items $W_i = \overline{W_i}$ along with item frequency C_i **(eliminated sampling step)**.
- The histogram is updated by each user using the greedy mechanism $\texttt{GU}(\overline{W_i}, C_i, \Gamma)$ showed below.

Phase 2: Iterate over the items, to output set union:

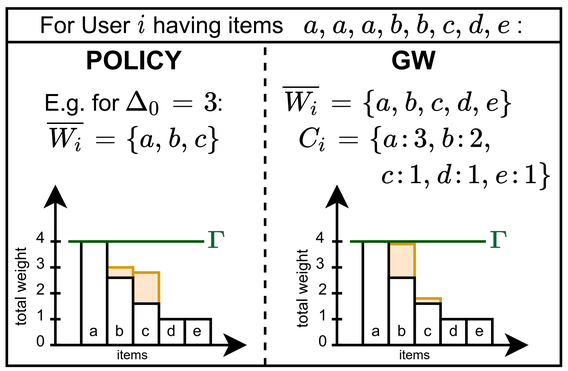
- Add noise $\xi = \texttt{Lap}(0, 1/\varepsilon)$ to each item in H.
- Output the items with noisy weight above the threshold $\rho = 1 - 1/\varepsilon \cdot \log 2\delta$.

GU: Greedy Update Algorithm

Input: H, $\overline{W_i}$, C_i, Γ
Output: Updated histogram H.

budget $= 1$, $S = \emptyset$, $O = \emptyset$
Filtering: Will only update items below Γ.
for $u \in \overline{W_i}$ **do**
  if $H[u] < \Gamma$ **then**
    $S \leftarrow S \cup u$
while budget > 0 **do**
  Item Selection: Get best item to update
  $u^\star = \operatorname{argmax}_{u \in S \setminus O} C_i[u]$
  Greedy update: Allocate budget to $u^\star$
  cost $= \Gamma - H[u^\star]$
  if cost $\leq$ budget **then** ▷ Use budget until Γ
    $H[u^\star] = H[u^\star] +$ cost
    budget $=$ budget $-$ cost
    $O = O \cup \{u^\star\}$
  else ▷ Cannot reach Γ with budget, use all
    $H[u^\star] = H[u^\star] +$ budget
    break
return H

Comparison to POLICY

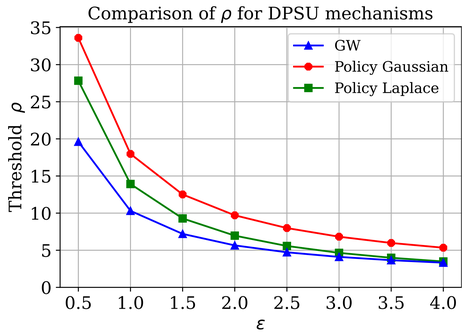


GW-KT: Knowledge Transfer

Replaces C_i in **GW** with C_i^{pub} from **public** data.

Idea: Gauge the common items in the private data and reach Γ quicker for them, leaving more budget to output the remaining items in the private data.

Threshold Comparison



Experiments

Dataset	Policy Lapl. (best Δ_0)	Policy Gaus. (best Δ_0)	GW
Reddit	15485 ± 63	16958 ± 37	**17051** ± 51
Twitter	33757 ± 15	34332 ± 49	**37697** ± 22
Finance	45323 ± 75	40724 ± 62	**49868** ± 23

Dataset	GW-KT (imdb)	GW-KT (covid)	GW-KT (songs)	GW-KT (wiki)	GW-KT (enron)
Reddit	18968	18811	18979	**19057**	19012
Twitter	40910	41332	41739	42060	**42808**
Finance	50451	**51059**	50409	50934	**51070**

- **GW** consistently outperforms POLICY mechanisms [1] by around 10% for Twitter and Finance datasets, whereas for Reddit it gets equivalent utility.
- **GW-KT** has best results as 12%, 25% and 13% better than [1] w.r.t. Reddit, Twitter and Finance.
- All public datasets tested were beneficial to DPSU with KT, even those from very diverse domains. Moreover, the larger the intersection between public and sensitive vocabularies, the better.

References

[1] Sivakanth Gopi, Pankaj Gulhane, Janardhan Kulkarni, Judy Hanwen Shen, Milad Shokouhi, and Sergey Yekhanin. Differentially private set union. *ICML*, 2020.

[2] Aleksandra Korolova, Krishnaram Kenthapadi, Nina Mishra, and Alexandros Ntoulas. Releasing search queries and clicks privately. *WWW*, 2009.

[3] Royce J Wilson, Celia Yuxin Zhang, William Lam, Damien Desfontaines, Daniel Simmons-Marengo, and Bryant Gipson. Differentially private sql with bounded user contribution. *PET*, 2020.