

CS 599: Formal Methods in Security and Privacy

Differential Privacy

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(ϵ, δ) -Differential Privacy

Definition

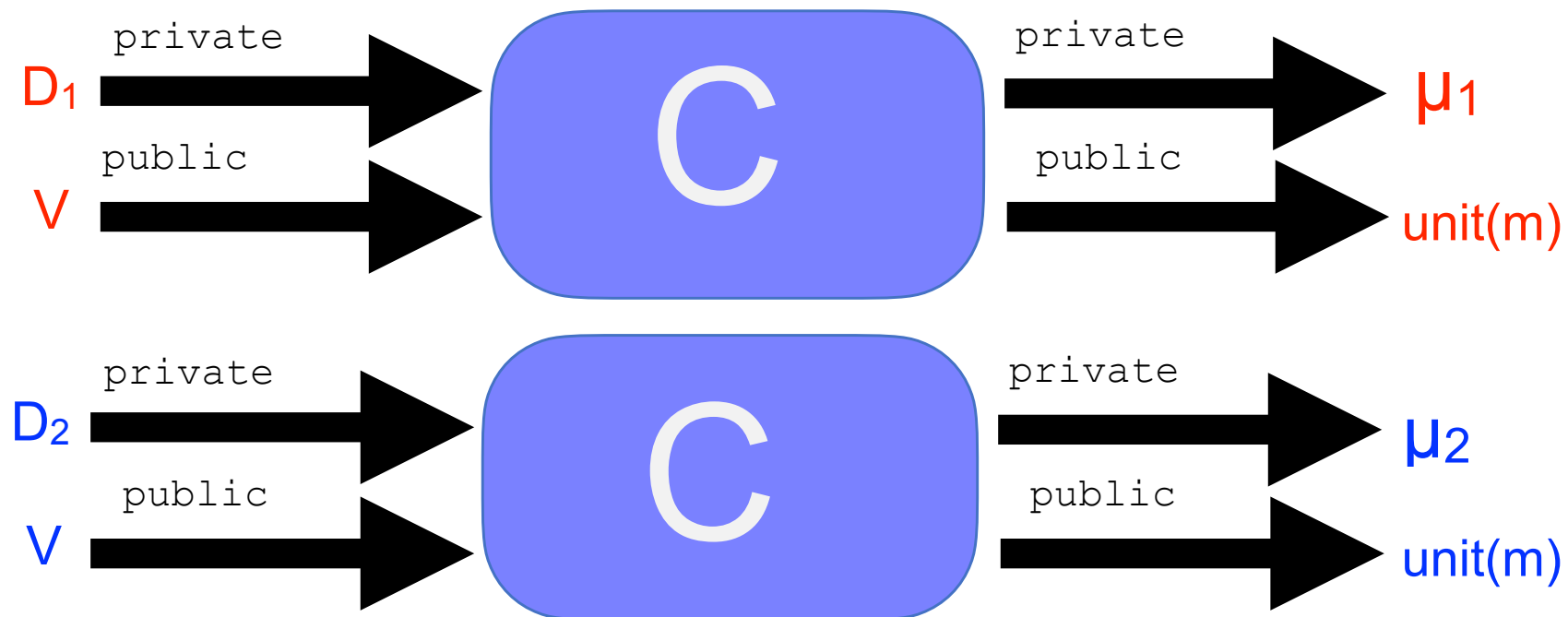
Given $\epsilon, \delta \geq 0$, a probabilistic query $Q: X^n \rightarrow R$ is (ϵ, δ) -differentially private iff for all adjacent databases b_1, b_2 and for every $S \subseteq R$:

$$\Pr[Q(b_1) \in S] \leq \exp(\epsilon) \Pr[Q(b_2) \in S] + \delta$$

Differential Privacy as a Relational Property

c is **differentially private** if and only if for every $m_1 \sim m_2$ (extending the notion of adjacency to memories):

$\{c\}_{m_1} = \mu_1$ and $\{c\}_{m_2} = \mu_2$ implies $\Delta_\epsilon(\mu_1, \mu_2) \leq \delta$



apRHL

Indistinguishability
parameter

Precondition
(a logical formula)

$$\vdash_{\epsilon, \delta} C_1 \sim C_2 : P \Rightarrow Q$$

Probabilistic
Program

Probabilistic
Program

Postcondition
(a logical formula)

Validity of apRHL judgments

We say that the 6-tuple $\vdash_{\varepsilon, \delta} c_1 \sim c_2 : P \Rightarrow Q$ is **valid** if and only if for every pair of memories m_1, m_2 such that $P(m_1, m_2)$ we have:
 $\{c_1\}_{m_1} = \mu_1$ and $\{c_2\}_{m_2} = \mu_2$ implies
 $Q_{\varepsilon, \delta}^*(\mu_1, \mu_2)$.

$R - (\varepsilon, \delta)$ -Coupling

Given two distributions $\mu_1 \in D(A)$, and $\mu_2 \in D(B)$, we have an $R - (\varepsilon, \delta)$ -coupling between them, for $R \subseteq A \times B$ and $0 \leq \delta \leq 1$, $\varepsilon \geq 0$, if there are two joint distributions $\mu_L, \mu_R \in D(A \times B)$ such that:

- 1) $\pi_1(\mu_L) = \mu_1$ and $\pi_2(\mu_R) = \mu_2$,
- 2) the support of μ_L and μ_R is contained in R .

That is, if $\mu_L(a, b) > 0$, then $(a, b) \in R$,
and if $\mu_R(a, b) > 0$, then $(a, b) \in R$.

- 3) $\Delta_\varepsilon(\mu_L, \mu_R) \leq \delta$

Example of R- (ε, δ) -Coupling

μ_1

00	0.25
01	0.25
10	0.25
11	0.25

$$R(a, b) = \{a=b\}$$

μ_2

00	0.20
01	0.25
10	0.25
11	0.30

μ_L	00	01	10	11
00	0.25			
01		0.25		
10			0.25	
11				0.25

μ_R	00	01	10	11
00	0.20			
01		0.25		
10			0.25	
11				0.30

$$\Delta_{0.3}(\mu_L, \mu_R) = 0$$

apRHL: skip rule

$$\vdash_{0,0} \text{skip} \sim \text{skip} : P \Rightarrow P$$

Correctness of Skip Rule

$$\overline{\vdash_{0,0} \text{skip} \sim \text{skip} : P \Rightarrow P}$$

To show this rule **correct** we need to show the **validity of the** $\vdash_{0,0} \text{skip} \sim \text{skip} : P \Rightarrow P$.

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For every m_1, m_2 such that **$P(m, m')$** we have $\{\text{skip}\}_m = \text{unit}(m)$ and $\{\text{skip}\}_{m'} = \text{unit}(m')$ we need $P^*_{0,0}(\text{unit}(m), \text{unit}(m'))$.

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μ_L	m_1	m_2	...	m'	...
m_1	0	0	...	0	0
m_2	0	0	...	0	0
...
m	0	0	...	1	0
...

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μ_L	m_1	m_2	...	m'	...
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m_2	0	0	...	0	0
...
m	0	0	...	1	0
...

μ_R	m_1	m_2	...	m'	...
m_1	0	0	...	0	0
m_2	0	0	...	0	0
...
m	0	0	...	1	0
...

Correctness of Skip Rule

$$\overline{\vdash_{0,0} \text{skip} \sim \text{skip} : P \Rightarrow P}$$

μ_L	m_1	m_2	...	m'	...
m_1	0	0	...	0	0
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...
m	0	0	...	1	0
...

μ_R	m_1	m_2	...	m'	...
m_1	0	0	...	0	0
m_2	0	0	...	0	0
...
m	0	0	...	1	0
...

We need to show:

- 1) $\pi_1(\mu_L) = \text{unit}(m)$ and $\pi_2(\mu_R) = \text{unit}(m')$
- 2) $(m, m') \in P$
- 3) $\Delta_0(\mu_L, \mu_R) \leq 0$

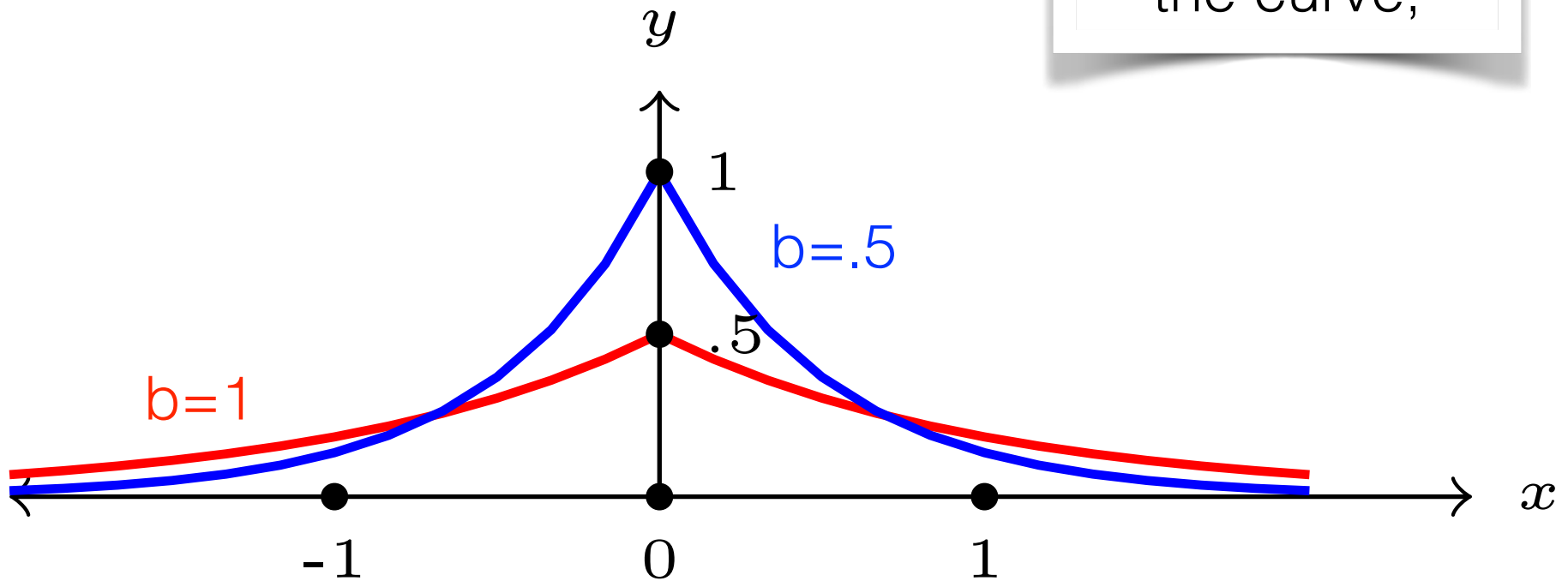
apRHL: Lap rule (simplified)

$$\begin{array}{l} \mathbb{X}_1 ::= \$ \text{ Lap } (1 / \varepsilon, y_1) \\ \sim \\ \vdash_{\varepsilon, 0} \mathbb{X}_2 ::= \$ \text{ Lap } (1 / \varepsilon, y_2) \\ \quad \bullet \quad |y_1 - y_2| \leq 1 \quad \Rightarrow \quad = \end{array}$$

Laplace Distribution

$$\text{Lap}(b, \mu)(X) = \frac{1}{2b} \exp\left(-\frac{|\mu - X|}{b}\right)$$

b regulates the skewness of the curve,



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To show this rule **correct** we need to show the validity of

$$\vdash_{\varepsilon,0} x_1 := \text{\$Lap}(1/\varepsilon, y_1) \sim x_2 := \text{\$Lap}(1/\varepsilon, y_2) : \\ |y_1 - y_2| \leq 1 \Rightarrow =.$$

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For every m_1, m_2 such that **P**(m, m') we have

$\{x_1 := \text{\$Lap}(1/\varepsilon, y_1)\}_m = \text{let } a = \{\text{Lap}(1/\varepsilon, y_1)\}_m$
in $\text{unit}(m[x_1 \leftarrow a])$ and

$\{x_2 := \text{\$Lap}(1/\varepsilon, y_2)\}_{m'} = \text{let } a = \{\text{Lap}(1/\varepsilon, y_2)\}_{m'}$
 m' in $\text{unit}(m'[x_2 \leftarrow a])$ we need to show that
these two terms are in the $(\varepsilon, 0)$ lifting of $=$.

Correctness of Lap Rule

We can take:

$$\mu_L(m_1, m_2) = \mathbb{1}_{m_1=m_2} * \text{Lap}(1/\varepsilon, m(y_1))(a) * \mathbb{1}_{m_1(x_1)=a}$$

and

$$\mu_R(m_1, m_2) = \mathbb{1}_{m_1=m_2} * \text{Lap}(1/\varepsilon, m'(y_2))(a) * \mathbb{1}_{m_1(x_2)=a}$$

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We need to show:

$$1) \pi_1(\mu_L) = \text{let } a = \{\text{Lap}(1/\varepsilon, y_1)\} m \text{ in unit}(m[x_1 \leftarrow a])$$

and

$$\pi_2(\mu_R) = \text{let } a = \{\text{Lap}(1/\varepsilon, y_2)\} m \text{ in unit}(m[x_2 \leftarrow a])$$

$$2) (m_1, m_2) \in =$$

$$3) \Delta_\varepsilon(\mu_L, \mu_R) \leq 0$$

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By the precondition we know $|y_1 - y_2| \leq 1$.

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Let's consider for example the case $y_1 = y_2 + 1$

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Let's consider for example the case $y_1 = y_2 + 1$

$$\frac{\exp(-\varepsilon |m(y_2) + 1 - a|)}{\exp(-\varepsilon |m(y_2) - a|)}$$

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$$\frac{\exp(-\varepsilon |m(y_2) + 1 - a|)}{\exp(-\varepsilon |m(y_2) - a|)} = \exp(\varepsilon |m(y_2) - a| - \varepsilon |m(y_2) + 1 - a|)$$

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apRHL: More general Lap rule (still restricted)

$$\begin{array}{c} \hline \mathbb{X}_1 := \$ \text{ Lap } (1 / \varepsilon, y_1) \\ \vdash_{k^* \varepsilon, 0} \sim \\ \mathbb{X}_2 := \$ \text{ Lap } (1 / \varepsilon, y_2) \\ \vdots \quad |y_1 - y_2| \leq k \Rightarrow = \end{array}$$

Correctness of Lap Rule

To show this rule **correct** we need to show the validity of

$$\vdash_{k^* \varepsilon, 0} x_1 := \text{Lap}(1/\varepsilon, y_1) \sim x_2 := \text{Lap}(1/\varepsilon, y_2) : \\ |y_1 - y_2| \leq k \Rightarrow =.$$

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For every m_1, m_2 such that $P(m, m')$ we have

$\{x_1 := \$Lap(1/\varepsilon, y_1)\}_m = \text{let } a = \{Lap(1/\varepsilon, y_1)\}_m$
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these two terms are in the $(k^* \varepsilon, 0)$ lifting of $=$.

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We can take:

$$\mu_L(m_1, m_2) = \mathbb{1}_{m_1=m_2} * \text{Lap}(1/\varepsilon, m(y_1))(a) * \mathbb{1}_{m_1(x_1)=a}$$

and

$$\mu_R(m_1, m_2) = \mathbb{1}_{m_1=m_2} * \text{Lap}(1/\varepsilon, m'(y_2))(a) * \mathbb{1}_{m_1(x_2)=a}$$

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and

$$\pi_2(\mu_R) = \text{let } a = \{\text{Lap}(1/\varepsilon, y_2)\} m \text{ in unit}(m[x_2 \leftarrow a])$$

$$2) (m_1, m_2) \in =$$

$$3) \Delta_{k^* \varepsilon}(\mu_L, \mu_R) \leq 0$$

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By the precondition we know $|y_1 - y_2| \leq k$.

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Let's consider for example the case $y_1 = y_2 + k$

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Let's consider for example the case $y_1 = y_2 + k$

$$\frac{\exp(-\varepsilon |m(y_2) + k - a|)}{\exp(-\varepsilon |m(y_2) - a|)}$$

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Releasing privately the mean of Some Data

```
Mean (d : private data) : public real
  i:=0;
  s:=0;
  while (i<size(d))
    s:=s + d[i]
    i:=i+1;
  z:=$ Lap(sens/eps, (s/i))
  return z
```

Composition

Let $M_1:DB \rightarrow R_1$ be a (ϵ_1, δ_1) -differentially private program and $M_2:DB \rightarrow R_2$ be a (ϵ_2, δ_2) -differentially private program. Then, their composition $M_{1,2}:DB \rightarrow R_1 \times R_2$ defined as

$$M_{1,2}(D) = (M_1(D), M_2(D))$$

is $(\epsilon_1 + \epsilon_2, \delta_1 + \delta_2)$ -differentially private.

Probabilistic Relational Hoare Logic

Composition

$$\frac{\vdash_{\varepsilon_1, \delta_1} C_1 \sim C_2 : P \Rightarrow R \quad \vdash_{\varepsilon_2, \delta_2} C_1' \sim C_2' : R \Rightarrow S}{\vdash_{\varepsilon_1 + \varepsilon_2, \delta_1 + \delta_2} C_1 ; C_1' \sim C_2 ; C_2' : P \Rightarrow S}$$

Releasing partial sums

```
DummySum (d : {0,1} list) : real list
  i := 0;
  s := 0;
  r := [];
  while (i < size d)
    s := s + d[i]
    z := $ Lap (eps, s)
    r := r ++ [z];
    i := i + 1;
  return r
```

I am using the easycrypt notation here where $\text{Lap}(\text{eps}, a)$ corresponds to adding to the value a a noise from the Laplace distribution with $b=1/\text{eps}$ and mean $\mu=0$.

Parallel Composition

Let $M_1:DB \rightarrow R$ be a (ϵ_1, δ_1) -differentially private program and $M_2:DB \rightarrow R$ be a (ϵ_2, δ_2) -differentially private program. Suppose that we partition D in a data-independent way into two datasets D_1 and D_2 . Then, the composition $M_{1,2}:DB \rightarrow R$ defined as

$$MP_{1,2}(D) = (M_1(D_1), M_2(D_2))$$

is $(\max(\epsilon_1, \epsilon_2), \max(\delta_1, \delta_2))$ -differentially private.

Probabilistic Relational Hoare Logic Composition

$$\frac{\vdash_{\varepsilon_1, \delta_1} C_1 \sim C_2 : P \Rightarrow R \quad \vdash_{\varepsilon_2, \delta_2} C_1' \sim C_2' : R \Rightarrow S}{\vdash_{\varepsilon_1 + \varepsilon_2, \delta_1 + \delta_2} C_1 ; C_1' \sim C_2 ; C_2' : P \Rightarrow S}$$

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  i:=0;
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  while (i<size d)
    z:=$ Lap (eps, d[i])
    s:= s + z
    r:= r ++ [s];
    i:= i+1;
  return r
```

apRHL awhile

$$P \wedge e_{\langle 1 \rangle} \leq 0 \Rightarrow \neg b_{1 \langle 1 \rangle}$$

$$\begin{aligned} \vdash \varepsilon_k, \delta_k \ c1 \sim c2 : P \wedge b_{1 \langle 1 \rangle} \wedge b_{2 \langle 2 \rangle} \wedge k = e_{\langle 1 \rangle} \wedge e_{\langle 1 \rangle} \leq n \\ \implies P \wedge b_{1 \langle 1 \rangle} = b_{2 \langle 2 \rangle} \wedge k < e_{\langle 1 \rangle} \end{aligned}$$

while b1 do c1 ~ while b2 do c2

$$\begin{aligned} \vdash \sum \varepsilon_k, \sum \delta_k : P \wedge b_{1 \langle 1 \rangle} = b_{2 \langle 2 \rangle} \wedge e_{\langle 1 \rangle} \leq n \\ \implies P \wedge \neg b_{1 \langle 1 \rangle} \wedge \neg b_{2 \langle 2 \rangle} \end{aligned}$$