

automated verification + differential privacy

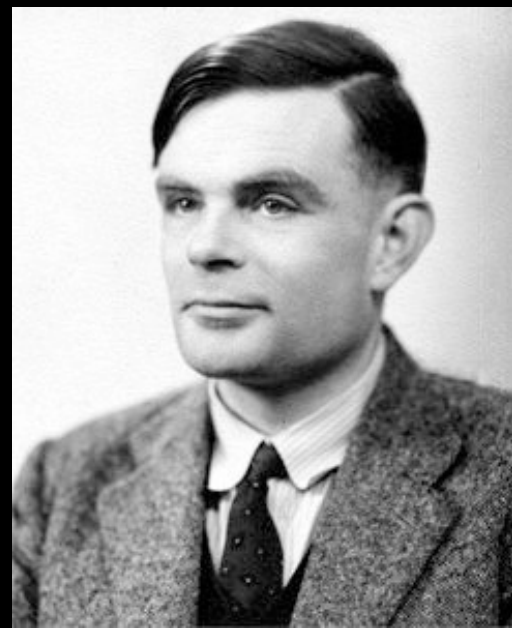
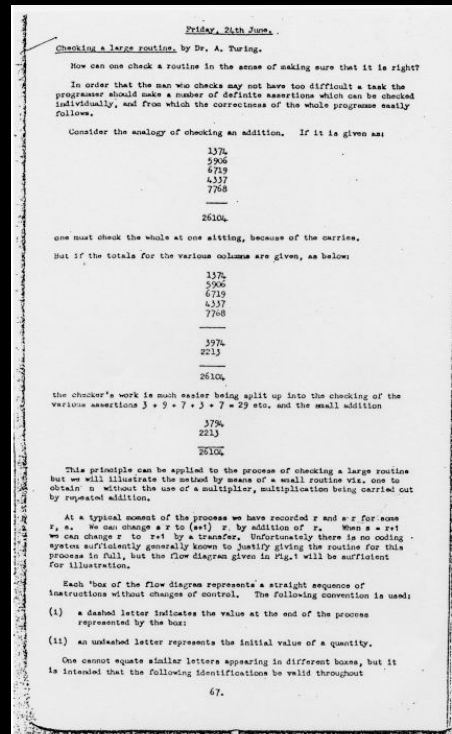
aws albarghouthi university of wisconsin–madison



calvin smith



justin hsu



program
logics

abstract interp
model checking

industrial
tools

1949

1960

1970

1980

1990

2000

`assert(x != null)`





use the notation $\Pr[i|\xi]$ to mean the probability that the output of the Report Noisy Max algorithm is i , conditioned on ξ .

We first argue that $\Pr[i|D, r_{-i}] \leq e^\epsilon \Pr[i|D', r_{-i}]$. Define

$$r^* = \min_{r_i} : c_i + r_i > c_j + r_j \quad \forall j \neq i.$$

Note that, having fixed r_{-i} , i will be the output (the argmax noisy count) when the database is D if and only if $r_i \geq r^*$.

We have, for all $1 \leq j \neq i \leq m$:

$$\begin{aligned} c_i + r^* &> c_j + r_j \\ \Rightarrow (1 + c'_i) + r^* &\geq c_i + r^* > c_j + r_j \geq c'_j + r_j \\ \Rightarrow c'_i + (r^* + 1) &> c'_j + r_j. \end{aligned}$$

Thus, if $r_i \geq r^* + 1$, then the i th count will be the maximum when the database is D' and the noise vector is (r_i, r_{-i}) . The probabilities below are over the choice of $r_i \sim \text{Lap}(1/\epsilon)$.

$$\begin{aligned} \Pr[r_i \geq 1 + r^*] &\geq e^{-\epsilon} \Pr[r_i \geq r^*] = e^{-\epsilon} \Pr[i|D, r_{-i}] \\ \Rightarrow \Pr[i|D', r_{-i}] &\geq \Pr[r_i \geq 1 + r^*] \geq e^{-\epsilon} \Pr[r_i \geq r^*] = e^{-\epsilon} \Pr[i|D, r_{-i}], \end{aligned}$$

which, after multiplying through by e^ϵ , yields what we wanted to show: $\Pr[i|D, r_{-i}] \leq e^\epsilon \Pr[i|D', r_{-i}]$.

We now argue that $\Pr[i|D', r_{-i}] \leq e^\epsilon \Pr[i|D, r_{-i}]$. Define

$$r^* = \min_{r_i} : c'_i + r_i > c'_j + r_j \quad \forall j \neq i.$$

Note that, having fixed r_{-i} , i will be the output (argmax noisy count) when the database is D' if and only if $r_i \geq r^*$.

We have, for all $1 \leq j \neq i \leq m$:

$$\begin{aligned} c'_i + r^* &> c'_j + r_j \\ \Rightarrow 1 + c'_i + r^* &> 1 + c'_j + r_j \\ \Rightarrow c'_i + (r^* + 1) &> (1 + c'_j) + r_j \\ \Rightarrow c_i + (r^* + 1) &\geq c'_i + (r^* + 1) > (1 + c'_j) + r_j \geq c_j + r_j. \end{aligned}$$

Thus, if $r_i \geq r^* + 1$, then i will be the output (the argmax noisy count) on database D with randomness (r_i, r_{-i}) . We therefore have, with probabilities taken over choice of r_i :

$$\Pr[i|D, r_{-i}] \geq \Pr[r_i \geq r^* + 1] \geq e^{-\epsilon} \Pr[r_i \geq r^*] = e^{-\epsilon} \Pr[i|D', r_{-i}],$$

Proof of Report Noisy Max

Proof. Fix $D = D' \cup \{a\}$. Let c , respectively c' , denote the vector of counts when the database is D , respectively D' . We use two properties:

1. *Monotonicity of Counts.* For all $j \in [m]$, $c_j \geq c'_j$; and
2. *Lipschitz Property.* For all $j \in [m]$, $1 + c'_j \geq c_j$.

Fix any $i \in [m]$. We will bound from above and below the ratio of the probabilities that i is selected with D and with D' .

Fix r_{-i} , a draw from $[\text{Lap}(1/\epsilon)]^{m-1}$ used for all the noisy counts except the i th count. We will argue for each r_{-i} independently. We

Proof of Exponential Mech

Proof. For clarity, we assume the range \mathcal{R} of the exponential mechanism is finite, but this is not necessary. As in all differential privacy proofs, we consider the ratio of the probability that an instantiation

of the exponential mechanism outputs some element $r \in \mathcal{R}$ on two neighboring databases $x \in \mathbb{N}^{|\mathcal{X}|}$ and $y \in \mathbb{N}^{|\mathcal{X}|}$ (i.e., $\|x - y\|_1 \leq 1$).

$$\begin{aligned} \frac{\Pr[\mathcal{M}_E(x, u, \mathcal{R}) = r]}{\Pr[\mathcal{M}_E(y, u, \mathcal{R}) = r]} &= \frac{\left(\frac{\exp(\frac{\epsilon u(x, r)}{2\Delta u})}{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(x, r')}{2\Delta u})} \right)}{\left(\frac{\exp(\frac{\epsilon u(y, r)}{2\Delta u})}{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(y, r')}{2\Delta u})} \right)} \\ &= \left(\frac{\exp(\frac{\epsilon u(x, r)}{2\Delta u})}{\exp(\frac{\epsilon u(y, r)}{2\Delta u})} \right) \cdot \left(\frac{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(y, r')}{2\Delta u})}{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(x, r')}{2\Delta u})} \right) \\ &= \exp\left(\frac{\epsilon(u(x, r) - u(y, r))}{2\Delta u}\right) \\ &\quad \cdot \left(\frac{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(y, r')}{2\Delta u})}{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(x, r')}{2\Delta u})} \right) \\ &\leq \exp\left(\frac{\epsilon}{2}\right) \cdot \exp\left(\frac{\epsilon}{2}\right) \cdot \left(\frac{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(x, r')}{2\Delta u})}{\sum_{r' \in \mathcal{R}} \exp(\frac{\epsilon u(x, r')}{2\Delta u})} \right) \\ &= \exp(\epsilon). \end{aligned}$$

Similarly, $\frac{\Pr[\mathcal{M}_E(y, u) = r]}{\Pr[\mathcal{M}_E(x, u) = r]} \geq \exp(-\epsilon)$ by symmetry. \square



```

function IDC
  (iter : Nat[i]) (eps : num[e])
  (db : [2 * i * e] db_type) (qs : query bag)
  (PA : (query bag) -> approx_db
    -> db_type -o[e] Circle query)
  (DUA : approx_db -> query -> num -> approx_db)
  (eval_q : query -> db_type -o[1] num)
  : Circle approx_db {
case iter of
  0      => return init_approx
| n + 1 =>
  sample approx = (IDC n eps db qs PA DUA);
  sample q = PA qs approx db;
  sample actual = add_noise eps (eval_q q db);
  return (DUA approx q actual)
}

```

Figure 11. Iterative Database Function in *DFuzz*

[Gupta, Roth, Ullman, TCC 2012]



short-term vision aid algorithm designers

long-term vision put theorists out of work

1 automatic proofs of accuracy [POPL19]

2 automatic proofs of differential privacy [POPL18]

theme

get rid of probability! long live logic!

$$\{x > 0\}$$

$$y = x + 1 \quad \longleftrightarrow \quad x > 0 \wedge y = x + 1 \implies y > 0$$

$$\{y > 0\}$$

solve with an **SAT/SMT** solver

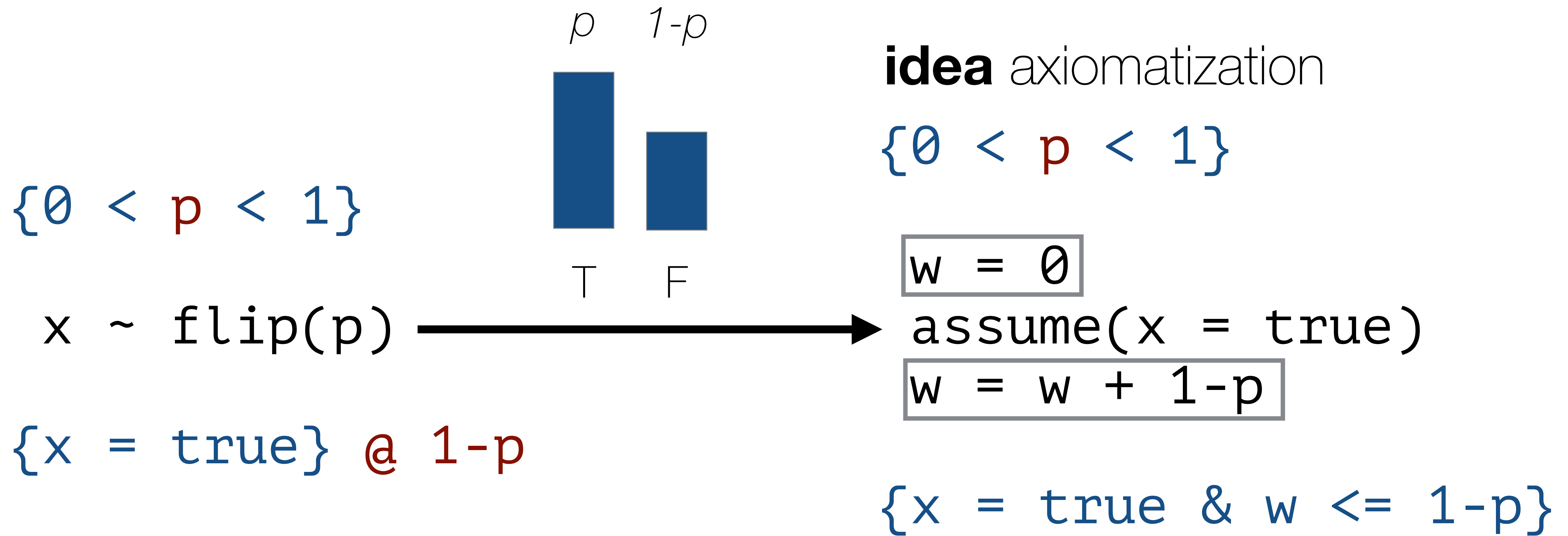
$$\{0 < p < 1\}$$

$$x \sim \text{flip}(p)$$

$$\{x = \text{true}\} @ 1-p$$



challenge how do we check this with first-order logic?



$$w = 0 \wedge x \wedge w' = w + 1 - p \implies x \wedge w' \leq 1 - p$$

challenge many different axiomatizations

$\{0 < p < 1\}$

$\{0 < p < 1\}$

$w = 0$

`assume(x = true)`

$w = w + 1-p$

$w = 0$

`assume(x = false)`

$w = w + p$

$\{x = \text{true} \ \& \ w \leq 1-p\}$

$\{x = \text{true} \ \& \ w \leq 1-p\}$

challenge many different axiomatizations

$$\{0 < p < 1\}$$

$$w = 0$$

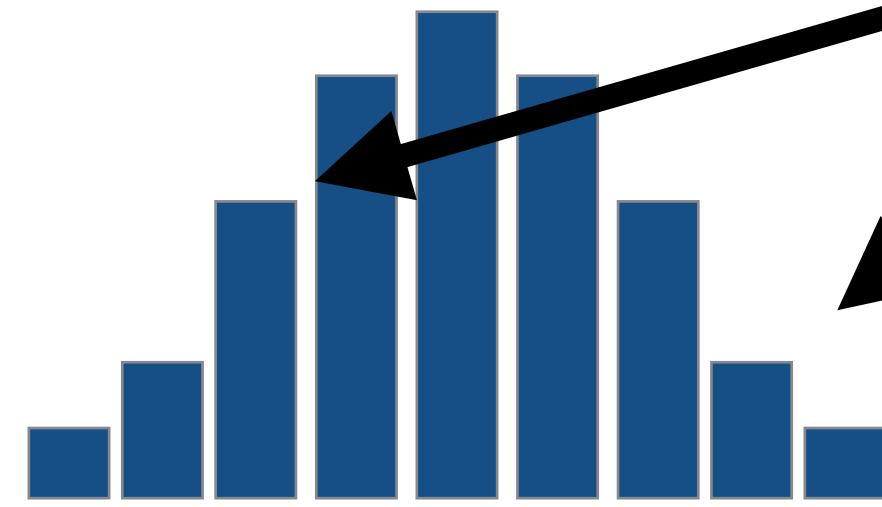
`assume(true)`

$$w = w + 0$$

$$\{x = \text{true} \ \& \ w \leq 1-p\}$$

challenge many different axiomatizations

$x \sim \text{dist}$



failure probability is

assume x is one of
those 3 values

$\{0 < p < 1\}$

$x \sim \text{flip}(p)$

$\{x = \text{true}\} @ 1-p$

idea synthesize axiomatization

$\{0 < p < 1\}$

$w = 0$

$\text{assume}(\text{phi}(x))$

$w = w + \text{pr}(\text{not } \text{phi}(x))$

$\{x = \text{true} \ \& \ w \leq 1-p\}$

$\exists \varphi . \forall w, w', x .$

$w = 0 \wedge \varphi(x) \wedge w' = w + \text{pr}(\varphi(x)) \implies x \wedge w' \leq 1 - p$

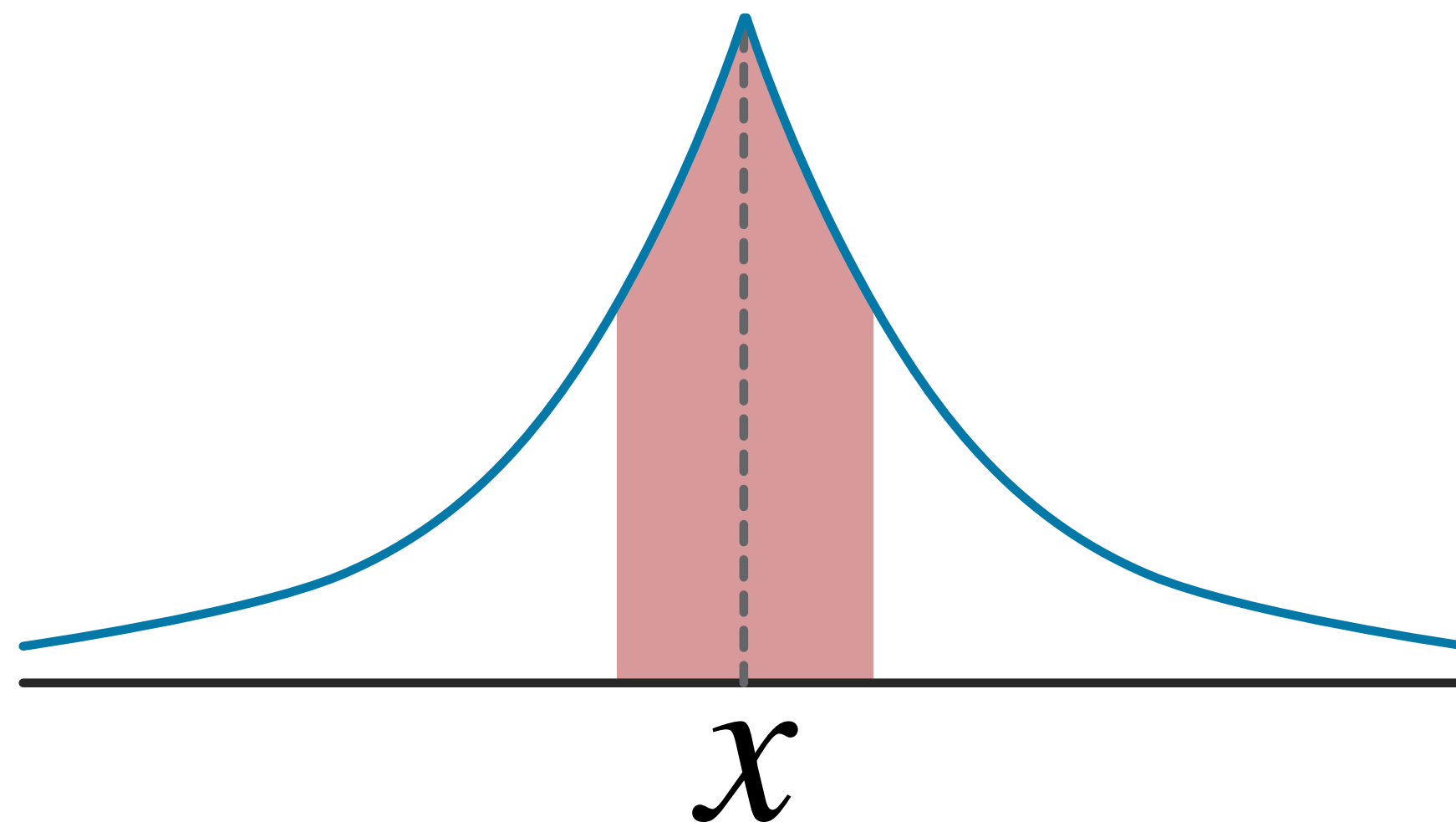
$$y \sim \text{Lap}(x, s)$$

axiom family

$$|x - y| \leq s \cdot \log \left(\frac{1}{f(V_I)} \right)$$

with failure probability

$$f(V_I) \in (0, 1]$$



$\{0 < p < 1\}$

```
def rnm(q):
```

```
    i, best, r = 0
```

```
    while i < len(q)
```

```
        d ~ Lap(q[i], 2/ε)
```

```
        if d > best || i = 0
```

```
            r = i
```

```
            best = d
```

```
            i = i + 1
```

```
    return r
```

$\{\forall j. q[r] \geq q[j] - 4/\epsilon \log(\text{len}(q)/p)\} @ p$

$$|q[i] - d| \leq \frac{2}{\epsilon} \cdot \log\left(\frac{\text{len}(q)}{p}\right)$$

with failure probability $\frac{p}{\text{len}(q)}$

- 1** automatic proofs of accuracy [POPL19]
- 2** automatic proofs of differential privacy [POPL18]

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$$p : D \rightarrow \Delta(\mathbb{Z})$$

$$\forall d, d', a, \epsilon . \text{adj}(d, d') \Rightarrow$$

$$\mathbb{P}[p(d) = a] \leq e^\epsilon \cdot \mathbb{P}[p(d') = a]$$

problems

proving differential privacy is hard and error-prone [Iyu et al. 16]

existing automated techniques only work for simple algorithms

goal

automatically prove differential privacy of advanced algorithms

key ideas

view differential privacy coupling proofs as games

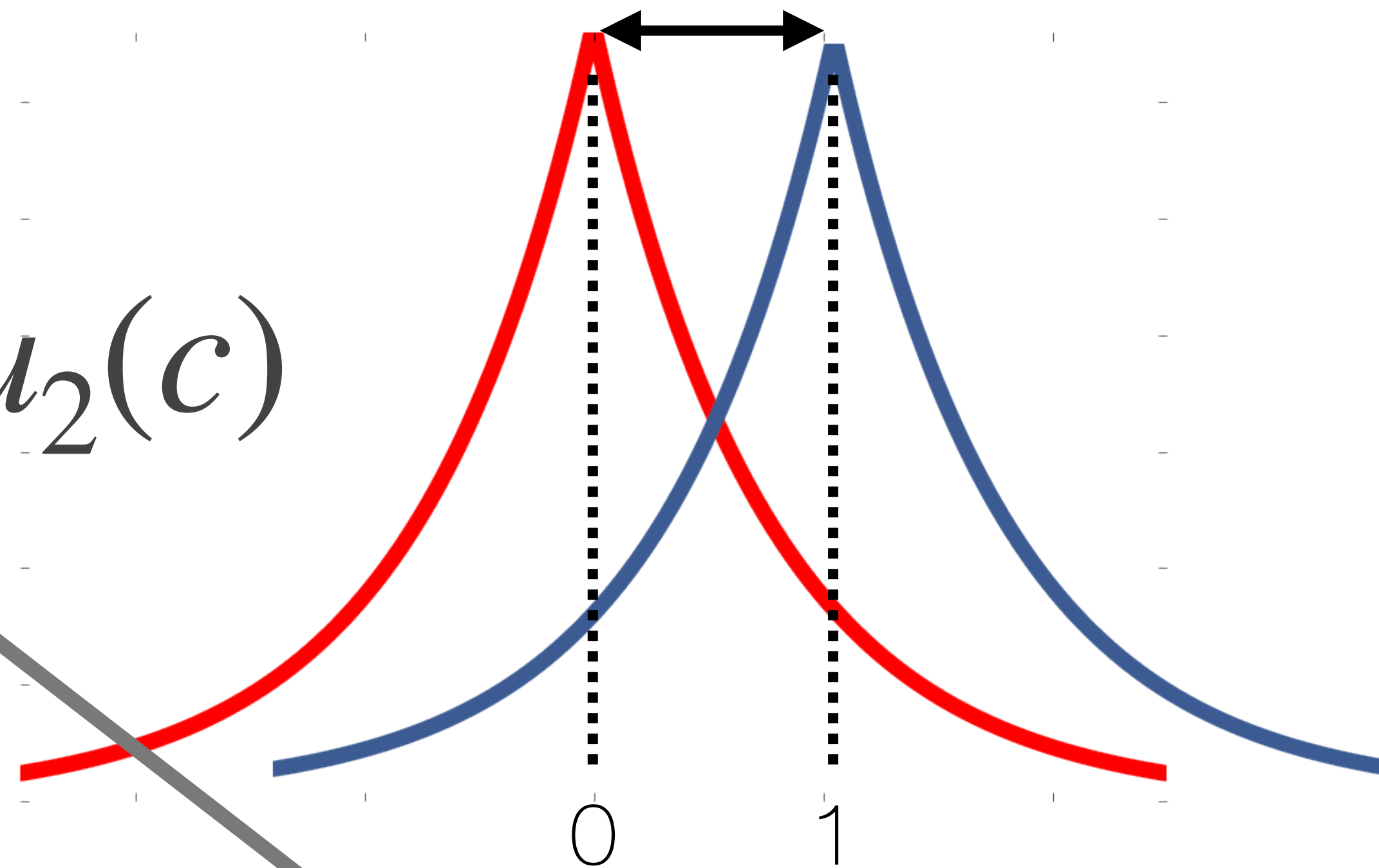
solve a program **synthesis/verification problem**

$$\exists q . \forall x . \varphi(q, x)$$

variable approximate couplings

scale of distributions is **$1/y$**

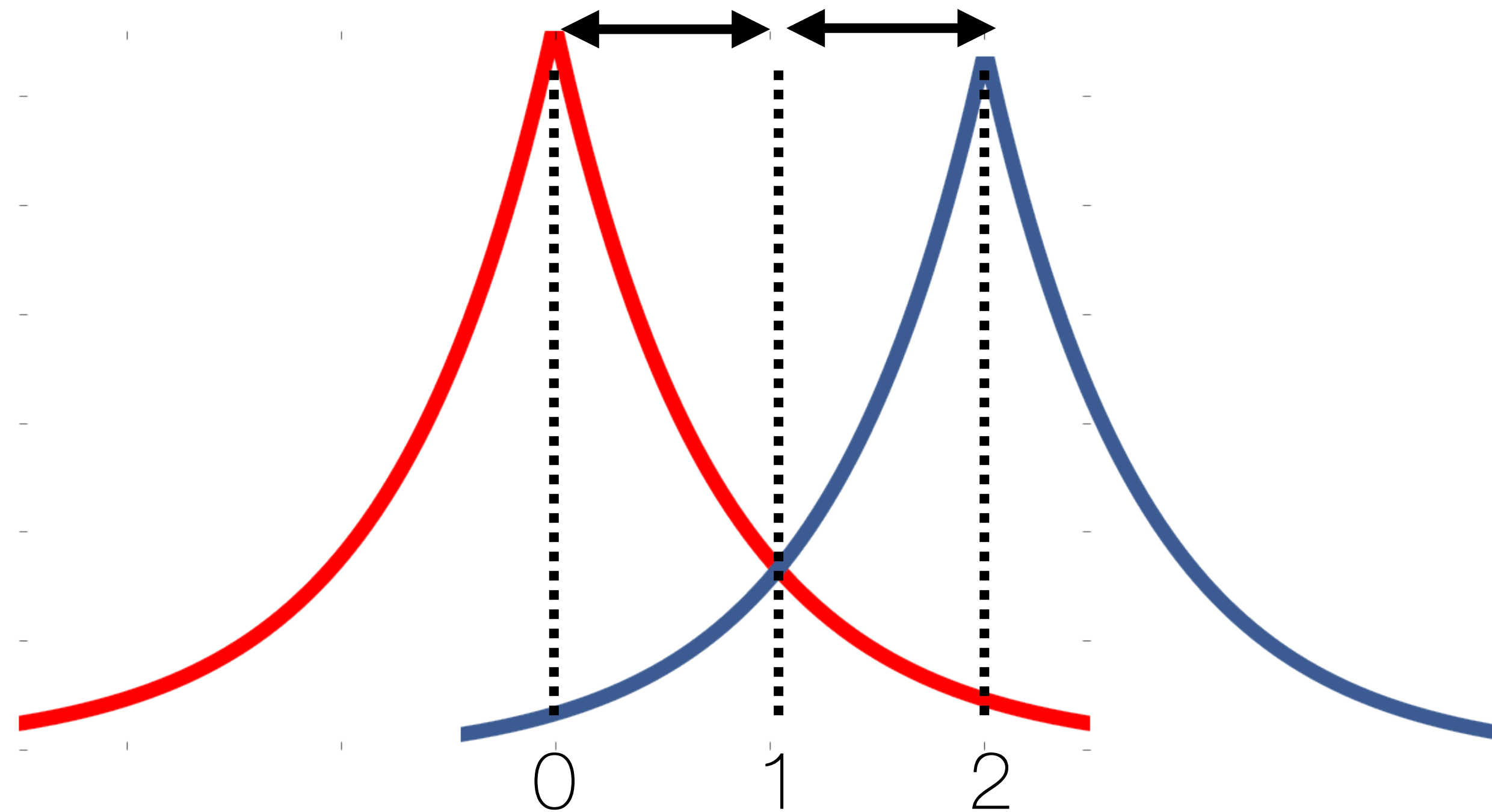
$$\mu_1(c) \leq e^y \cdot \mu_2(c)$$



$$\{(c, c, \boxed{y}) \mid c \in \mathbb{Z}\}$$

variable approximate couplings

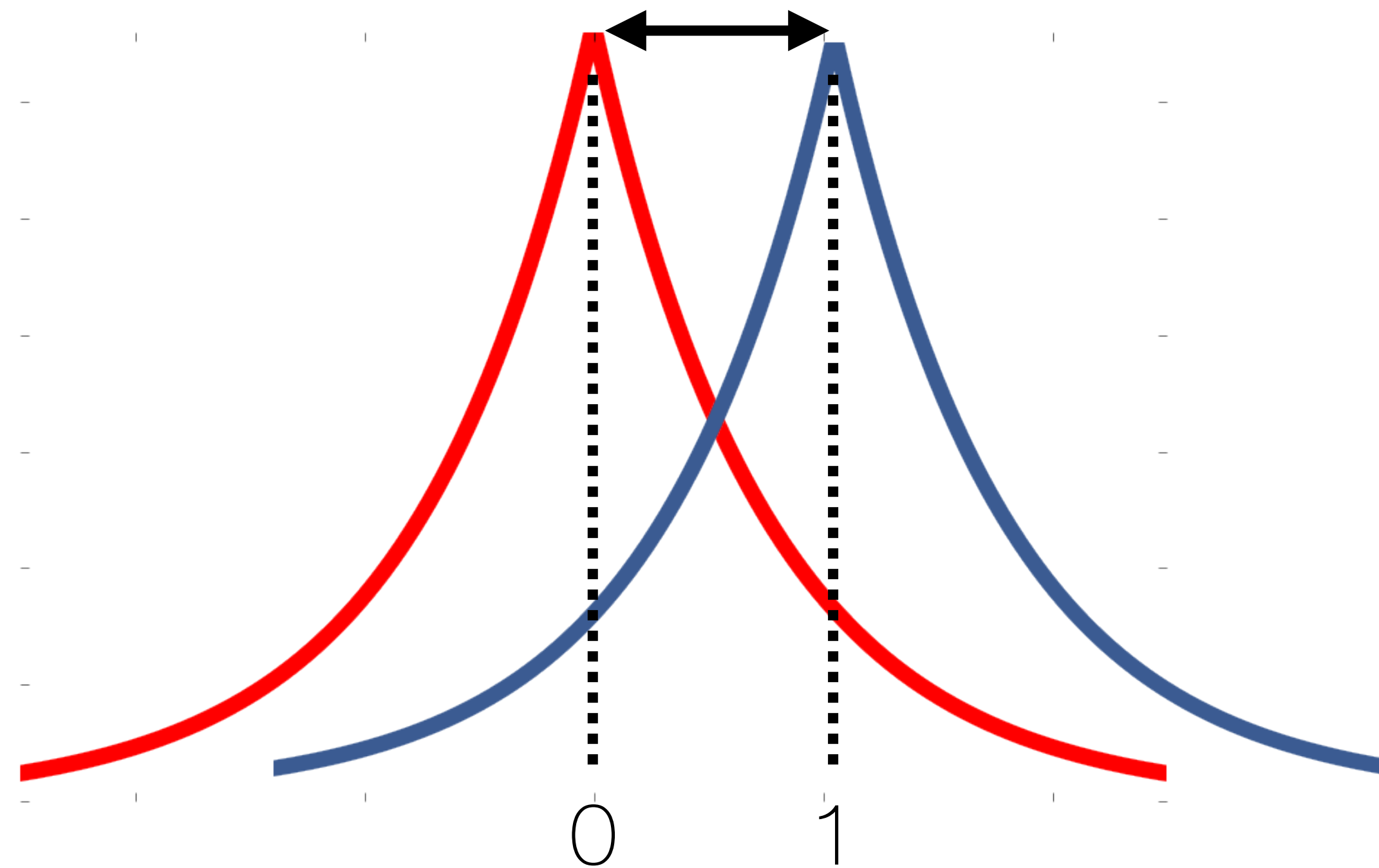
scale of distributions is $1/y$



$$\{(c, c, 2y) \mid c \in \mathbb{Z}\}$$

variable approximate couplings

scale of distributions is $1/y$



$$\{(c, c + 1, 0) \mid c \in \mathbb{Z}\}$$

proof rule

p is DP if $\forall d, d', \epsilon . \exists \mathcal{C} .$

\mathcal{C} couples $p(d), p(d')$

$\mathcal{C} = \{(c, c, y) \mid y \leq \epsilon\}$

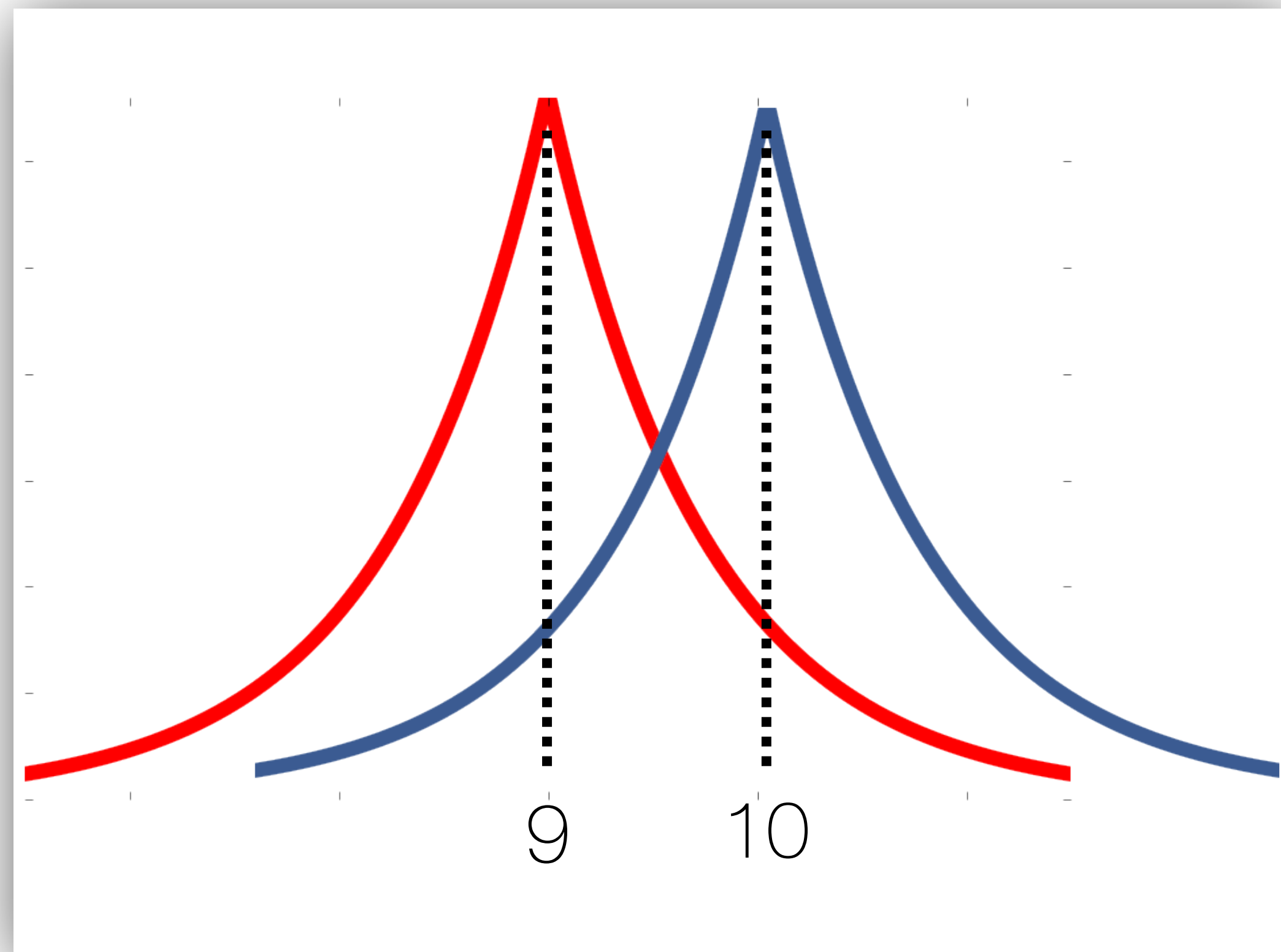
let's play!

```
def rnm(q):
```

```
    i, best, r = 0
```

```
    while i < len(q)
```

```
        d ~ Lap(q[i], 2/ε)
```



[dwork & rohn 14]

```
q1 = [9, 0]
```

```
q2 = [10, 1]
```

```
    cost = 0
```

```
    r1 = 0
```

```
    r2 = 0
```

```
    r1 = 0
```

```
    r2 = 0
```

```
    d1 = c
```

```
    d2 = c
```

```
    cost = ε/2
```

non-deterministically pick from

$$\{(c, c, \epsilon/2) \mid c \in \mathbb{Z}\}$$

```
    cost = ε
```

```
{r1 = r2 && cost <= ε}
```

~~our game strategy~~

~~in every iteration, couple samples using~~

$$\{(c, c, \epsilon/2) \mid c \in \mathbb{Z}\}$$

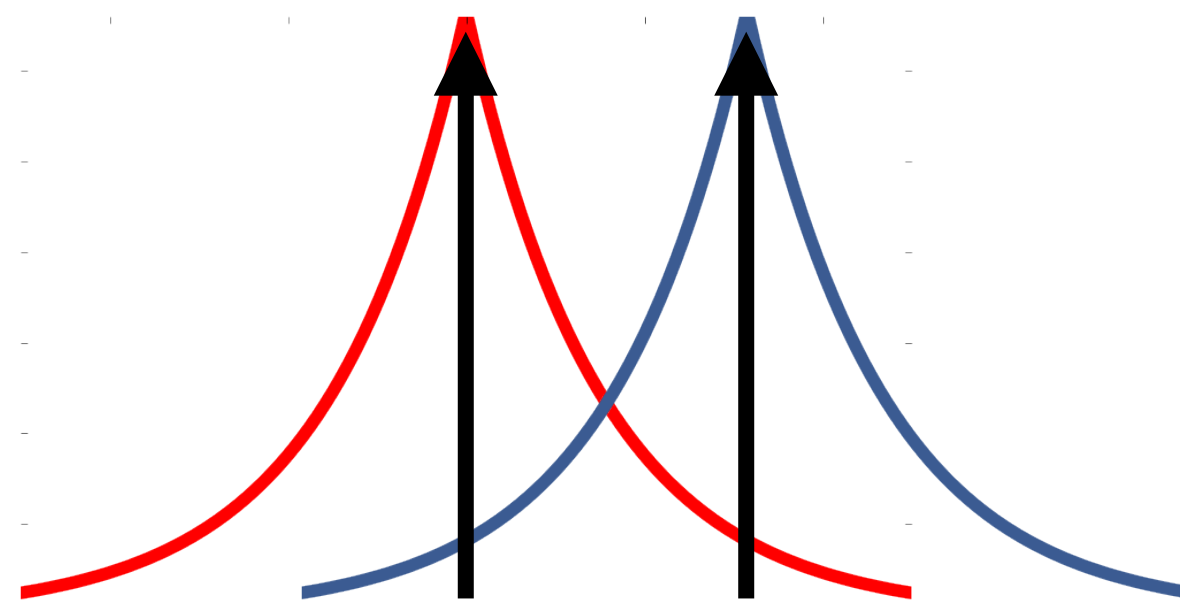
$$\frac{n \cdot \epsilon}{2} \text{ differential privacy}$$

a winning strategy

use this coupling in 1 iteration only

$$\{(c, c + 1, \epsilon) \mid c \in \mathbb{Z}\}$$

in all other iterations pay **zero cost**



winning strategies are programs

if *condition*

use coupling C1

else

use coupling C2

evaluation

PARTIALSUM	Compute the noisy sum of a list of queries.
PREFIXSUM	Compute the noisy sum for every prefix of a list of queries.
SMARTSUM	Advanced version of PREFIXSUM that chunks the list [Chan et al. 2011; Dwork et al. 2010].
REPORTNOISYMAX	Find the element with the highest quality score [Dwork and Roth 2014].
EXPMECH	Variant of REPORTNOISYMAX using the exponential distribution [Dwork and Roth 2014; McSherry and Talwar 2007].
ABOVETHRESHOLD	Find the index of the first query above threshold [Dwork and Roth 2014].
ABOVETHRESHOLDN	Find the indices of the first N queries with answer above threshold [Dwork and Roth 2014; Lyu et al. 2017].
NUMERICSPARSE	Return the index and answer of the first query above threshold [Dwork and Roth 2014].
NUMERICSPARSEN	Return the indices and answers of the first N queries above threshold [Dwork and Roth 2014; Lyu et al. 2017].

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