## Collecting Preference Rankings under Local Differential Privacy (technical report)

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Theoretical Analysis of SAFA. We theoretically analyze the privacy and utility guarantees of SAFA. We first establish the privacy guarantee of SAFA in the following theorem.

**Theorem 1.** For any user  $u_i$  with privacy budget  $\varepsilon'$ , SAFA is  $\varepsilon'$ -LDP for  $u_i$ .

*Proof.* By definition, for any two different tuples  $t_i, t_i'$ , and any perturbed value index  $\tilde{k}_i^j$  where  $j \in \{1, \dots, |\mathcal{A}|\}$  is the attribute index selected by the data collector, we need to prove that

$$\frac{\Pr[SAFA(t_i,\varepsilon') = \widetilde{k}_i^j]}{\Pr[SAFA(t_i',\varepsilon') = \widetilde{k}_i^j]} \le e^{\varepsilon'}.$$

Due to the random sampling of the attribute index j, we have

$$\begin{split} &\frac{\Pr[SAFA(t_{i},\varepsilon')=\widetilde{k}_{i}^{j}]}{\Pr[SAFA(t_{i}',\varepsilon')=\widetilde{k}_{i}^{j}]} \\ &=\frac{\Pr[j \text{ is sampled}] \cdot \Pr[LR(j,t_{i},\varepsilon')=\widetilde{k}_{i}^{j}]}{\Pr[j \text{ is sampled}] \cdot \Pr[LR(j,t_{i}',\varepsilon')=\widetilde{k}_{i}^{j}]} \\ &=\frac{\Pr[LR(j,t_{i},\varepsilon')=\widetilde{k}_{i}^{j}]}{\Pr[LR(j,t_{i}',\varepsilon')=\widetilde{k}_{i}^{j}]} \\ &=\frac{\Pr[\widetilde{k}_{i}^{j}|I(t_{i}[A_{j}])]}{\Pr[\widetilde{k}_{i}^{j}|I(t_{i}'[A_{j}])]}. \end{split} \tag{1}$$

We discuss (1) in all four possible cases:

Case 1: if 
$$I(t_i[A_j]) = \widetilde{k}_i^j$$
 and  $I(t_i'[A_j]) = \widetilde{k}_i^j$ , 
$$\frac{\Pr[\widetilde{k}_i^j|I(t_i[A_j])]}{\Pr[\widetilde{k}_i^j|I(t_i'[A_j])]} = \frac{e^{\varepsilon'}}{e^{\varepsilon'} + |dom(A_j)| - 1} / \frac{e^{\varepsilon'}}{e^{\varepsilon'} + |dom(A_j)| - 1} = 1;$$
Case 2: if  $I(t_i[A_j]) \neq \widetilde{k}_i^j$  and  $I(t_i'[A_j]) = \widetilde{k}_i^j$ , 
$$\frac{\Pr[\widetilde{k}_i^j|I(t_i[A_j])]}{\Pr[\widetilde{k}_i^j|I(t_i'[A_j])]} = \frac{1}{e^{\varepsilon'} + |dom(A_j)| - 1} / \frac{e^{\varepsilon'}}{e^{\varepsilon'} + |dom(A_j)| - 1} = e^{-\varepsilon'};$$

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$$\begin{array}{lll} \textit{Case} & 3 \text{: if } & I(t_i[A_j]) & = & \widetilde{k}_i^j & \text{and } & I(t_i'[A_j]) & \neq & \widetilde{k}_i^j, \\ \frac{\Pr[\widetilde{k}_i^j|I(t_i'[A_j])]}{\Pr[\widetilde{k}_i^j|I(t_i'[A_j])]} & = & \frac{e^{\varepsilon'}}{e^{\varepsilon'} + |dom(A_j)| - 1} \middle/ \frac{1}{e^{\varepsilon'} + |dom(A_j)| - 1} & = e^{\varepsilon'}; \\ \textit{Case} & 4 \text{: if } & I(t_i[A_j]) & \neq & \widetilde{k}_i^j & \text{and } & I(t_i'[A_j]) & \neq & \widetilde{k}_i^j, \\ \frac{\Pr[\widetilde{k}_i^j|I(t_i[A_j])]}{\Pr[\widetilde{k}_i^j|I(t_i'[A_j])]} & = & \frac{1}{e^{\varepsilon'} + |dom(A_j)| - 1} \middle/ \frac{1}{e^{\varepsilon'} + |dom(A_j)| - 1} & = 1. \end{array}$$

Therefore, we have  $\frac{\Pr[SAFA(t_i,\varepsilon')=\widetilde{k}_i^j]}{\Pr[SAFA(t_i',\varepsilon')=\widetilde{k}_i^j]} \leq e^{\varepsilon'}$ . As such, SAFA is  $\varepsilon'$ -LDP for  $u_i$ .

In what follows, we give the utility guarantee of SAFA. In particular, we have the following theorems.

**Theorem 2.** Let  $\mathbf{f}_j[k]$  be the true frequency of the k-th value in  $dom(A_j)$  for n users. Then, for any attribute index  $j \in \{1, \ldots, |\mathcal{A}|\}$  and value index  $k \in \{1, \ldots, |dom(A_j)|\}$ , we have

$$\mathbb{E}\left[\mathbf{z}_{j}[k]\right] = \mathbf{f}_{j}[k].$$

*Proof.* To start with, we define a function

$$\mathbb{Y}_{j}^{k}(i) = \begin{cases} 1, & \text{if DC sends } j \text{ to } u_{i} \text{ and } \widetilde{k}_{i}^{j} = k \\ 0, & \text{else} \end{cases}$$

Then, we have

$$\mathbb{E}\left[\mathbf{z}_{j}[k]\right]$$

$$= \mathbb{E}\left[\frac{1}{n} \cdot \frac{|\mathcal{A}| \sum_{i}^{n} \mathbb{Y}_{j}^{k}(i) - nq_{j}}{p_{j} - q_{j}}\right]$$

$$= \frac{1}{p_{j} - q_{j}} \cdot \left[\frac{|\mathcal{A}|}{n} \cdot \mathbb{E}\left[\sum_{i}^{n} \mathbb{Y}_{j}^{k}(i)\right] - q_{j}\right]. \tag{2}$$

Due to the random sampling of the attribute index j, the attribute  $A_j$  is selected with probability  $\frac{1}{|\mathcal{A}|}$ . Hence,

we have

$$\mathbb{E}\left[\sum_{i}^{n} \mathbb{Y}_{j}^{k}(i)\right]$$

$$= \frac{n}{|\mathcal{A}|} \cdot \left[\mathbf{f}_{j}[k] \cdot p_{j} + (1 - \mathbf{f}_{j}[k]) \cdot q_{j}\right]$$

$$= \frac{n}{|\mathcal{A}|} \cdot \left[\mathbf{f}_{j}[k] \cdot (p_{j} - q_{j}) + q_{j}\right]. \tag{3}$$

By substituting (3) into (2), we obtain  $\mathbb{E}\left[\mathbf{z}_{j}[k]\right] = \mathbf{f}_{j}[k]$ . This completes the proof.

Theorem 2 shows that SAFA is an unbiased estimator and explains why the untrusted data collector can learn useful information regarding the true frequency of every possible value of each attribute in  $\mathcal{A}$ . The following theorem (i.e., Theorem 3) shows the variation of the estimated frequency of every possible value of each attribute in  $\mathcal{A}$ .

**Theorem 3.** Let  $\mathbf{f}_j[k]$  be the true frequency of the k-th value in  $dom(A_j)$  for n users. Then, for any attribute index  $j \in \{1, \ldots, |\mathcal{A}|\}$  and value index  $k \in \{1, \ldots, |dom(A_j)|\}$ , the variance of  $\mathbf{z}_i[k]$  is

$$Var\left[\mathbf{z}_{j}[k]\right] pprox rac{\left(e^{arepsilon'} + |dom(A_{j})| - 1
ight) \cdot |\mathcal{A}| - 1}{n \cdot \left(e^{arepsilon'} - 1
ight)^{2}}.$$

Proof. Initially, we have

$$Var\left[\mathbf{z}_{j}[k]\right]$$

$$= Var\left[\frac{1}{n} \cdot \frac{|\mathcal{A}| \sum_{i}^{n} \mathbb{Y}_{j}^{k}(i) - nq_{j}}{p_{j} - q_{j}}\right]$$

$$= \frac{|\mathcal{A}|^{2}}{n^{2} \cdot (p_{j} - q_{j})^{2}} \cdot Var\left[\sum_{i}^{n} \mathbb{Y}_{j}^{k}(i)\right]. \tag{4}$$

The random variable  $\sum_{i=1}^{n} \mathbb{Y}_{j}^{k}(i)$  is the summation of n independent random variables drawn from the Bernoulli distribution. For n users,  $n \cdot \mathbf{f}_{j}[k]$  (resp.  $n \cdot (1 - \mathbf{f}_{j}[k])$ ) of these random variables are from the Bernoulli distribution with parameter  $\frac{p_{j}}{|A|}$  (resp.  $\frac{q_{j}}{|A|}$ ). Thus, we have

$$Var\left[\sum_{i}^{n} \mathbb{Y}_{j}^{k}(i)\right]$$

$$= n \cdot \mathbf{f}_{j}[k] \cdot \left[\frac{p_{j}}{|\mathcal{A}|} \cdot \left(1 - \frac{p_{j}}{|\mathcal{A}|}\right)\right]$$

$$+ n \cdot \left(1 - \mathbf{f}_{j}[k]\right) \cdot \left[\frac{q_{j}}{|\mathcal{A}|} \cdot \left(1 - \frac{q_{j}}{|\mathcal{A}|}\right)\right]. \tag{5}$$

By substituting (5) into (4), we obtain

$$Var \left[\mathbf{z}_{j}[k]\right]$$

$$= \frac{\mathbf{f}_{j}[k] \cdot \left[p_{j} \cdot (|\mathcal{A}| - p_{j})\right] + \left(1 - \mathbf{f}_{j}[k]\right) \cdot \left[q_{j} \cdot (|\mathcal{A}| - q_{j})\right]}{n \cdot (p_{j} - q_{j})^{2}}$$

$$= \frac{q_{j} \cdot (|\mathcal{A}| - q_{j})}{n \cdot (p_{j} - q_{j})^{2}} + \frac{\mathbf{f}_{j}[k] \cdot \left[|\mathcal{A}| \cdot (p_{j} - q_{j}) - (p_{j}^{2} - q_{j}^{2})\right]}{n \cdot (p_{j} - q_{j})^{2}}$$

$$\downarrow^{j}[k]. \quad \approx \frac{q_{j} \cdot (|\mathcal{A}| - q_{j})}{n \cdot (p_{j} - q_{j})^{2}}$$

$$= \frac{\left(e^{\varepsilon'} + |dom(A_{j})| - 1\right) \cdot |A| - 1}{n \cdot (e^{\varepsilon'} - 1)^{2}}.$$
(6)

This completes the proof.

**Theorem 4.** For any attribute index  $j \in \{1,..., |A|\}$ , compared with Harmony, SAFA can achieve higher accuracy of the frequency of every possible value of  $A_j$  when

$$|dom(A_j)| < \frac{(2|\mathcal{A}|-1)\cdot \left(e^{\varepsilon'}+1\right)^2+1}{|\mathcal{A}|} - e^{\varepsilon'}+1.$$

*Proof.* Based on the analysis of Binary Local Hashing in [1], we can derive that the variance of  $\mathbf{z}_{j}[k]$  collected by Harmony is

$$Var_{H}\left[\mathbf{z}_{j}[k]\right] \approx \frac{\left(2|\mathcal{A}|-1\right)\cdot\left(e^{\varepsilon'}+1\right)^{2}}{n\cdot\left(e^{\varepsilon'}-1\right)^{2}}.$$
 (7)

Let (6) < (7), then we have

$$|dom(A_j)| < \frac{(2|\mathcal{A}| - 1) \cdot (e^{\varepsilon'} + 1)^2 + 1}{|\mathcal{A}|} - e^{\varepsilon'} + 1.$$
 (8)

This completes the proof.

## References

[1] T. Wang, J. Blocki, N. Li, and S. Jha, "Locally differentially private protocols for frequency estimation," in *USENIX Security*, 2017.