

# Supplements:

## Differentially Private Selection using Smooth Sensitivity

This provides the omitted proofs in the main paper.

### I. PROOFS

#### A. Theorem 3

**Theorem 3.** If  $Z_r$  are derived from  $g$ , the smooth private selection mechanism satisfies  $\left(\left(k + \frac{|\mathcal{R}|-1}{2} \cdot l\right) \cdot \epsilon\right)$   $\left(k + \frac{|\mathcal{R}|}{2} \cdot l\right)$ -differential privacy.

*Proof.* The following proof is wrong. The correct proof is the same as that of Theorem 2. That is, regardless of whether the noise is two-sided or one-sided, the mechanism's privacy guarantee is  $\left(k + \frac{|\mathcal{R}|}{2} \cdot l\right)$ -differential privacy.

We let  $\mathcal{R} = \{1, 2, \dots, m\}$  as in the proof of Theorem 2. It is sufficient to show that, for all neighboring datasets  $x, y \in D^n$ ,

$$\begin{aligned} & \Pr[M(x) = 1] \\ & \leq \exp\left(\left(k + \frac{m-1}{2} \cdot l\right) \cdot \epsilon\right) \cdot \Pr[M(y) = 1]. \end{aligned} \quad (1)$$

Here, the relations

$$\begin{aligned} \Pr[M(x) = 1] &= \int_{v \in (-\infty, \infty)} \Pr\left[Z_1 = \frac{\alpha'(v - u(x, 1) + S(x))}{S(x)}\right] \\ & \quad \cdot \Pr\left[Z_2 \leq \frac{\alpha'(v - u(x, 2))}{S(x)}\right] \\ & \quad \cdots \Pr\left[Z_m \leq \frac{\alpha'(v - u(x, m))}{S(x)}\right] \end{aligned} \quad (2)$$

and

$$\begin{aligned} & \Pr[M(y) = 1] \\ & \geq \int_{v \in (-\infty, \infty)} \Pr\left[Z_1 = \frac{\alpha'(v - u(y, 1) + S(y))}{S(y)}\right] \\ & \quad \cdot \Pr\left[Z_2 \leq \frac{\alpha'(v - u(y, 2))}{S(y)}\right] \\ & \quad \cdots \Pr\left[Z_m \leq \frac{\alpha'(v - u(y, m))}{S(y)}\right] \end{aligned} \quad (3)$$

hold as in the proof of Theorem 2, and in particular, we should note  $u(x, 1) - u(y, 1) + S(x) \geq 0$ .

(I) When  $S(x) \geq S(y)$ :

Because  $\forall r \in \{2, 3, \dots, m\}$ :

$$\Pr\left[Z_r \leq \frac{\alpha'(v - u(x, r))}{S(y)}\right] \geq \Pr\left[Z_r \leq \frac{\alpha'(v - u(x, r))}{S(x)}\right],$$

[ $\because$  the property of  $g$ ]

$\leftarrow$  This is wrong.

$$\begin{aligned} (3) & \geq \int_{v \in (-\infty, \infty)} \Pr\left[Z_1 = \frac{\alpha'(v - u(y, 1) + S(x))}{S(y)}\right] \\ & \quad \cdot \Pr\left[Z_2 \leq \frac{\alpha'(v - u(x, 2))}{S(x)}\right] \\ & \quad \cdots \Pr\left[Z_m \leq \frac{\alpha'(v - u(x, m))}{S(x)}\right]. \end{aligned} \quad (4)$$

From (2) and (4), the following relation holds:

$$\Pr[M(x) = 1] \leq \exp\left(\left(k + \frac{l}{2}\right) \cdot \epsilon\right) \cdot \Pr[M(y) = 1].$$

(II) When  $S(x) < S(y)$ :

Because

$$\begin{aligned} & \Pr\left[Z_1 = \frac{\alpha'(v - u(y, 1) + S(x))}{S(y)}\right] \\ & \geq \Pr\left[Z_1 = \frac{\alpha'(v - u(y, 1) + S(x))}{S(x)}\right], \end{aligned}$$

[ $\because$  the property of  $g$ ]

$\leftarrow$  This is wrong.

$$\begin{aligned} (3) & \geq \int_{v \in (-\infty, \infty)} \Pr\left[Z_1 = \frac{\alpha'(v - u(y, 1) + S(x))}{S(x)}\right] \\ & \quad \cdot \Pr\left[Z_2 \leq \frac{\alpha'(v - u(x, 2))}{S(y)}\right] \\ & \quad \cdots \Pr\left[Z_m \leq \frac{\alpha'(v - u(x, m))}{S(y)}\right]. \end{aligned} \quad (5)$$

From (2) and (5), the relation (1) holds.  $\square$

#### B. Theorem 5

**Theorem 5.** Given a threshold  $T$ , we let the set of  $x$  satisfying  $LS_f(x) > T$  be  $U$ . For any  $\beta (> 0)$  satisfying

$$\beta \leq \min_{x \notin U} \frac{1}{ud(x)} \cdot \ln\left(\frac{GS_f}{LS_f(x)}\right), \quad (6)$$

where  $ud(x) := \min_{y \in U} d(y, x)$  represents the shortest distance between  $x$  and  $U$ , the following function  $S$  is a  $\beta$ -smooth upper bound:

$$S(x) = GS_f \cdot e^{-\beta \cdot ud(x)}.$$

*Proof.* From (6), for all  $x \notin U$ ,

$$\beta \leq \frac{1}{ud(x)} \cdot \ln \left( \frac{GS_f}{LS_f(x)} \right) \\ \iff LS_f(x) \leq GS_f \cdot e^{-\beta \cdot ud(x)}.$$

Therefore, from Definition 4 (for  $\beta$ -smooth upper bound), it is sufficient to show that

$$\forall x, y, d(x, y) = 1 : S(x) \leq e^\beta \cdot S(y). \quad (7)$$

(I) When  $x, y \in U$ :

Because  $S(x) = S(y) = GS_f$ , the relation (7) holds.

(II) When  $x \in U$  and  $y \notin U$ :

Because  $S(x) = GS_f$  and

$$S(y) = GS_f \cdot e^{-\beta}, \quad [\cdot : ud(y) = d(x, y) = 1]$$

the relation (7) holds.

(III) When  $x \notin U$  and  $y \in U$ :

Similar to Case (II),  $S(x) = GS_f \cdot e^{-\beta}$  and  $S(y) = GS_f$ ; therefore, the relation (7) holds.

(IV) When  $x, y \notin U$ :

Where  $X$  satisfies  $X \in U$  and  $d(X, x) = ud(x)$ , and  $Y$  satisfies  $Y \in U$  and  $d(Y, y) = ud(y)$ ,

$$\begin{aligned} e^\beta \cdot S(y) &= e^\beta \cdot GS_f \cdot e^{-\beta \cdot d(Y, y)} \\ &\geq e^\beta \cdot GS_f \cdot e^{-\beta \cdot d(X, y)} \quad [\cdot : d(Y, y) \leq d(X, y)] \\ &\geq e^\beta \cdot GS_f \cdot e^{-\beta \cdot (d(X, x) + d(x, y))} \\ &\quad [\cdot : d(X, y) \leq d(X, x) + d(x, y)] \\ &= GS_f \cdot e^{-\beta \cdot d(X, x)} = S(x). \quad [\cdot : d(x, y) = 1] \end{aligned}$$

Therefore, the relation (7) holds.  $\square$

*C. Lemma 2*

**Lemma 2.**  $(b, c)$  satisfies  $LS_{\chi_{TDT}^2}((b, c)) > 6$  when

$$\begin{aligned} 0 \leq c < \frac{b-8}{7} \vee 2 \leq b < \frac{c+8}{7} \\ \vee \quad 0 \leq b < \frac{c-8}{7} \vee 2 \leq c < \frac{b+8}{7}. \end{aligned}$$

*Proof.*  $LS_{\chi_{TDT}^2}(x) > 6$  can be satisfied only if  $x = (b, c)$  and  $y = (b-2, c+2) \vee (b+2, c-2)$ .

When  $y = (b-2, c+2)$  is possible,  $b \geq 2$  and  $c \geq 0$ . In this case,

$$\begin{aligned} &\chi_{TDT}^2(b, c) - \chi_{TDT}^2(b-2, c+2) \\ &= \frac{(b-c)^2}{b+c} - \frac{(b-c-4)^2}{b+c} = \frac{8(b-c-2)}{b+c}. \quad (8) \end{aligned}$$

$|8| > 6 \iff c < \frac{b-8}{7} \vee b < \frac{c+8}{7}$ ; therefore,  $(b, c)$  satisfies  $LS_{\chi_{TDT}^2}((b, c)) > 6$  when  $0 \leq c < \frac{b-8}{7} \vee 2 \leq b < \frac{c+8}{7}$ .

Similarly when  $y = (b+2, c-2)$  is possible, we can obtain  $0 \leq b < \frac{c-8}{7} \vee 2 \leq c < \frac{b+8}{7}$ .  $\square$

*D. Lemma 3*

**Lemma 3.** The Hamming distance for TDT datasets can be

$$\begin{aligned} &d(T(b, c), T(b', c')) \\ &= \begin{cases} \left\lceil \frac{|(b+c) - (b'+c')|}{2} \right\rceil & ((b-b') \cdot (c-c') \geq 0) \\ \left\lceil \frac{\max\{|b-b'|, |c-c'|\}}{2} \right\rceil & ((b-b') \cdot (c-c') < 0) \end{cases}, \end{aligned}$$

where  $T(b, c)$  represents a table that can be formed as the following table:

		Non-Transmitted Allele		Total
		$A_1$	$A_2$	
Transmitted Allele	$A_1$	$a$	$b$	$a+b$
	$A_2$	$c$	$d$	$c+d$
Total		$a+c$	$b+d$	$2N$

*Proof.* The possible changes in  $(b, c)$  between neighboring datasets are

$(b, c)$

$$\begin{aligned} \rightarrow & (b-2, c), (b-2, c+1), (b-2, c+2), \\ & (b-1, c-1), (b-1, c), (b-1, c+1), (b-1, c+2), \\ & (b, c-2), (b, c-1), (b, c), (b, c+1), (b, c+2), \\ & (b+1, c-2), (b+1, c-1), (b+1, c), (b+1, c+1), \\ & (b+2, c-2), (b+2, c-1), (b+2, c). \end{aligned}$$

Therefore, the maximum change in the value of  $b+c$  is 2; when  $(b-b') \cdot (c-c') \geq 0$ , the Hamming distance can be

$$d(T(b, c), T(b', c')) = \left\lceil \frac{|(b+c) - (b'+c')|}{2} \right\rceil.$$

When  $(b-b') \cdot (c-c') < 0$ , using the changes  $(b, c) \rightarrow (b-2, c), (b-2, c+1), (b-2, c+2), (b+2, c-2), (b+2, c-1), (b+2, c)$ , the Hamming distance can be

$$d(T(b, c), T(b', c')) = \left\lceil \frac{\max\{|b-b'|, |c-c'|\}}{2} \right\rceil. \quad \square$$