## **Differentially Private Bayesian Inference**

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## **Abstract**

## 1. Setting up

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The Bayesian inference process is denoted as  $\mathsf{BI}(x,prior)$  taking an observed data set  $x \in \mathcal{X}^n$  and a prior distribution as input, outputting a posterior distribution posterior. For conciseness, when prior is given, we use  $\mathsf{BI}(x)$ .

For now, we already have a prior distribution prior, an observed data set x.

## 1.1. Exponential Mechanism with Global Sensitivity

### 1.1.1. MECHANISM SET UP

In exponential mechanism, candidate set R can be obtained by enumerating  $y \in \mathcal{X}^n$ , i.e.

$$R = \{ \mathsf{BI}(y) \mid y \in \mathcal{X}^n \}.$$

Hellinger distance H is used here to score these candidates. The utility function:

$$u(x,r) = -\mathsf{H}(\mathsf{BI}(x),r); r \in R. \tag{1}$$

Exponential mechanism with global sensitivity selects and outputs a candidate  $r \in R$  with probability proportional to  $exp(\frac{\epsilon u(x,r)}{2\Delta_{\sigma}u})$ :

$$P[r] = \frac{exp(\frac{\epsilon u(x,r)}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})},$$

where global sensitivity is calculated by:

$$\begin{split} \Delta_g u &= \mathsf{H}(\mathsf{BI}(x'), r) - \mathsf{H}(\mathsf{BI}(y'), r)| \\ \max_{\{|x', y'| \leq 1; x', y' \in \mathcal{X}^n\}} \max_{\{r \in R\}}. \end{split}$$

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## 1.1.2. SECURITY ANALYSIS

It can be proved that exponential mechanism with global sensitivity is  $\epsilon$ -differentially private. We denote the BI with privacy mechanism as PrivInfer. For adjacent data set  $||x,y||_1=1$ :

$$\begin{split} &\frac{P[\mathsf{PrivInfer}(x,u,R)=r]}{P[\mathsf{PrivInfer}(y,u,R)=r]} \\ &= \frac{\frac{exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}}{\frac{exp(\frac{\epsilon u(y,r')}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(y,r')}{2\Delta_g u})}} \\ &= \left(\frac{exp(\frac{\epsilon u(x,r)}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(y,r')}{2\Delta_g u})}\right) \cdot \left(\frac{\sum_{r' \in R} exp(\frac{\epsilon u(y,r')}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}\right) \\ &= exp\left(\frac{\epsilon(u(x,r)-u(y,r))}{2\Delta_g u}\right) \\ &\cdot \left(\frac{\sum_{r' \in R} exp(\frac{\epsilon u(y,r')}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}\right) \\ &\leq exp(\frac{\epsilon}{2}) \cdot exp(\frac{\epsilon}{2}) \cdot \left(\frac{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_g u})}\right) \\ &= exp(\epsilon). \end{split}$$

Then,  $\frac{P[\mathsf{PrivInfer}(x,u,R)=r]}{P[\mathsf{PrivInfer}(y,u,R)=r]} \ge exp(-\epsilon)$  can be obtained by symmetry.

## 1.2. Exponential Mechanism with Local Sensitivity

## 1.2.1. MECHANISM SET UP

Exponential mechanism with local sensitivity share the same candidate set and utility function as it with global sensitivity. This outputs a candidate  $r \in R$  with probability proportional to  $exp(\frac{\epsilon u(x,r)}{2\Delta_1 u})$ :

$$P[r] = \frac{exp(\frac{\epsilon u(x,r)}{2\Delta_l u})}{\sum_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_l u})},$$

where local sensitivity is calculated by:

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 $\max_{\{|x,y'|\leq 1;y'\in\mathcal{X}^n\}}\max_{\{r\in R\}}.$ 

holds.

i.e.

Then we can have:

 $> exp(\frac{\epsilon}{2} * 2)$ 

it is non-differentially private.

1.3.2. SECURITY ANALYSIS

1.4.2. SECURITY ANALYSIS

2. Privacy Fix

2.1. Propositions

 $x_0$  to denote:

the statements.

 $x_0$ ;

if n is even

1.3.1. MECHANISM SETTING UP

1.4.1. MECHANISM SETTING UP

if BayesInfer $(x) = beta(a_1 + 1, b_1 + 1)$ 

then  $BI(x_0) = beta(\frac{n}{2} + 1, \frac{n}{2} + 1)$ 

else  $BI(x_0) = \{beta(\frac{n+1}{2} + 1, \frac{n-1}{2} + 1)\}$ 

beta $(\alpha, \beta)$  is the beta function with two arguments  $\alpha$  and

Then, we have the following three statements, and proofs of

I  $H(BI(x), BI(x+1)) < H(BI(x+1), BI(x+2)) \forall x >$ 

 $= exp(\epsilon),$ 

 $exp(\frac{\epsilon}{2}(\frac{u(x,r)+u(y,r)}{\Delta_l u(y)} - \frac{u(x,r)+u(y,r)}{\Delta_l u(x)}))$ 

 $\frac{P[\mathsf{PrivInfer}(x, u, R) = r]}{P[\mathsf{PrivInfer}(u, u, R) = r]} > exp(\epsilon).$ 

Since there are cases where exponential mechanism with local sensitivity's privacy loss is greater than  $e^{\epsilon}$ , we can say

1.3. Exponential Mechanism of Varying Sensitivity

1.4. Exponential Mechanism of Smooth Sensitivity

Assume we have a prior distribution beta(1, 1), an observed data set  $x \in \{0,1\}^n$ , n > 0. We use the x + 1 and x - 1 to

then BayesInfer $(x + 1) = beta((a_1 + 1) + 1, (b_1 - 1) + 1)$ 

BayesInfer $(x-1) = beta((a_1-1)+1,(b_1+1)+1),$ 

 $beta(\frac{n-1}{2}+1,\frac{n+1}{2}+1)$ 

 $\Delta_l u(x) = \mathsf{H}(\mathsf{BI}(x), r) - \mathsf{H}(\mathsf{BI}(y'), r)|$ 

We will then prove that exponential mechanism with local

 $= exp\left(\frac{\epsilon u(x,r)}{2\Delta_l u(x)} - \frac{\epsilon u(y,r)}{2\Delta_l u(y)}\right) \cdot \left(\frac{\sum\limits_{r' \in R} exp(\frac{\epsilon u(y,r')}{2\Delta_l u(y)})}{\sum\limits_{r' \in R} exp(\frac{\epsilon u(x,r')}{2\Delta_l u(x)})}\right)$ 

Without loss of generality, we consider the case that

 $arg(\min_{r'\in R}\{u(y,r')\})$  and  $\Delta_l u(y) = u(x,r) - u(y,r)$ . We have:

 $= exp\big(\frac{\epsilon}{2}(\frac{u(x,r)+u(y,r)}{\Delta_l u(x)} - \frac{u(x,r)+u(y,r)}{\Delta_l u(y)})\big).$ 

From Eq. 1,  $\{u(x,r') \le 0 | r' \in R\}$  and  $\{u(y,r') \le 0 | r' \in R\}$ 

R}, we can infer that  $r = arg(\max_{r \in R} \{u(x, r')\}) = \mathsf{BI}(x)$ 

and u(x,r) = 0.From  $\Delta_l u(y) = u(x,r) - u(y,r)$ , we can

also infer that  $\Delta_l u(y) = -u(y,r)$ . Then, the following

relationship between u(x,r), u(y,r),  $\Delta_l u(x)$  and  $\Delta_l u(y)$ :

 $-\Delta_l u(x) < \Delta_l u(y)$ 

 $\Delta_l u(x) - \Delta_l u(y) < 2\Delta_l u(x)$ 

 $-\Delta_l u(y)(\Delta_l u(y) - \Delta_l u(x)) < 2\Delta_l u(x)\Delta_l u(y)$ 

 $u(y,r)(\Delta_l u(y) - \Delta_l u(x)) < 2\Delta_l u(x)\Delta_l u(y)$ 

 $\Delta_l u(y) < \Delta_l u(x), \quad r = arg(\max_{r' \in R} \{u(x, r')\})$ 

1.2.2. SECURITY ANALYSIS

 $\frac{P[\mathsf{PrivInfer}(x,u,R)=r]}{P[\mathsf{PrivInfer}(y,u,R)=r]}$ 

sensitivity is non-differentialy private.

 $= \frac{\sum\limits_{r' \in R} exp(\frac{\epsilon u(x,r)}{2\Delta_l u(x)} + \frac{\epsilon u(y,r')}{2\Delta_l u(y)})}{\sum\limits_{r' \in R} exp(\frac{\epsilon u(y,r)}{2\Delta_l u(y)} + \frac{\epsilon u(x,r')}{2\Delta_l u(x)})}.$ 

 $\frac{\sum\limits_{r' \in R} exp(\frac{\epsilon u(x,r)}{2\Delta_l u(x)} + \frac{\epsilon u(y,r')}{2\Delta_l u(y)})}{\sum\limits_{x' \in R} exp(\frac{\epsilon u(y,r)}{2\Delta_l u(y)} + \frac{\epsilon u(x,r')}{2\Delta_l u(x)})}$ 

 $> \frac{\sum\limits_{r' \in R} exp(\frac{\epsilon(u(x,r) + u(y,r'))}{2\Delta_l u(x)})}{\sum\limits_{r' \in R} exp(\frac{\epsilon(u(y,r) + u(x,r'))}{2\Delta_l u(y)})}$ 

 $> \frac{|R| \exp(\frac{\epsilon(u(x,r) + u(y,r))}{2\Delta_l u(x)})}{|R| \exp(\frac{\epsilon(u(y,r) + u(x,r))}{2\Delta_l u(y)})}$ 

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 $\frac{u(x,r) + u(y,r)}{\Delta_l u(x)} - \frac{u(x,r) + u(y,r)}{\Delta_l u(y)} > 2.$ 

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or  $\mathsf{H}(\mathsf{BI}(x),\mathsf{BI}(x+1)) > \mathsf{H}(\mathsf{BI}(x+1),\mathsf{BI}(x+2)) \forall x \leq x_0.$ 

II 
$$\Delta_l u(x) = \mathsf{H}(\mathsf{BI}(x), \mathsf{BI}(x+1)), \forall x \geq x_0;$$

$$\Delta_l u(x) = \mathsf{H}(\mathsf{BI}(x), \mathsf{BI}(x-1)), \forall x \leq x_0.$$

III 
$$\forall x \neq x_0 : \Delta_l u(x) > \Delta_l u(x_0).$$

## 2.2. proof

# 2.2.1. STATEMENT I

 We use the MI (Mathematical Induction) method to prove the first statement.

*Proof.* Since the Hellinger distance is symmetric, if we prove the  $H(BI(x), BI(x+1)) < H(BI(x+1), BI(x+2)) \forall x \ge x_0$ , the other part when  $\forall x \le x_0$  also holds.

1. if  $x = x_0$ ,  $H(BI(x_0), BI(x_0 + 1)) < H(BI(x_0 + 1), BI(x_0 + 2))$  holds:

 $\sqrt{1-\frac{\det(\frac{\frac{n}{2}+1+m+\frac{n}{2}+1+m+1}{2},\frac{\frac{n}{2}+1-m+\frac{n}{2}+1-m-1}{2})}{\sqrt{\det(\frac{n}{2}+1+m,\frac{n}{2}+1-m)}}}} \\ < \sqrt{1-\frac{\det(\frac{n}{2}+1+m,\frac{n}{2}+1-m)\det(\frac{n}{2}+2+m,\frac{n}{2}-m)}{2}} \\ < \sqrt{1-\frac{\det(\frac{\frac{n}{2}+1+m+1+\frac{n}{2}+1+m+2}{2},\frac{\frac{n}{2}+1-m-1+\frac{n}{2}+1-m-2}{2})}{\sqrt{\det(\frac{n}{2}+2+m,\frac{n}{2}-m)\det(\frac{n}{2}+3+m,\frac{n}{2}-m-1)}}}$ 

$$\begin{aligned} &\frac{\text{beta}(\frac{n+2m+3}{2},\frac{n-2m+1}{2})}{\sqrt{\text{beta}(\frac{n}{2}+1+m,\frac{n}{2}+1-m)\text{beta}(\frac{n}{2}+2+m,\frac{n}{2}-m)}} \\ > &\frac{\text{beta}(\frac{n+2m+5}{2},\frac{n-2m-1}{2})}{\sqrt{\text{beta}(\frac{n}{2}+2+m,\frac{n}{2}-m)\text{beta}(\frac{n}{2}+3+m,\frac{n}{2}-m-1)}} \end{aligned}$$

Now, we need to proof  $\mathsf{H}(beta(\frac{n}{2}+1+m+1,\frac{n}{2}+1-m-1),beta(\frac{n}{2}+1+m+2,\frac{n}{2}+1-m-2)) < \mathsf{H}(beta(\frac{n}{2}+1+m+2,\frac{n}{2}+1-m-2),beta(\frac{n}{2}+1+m+3,\frac{n}{2}+1-m-3))$  by using what we know.

From  $x=x_0+m$  and property of beta $(\alpha,\beta)$  function, we know:

$$\begin{array}{l} \mathsf{H}(beta(\frac{n}{2}+1,\frac{n}{2}+1),beta(\frac{n}{2}+1+1,\frac{n}{2}+1-1)) < \mathsf{H}(beta(\frac{n}{2}+1+1,\frac{n}{2}+1-1),beta(\frac{n}{2}+1+2,\frac{n}{2}+1-2)) \\ \sqrt{\mathsf{heta}(\frac{n}{2}+1,\frac{n}{2}+1)\mathsf{heta}(\frac{n}{2}+1+1,\frac{n}{2}+1-1)} < \sqrt{1 - \frac{\mathsf{beta}(\frac{n+3}{2},\frac{n+1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}+1)\mathsf{beta}(\frac{n}{2}+1+1,\frac{n}{2}+1-1)}} < \sqrt{1 - \frac{\mathsf{beta}(\frac{n+3}{2},\frac{n+1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}+1)\mathsf{beta}(\frac{n}{2}+2,\frac{n}{2})}} < \sqrt{1 - \frac{\mathsf{beta}(\frac{n+5}{2},\frac{n-1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}+1)\mathsf{beta}(\frac{n}{2}+2,\frac{n}{2})}} < \sqrt{1 - \frac{\mathsf{beta}(\frac{n+5}{2},\frac{n-1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+2,\frac{n}{2})\mathsf{beta}(\frac{n}{2}+3,\frac{n}{2}-1)}} \\ \frac{\mathsf{beta}(\frac{n+3}{2},\frac{n+1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}+1)\mathsf{beta}(\frac{n}{2}+2,\frac{n}{2})}} > \frac{\mathsf{beta}(\frac{n+5}{2},\frac{n-1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+2,\frac{n}{2})\mathsf{beta}(\frac{n}{2}+3,\frac{n}{2}-1)}} \\ \frac{\mathsf{beta}(\frac{n+3}{2},\frac{n-1}{2})\frac{n-1}{\frac{n-1}{2}+1+\frac{n+2}{2}}}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}-1)\frac{n-1}{\frac{n}{2}-1+\frac{n+2}{2}+1}}} > \frac{\mathsf{beta}(\frac{n+3}{2},\frac{n-1}{2})\frac{n+3}{\frac{n+3}{2}+1}}{\sqrt{\mathsf{beta}(\frac{n}{2}+1,\frac{n}{2}-1)\frac{n+3}{\frac{n}{2}+1+\frac{n}{2}-1}}} \\ \frac{n-1}{\sqrt{(\frac{n}{2}-1)(\frac{n}{2})}} > \frac{\frac{n+3}{2}}{\sqrt{(\frac{n}{2}+1)(\frac{n}{2}+2)}} \\ (n-1)^2(n+2)(n+4) > (n+3)^2n(n-2) \\ n > -1. \end{array}$$

Since n > 0, it always holds.

2. if  $x = x_0 + m$  holds, then also  $x = x_0 + m + 1$  holds:

i.e 
$$\mathsf{H}(beta(\frac{n}{2}+1+m,\frac{n}{2}+1-m),beta(\frac{n}{2}+1+m+1,\frac{n}{2}+1-m-1)) < \mathsf{H}(beta(\frac{n}{2}+1+m+1,\frac{n}{2}+1-m-1),beta(\frac{n}{2}+1+m+2,\frac{n}{2}+1-m-2))$$
 is what we know:

$$\begin{aligned} & \frac{\det(\frac{n+2m+5}{2},\frac{n-2m-1}{2})\frac{n-2m-1}{n+2m+3}}{\sqrt{\det(\frac{n}{2}+2+m,\frac{n}{2}-m)\det(\frac{n}{2}+3+m,\frac{n}{2}-m-1)\frac{n-2m}{n+2m+2}}}\\ > & \frac{\det(\frac{n+2m+7}{2},\frac{n-2m-3}{2})\frac{n-2m-3}{n+2m+5}}{\sqrt{\det(\frac{n}{2}+2+m,\frac{n}{2}-m)\det(\frac{n}{2}+3+m,\frac{n}{2}-m-1)\frac{n-2m-2}{n+2m+6}}} \end{aligned}$$

 $\frac{\mathsf{beta}(\frac{n+2m+5}{2},\frac{n-2m-1}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+2+m,\frac{n}{2}-m)\mathsf{beta}(\frac{n}{2}+3+m,\frac{n}{2}-m-1)}}$ 

 $\frac{\mathsf{beta}(\frac{n+2m+7}{2},\frac{n-2m-3}{2})}{\sqrt{\mathsf{beta}(\frac{n}{2}+2+m,\frac{n}{2}-m)\mathsf{beta}(\frac{n}{2}+3+m,\frac{n}{2}-m-1)}}$ 

$$\begin{split} \sqrt{1 - \frac{\text{beta}(\frac{n+2m+5}{2}, \frac{n-2m-1}{2})}{\sqrt{\text{beta}(\frac{n}{2} + 2 + m, \frac{n}{2} - m)\text{beta}(\frac{n}{2} + 3 + m, \frac{n}{2} - m - 1)}}} \\ < \sqrt{1 - \frac{\text{beta}(\frac{n+2m+7}{2}, \frac{n-2m-3}{2})}{\sqrt{\text{beta}(\frac{n}{2} + 2 + m, \frac{n}{2} - m)\text{beta}(\frac{n}{2} + 3 + m, \frac{n}{2} - m - 1)}}} \end{split}$$

i.e.  $x = x_0 + m + 1$  also holds when  $x = x_0 + m$  is

 $\therefore \quad \Delta_l u(x) = |\mathsf{H}(\mathsf{BI}(x), r) - \mathsf{H}(\mathsf{BI}(y'), r)|,$ 

 $\Delta_l u(x) = \max\{\mathsf{H}(\mathsf{BI}(x),\mathsf{BI}(x+1)),$ 

According to Statement I:

 $< \mathsf{H}(\mathsf{BI}(x),\mathsf{BI}(x+1));$ 

then  $\Delta_l u(x) = H(BI(x), BI(x+1));$ 

> H(BI(x), BI(x+1)):

then  $\Delta_I u(x) = \mathsf{H}(\mathsf{BI}(x), \mathsf{BI}(x-1))$ ;

 $\Delta_l u(x_0) = \mathsf{H}(\mathsf{BI}(x_0), \mathsf{BI}(x_0-1))$ 

 $= H(BI(x_0), BI(x_0 + 1)).$ 

H(BI(x), BI(x-1));

 $\max_{\{|x,y'| \le 1; y' \in \mathcal{X}^n\}} \max_{\{r \in R\}};$ 

 $\therefore$  H(BI(x), r) - H(BI(y'), r)  $\leq \mathsf{H}(\mathsf{BI}(x),\mathsf{BI}(y'));$ 

 $\Delta_l u(x) = \mathsf{H}(\mathsf{BI}(x), \mathsf{BI}(y')),$ 

 $\max_{\{|x,y'|\leq 1; y'\in\mathcal{X}^n\}};$ 

then H(BI(x), BI(x-1))

then H(BI(x), BI(x-1))

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Proof.

2.2.2. STATEMENT II

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if  $x > x_0$ 

if  $x < x_0$ 

From above, we can conclude the Statement II.

## 2.2.3. STATEMENT III

Proof. From Statement I and Statement II, we can conclude that:

$$\begin{array}{ll} \text{when} & x>x_0\\ & \text{H}(\mathsf{BI}(x),\mathsf{BI}(x+1)\\ & > \mathsf{H}(\mathsf{BI}(x_0),\mathsf{BI}(x_0+1);\\ & i.e.\ \Delta_l u(x)>\Delta_l u(x_0)\\ \\ \text{when} & x< x_0\\ & \text{H}(\mathsf{BI}(x),\mathsf{BI}(x-1)\\ & > \mathsf{H}(\mathsf{BI}(x_0),\mathsf{BI}(x_0-1);\\ & i.e.\ \Delta_l u(x)>\Delta_l u(x_0). \end{array}$$

$$\begin{split} & \mathsf{H}(beta(\frac{n}{2}+2+m,\frac{n}{2}-m),beta(\frac{n}{2}+3+m,\frac{n}{2}-1-m)) \\ < & \mathsf{H}(beta(\frac{n}{2}+m+3,\frac{n}{2}-1-m),beta(\frac{n}{2}+m+4,\frac{n}{2}-m-2)) \\ \end{split} \\ \dot{\mathbf{i}}.e \ \forall \ x \neq x_0, \Delta_l u(x) > \Delta_l u(x_0). \end{split}$$

# 3. Experimental Evaluations

We got some results from these mechanisms.

# 4. Dilation Property of Laplace Noise

*Proof.* We take 1-dimensional Laplace distribution, h(z) = $\frac{1}{2}e^{-|z|}$ . The dilation property is:

$$Pr[z \in S] \le e^{\frac{\epsilon}{2}} Pr[z \in e^{\lambda} S] + \frac{\delta}{2}$$

In this case, we have  $\alpha = \frac{\epsilon}{2}$ ,  $\beta = \frac{\epsilon}{2\rho_{\delta/3}(|z|)}$  or  $\frac{\epsilon}{2ln(2/\delta)}$ . We have some prior knowledge that  $|\lambda| \leq \beta$ .

## • case 1: $\lambda > 0$

$$\begin{split} & \because h(e^{\lambda}z) = \frac{1}{2}e^{-|e^{\lambda}z|} < \frac{1}{2}e^{-|z|} = h(z) \\ & \therefore \frac{Pr[z \in e^{\lambda}S]}{Pr[z \in S]} = \frac{\int_{e^{\lambda}S} \frac{1}{2}e^{-|z|}dz}{\int_{S} \frac{1}{2}e^{-|z|}dz} = \frac{\int_{S} \frac{1}{2}e^{-|e^{\lambda}z|}e^{\lambda}dz}{\int_{S} \frac{1}{2}e^{-|z|}dz} \\ & = \frac{e^{-|e^{\lambda}z|}e^{\lambda}}{e^{-|z|}} = \frac{e^{\lambda}h(e^{\lambda}z)}{h(z)} \le e^{\lambda} \\ & \therefore \ln(\frac{e^{\lambda}h(e^{\lambda}z)}{h(z)}) \le \lambda \\ & \because \lambda \le \beta = \frac{\epsilon}{2\ln(3/\delta)}, \delta < 1 \\ & \therefore \lambda \le \frac{\epsilon}{2} \\ & \therefore \frac{Pr[z \in e^{\lambda}S]}{Pr[z \in S]} \le \frac{\epsilon}{2} \end{split}$$

## • case 2: $\lambda < 0$

From integral property, we firstly have:

$$\frac{Pr[z \in e^{\lambda}S]}{Pr[z \in S]} = \frac{e^{-|e^{\lambda}z|}e^{\lambda}}{e^{-|z|}} = \frac{h(e^{\lambda}z)e^{\lambda}}{h(z)} = e^{\lambda}e^{|z|(1-e^{\lambda})}$$

$$\therefore 1 - e^{\lambda} \le |\lambda|$$

$$\therefore \ln(\frac{h(e^{\lambda}z)e^{\lambda}}{h(z)}) \le \lambda + |z||\lambda|$$

$$\therefore \lambda < 0$$

$$\therefore \ln(\frac{h(e^{\lambda}z)e^{\lambda}}{h(z)}) \le |z||\lambda|$$

By setting  $h'(z) = e^{\lambda} h(e^{\lambda} z)$ , we can get:

$$\ln(\frac{h'(z)}{h(z)}) \le |z||\lambda|$$

$$\Rightarrow h'(z) \le e^{|z||\lambda|}h(z)$$

By exchanging the notation of h' and h, we have:

$$h(z) \le e^{|z||\lambda|} h'(z)$$

i.e.

$$\Pr_{z \sim h}[z \in S] \leq e^{|z||\lambda|} \Pr_{z \sim h'}[z \in S] = e^{|z||\lambda|} \Pr_{z \sim h}[z \in e^{\lambda}S]$$

We consider an event  $G = \{z | |z| \le log(\frac{2}{\delta})\}$ . Under this event, we have:

$$\begin{split} |z||\lambda| &\leq \log(\frac{2}{\delta})|\lambda| \\ &\leq \log(\frac{2}{\delta})\beta \\ &\leq \log(\frac{2}{\delta})\frac{\epsilon}{2\log(\frac{3}{\delta})} \\ &\leq \frac{\epsilon}{2}. \end{split}$$

Then:

$$\begin{aligned} \Pr_{z \sim h}[z \in S \cap G] &\leq e^{|z||\lambda|} \Pr_{z \sim h'}[z \in S \cap G] \\ &\leq e^{\frac{\epsilon}{2}} \Pr_{z \sim h'}[z \in S \cap G] \end{aligned}$$

We also have:

$$Pr[\overline{G}] = Pr[|z| > log(\frac{2}{\delta})] = exp(-log(\frac{2}{\delta})) = \frac{\delta}{2}$$

Then, we can get

$$\begin{split} \Pr_{z \sim h}[z \in S] &\leq \Pr_{z \sim h}[z \in S \cap G] + \Pr_{z \sim h}[z \in \overline{G}] \\ &\leq e^{\frac{\epsilon}{2}} \Pr_{z \sim h'}[z \in S \cap G] + \frac{\delta}{2} \\ &\leq e^{\frac{\epsilon}{2}} \Pr_{z \sim h'}[z \in S] + \frac{\delta}{2} \\ &= e^{\frac{\epsilon}{2}} \Pr_{z \sim h}[z \in e^{\lambda}S] + \frac{\delta}{2} \end{split}$$

i.e. the dilation property.