

Verifying Snapping Mechanism

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In order to verify the differential privacy property of the snapping mechanism[3], we follow the logic rules designed from [1].

Some new rules are added into this logic in Figure 1 following with correctness proof. Then we formalized the snapping mechanism and verified its differential privacy property under these logic rules.

1 Extended Programming Logic[1]

Definition 1 (Laplace mechanism [2])

Let $\epsilon > 0$. The Laplace mechanism $\mathcal{L}_\epsilon: \mathbb{R} \rightarrow \text{Distr}(\mathbb{R})$ is defined by $\mathcal{L}(t) = t + v$, where $v \in \mathbb{R}$ is drawn from the Laplace distribution $\text{Laplace}(\frac{1}{\epsilon})$.

Definition 2

Let $\epsilon \leq 0$. The ϵ -DP divergence $\Delta_\epsilon(\mu_1, \mu_2)$ between two sub-distributions $\mu_1 \in \text{Distr}(U)$, $\mu_2 \in \text{Distr}(U)$ is defined as:

$$\sup_{E \in \mathcal{U}} \left(\Pr_{x \leftarrow \mu_1} [x \in E] - \exp(\epsilon) \Pr_{x \leftarrow \mu_2} [x \in E] \right)$$

Definition 3 ((ϵ, δ) - lifting [1])

Two sub-distributions $\mu_1 \in \text{Distr}(U_1)$, $\mu_2 \in \text{Distr}(U_2)$ are related by the (ϵ, δ) - dilation lifting of $\Psi \subseteq U_1 \times U_2$, written $\mu_1 \Psi^{\#(\epsilon, \delta)} \mu_2$, if there exist two witness sub-distributions $\mu_L \in \text{Distr}(U_1 \times U_2)$ and $\mu_R \in \text{Distr}(U_1, U_2)$ s.t.:

1. $\pi_1(\mu_L) = \mu_1$ and $\pi_2(\mu_R) = \mu_2$;
2. $\text{supp}(\mu_L) \subseteq \Psi$ and $\text{supp}(\mu_R) \subseteq \Psi$; and
3. $\Delta_\epsilon(\mu_L, \mu_R) \leq \delta$.

The logic rules we are using in our work is presented in Figure 1. The correctness of rules is proved in Theorem 1 and Theorem 2

Theorem 1

Let $\mu_1 \in \text{Distr}(\mathbb{R})$, $\mu_2 \in \text{Distr}(\mathbb{R})$ are defined:

$$\mu_1(x) = \text{unif}(x)$$

$$\mu_2(y) = \text{unif}(y)$$

$$\begin{array}{c}
\frac{}{\vdash u_1 \xleftarrow{\$} \mu \sim_{\epsilon,0} u_2 \xleftarrow{\$} \mu : \top \Rightarrow e^{-\epsilon} u_2 \leq u_1 \leq e^{\epsilon} u_2} \text{AxUNIF} \\
\\
\frac{}{\vdash y_1 \xleftarrow{\$} \mathcal{L}_{\epsilon}(e_1) \sim_{k',\epsilon,0} y_2 \xleftarrow{\$} \mathcal{L}_{\epsilon}(e_2) : |k + e_1 - e_2| \leq k' \Rightarrow y_1 + k = y_2} \text{LAPGEN} \\
\\
\frac{}{\vdash y_1 \xleftarrow{\$} \mathcal{L}_{\epsilon}(e_1) \sim_{0,0} y_2 \xleftarrow{\$} \mathcal{L}_{\epsilon}(e_2) : \top \Rightarrow y_1 - y_2 = e_1 - e_2} \text{LAPNULL} \\
\\
\frac{}{\vdash y_1 \xleftarrow{\$} \mu \sim_{0,0} y_2 \xleftarrow{\$} \mu : \top \Rightarrow y_1 = y_2} \text{AxNULL} \quad \frac{}{\vdash y_1 = f(x_1) \sim_{0,0} y_2 = f(x_2) : \Phi_1 \Rightarrow f(\Phi_1)} \text{TRANS} \\
\\
\frac{p_1 \sim_{k,0} p_2 : \Phi_1 \Rightarrow \Phi'_1 \quad c_1 \sim_{k',0} c_2 : \Phi'_1 \Rightarrow \Phi_2}{\vdash p_1; c_1 \sim_{k+k',0} p_2; c_2 : \Phi_1 \Rightarrow \Phi_2} \text{COMP} \quad f(\Phi) \equiv \text{let } y = f(x) \text{ in } \forall x. \Phi_1[x \mapsto f^{-1}(y)]
\end{array}$$

Figure 1: Logic Rules Extended from [1]

where unif is uniform distribution over $[0, 1]$ whose pdf. is defined as:

$$\text{pdf}_{\text{unif}}(x) = \begin{cases} 1 & x \in [0, 1] \\ 0 & o.w. \end{cases}.$$

Then, $\mu_1 \Psi^{\#(\epsilon,0)} \mu_2$, where

$$\Psi = \{(x, y) \in \mathbb{R} \times \mathbb{R} \mid x \cdot e^{-\epsilon} \leq y \leq x \cdot e^{\epsilon}\}$$

Theorem 2

For any distributions $\mu_1 \in \text{Distr}(\mathbb{R})$, $\mu_2 \in \text{Distr}(\mathbb{R})$, $\mu_1 \Psi^{\#(0,0)} \mu_2$, where

$$\Psi = \{(x, y) \in \mathbb{R} \times \mathbb{R} \mid x = y\}$$

Proof of Theorem 1. Existing $\mu_L, \mu_R \in \text{Distr}(\mathbb{R} \times \mathbb{R})$:

$$\mu_L(x, y) = \begin{cases} \text{unif}(x) & x \cdot e^{-\epsilon} = y \wedge x \in [0, 1] \\ 0 & o.w. \end{cases} \quad \mu_R(x, y) = \begin{cases} \text{unif}(y) & x \cdot e^{-\epsilon} = y \wedge y \in [0, 1] \\ 0 & o.w. \end{cases}.$$

Their pdf. are defined:

$$\begin{aligned}
\text{pdf}_{\mu_L}(x, y) &= \begin{cases} \text{pdf}_{\text{unif}}(x) & x \cdot e^{-\epsilon} = y \wedge x \in [0, 1] \\ 0 & o.w. \end{cases} \\
\text{pdf}_{\mu_R}(x, y) &= \begin{cases} \text{pdf}_{\text{unif}}(y) & x \cdot e^{-\epsilon} = y \wedge y \in [0, 1] \\ 0 & o.w. \end{cases}.
\end{aligned}$$

- $\text{supp}(\mu_L) \in \Psi \wedge \text{supp}(\mu_R) \in \Psi$

- $\text{supp}(\mu_L) \subseteq \Psi$

By definition of the pdf of μ_L , we have: $\Pr_{(x,y) \xleftarrow{\$} \mu_L} [(x, y) \notin \Psi] = 0$.

Then we can derive $\text{supp}(\mu_L) \in \Psi$

– $\text{supp}(\mu_R) \subseteq \Psi$

By definition of the pdf of μ_R , we have: $\Pr_{(x,y) \xleftarrow{\$} \mu_R} [(x,y) \notin \Psi] = 0$.

Then we can derive $\text{supp}(\mu_L) \in \Psi$

• $\pi_1(\mu_L) = \mu_1 \wedge \pi_2(\mu_R) = \mu_2$

– $\pi_1(\mu_L) = \mu_1$

By definition of the π_1 and pdf of μ_L , we have $\forall x \in \mathbb{R}$:

$$\text{pdf}_{\pi_1(\mu_L)}(x) = \begin{cases} \int_y \text{pdf}_{\text{unif}}(x) & (x,y) \in \Psi \wedge x \in [0,1) \\ 0 & \text{o.w.} \end{cases} = \begin{cases} \text{pdf}_{\text{unif}}(x) & x \in [0,1) \\ 0 & \text{o.w.} \end{cases} = \text{pdf}_{\mu_1}(x)$$

– $\pi_1(\mu_R) = \mu_2$

Equivalent to show $\text{pdf}_{\pi_2(\mu_R)} = \text{pdf}_{\mu_2}$.

By definition of the π_2 and pdf of μ_R , we have $\forall y \in \mathbb{R}$:

$$\text{pdf}_{\pi_2(\mu_R)}(y) = \begin{cases} \int_x \text{pdf}_{\text{unif}}(y) & (x,y) \in \Psi \wedge y \in [0,1) \\ 0 & \text{o.w.} \end{cases} = \begin{cases} \text{pdf}_{\text{unif}}(y) & y \in [0,1) \\ 0 & \text{o.w.} \end{cases} = \text{pdf}_{\mu_2}(y)$$

• $\Delta_\epsilon(\mu_L, \mu_R) \leq 0$

By definition of ϵ -DP divergence, we have:

$$\begin{aligned} \Delta_\epsilon(\mu_L, \mu_R) &= \sup_S \left(\Pr_{(x,y) \xleftarrow{\$} \mu_L} [(x,y) \in S] - e^\epsilon \Pr_{(x,y) \xleftarrow{\$} \mu_R} [(x,y) \in S] \right) \\ &= \sup_S \left(\int_{(x,y) \in S} \text{pdf}_{\mu_L}(x,y) - e^\epsilon \int_{(x,y) \in S} \text{pdf}_{\mu_R}(x,y) \right) \end{aligned}$$

case $S \subseteq \{(x,y) | x \in [0,1) \wedge x \cdot e^{-\epsilon} = y\}$:

$$\begin{aligned} \Delta_\epsilon(\mu_L, \mu_R) &= \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(x) - e^\epsilon \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(y) \\ &= \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(x) - e^\epsilon \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(x \cdot e^{-\epsilon}) \\ &= \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(x) - e^\epsilon \cdot e^{-\epsilon} \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(x) \\ &= 0 \end{aligned}$$

case $S \subseteq \{(x,y) | x \in [1, e^\epsilon) \wedge x \cdot e^{-\epsilon} = y\}$:

$$\begin{aligned} \Delta_\epsilon(\mu_L, \mu_R) &= 0 - e^\epsilon \int_{(x,y) \in S} \text{pdf}_{\text{unif}}(y) \\ &< 0 \end{aligned}$$

case o.w.

$$\Delta_\epsilon(\mu_L, \mu_R) = 0 - 0 = 0$$

□

$$\begin{array}{c}
\frac{}{u_1 \xleftarrow{\$} \mu \sim_{\epsilon,0} u_2 \xleftarrow{\$} \mu : \top \Rightarrow e^{-\epsilon} u_2 \leq u_1 \leq e^{\epsilon} u_2} \text{AxUnif} \\
\\
\frac{}{y_1 = \frac{\ln(u_1)}{\epsilon} \sim_{0,0} y_2 = \frac{\ln(u_2)}{\epsilon} : e^{-\epsilon} u_2 \leq u_1 \leq e^{\epsilon} u_2 \Rightarrow y_2 - 1 \leq y_1 \leq 1 + y_2} \text{AxNull} \\
\\
\frac{}{s_1 \xleftarrow{\$} \{-1, 1\} \sim_{0,0} s_2 \xleftarrow{\$} \{-1, 1\} : \top \Rightarrow s_1 = s_2} \text{AxNull} \\
\\
\frac{}{z_1 = s_1 * y_1 \sim_{0,0} z_2 = s_2 * y_2 : s_1 = s_2 \wedge y_2 - 1 \leq y_1 \leq 1 + y_2 \Rightarrow |z_1 - z_2| \leq 1} \text{AxNull} \\
\\
\frac{}{x_1 = f(a_1) \sim_{0,0} x_2 = f(a_2) : a_1 = a_2 + 1 \wedge f(a_1) = f(a_2) + 1 \Rightarrow x_1 = x_2 + 1} \text{AxNull} \\
\\
\frac{}{w_1 = x_1 + z_1 \sim_{0,0} w_2 = x_2 + z_2 : x_1 = x_2 + 1 \wedge |z_1 - z_2| \leq 1 \wedge -2 \leq k \leq 0 \Rightarrow w_1 + k = w_2} \text{AxNull} \\
\\
\frac{}{w'_1 = \lfloor w_1 \rfloor_{\Lambda} \sim_{0,0} w'_2 = \lfloor w_2 \rfloor_{\Lambda} : w_1 + k = w_2 \wedge -2 \leq k \leq 0 \Rightarrow w'_1 + k = w'_2} \text{AxNull} \\
\\
\frac{}{r_1 = \text{clamp}_B(w'_1) \sim_{0,0} r_2 = \text{clamp}_B(w'_2) : w'_1 + k = w'_2 \wedge -2 \leq k \leq 0 \Rightarrow r_1 + k = r_2} \text{AxNull} \\
\\
\frac{\dots}{r_1 = \text{Snap}(a_1) \sim_{\epsilon,0} r_2 = \text{Snap}(a_2) : a_1 = a_2 + 1 \wedge f(a_1) = f(a_2) + 1 \wedge |k + f(a_1) - f(a_2)| \leq 1 \Rightarrow r_1 + k = r_2} \text{Comp}
\end{array}$$

Figure 2: Coupling Derivation of two Snap mechanisms: $\text{Snap}(a_1)$, $\text{Snap}(a_2)$

2 Formalization of Snap Mechanism in Probabilistic Logic

Definition 4 ($\text{Snap}(a) : A \rightarrow \text{Distr}(B)$)

The ideal Snapping mechanism $\text{Snap}(a)$ is defined as:

$$u \xleftarrow{\$} \mu; y = \frac{\ln(u)}{\epsilon}; s \xleftarrow{\$} \{-1, 1\}; z = s * y; x = f(a); w = x + z; w' = \lfloor w \rfloor_{\Lambda}; r = \text{clamp}_B(w')$$

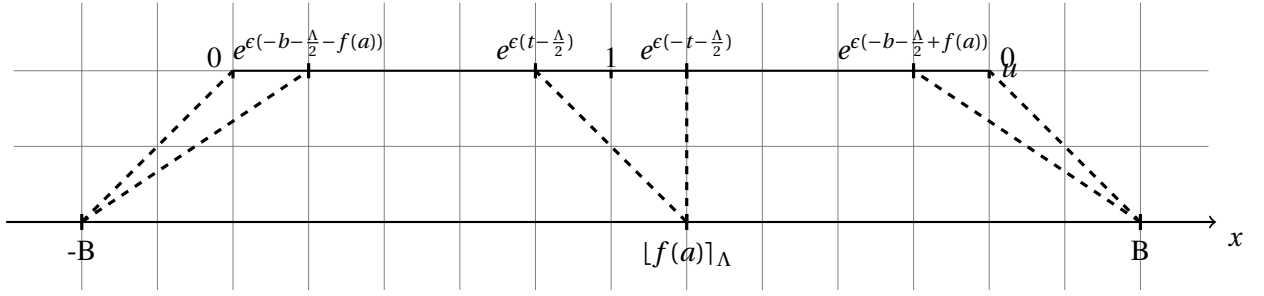
where f is the query function over input $a \in A$, ϵ is the privacy budget, B is the clamping bound and Λ is the rounding argument satisfying $\lambda = 2^k$ where 2^k is the smallest power of 2 greater or equal to the $\frac{1}{\epsilon}$.

Theorem 3 (The Snap mechanism is ϵ -differentially private)

Proof. The proof follows the derivation in Figure 2. □

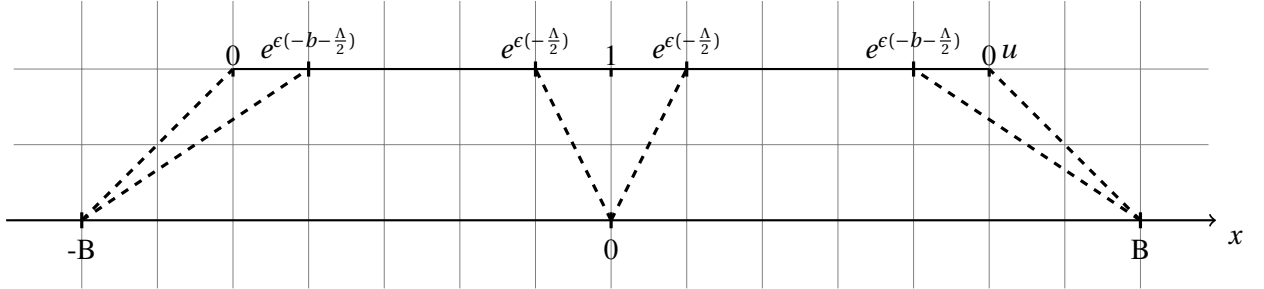
3 Proof of Differential Privacy for Snap Mechanism

Assume x be the output of Snap mechanism, we have following maps from the output of Snap mechanism to uniformly distributed $u \in (0, 1]$.



where b is the greatest rounding of Λ that is smaller than B and $t = \lfloor f(a) \rfloor_{\Lambda} - f(a)$.

Given the $f(a) = \lfloor f(a) \rfloor_{\Lambda} = 0$, we have following maps from the output of Snap mechanism to uniformly distributed $u \in (0, 1]$.



Assuming that $f(a) \in [-B, B]$, otherwise we can always redefine the $f(a)$ restricting its output in this range. The probability of obtaining output x from Snap mechanism can be calculated by cases of x :

case $x = -B$

In this case, we know $s = 1$.

We have: $\lfloor f(a) + \frac{1}{\epsilon} \ln(u) \rfloor_{\Lambda} \leq -B$.

Since b is the greatest rounding of Λ that is smaller than B , then $-b$ is the smallest rounding of Λ that is greater than $-B$, we have: $f(a) + \frac{1}{\epsilon} \ln(u) < -b - \frac{\Lambda}{2}$.

Then we get: $u \in (0, e^{\epsilon(-b - \frac{\Lambda}{2} - f(a))})$

case $x \in (-B, \lfloor f(a) \rfloor_{\Lambda})$

In this case, we know $s = 1$ and $x \in [-b, \lfloor f(a) \rfloor_{\Lambda} - \Lambda]$.

We have: $\lfloor f(a) + \frac{1}{\epsilon} \ln(u) \rfloor_{\Lambda} = x$.

By the rule of rounding, we get: $u \in [e^{\epsilon(x - \frac{\Lambda}{2} - f(a))}, e^{\epsilon(x + \frac{\Lambda}{2} - f(a))})$.

By the range of x , we get: $u \in [e^{\epsilon(-b - \frac{\Lambda}{2} - f(a))}, e^{\epsilon(t - \frac{\Lambda}{2})})$.

case $x = \lfloor f(a) \rfloor_{\Lambda}$

subcase $s = 1$

In this case, we have: $\lfloor f(a) + \frac{1}{\epsilon} \ln(u) \rfloor_{\Lambda} = \lfloor f(a) \rfloor_{\Lambda}$.

Then we can get: $u \in [e^{\epsilon(t - \frac{\Lambda}{2})}, e^{\epsilon(t + \frac{\Lambda}{2})}]$.

Since $t = \lfloor f(a) \rfloor_{\Lambda} - f(a)$, we know: $-\frac{\Lambda}{2} \leq t \leq \frac{\Lambda}{2}$. So we can get: $e^{\epsilon(t + \frac{\Lambda}{2})} > 1$.

Since $u \in (0, 1]$, we have: $u \in [e^{\epsilon(t - \frac{\Lambda}{2})}, 1]$.

subcase $s = -1$

By the symmetric of the range, we can get: $u \in [e^{\epsilon(-t - \frac{\Lambda}{2})}, 1]$.

case $x \in (\lfloor f(a) \rfloor_\Lambda, B)$

In this case, we know $s = -1$ and $x \in [\lfloor f(a) \rfloor_\Lambda + \Lambda, b]$.

We have: $\lfloor f(a) - \frac{1}{\epsilon} \ln(u) \rfloor_\Lambda = x$.

By the rule of rounding, we get: $u \in \left[e^{\epsilon(f(a) - \frac{\Lambda}{2} - x)}, e^{\epsilon(f(a) + \frac{\Lambda}{2} - x)} \right]$.

By the range of x , we get: $u \in \left[e^{\epsilon(-b - \frac{\Lambda}{2} + f(a))}, e^{\epsilon(-t - \frac{\Lambda}{2})} \right]$.

case $x = B$

In this case, we know $s = -1$.

We have: $\lfloor f(a) - \frac{1}{\epsilon} \ln(u) \rfloor_\Lambda \geq B$.

Since b is the greatest rounding of Λ that is smaller than B , we have: $f(a) - \frac{1}{\epsilon} \ln(u) \geq b + \frac{\Lambda}{2}$.

Then we get: $u \in (0, e^{\epsilon(-b - \frac{\Lambda}{2} + f(a))})$

Theorem 4 (Snap mechanism is ϵ -differentially private.)

Proof. Consider two arbitrary adjacent database a and a' , we have $|f(a) - f(a')| \leq 1$. Without loss of generalization, we assume $f(a) + 1 = f(a')$ (\diamond). The proof is developed by cases of the output space E of Snap mechanism, where $x = \text{Snap}(a)$, $y = \text{Snap}(a')$.

case $E = -B$

$$\frac{\Pr[x \in E]}{\Pr[y \in E]} = \frac{\frac{1}{2}(e^{(-b - \frac{\Lambda}{2} - f(a))\epsilon})}{\frac{1}{2}(e^{(-b - \frac{\Lambda}{2} - f(a'))\epsilon})} = \frac{\frac{1}{2}(e^{(-b - \frac{\Lambda}{2} - f(a))\epsilon})}{\frac{1}{2}(e^{(-b - \frac{\Lambda}{2} - f(a) - 1)\epsilon})} = e^\epsilon$$

case $E = (-B, \lfloor f(a) \rfloor_\Lambda)$

From (\diamond), we have $0 \leq \lfloor f(a') \rfloor_\Lambda - \lfloor f(a) \rfloor_\Lambda \leq 1 + \Lambda$. So we have $(-B, \lfloor f(a) \rfloor_\Lambda) \subset (-B, \lfloor f(a') \rfloor_\Lambda)$.

$$\frac{\Pr[x \in E]}{\Pr[y \in E]} = \frac{\frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - f(a) - \frac{\Lambda}{2}\epsilon} - e^{(-b - \frac{\Lambda}{2} - f(a))\epsilon})}{\frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - \frac{\Lambda}{2} - f(a')\epsilon} - e^{(-b - \frac{\Lambda}{2} - f(a'))\epsilon})} = \frac{\frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - f(a) - \frac{\Lambda}{2}\epsilon} - e^{(-b - \frac{\Lambda}{2} - f(a))\epsilon})}{\frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - \frac{\Lambda}{2} - f(a) - 1\epsilon} - e^{(-b - \frac{\Lambda}{2} - f(a) - 1)\epsilon})} = e^\epsilon$$

case $E = \lfloor f(a) \rfloor_\Lambda$

$$\frac{\Pr[x \in E]}{\Pr[y \in E]} = \frac{(1 - \frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - f(a) - \frac{\Lambda}{2}\epsilon} + e^{(f(a) - \lfloor f(a) \rfloor_\Lambda - \frac{\Lambda}{2})\epsilon})}{\frac{1}{2}(e^{\lfloor f(a) \rfloor_\Lambda - f(a') + \frac{\Lambda}{2}\epsilon} - e^{\lfloor f(a) \rfloor_\Lambda - f(a') - \frac{\Lambda}{2}\epsilon})} \quad (\star)$$

Let $t = \lfloor f(a) \rfloor_\Lambda - f(a)$, we have $-\frac{\Lambda}{2} \leq t \leq \frac{\Lambda}{2}$ and:

$$(\star) = \frac{1 - \frac{1}{2}(e^{(t - \frac{\Lambda}{2})\epsilon} + e^{-(t - \frac{\Lambda}{2})\epsilon})}{\frac{1}{2}(e^{(t - 1 + \frac{\Lambda}{2})\epsilon} - e^{(t - 1 - \frac{\Lambda}{2})\epsilon})} \leq \frac{\frac{1}{2}(e^{(t + \frac{\Lambda}{2})\epsilon} + e^{-(t + \frac{\Lambda}{2})\epsilon}) - \frac{1}{2}(e^{(t - \frac{\Lambda}{2})\epsilon} + e^{-(t - \frac{\Lambda}{2})\epsilon})}{\frac{1}{2}(e^{(t - 1 + \frac{\Lambda}{2})\epsilon} - e^{(t - 1 - \frac{\Lambda}{2})\epsilon})} \leq \frac{e^{(t + \frac{\Lambda}{2})\epsilon} - e^{(t - \frac{\Lambda}{2})\epsilon}}{e^{(t - 1 + \frac{\Lambda}{2})\epsilon} - e^{(t - 1 - \frac{\Lambda}{2})\epsilon}} \leq e^\epsilon$$

case $E = (\lfloor f(a) \rfloor_\Lambda, \lfloor f(a') \rfloor_\Lambda)$

$$\frac{\Pr[x \in E]}{\Pr[y \in E]} = \frac{\frac{1}{2}(e^{(f(a) - \frac{\Lambda}{2} - \lfloor f(a) \rfloor_\Lambda)\epsilon} - e^{(f(a) + \frac{\Lambda}{2} - \lfloor f(a') \rfloor_\Lambda)\epsilon})}{\frac{1}{2}(e^{(\lfloor f(a') \rfloor_\Lambda - \frac{\Lambda}{2} - f(a'))\epsilon} - e^{(\lfloor f(a) \rfloor_\Lambda + \frac{\Lambda}{2} - f(a'))\epsilon})} \quad (\star)$$

Let $t = \lfloor f(a') \rfloor_\Lambda - f(a')$, we have $-\frac{\Lambda}{2} \leq t \leq \frac{\Lambda}{2}$. We also have $\lfloor f(a') \rfloor_\Lambda - 1 - \Lambda \leq \lfloor f(a) \rfloor_\Lambda \leq \lfloor f(a') \rfloor_\Lambda$ by adjacency of a and a' . So we can get:

$$(\star) \geq \frac{\frac{1}{2}(e^{(-t-\frac{\Lambda}{2}-1)\epsilon} - e^{(-t+\frac{\Lambda}{2}-1)\epsilon})}{\frac{1}{2}(e^{(t-\frac{\Lambda}{2})\epsilon} - e^{(t+\frac{\Lambda}{2})\epsilon})} \stackrel{?}{\geq} e^{-\epsilon} \quad \text{and} \quad (\star) \leq \frac{\frac{1}{2}(e^{(-t+\frac{\Lambda}{2})\epsilon} - e^{(-t-\frac{\Lambda}{2}-1)\epsilon})}{\frac{1}{2}(e^{(t-\frac{\Lambda}{2})\epsilon} - e^{(t+\frac{\Lambda}{2}-1)\epsilon})} \stackrel{?}{\leq} e^\epsilon$$

case $E = \lfloor f(a') \rfloor_\Lambda$

$$\frac{Pr[x \in E]}{Pr[y \in E]} = \frac{\frac{1}{2}(e^{(f(a)-\lfloor f(a') \rfloor_\Lambda + \frac{\Lambda}{2})\epsilon} - e^{(f(a)-\lfloor f(a') \rfloor_\Lambda - \frac{\Lambda}{2})\epsilon})}{1 - \frac{1}{2}(e^{(\lfloor f(a) \rfloor_\Lambda - f(a') - \frac{\Lambda}{2})\epsilon} + e^{(f(a)-\lfloor f(a') \rfloor_\Lambda - \frac{\Lambda}{2})\epsilon})} \quad (\star)$$

Let $t = f(a') - \lfloor f(a') \rfloor_\Lambda$, we have $-\frac{\Lambda}{2} \leq t \leq \frac{\Lambda}{2}$ and:

$$(\star) = \frac{\frac{1}{2}(e^{(t+\frac{\Lambda}{2}-1)\epsilon} + e^{t-\frac{\Lambda}{2}-1)\epsilon})}{1 - \frac{1}{2}(e^{(-t+\frac{\Lambda}{2})\epsilon} - e^{(t-\frac{\Lambda}{2})\epsilon})} \geq \frac{\frac{1}{2}(e^{(t-\frac{\Lambda}{2}-1)\epsilon} + e^{(t-\frac{\Lambda}{2}-1)\epsilon})}{\frac{1}{2}(e^{(-t+\frac{\Lambda}{2})\epsilon} + e^{(t+\frac{\Lambda}{2})\epsilon}) - \frac{1}{2}(e^{(-t+\frac{\Lambda}{2})\epsilon} - e^{(t-\frac{\Lambda}{2})\epsilon})} \geq \frac{e^{(t+\frac{\Lambda}{2}-1)\epsilon} - e^{(t-\frac{\Lambda}{2}-1)\epsilon}}{e^{(t+\frac{\Lambda}{2})\epsilon} - e^{(t-\frac{\Lambda}{2})\epsilon}} \geq e^{-\epsilon}$$

case $E = (\lfloor f(a') \rfloor_\Lambda, B)$

From (\star) , we have $0 \leq \lfloor f(a') \rfloor_\Lambda - \lfloor f(a) \rfloor_\Lambda \leq 1 + \Lambda$. So we have $(\lfloor f(a') \rfloor_\Lambda, B) \subset (\lfloor f(a) \rfloor_\Lambda, B)$.

$$\frac{Pr[x \in E]}{Pr[y \in E]} = \frac{\frac{1}{2}(e^{(f(a)-\frac{\Lambda}{2}-\lfloor f(a') \rfloor_\Lambda)\epsilon} - e^{(f(a)-b-\frac{\Lambda}{2})\epsilon})}{\frac{1}{2}(e^{f(a')-\lfloor f(a') \rfloor_\Lambda-\frac{\Lambda}{2}\epsilon} - e^{(f(a')-b-\frac{\Lambda}{2})\epsilon})} = \frac{\frac{1}{2}(e^{(f(a)-\frac{\Lambda}{2}-\lfloor f(a') \rfloor_\Lambda)\epsilon} - e^{(f(a)-b-\frac{\Lambda}{2})\epsilon})}{\frac{1}{2}(e^{f(a)+1-\lfloor f(a') \rfloor_\Lambda-\frac{\Lambda}{2}\epsilon} - e^{(f(a)+1-b-\frac{\Lambda}{2})\epsilon})} = e^{-\epsilon}$$

case $E = B$

$$\frac{Pr[x \in E]}{Pr[y \in E]} = \frac{\frac{1}{2}(e^{(-b-\frac{\Lambda}{2}+f(a))\epsilon})}{\frac{1}{2}(e^{(-b-\frac{\Lambda}{2}+f(a'))\epsilon})} = \frac{\frac{1}{2}(e^{(-b-\frac{\Lambda}{2}+f(a))\epsilon})}{\frac{1}{2}(e^{(-b-\frac{\Lambda}{2}+f(a)+1)\epsilon})} = e^{-\epsilon}$$

□

References

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