A PROOF OF THEOREM 5.1

Proof. By the Lagrangian multiplier method, Equ. 9 is rewritten as

$$l = \sum_{k=1}^{d} P_{x_k} ln\hat{x_k} + \sum_{j=d'/2+1}^{d'} P_{y_j} ln\hat{y_j}$$
$$+ \lambda_1(\sum_{k=1}^{d} \hat{x_k} - 1 + \gamma_0) + \lambda_2(\sum_{j=d'/2+1}^{d'} \hat{y_j} - \gamma_0),$$

where λ_1 and λ_2 are two constants and the first-order partial derivatives of l w.r.t. $\hat{x_k}$ and $\hat{y_j}$ are

$$\frac{\partial l}{\partial \hat{x_k}} = \frac{P_{x_k}}{\hat{x_k}} + \lambda_1,\ \frac{\partial l}{\partial \hat{y_j}} = \frac{P_{y_j}}{\hat{y_j}} + \lambda_2.$$

Let $\frac{\partial l}{\partial \hat{x_k}}$ and $\frac{\partial l}{\partial \hat{y_j}}$ be zero, and we have

$$P_{x_k} + \lambda_1 \hat{x_k} = 0, \tag{10}$$

$$P_{y_j} + \lambda_2 \hat{y_j} = 0. \tag{11}$$

From the restrictions in Equ. 9, we can deduce that

$$\lambda_1 = \frac{\sum_{i=1}^{d} P_{x_i}}{\gamma_0 - 1},\ \lambda_2 = \frac{\sum_{i=d'/2+1}^{d'} P_{y_i}}{-\gamma_0}.$$

Replacing them in Equ. 10 and Equ. 11, we can reach that

$$\hat{x_k} = (1-\gamma_0)\frac{Px_k}{\sum_{i=1}^{d} P_{x_i}},\ \hat{y_j} = \gamma_0 \frac{Py_j}{\sum_{i=d'/2+1}^{d'} P_{y_i}}.$$

□

B PROOF OF THEOREM 5.2

Proof. Let $\mathcal{B} = \{B_{y_1}, ..., B_{y_t}\}$, and $\overline{\mathcal{B}} = \{B_{y_{t+1}}, ..., B_{y_{d'}}\}$. We start from the state where all buckets hold non-zero values, i.e., $B_{y_i} \neq 0, i \in \{1, ..., d'\}$, and reconstruct the frequency histogram for poison values in $[-C, C]$. The likelihood estimator in Equ. 1 becomes

$$l(F) = \sum_{i=1}^{N} ln(\sum_{k=1}^{d} \hat{x_k} Pr[v_i' | v_i \in B_{x_k}] + \sum_{j=1}^{d'} \hat{y_j} Pr[v_i' | v_i \in B_{y_j}])$$
$$= \sum_{t=1}^{d'} n_t ln(\sum_{k=1}^{d} \hat{x_k} M_{b_t x_k} + \sum_{j=1}^{d'} \hat{y_j} M_{b_t y_j}).$$

Note that $\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{d'} \hat{y_j} = 1$, we employ the Lagrangian multiplier method to derive the extremum. The Lagrangian function can be written as:

$$L(F) = l(F) + \lambda(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{d'} \hat{y_j} - 1). \tag{12}$$

Let all first-order partial derivatives of L w.r.t. $\hat{x_k}$ and $\hat{y_j}$ equal zero

$$\frac{\partial L(F)}{\partial \hat{x_k}} = \sum_{t=1}^{d'} n_t \frac{M_{b_t x_k}}{\sum_{k=1}^{d} \hat{x_k} M_{b_t x_k} + \hat{y_t}} + \lambda = 0,\ k \in \{1, ..., d\}$$
$$\frac{\partial L(F)}{\partial \hat{y_j}} = \sum_{t=1}^{d'} n_t \frac{M_{b_t y_j}}{\sum_{k=1}^{d} \hat{x_k} M_{b_t x_k} + \hat{y_t}} + \lambda = 0,\ j \in \{1, ..., d'\},$$

we have:

$$\hat{x_k} = 0,\ k \in \{1, ..., d\},\ \ \hat{y_j} = \frac{n_j}{N},\ j \in \{1, ..., d'\},\ \lambda = -N.$$

This result shows all collected values converge to poison values if no bucket is suppressed, and we can obtain:

$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_i \neq 0, i \in \{1, \ldots, d'\}} = \sum_{j=1}^{t} \frac{n_j}{N}.$$

When we suppress the bucket $B_{y_{d'}}$ (by setting $\hat{y_{d'}} = 0$) and carry out EMF. The collected values in $B'_{b_{d'}}$ will converge to all buckets for normal users, because normal values from each $B_{x_k} (k \in \{1, ..., d\})$ can be perturbed into $B'_{b_{d'}}$. Hence, every $\hat{x_k}$ will increase. However, normal values from buckets B_{x_k} can be perturbed into other buckets $B'_{b_i} (i \in \{1, ..., d'-1\})$, so some collected data in $B'_{b_i} (i \in \{1, ..., d'-1\})$ will also converge to normal values and those collected values converge to poison values decrease. Therefore, suppressing $B_{y_{d'}}$ leads to the increase of all $\hat{x_k}$, which in turn results in the decrease of all $\hat{y_j}$. However, since the decrease of $\hat{y_j} (j \in 1, ..., t)$ is a part of increment of $\hat{x}$, we can figure out:

$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_i \neq 0, i \in \{1, \ldots, d'\}} \leq (\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0}.$$

Then suppress the bucket $B_{y_{d'-1}}$, similarly, we have:

$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0} \leq (\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0, y_{d'-1}=0}. \tag{13}$$

Suppress all buckets in $\overline{\mathcal{B}}$, we have:

$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_i \neq 0, i \in \{1, \ldots, d'\}} \leq (\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0} \leq$$
$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0, y_{d'-1}=0} \leq \ldots \leq (\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0, \ldots, y_{t+1}=0}.$$

When the number of suppressed buckets in $\overline{\mathcal{B}}$ increases, the corresponding interference of $\overline{\mathcal{B}}$ decreases. Therefore, the collected values more accurately converge to the buckets that they should belong to, and thus achieve a better convergence result.

After suppressing all buckets in $\overline{\mathcal{B}}$, all collected data will convergence to normal values and poison values in $B_{y_j} (j \in 1, ..., t)$ and we can infer that:

$$(\sum_{k=1}^{d} \hat{x_k} + \sum_{j=1}^{t} \hat{y_j})\Big|_{y_{d'}=0, \ldots, y_{t+1}=0} = 1,$$

which is the optimal case where none of the collected values will converge to buckets in $\overline{\mathcal{B}}$. □

C PROOF OF THEOREM 5.3

Proof. Let v_{tj} denote the j-th value in group G_t, v'_{tj} denote the perturbed v_{tj}, and M_t denote the mean value of v'_{tj}. The variance of $\tilde{M}$, which is a linear combination of M_t, can be written as:

$$\begin{aligned} Var(\tilde{M}) &= Var(\sum_{t=1}^{h} w_t M_t) = \sum_{t=1}^{h} w_t^2 Var(M_t) \\ &= \sum_{t=1}^{h} w_t^2 Var(\frac{\sum_{j=1}^{n'} v'_{tj}}{n'}) = \sum_{t=1}^{h} \frac{w_t^2}{n'^2} \sum_{j=1}^{n'} Var(v'_{tj}), \end{aligned} \tag{14}$$

where $\sum w_t = 1$, and n' is the number of normal users in each group.

Since $Var(v'_{tj})$ in Equ. 14 relies on the input of each user, we consider the worst-case at the maximum variance, i.e., all inputs v_{tj} are either 1 or -1. The worst-case variance $Var_{worst}(v'_{tj})$ can be expressed as:

$$\begin{aligned} Var_{worst}(v'_{tj}) &= \frac{v_{tj}^2}{e^{\epsilon_t/2}-1} + \frac{e^{\epsilon_t/2}+3}{3(e^{\epsilon_t/2}-1)^2}\bigg|_{v_{tj}=\pm 1} \\ &= \frac{1}{e^{\epsilon_t/2}-1} + \frac{e^{\epsilon_t/2}+3}{3(e^{\epsilon_t/2}-1)^2}. \end{aligned}$$

Let $B_t = n'Var_{worst}(v'_{tj})$. Equ. 14 can be rewritten as:

$$Var(\tilde{M}) = \sum_{t=1}^{h} \frac{w_i^2}{n'^2} B_t. \tag{15}$$

We regard the variance as a function of w_t, and the minimal variance is the extreme point of Equ. 15. By the Lagrangian method, we have:

$$\mathcal{L} = \sum_{t=1}^{h} \frac{w_t^2}{n'^2} B_t + C_0(1 - \sum_{t=1}^{h} w_t).$$

The first partial derivatives of $\mathcal{L}$ w.r.t. w_t is:

$$\frac{\partial \mathcal{L}}{\partial w_t} = \frac{2w_t}{n'^2} B_t - C_0.$$

Let $\frac{\partial \mathcal{L}}{\partial w_t} = 0$, then we have $wt = \frac{C_0 n'^2}{2B_t}$. Through the restriction $\sum_{t=1}^{h} w_t = 1$, we figure out

$$C_0 = \frac{2}{n'^2 \sum_{t=1}^{h} \frac{1}{B_t}}, \; w_t = \frac{1}{B_t \sum_{i=1}^{h} \frac{1}{B_i}}.$$

And the final minimal variance of $\tilde{M}$ is:

$$Var(\tilde{M})_{min} = [\sum_{t=1}^{h} \frac{n'^2}{B_t}]^{-1}.$$

□