

privacy and automated verification

aws albarghouthi university of wisconsin–madison



calvin smith



justin hsu



1949

1960

1970

1980

1990

2000

Checking a Large Addition, by Dr. A. Forster.

How can we check a total in the case of adding more than 10 is right?

In order that the sum we check may not have too difficult a task the program should have a number of definite results which can be checked individually, and from which the correctness of the whole program easily follows.

Consider the example of checking an addition. If it is given as

113
126
417
150
—
806

we must check the whole at one sitting, because of the carries.

But if the totals for the various columns are given, as below:

113
126
417
150
—
806
253
—
553

the student's work is much easier being split up into the checking of the various operations $3 + 6 + 7 + 0 = 16$ etc. and the small addition

113
126
417
150
—
553

This principle can be applied to the process of checking a large machine but will illustrate the method by means of a small machine which can be checked by means of the use of a multiplier, multiplication being carried out by repeated addition.

As a typical example of the process we have recorded a set of 20 runs of the machine at the level of 1000 by addition of 100. With a set of 20 runs the machine is checked by multiplying the total by 100. The machine is checked by multiplying the total by 100. The machine is checked by multiplying the total by 100.

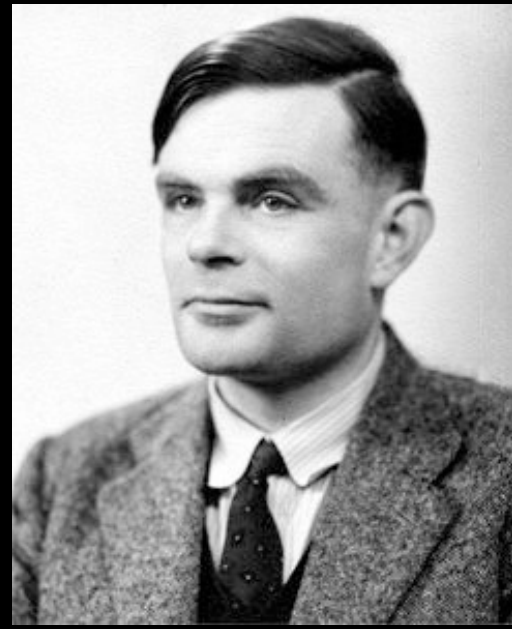
Each one of the five stages represents a single program of instructions without change of model. The following convention is used:

(1) a dotted letter indicates the value at the end of the process represented by the box.

(2) an unboxed letter represents the initial value of a quantity.

The dotted and unboxed letters appearing in different boxes, but it is assumed that the identical identification is valid throughout.

87.



1949

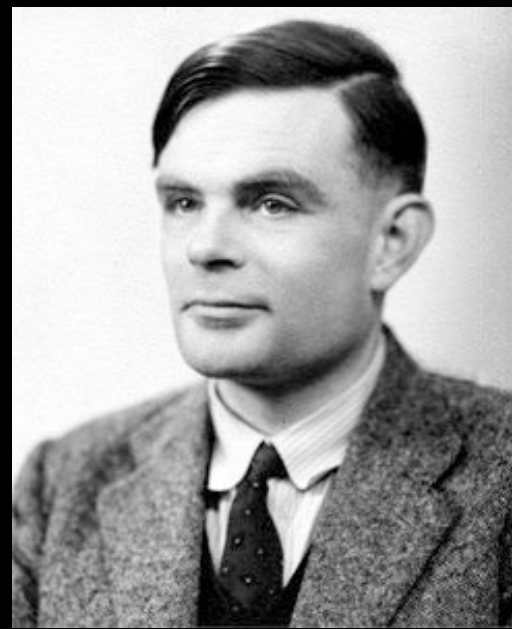
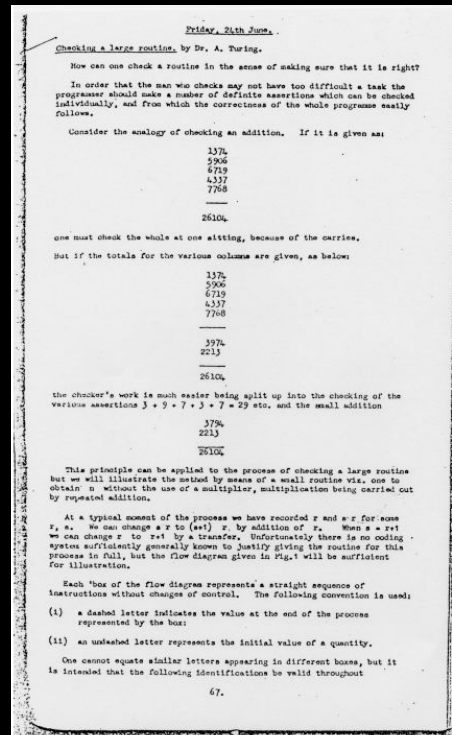
1960

1970

1980

1990

2000



program
logics

abstract interp
model checking

industrial
tools

1949

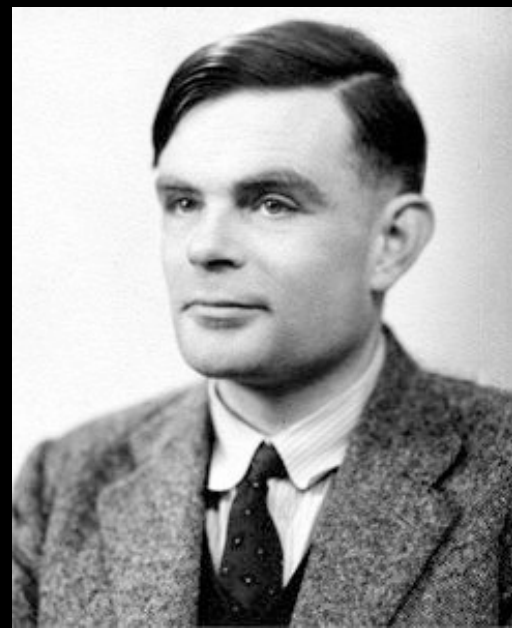
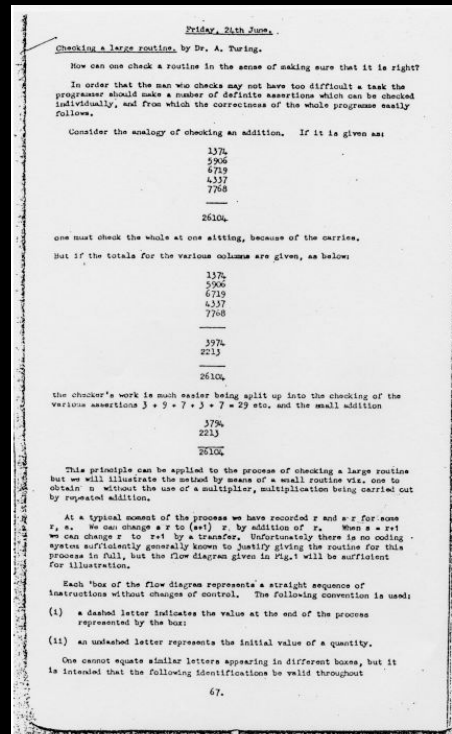
1960

1970

1980

1990

2000



program
logics

abstract interp
model checking

industrial
tools

1949

1960

1970

1980

1990

2000

`assert(x ≠ null)`

1 is my data private?

2 is the algorithm fair?

- 1 is my data private?
- 2 is the algorithm fair?

Robust De-anonymization of Large Sparse Datasets

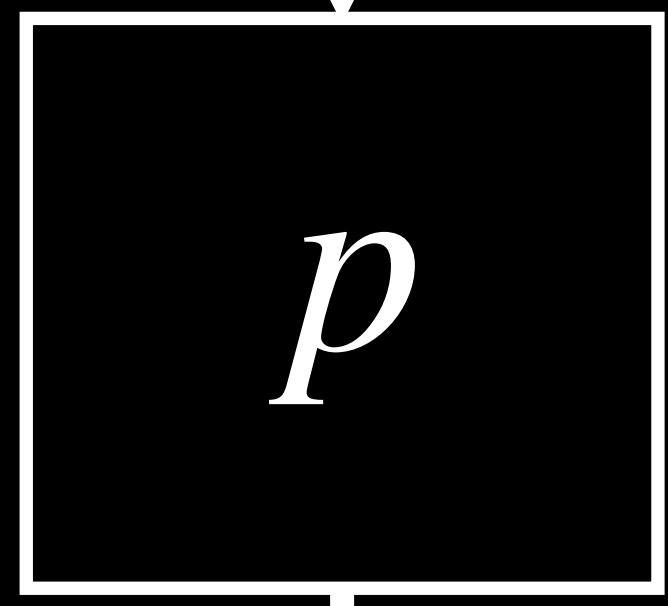
Arvind Narayanan and Vitaly Shmatikov
The University of Texas at Austin

Identifying Participants in the Personal Genome Project by Name

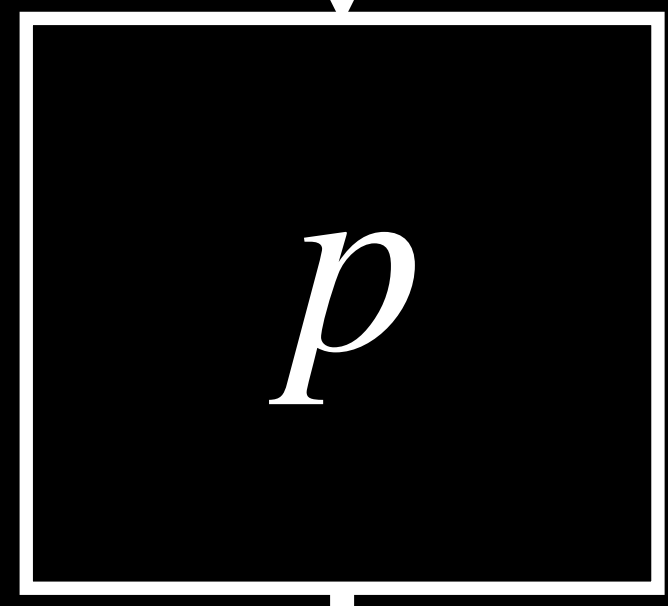
Latanya Sweeney, Akua Abu, Julia Winn

Harvard College

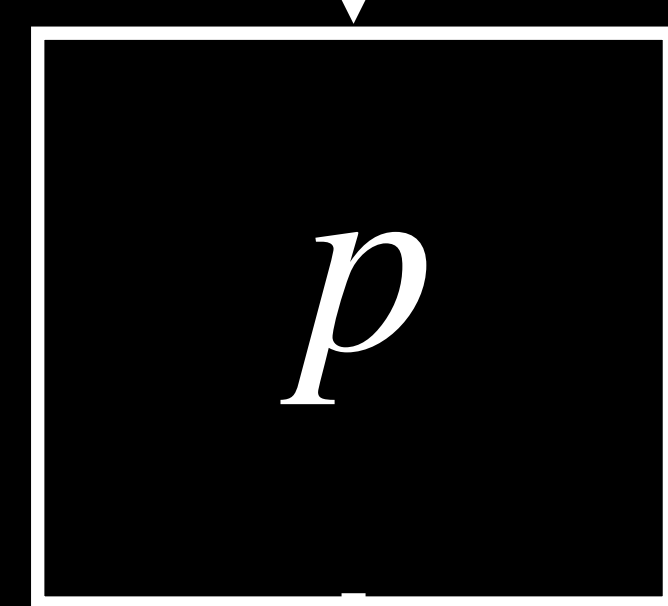
A	6
B	6
C	2



A	6
B	6
C	2

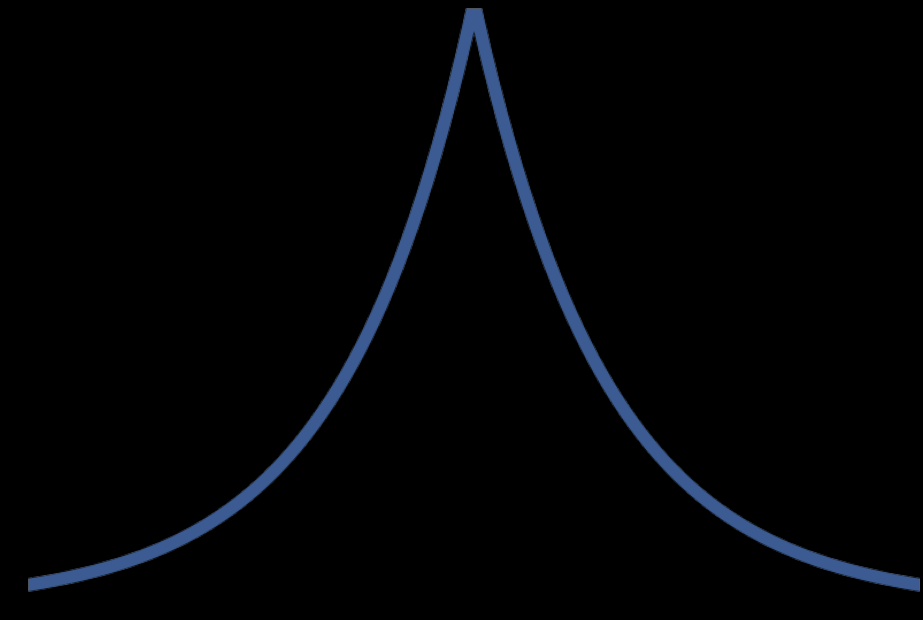
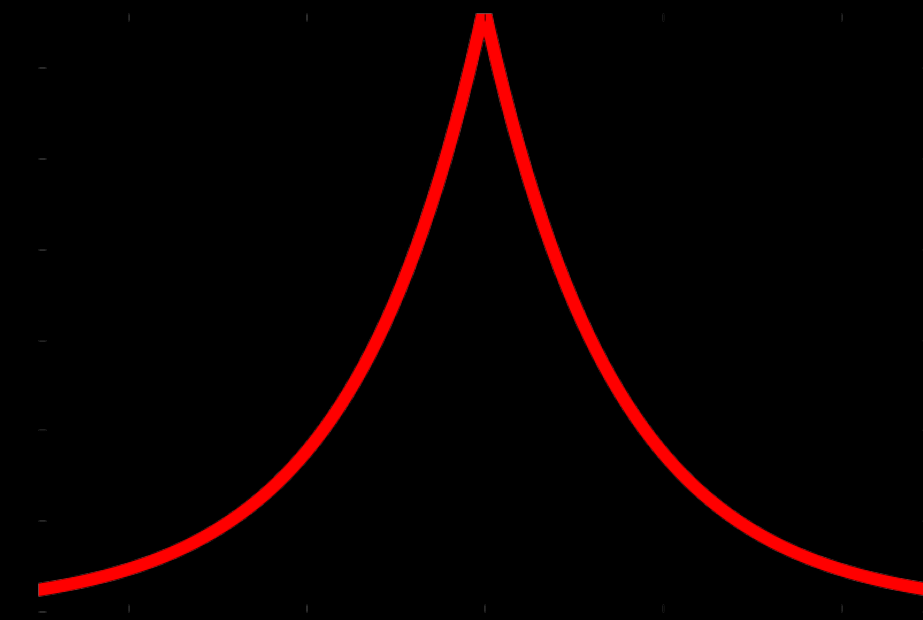
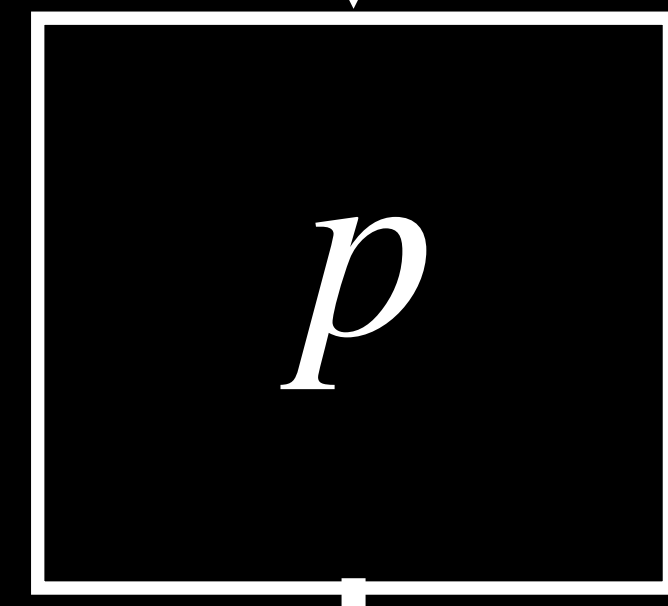
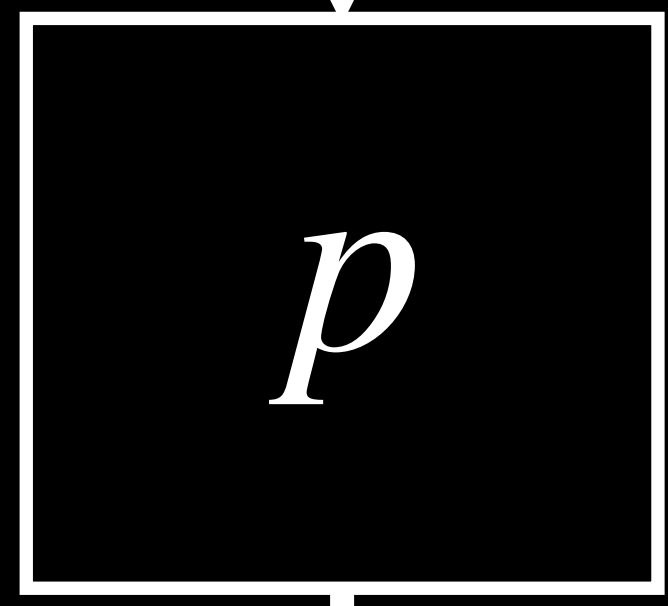


A	6
B	7
C	2



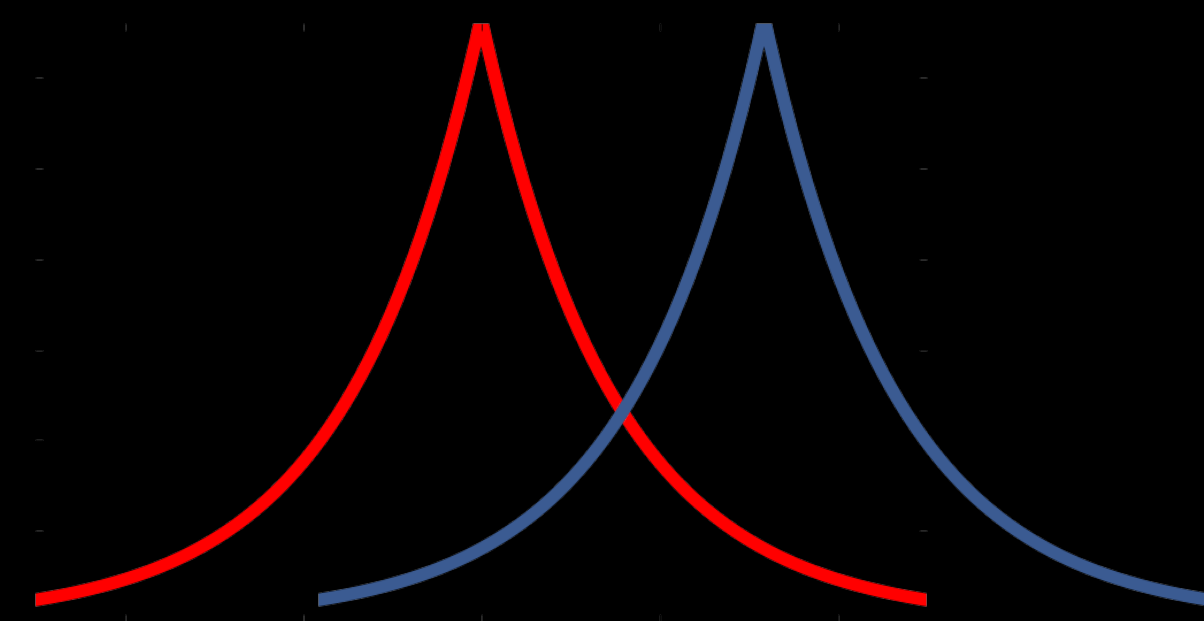
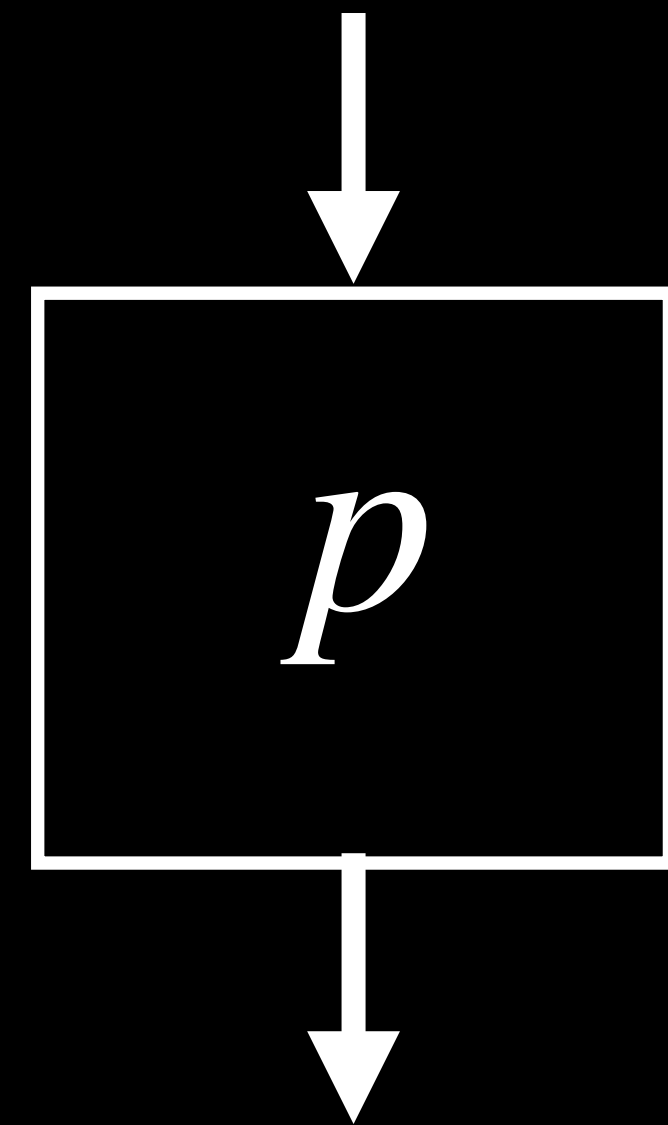
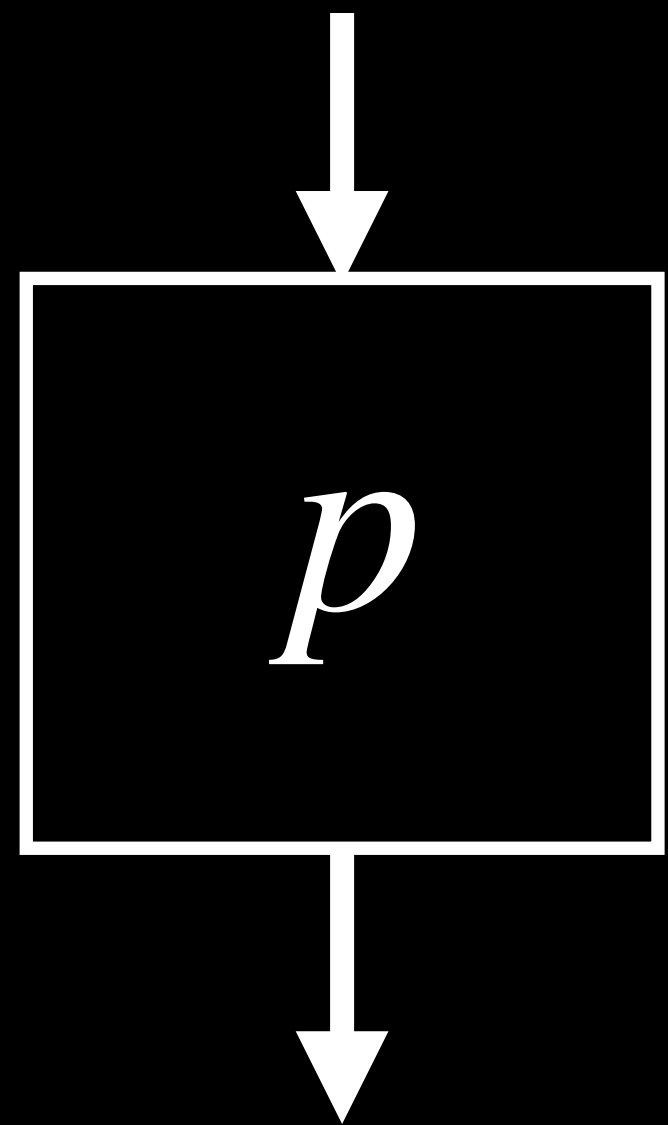
A	6
B	6
C	2

A	6
B	7
C	2



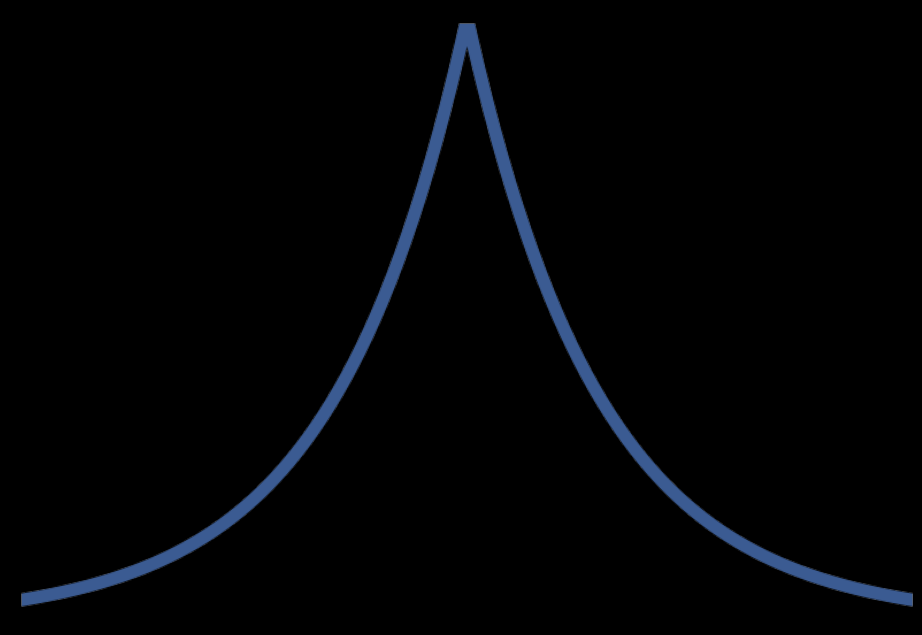
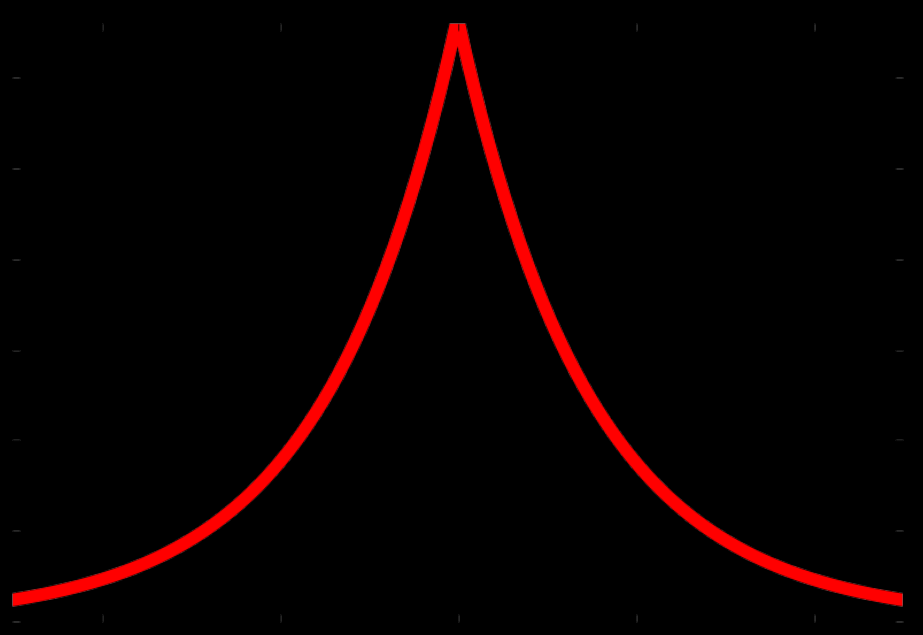
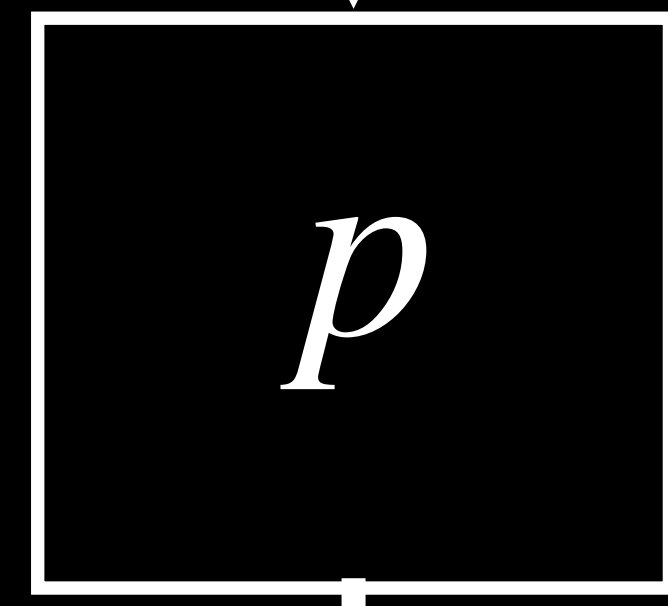
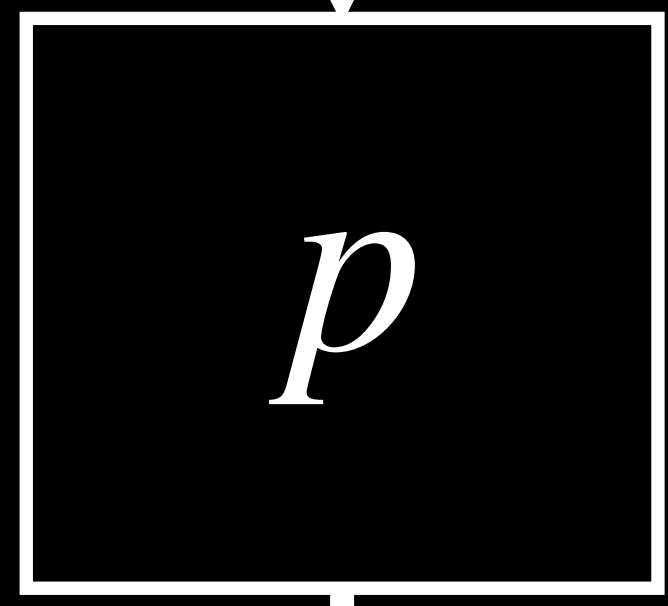
A	6
B	6
C	2

A	6
B	7
C	2



A	6
B	6
C	2

A	6
B	7
C	2



To Reduce Privacy Risks, the Census Plans to Report Less Accurate Data

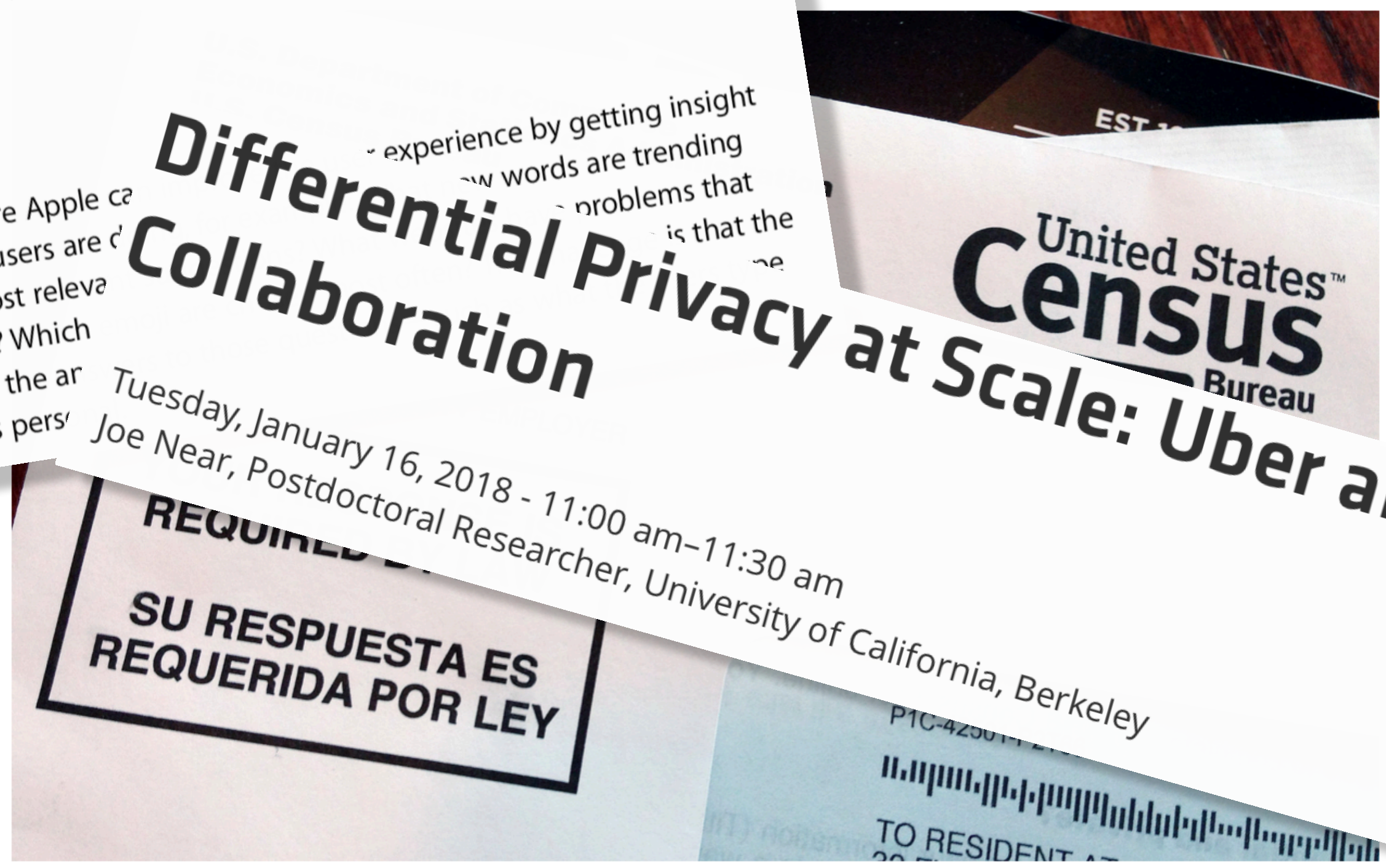
Guaranteeing people's confidentiality has become more of a challenge but... at the new system will

Differential Privacy

There are situations where Apple can learn from what many of our users are doing and might make the most relevant data which could affect battery life? Which data which could drive the app on their keyboards—is pers...

Differential Privacy at Scale: Uber and Berkeley Collaboration

Tuesday, January 16, 2018 - 11:00 am-11:30 am
Joe Near, Postdoctoral Researcher, University of California, Berkeley



A 2018 census test letter mailed to a resident in Providence, R.I. The nation's test run of the 2020 Census is in Rhode Island. Michelle R. Smith/Associated Press

google chrome
apple iOS
uber internally
census bureau

...

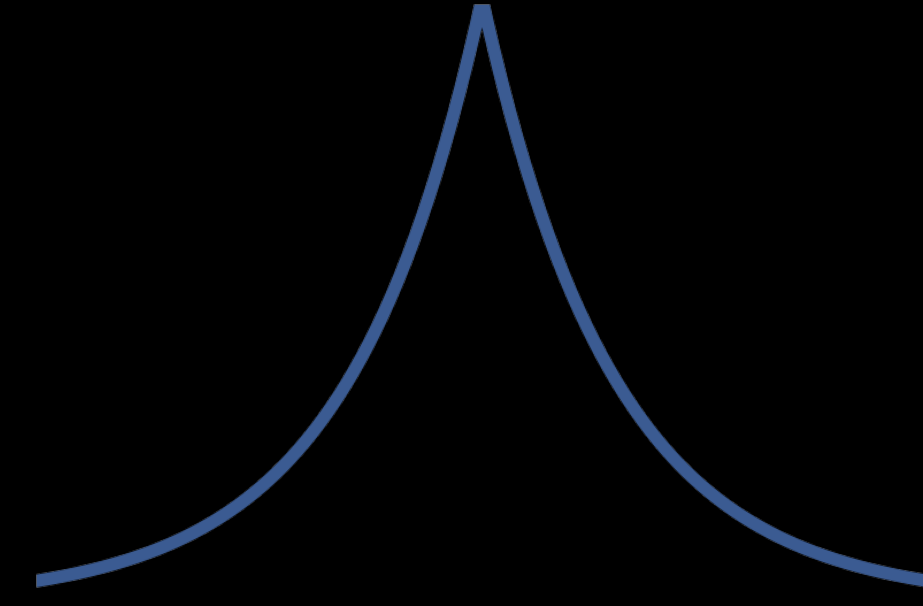
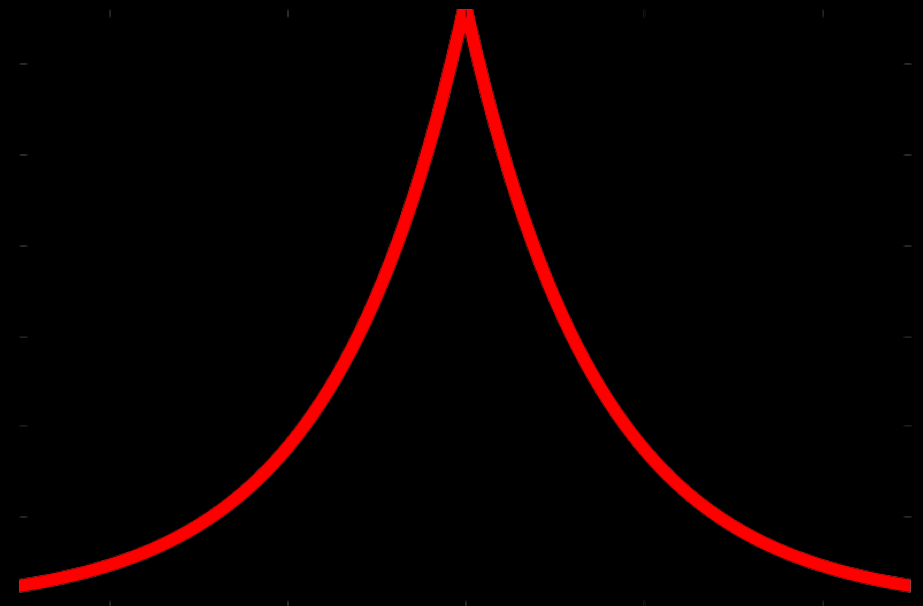
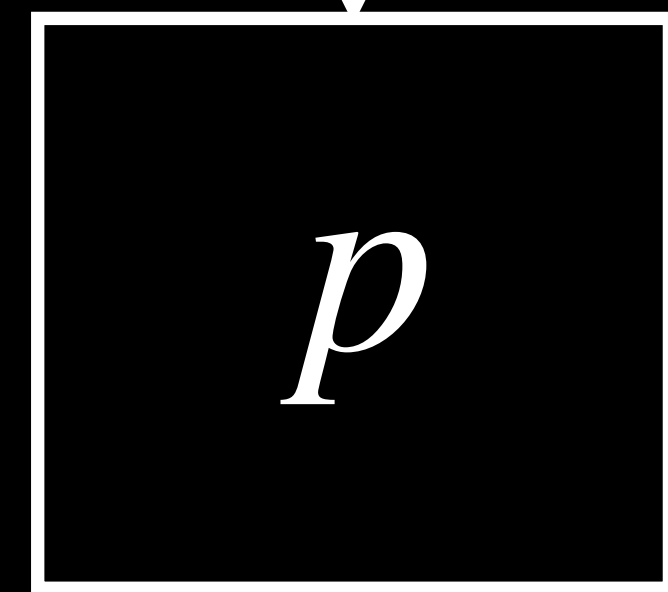
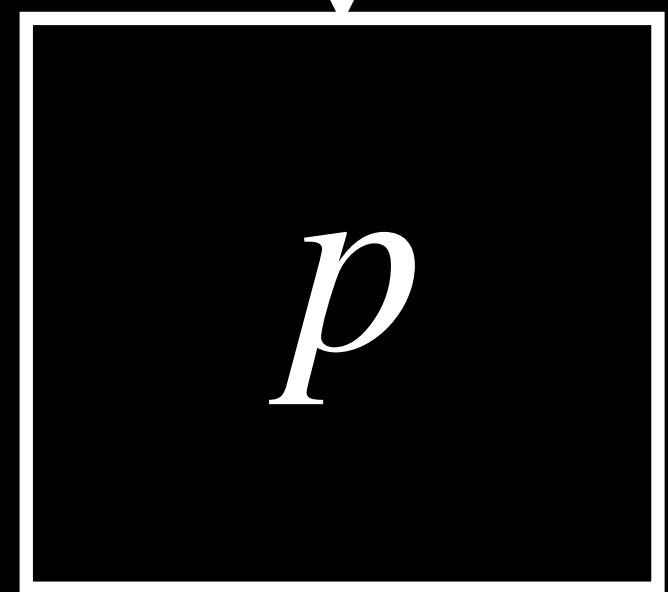
By Mark Hansen

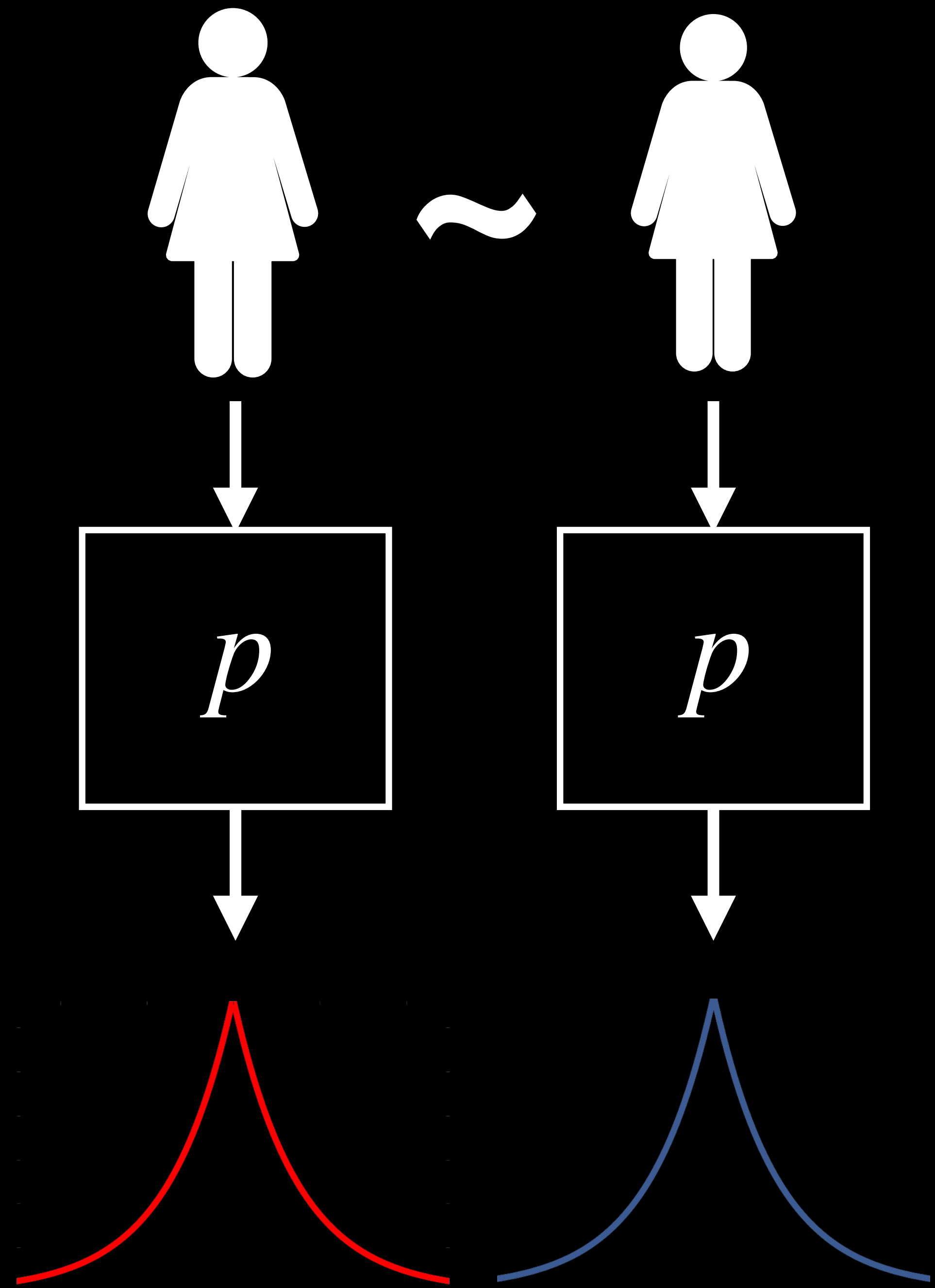
Dec. 5, 2018



A	6
B	6
C	2

A	6
B	7
C	2



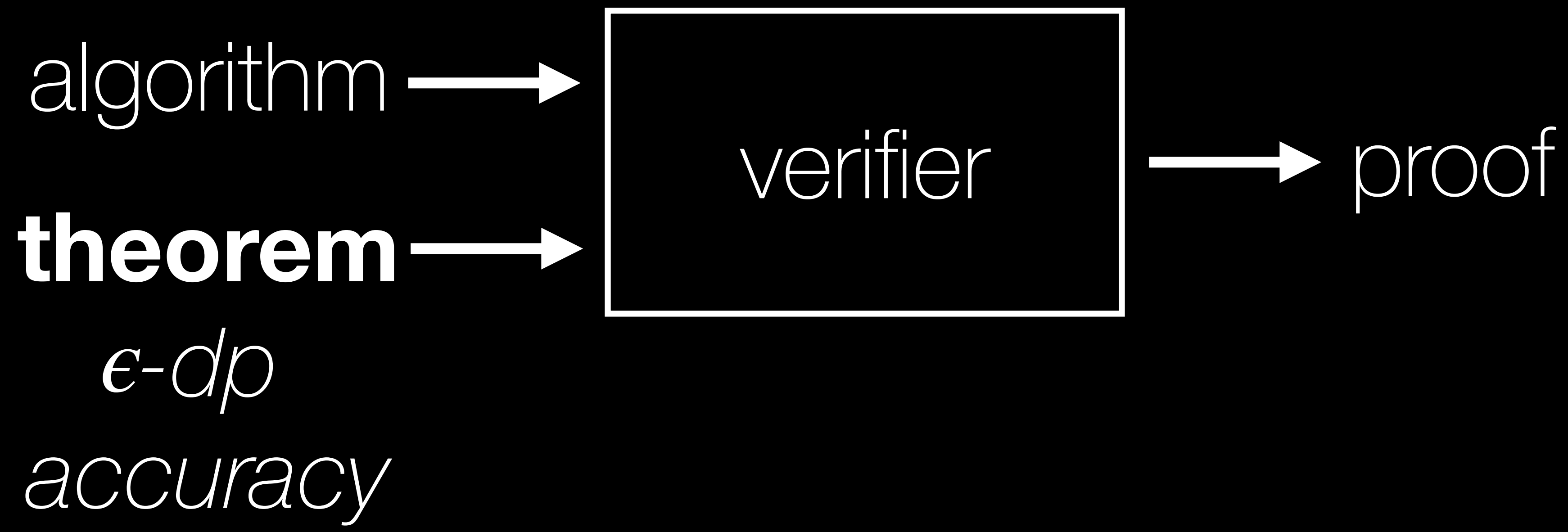


algorithm →

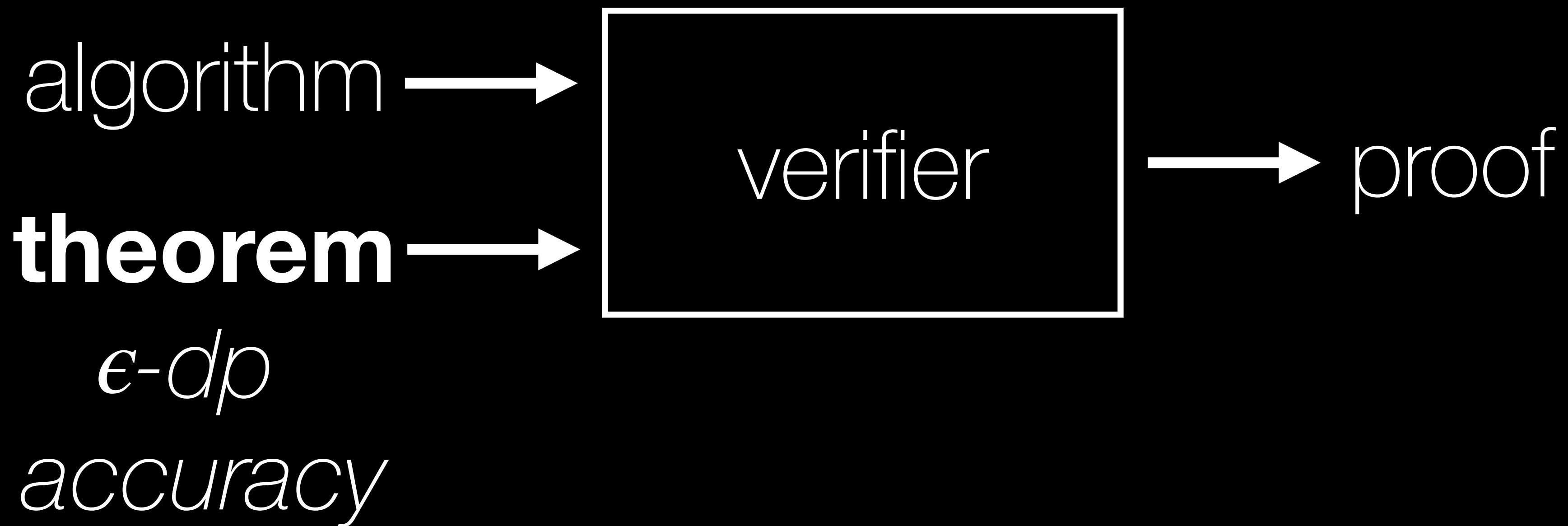
theorem →

*ϵ -dp
accuracy*



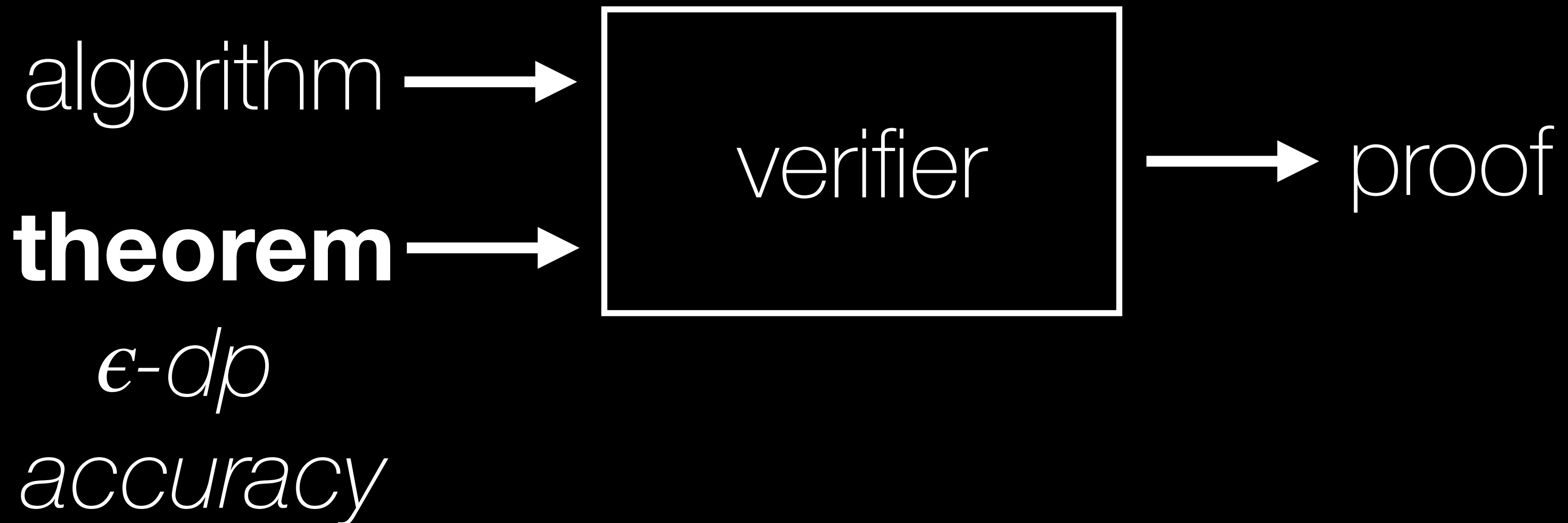


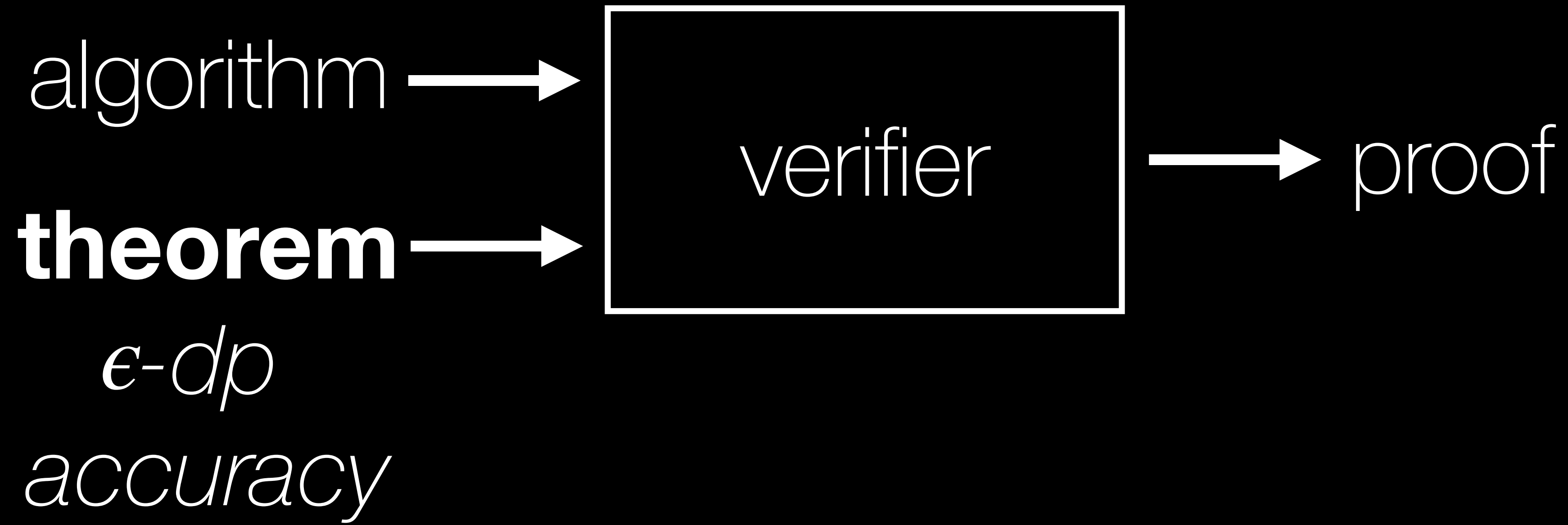
$$\forall d \sim d'. \mathbb{P}[p(d) = a] \leq e^\epsilon \cdot \mathbb{P}[p(d') = a]$$

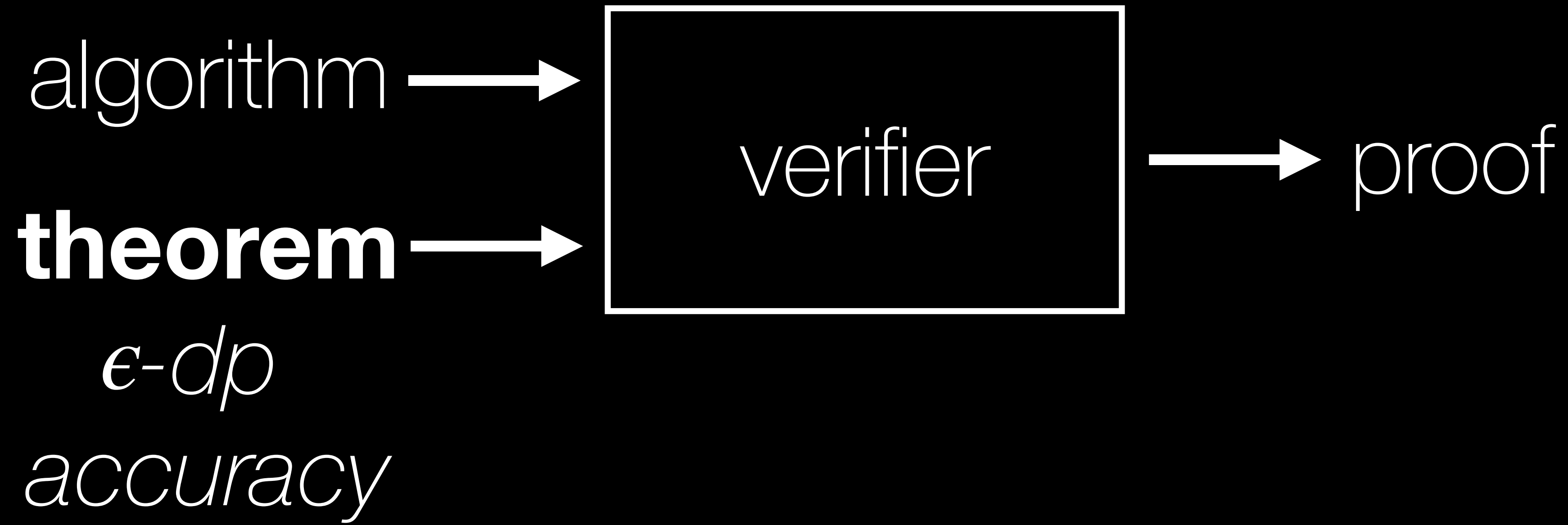


$$\forall d \sim d'. \mathbb{P}[p(d) = a] \leq e^\epsilon \cdot \mathbb{P}[p(d') = a]$$

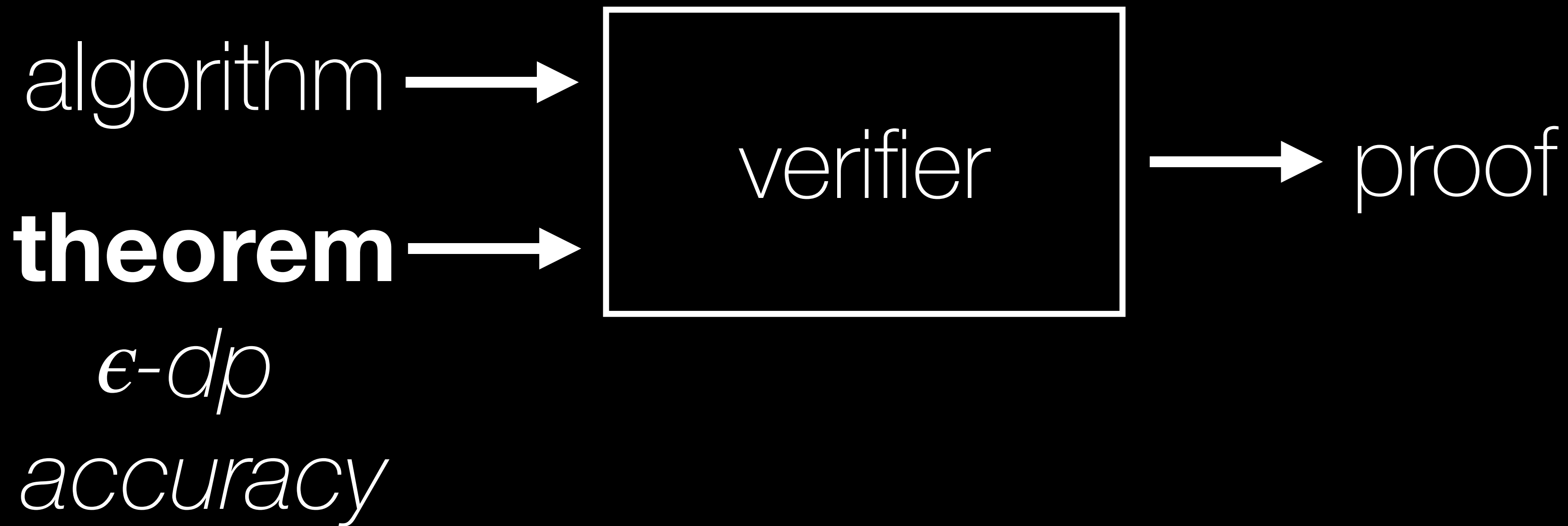
$$p(d) - p_{exact}(d) \leq \theta \quad \text{except with prob. } \delta$$







short-term vision aid algorithm designers



short-term vision aid algorithm designers

long-term vision put theorists out of work

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

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 $\Pr[i|D, r_{-i}] \leq e^\varepsilon \Pr[i|D', r_{-i}]$. 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 $r_i \sim \text{Lap}(1/\varepsilon)$.

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

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

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

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

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

[dwork/roth book]

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 $\Pr[i|D, r_{-i}] \leq e^\varepsilon \Pr[i|D', r_{-i}]$. 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 $r_i \sim \text{Lap}(1/\varepsilon)$.

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

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

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

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

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., $\|x - y\|_1 \leq 1$).

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

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

logics

barthe et al. 2018
chadha et al. 2007
den harton 2002
rand and zdancewic 2015
...

pre-expectation calculus

kozen 1985
morgan et al. 1996
...

martingales

chakarov and sankaranarayan 2013
chatterjee et al. 2016{a, b}, 2017
mcIver et al. 2018
...

probabilistic model checking

survey by katoen 2016
hermanns et al. 2008
kattenbelt et al. 2009, 2010
tiege and fränzle 2011
...

...and more!

logics

not automated

pre-expectation calculus

kozen 1985

morgan et al. 1996

...

martingales

chakarov and sankaranarayan 2013

chatterjee et al. 2016{a, b}, 2017

mclver et al. 2018

...

probabilistic model checking

survey by katoen 2016

hermanns et al. 2008

kattenbelt et al. 2009, 2010

tiege and fränzle 2011

...

...and more!

logics

not automated

martingales

require additional manual reasoning

pre-expectation calculus

kozen 1985

morgan et al. 1996

...

probabilistic model checking

survey by katoen 2016

hermanns et al. 2008

kattenbelt et al. 2009, 2010

tiege and fränzle 2011

...

...and more!

logics

not automated

martingales

**require additional manual
reasoning**

pre-expectation calculus

complex integrals

probabilistic model checking

survey by katoen 2016

hermanns et al. 2008

kattenbelt et al. 2009, 2010

tiege and fränzle 2011

...

...and more!

logics

not automated

martingales

**require additional manual
reasoning**

pre-expectation calculus

complex integrals

probabilistic model checking

**(mostly) finite state and no
symbolic distributions**

...and more!

1 automatic proofs of accuracy [POPL19]

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

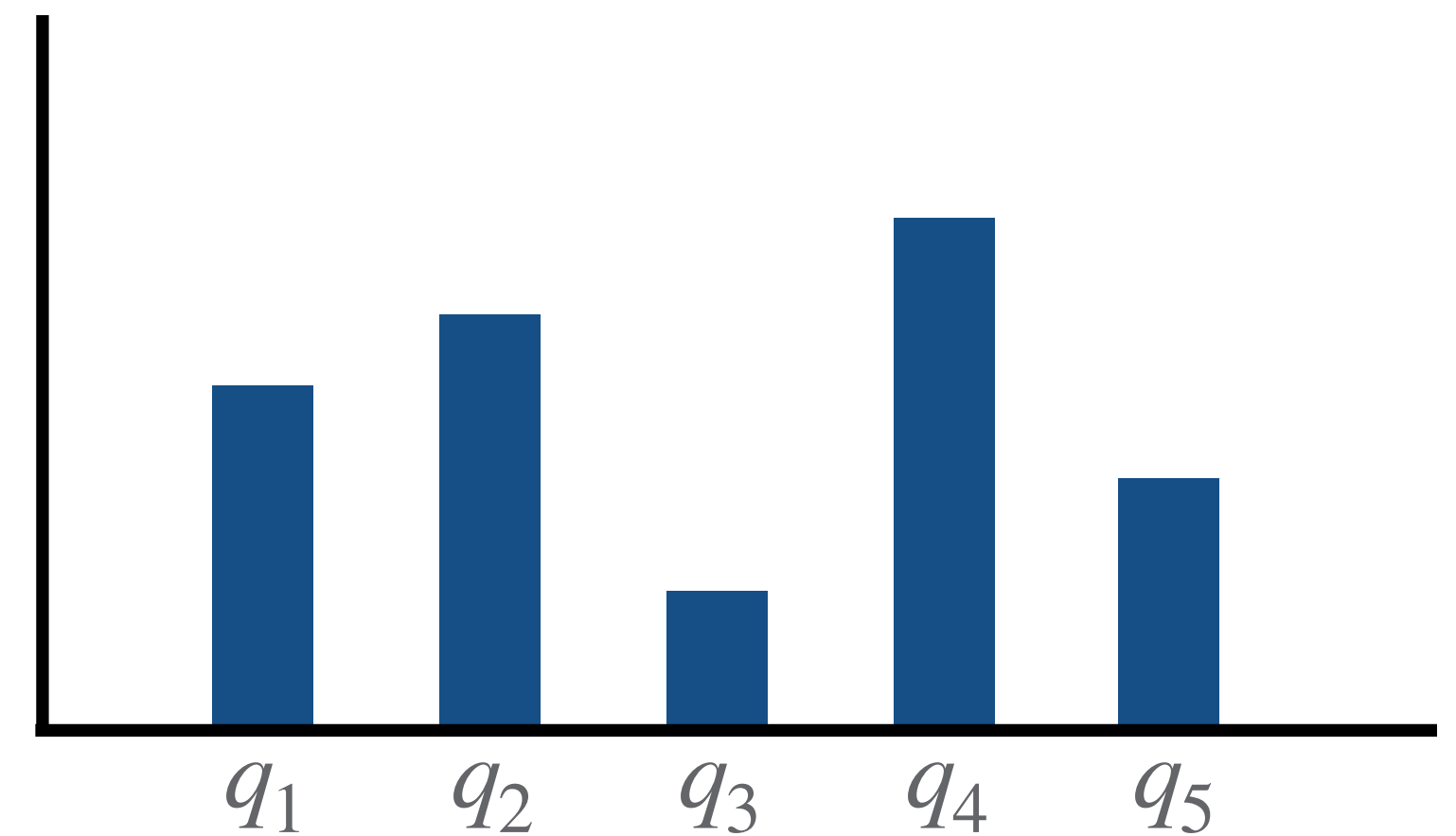
- 1** automatic proofs of accuracy [POPL19]
- 2** automatic proofs of differential privacy [POPL18]
synthesis of privacy-preserving algorithms [ICFP 19]

- 1** automatic proofs of accuracy [POPL19]
- 2** automatic proofs of differential privacy [POPL18]
synthesis of privacy-preserving algorithms [ICFP 19]

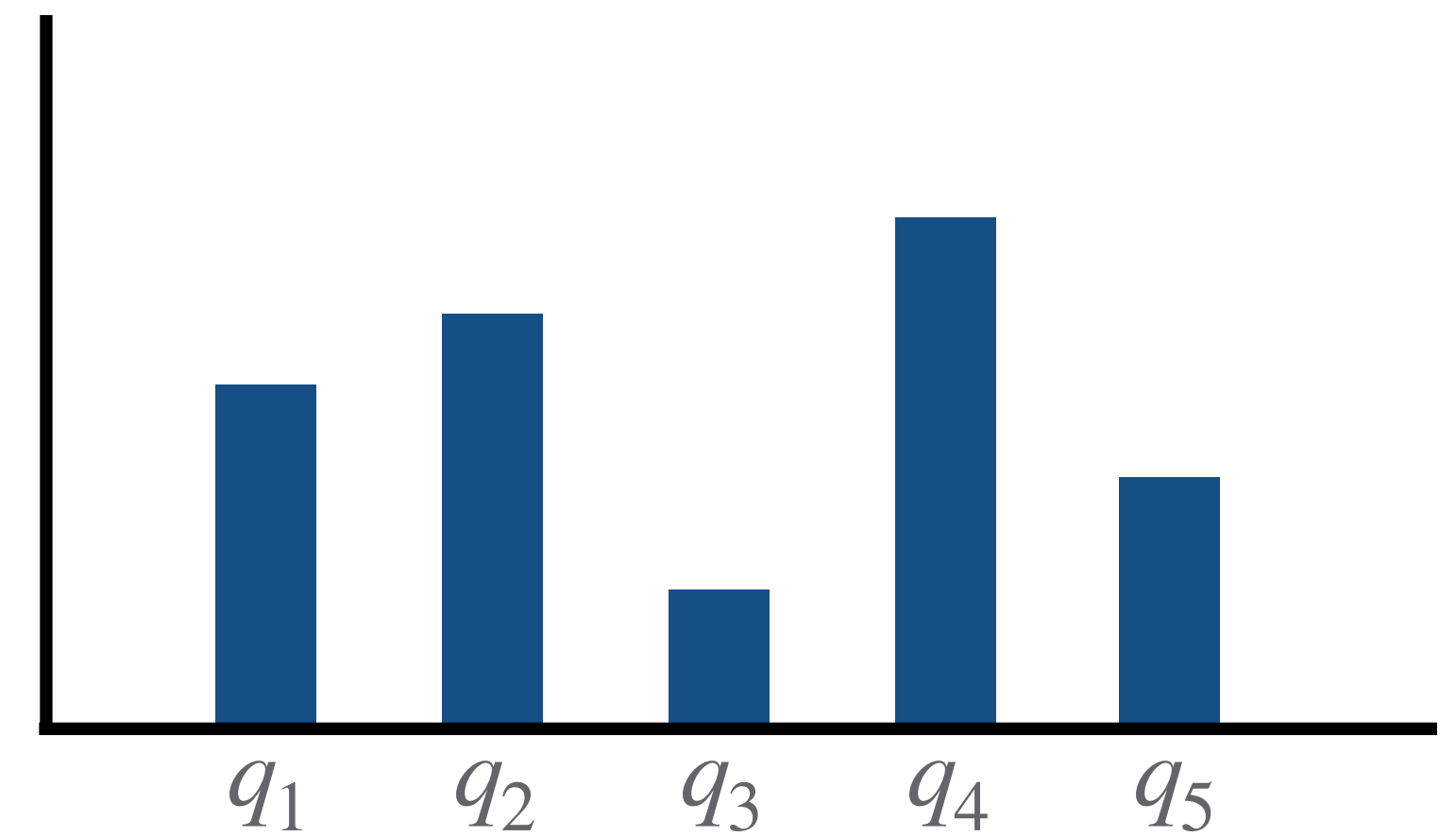
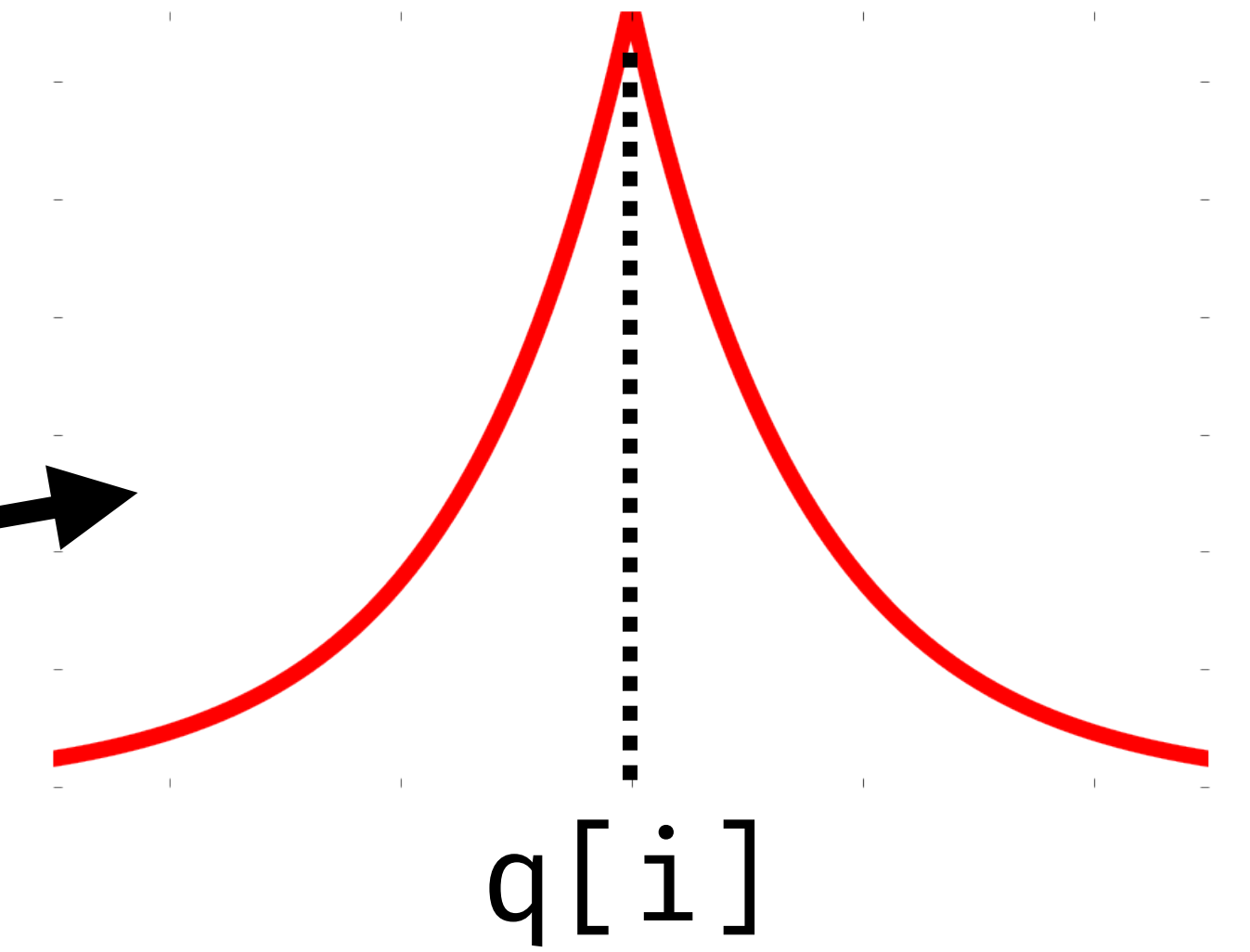
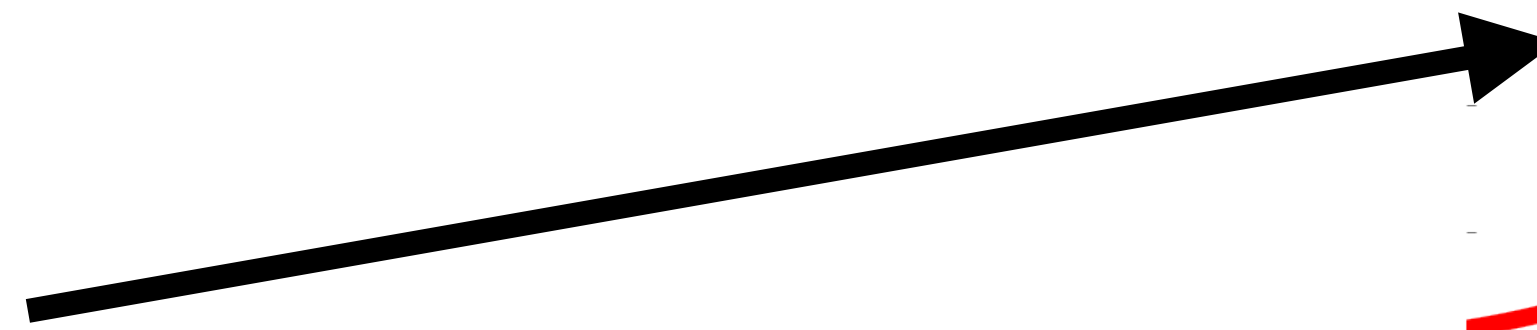
theme get rid of probability! long live logic!

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```

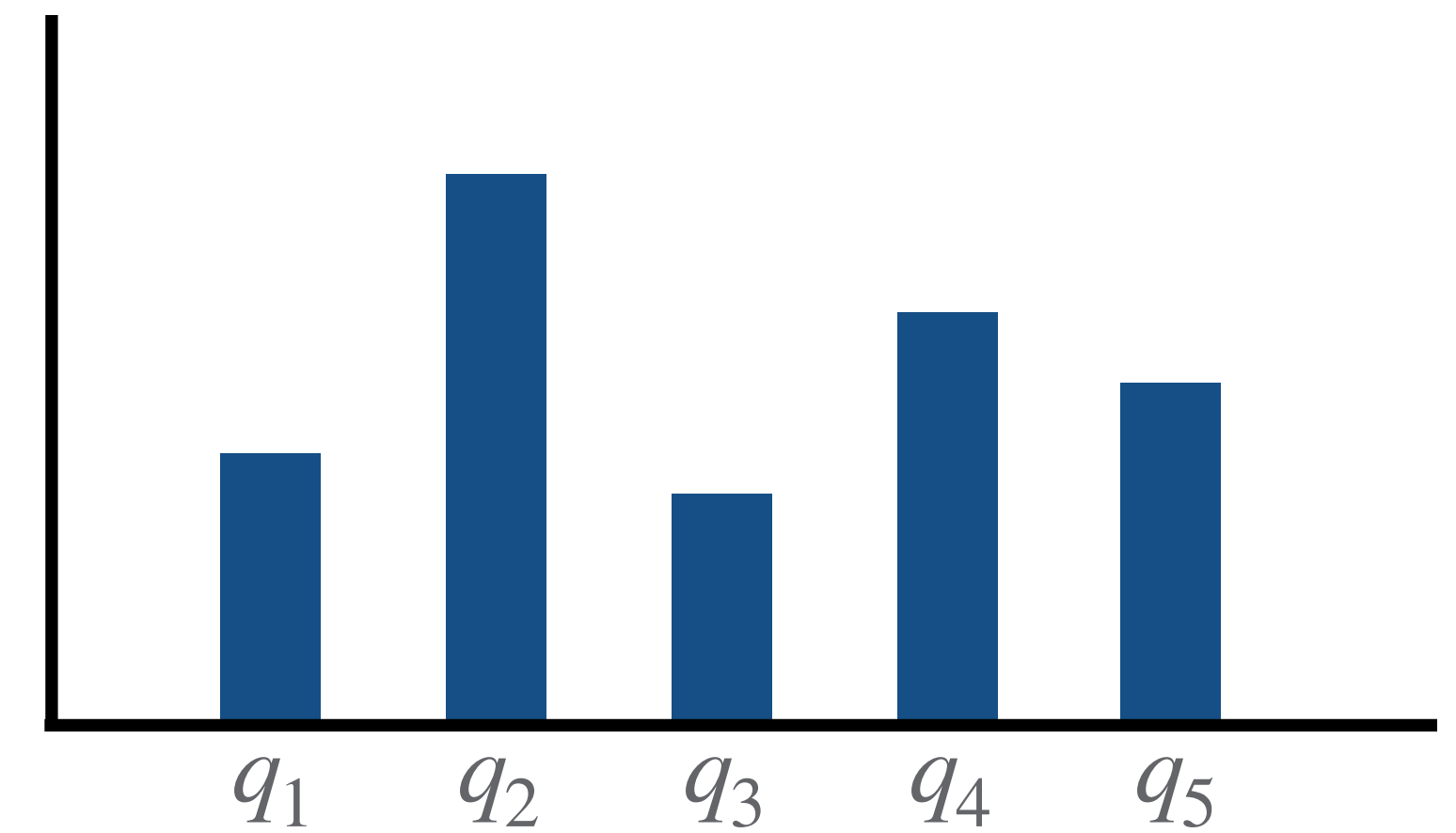
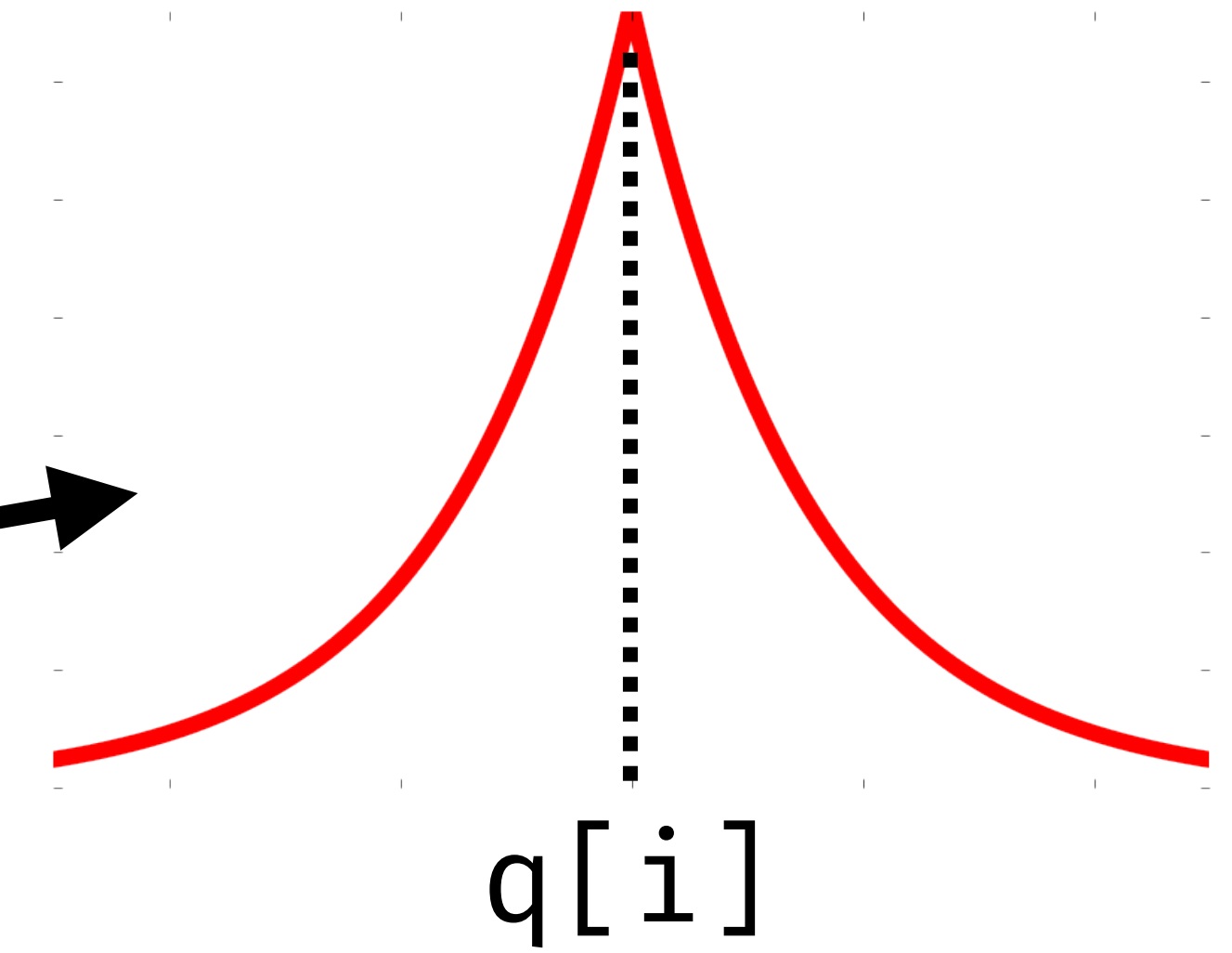
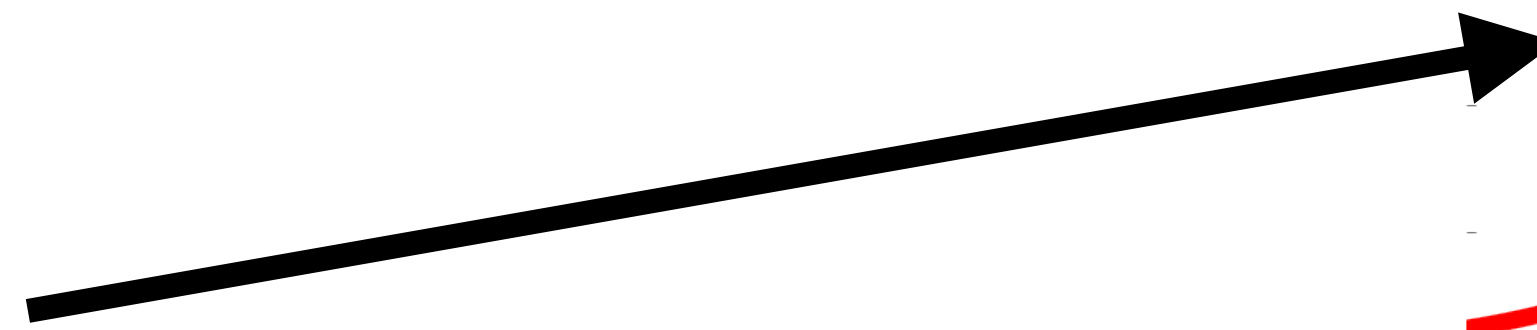
```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```



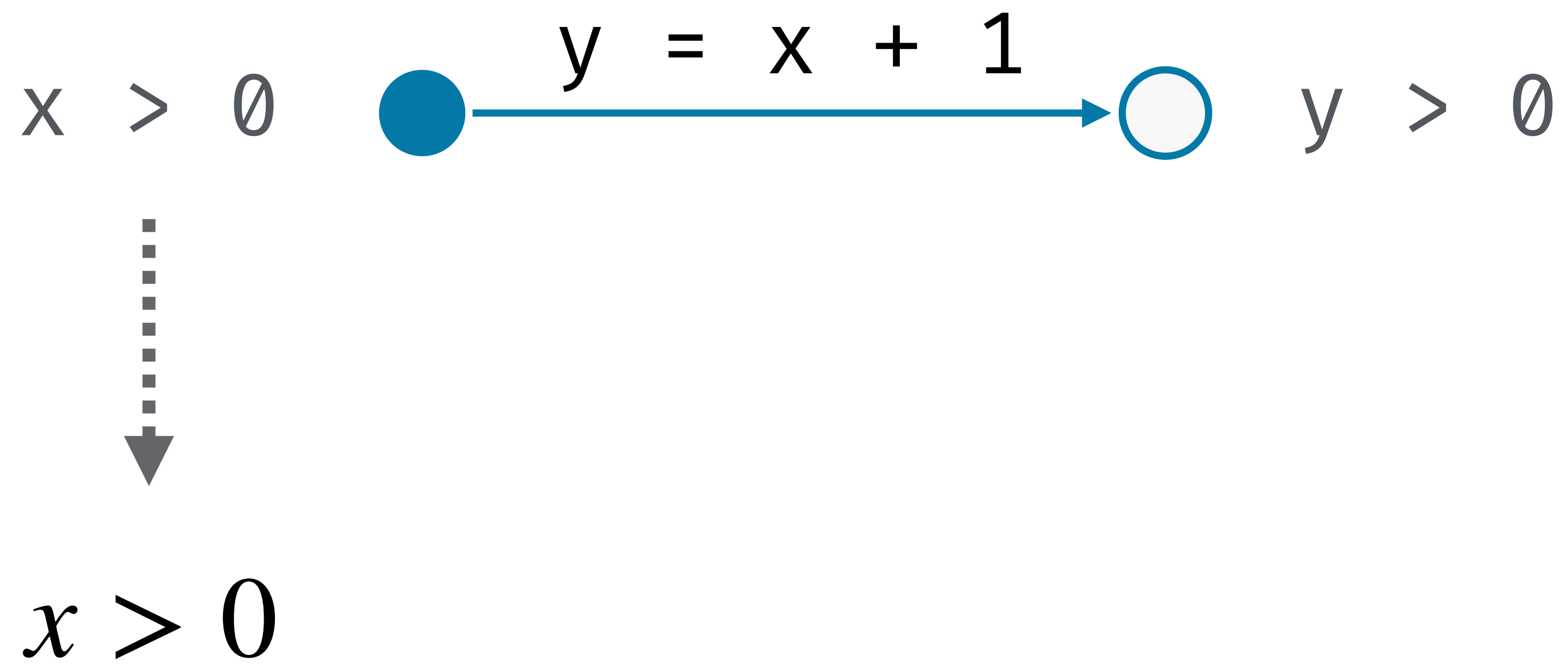
```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```

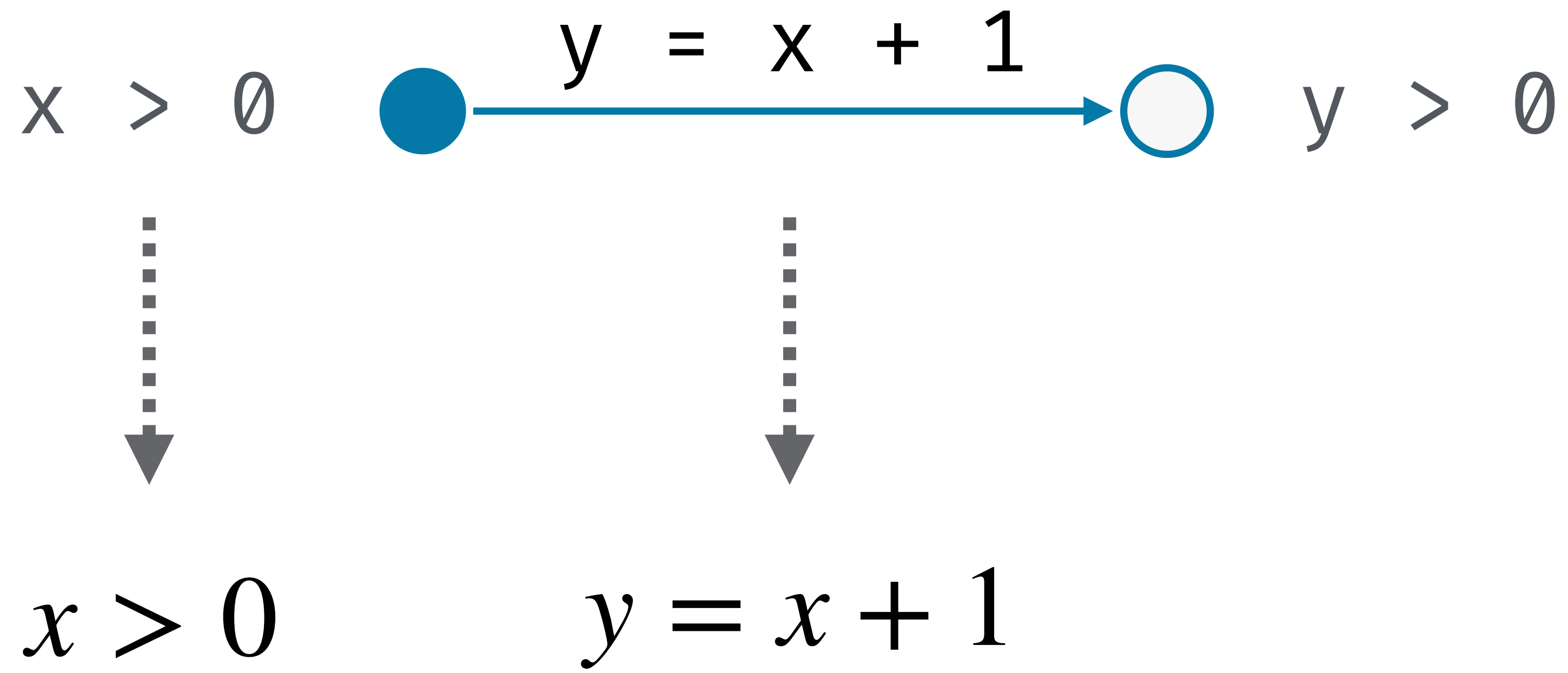


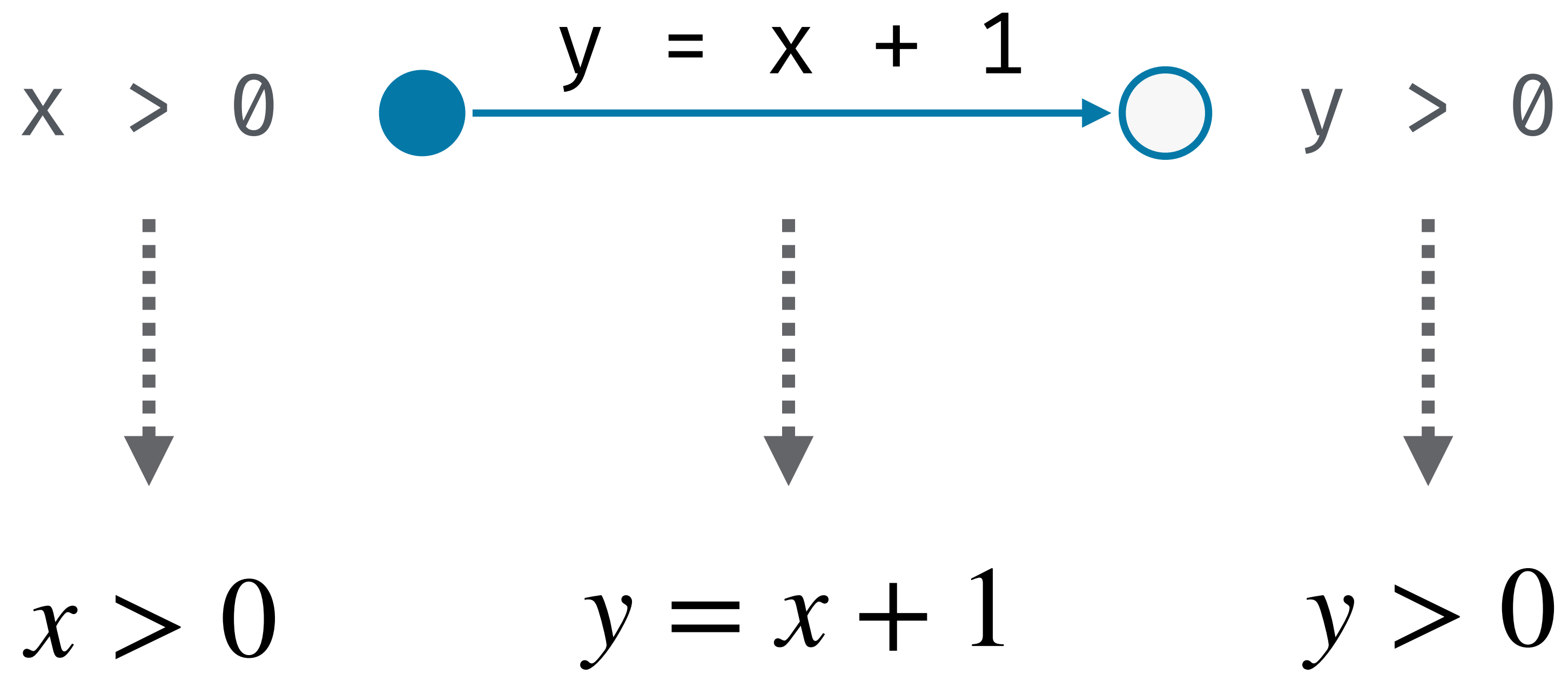
```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```

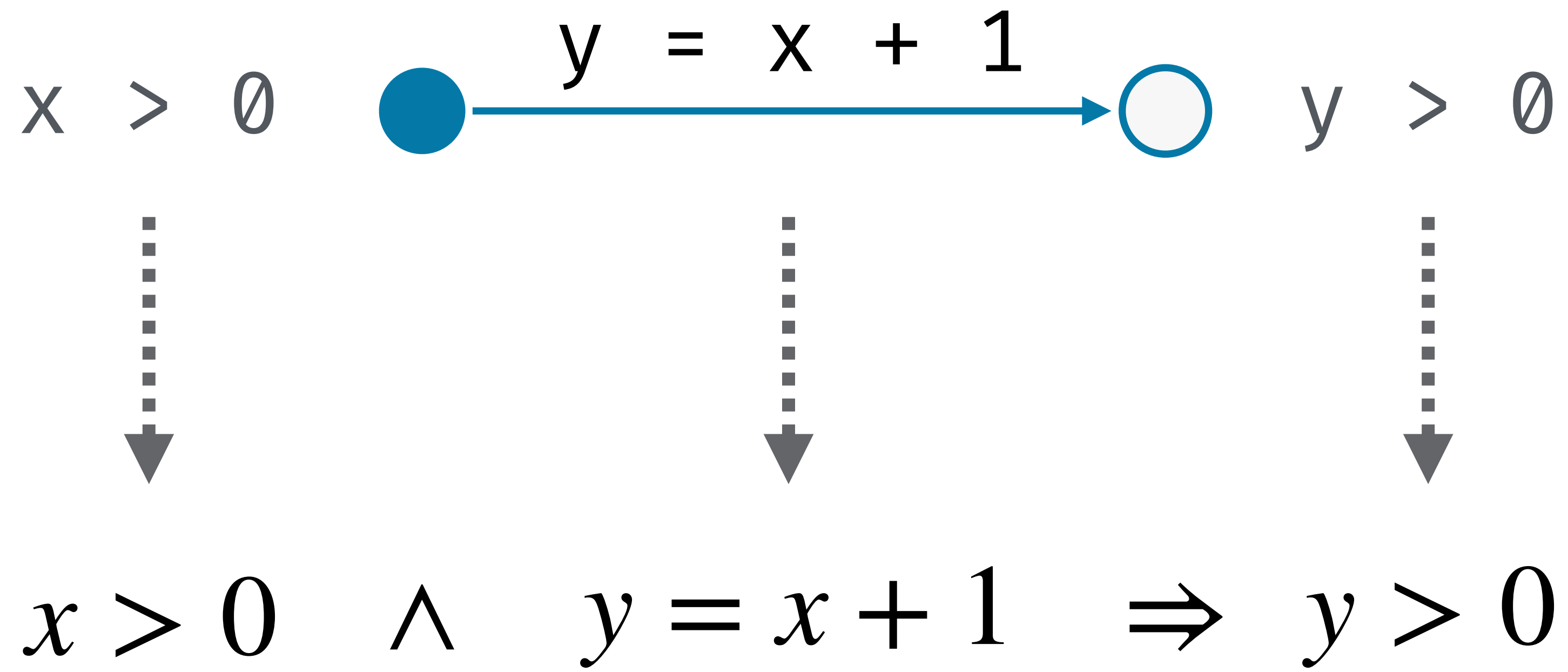


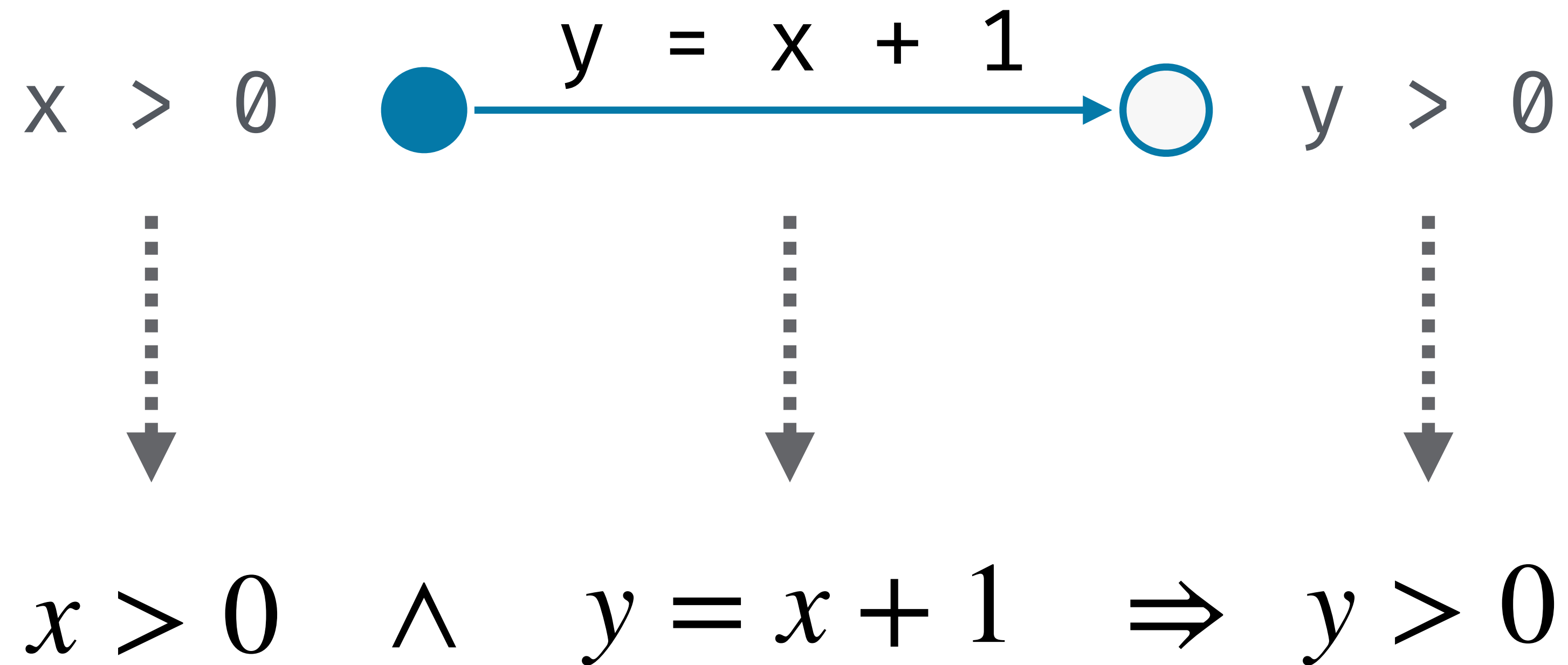




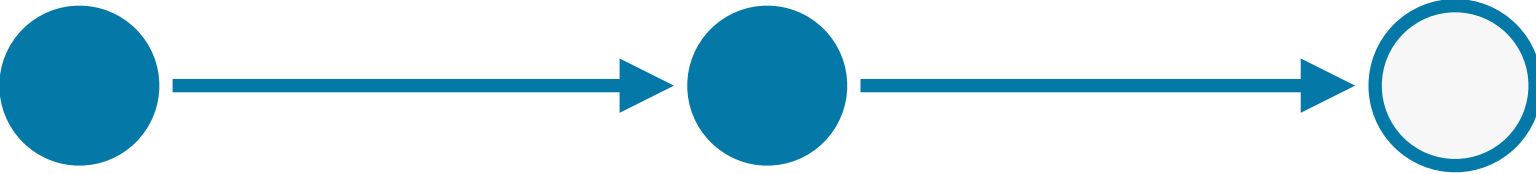


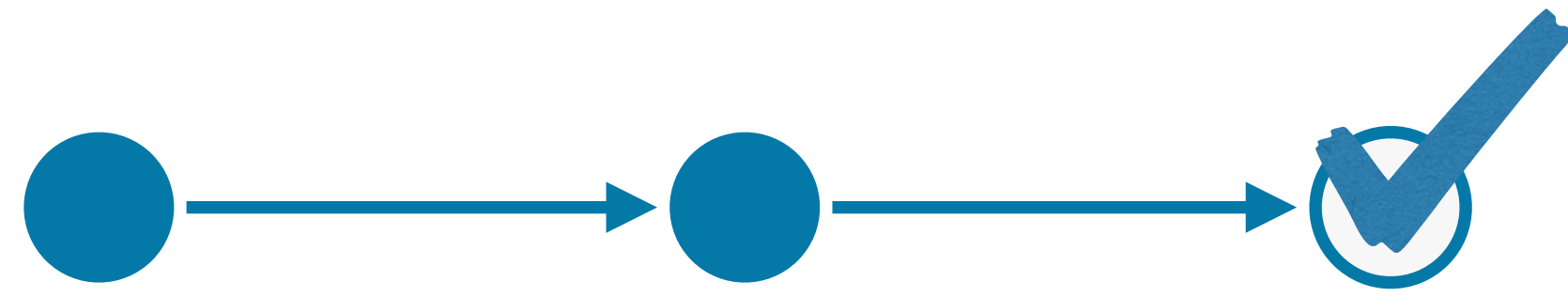


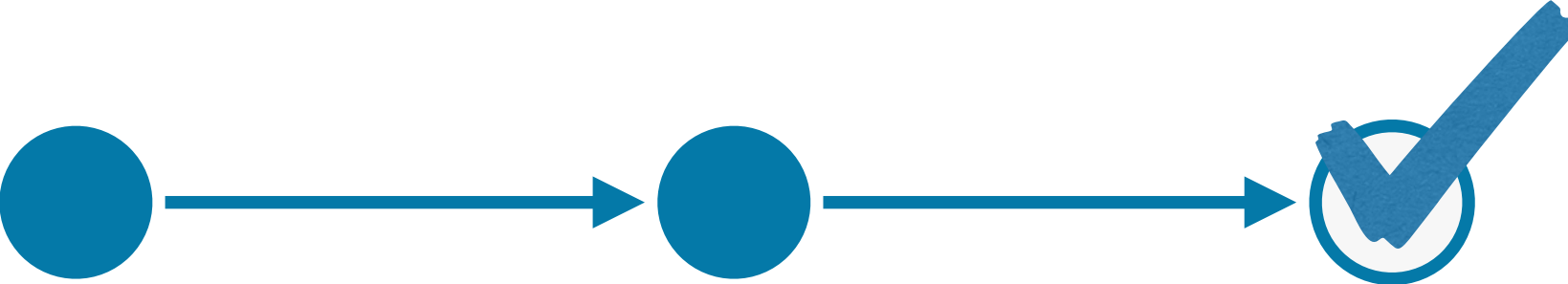


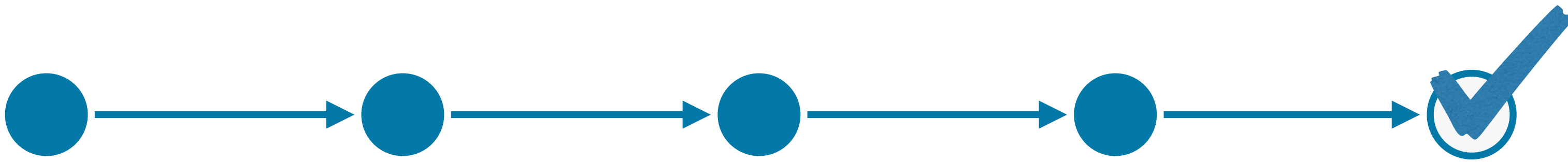
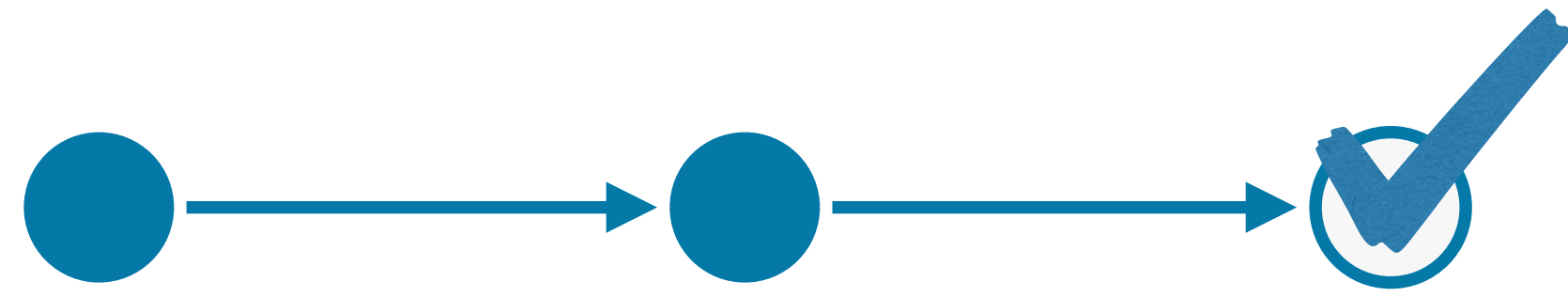


solve with a **SAT/SMT** solver



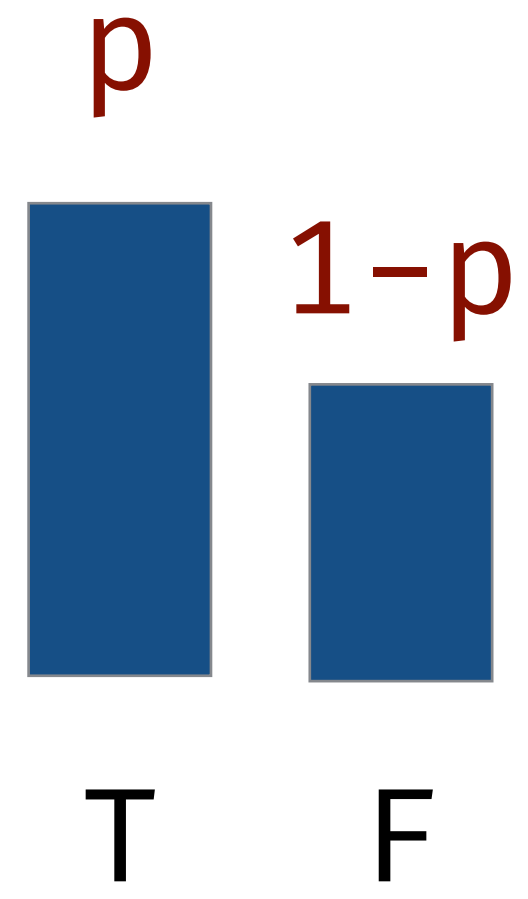


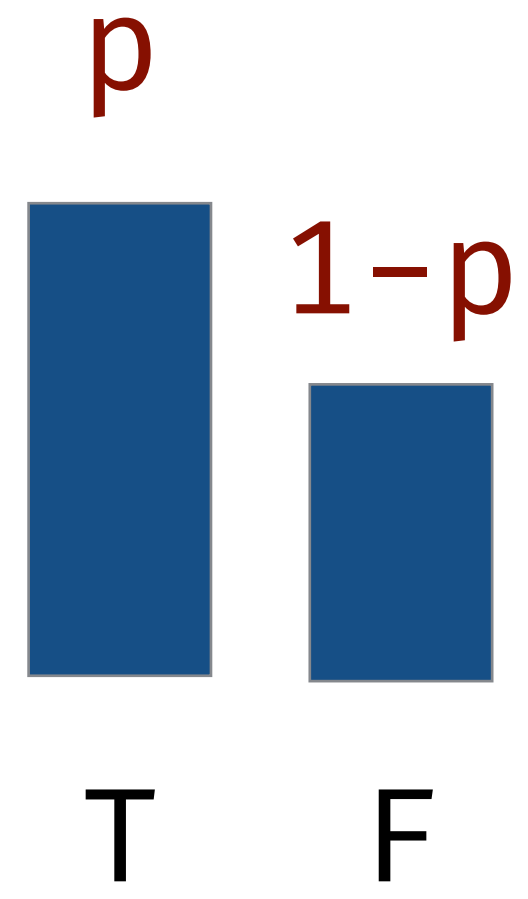




⋮



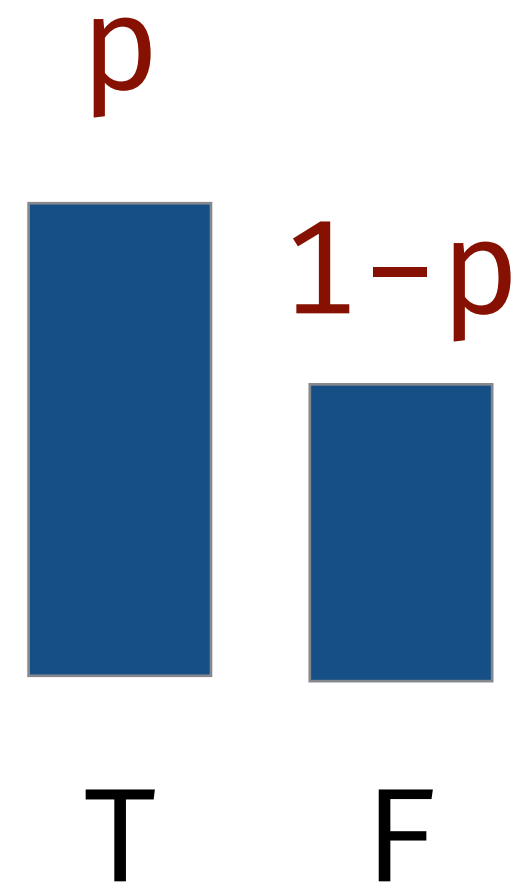




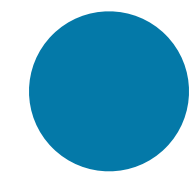
$p \in (0, 1)$



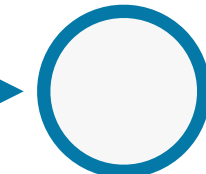
$x \sim \text{flip}(p)$



$p \in (0, 1)$

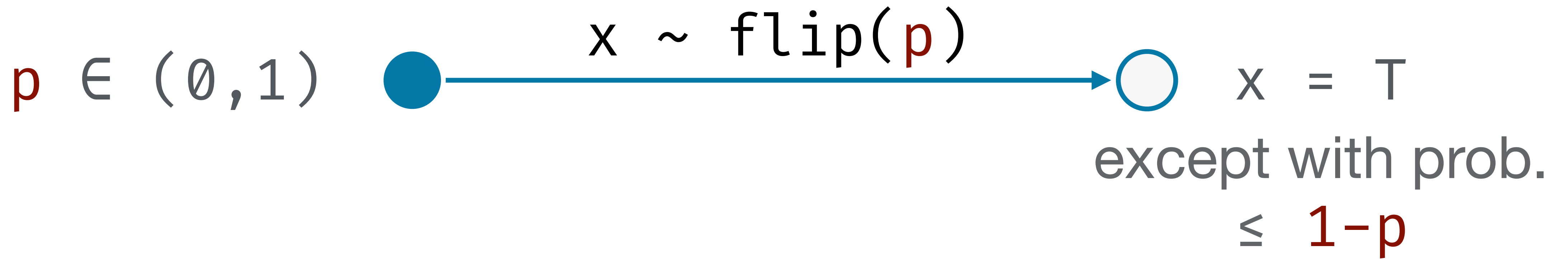
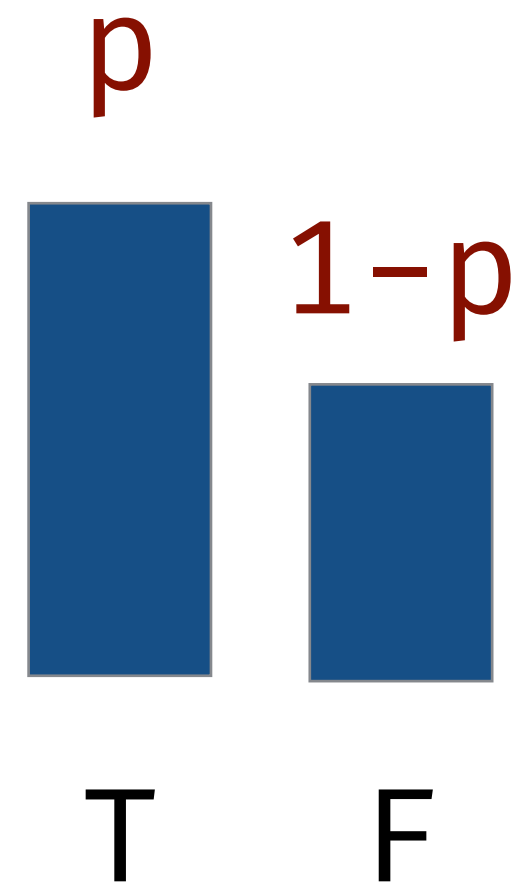


$x \sim \text{flip}(p)$

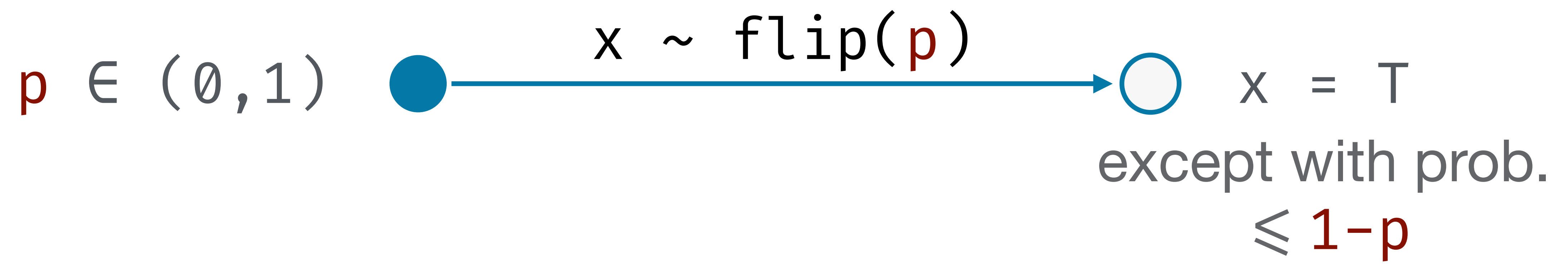


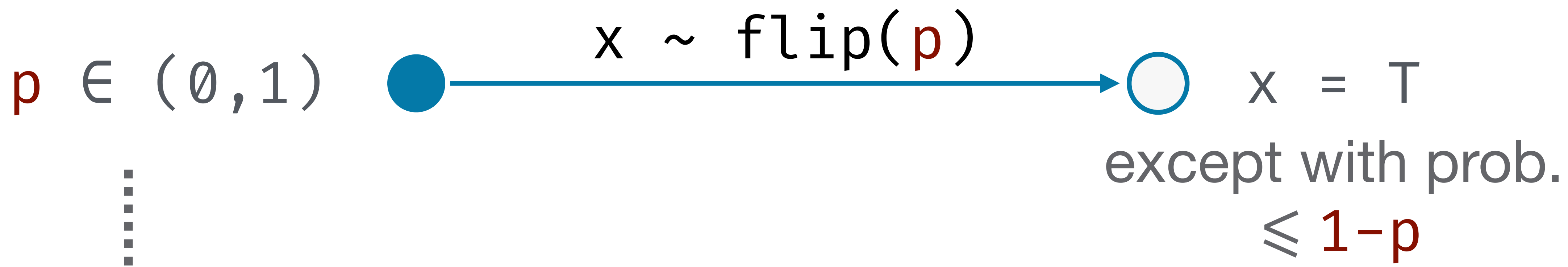
$x = T$

except with prob.
 $\leq 1-p$

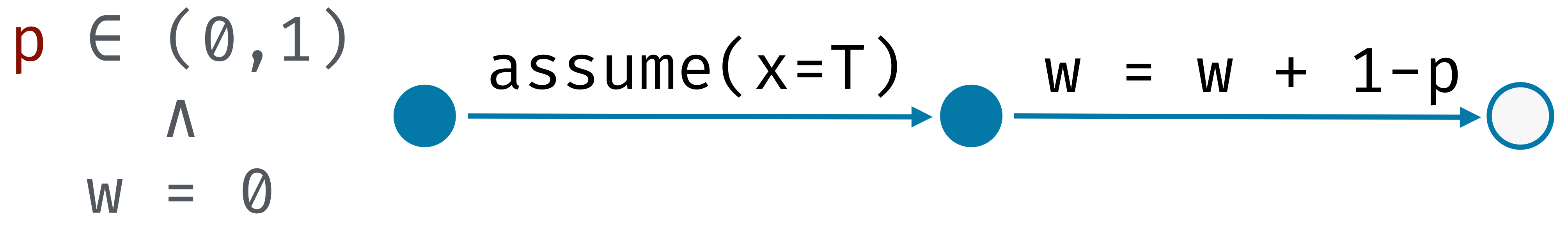
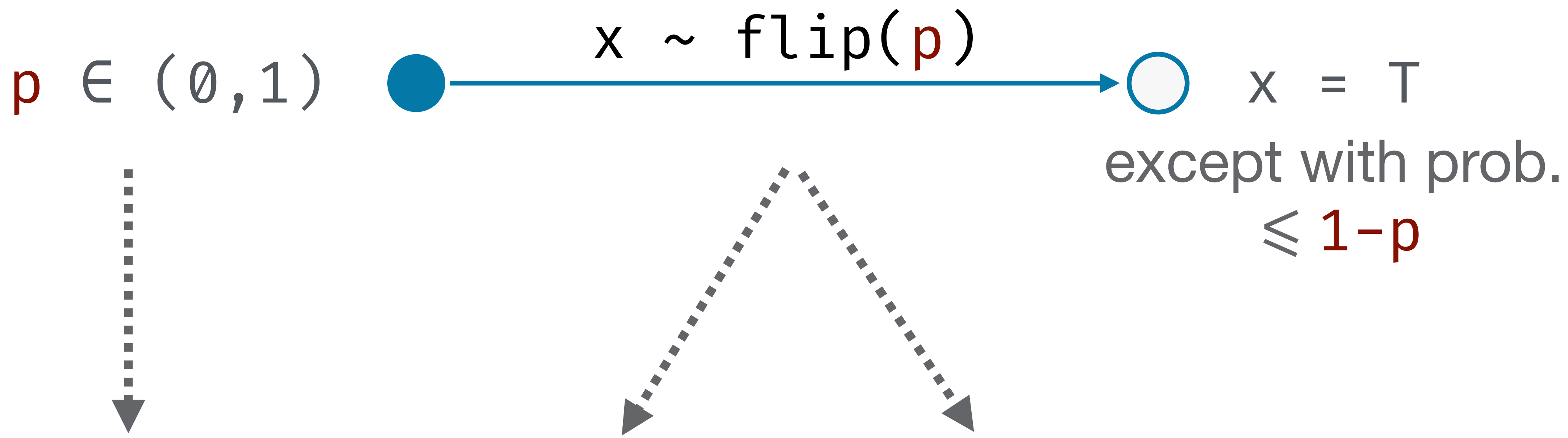


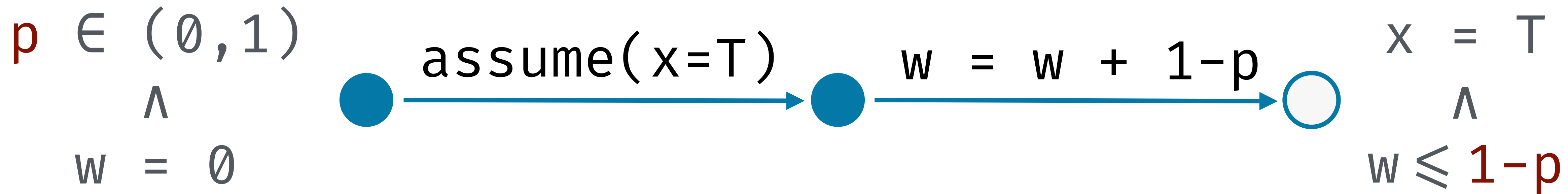
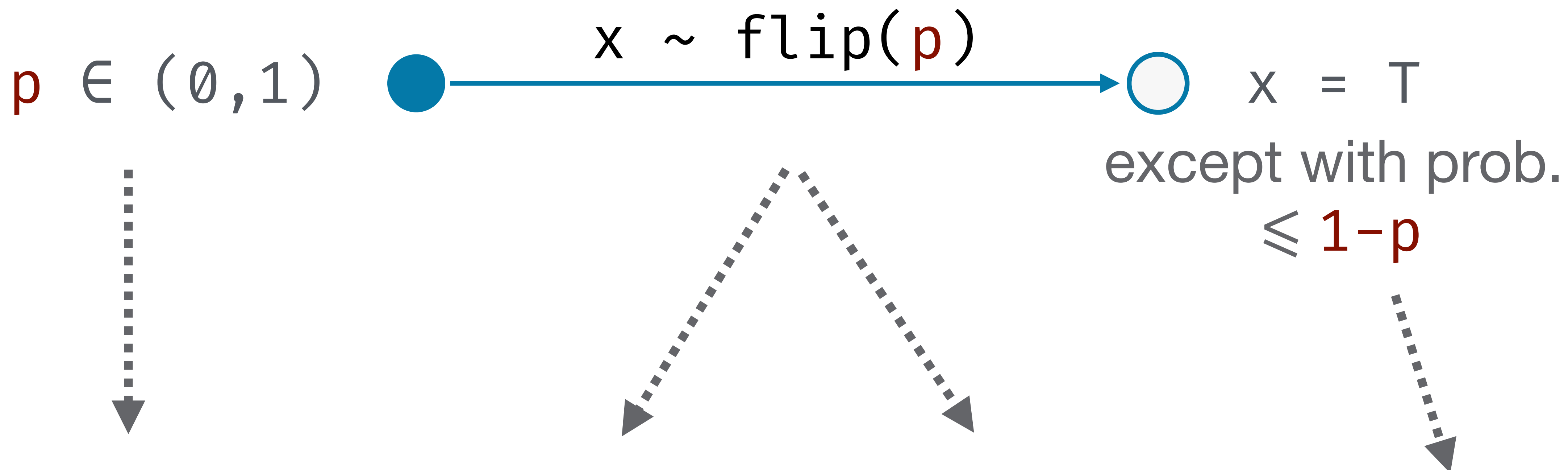
challenge how do we check this with first-order logic?

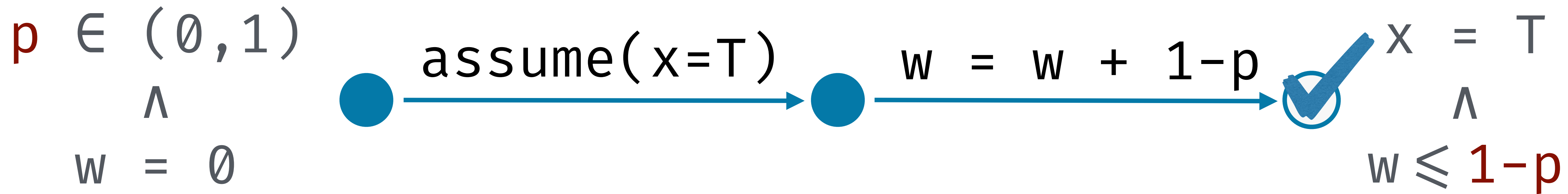
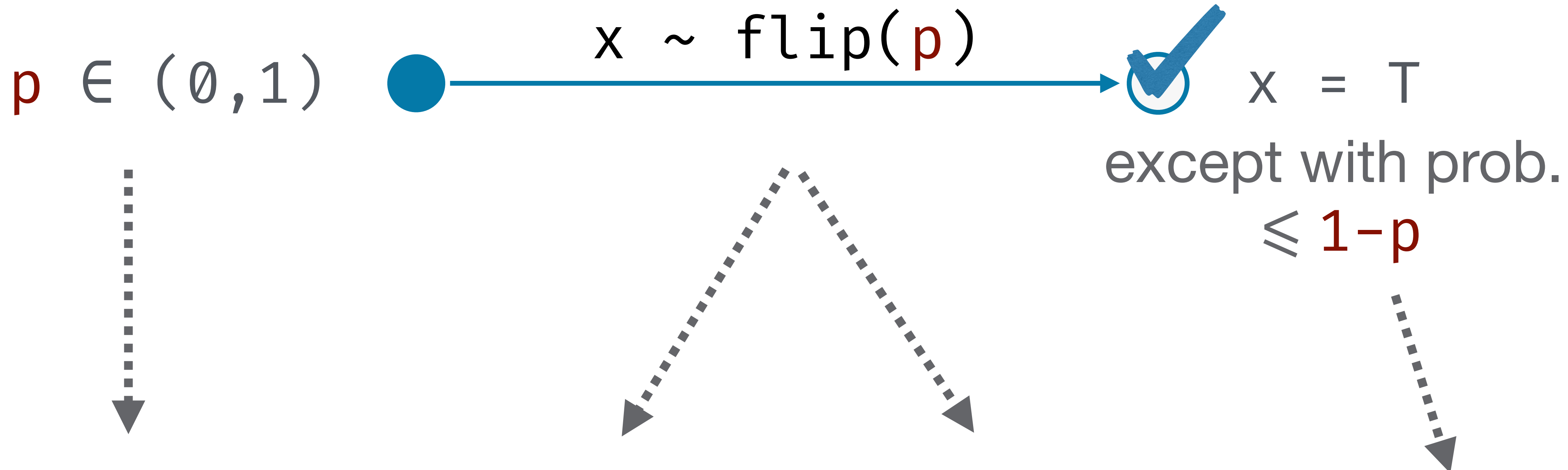




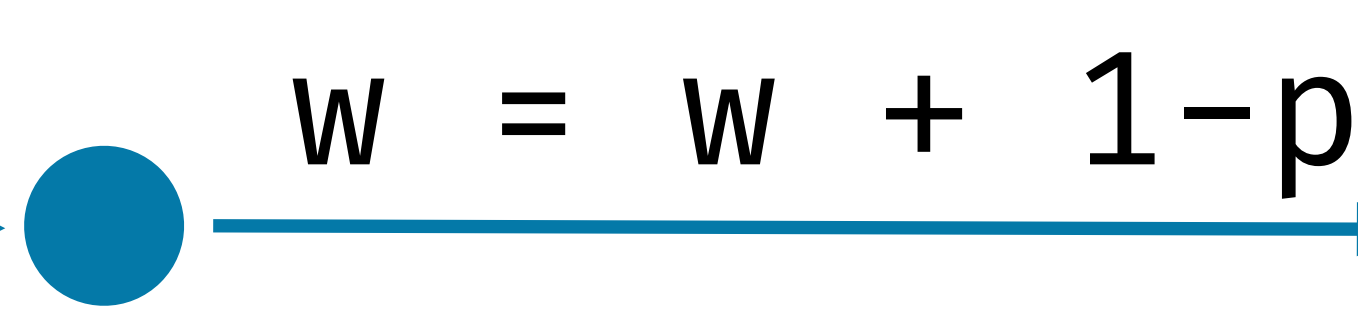
$p \in (0, 1)$
 \wedge
 $w = 0$








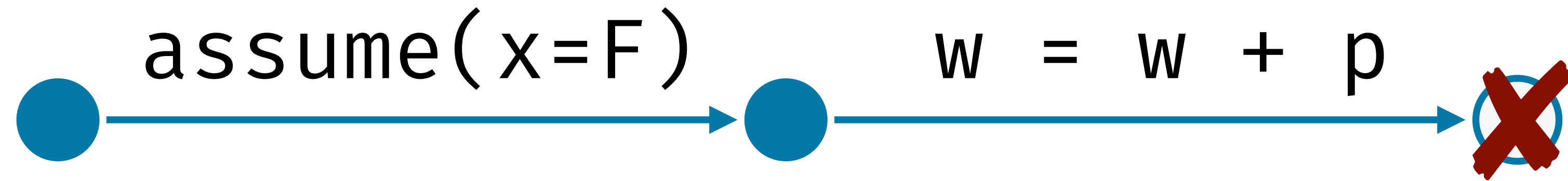
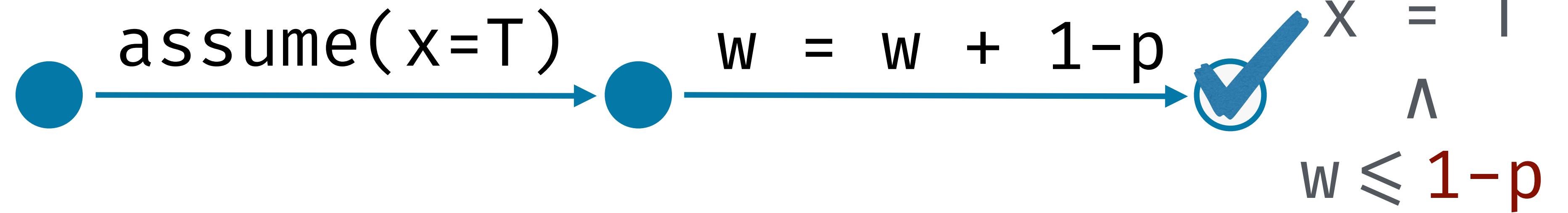
$$p \in (0, 1) \\ \wedge \\ w = 0$$




$$x = T \\ \wedge \\ w \leq 1-p$$

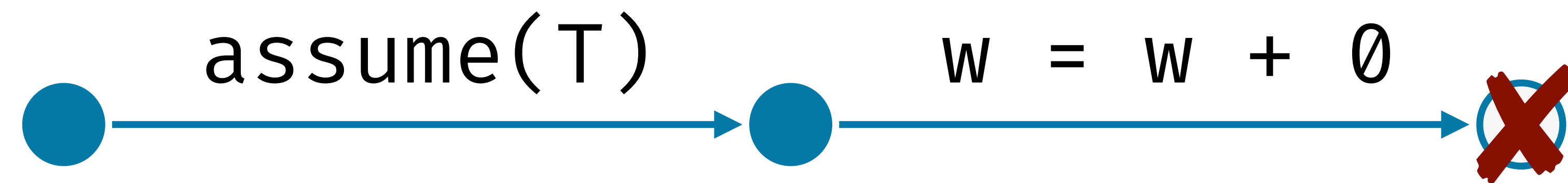
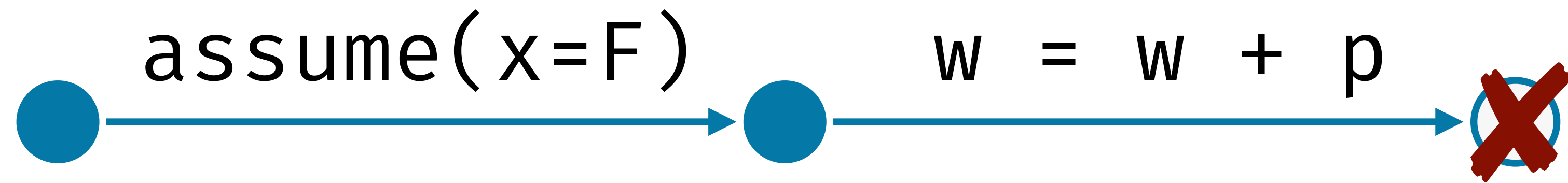
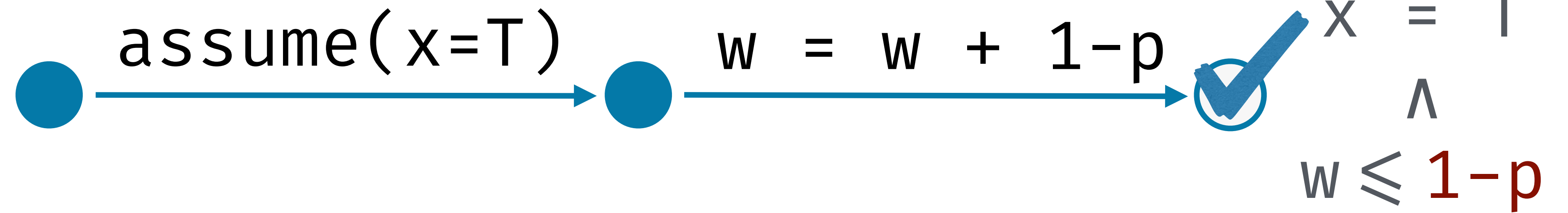
challenge many different axiomatizations

$p \in (0, 1)$
 \wedge
 $w = 0$



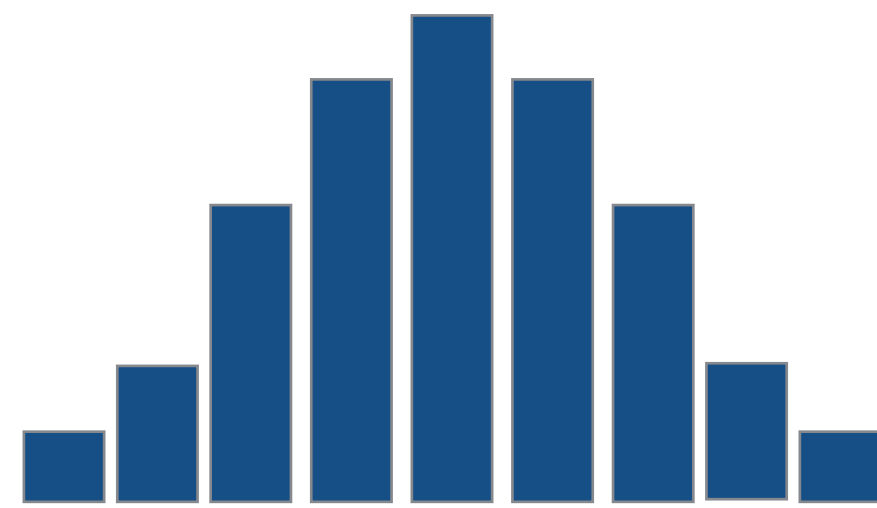
challenge many different axiomatizations

$p \in (0, 1)$
 \wedge
 $w = 0$



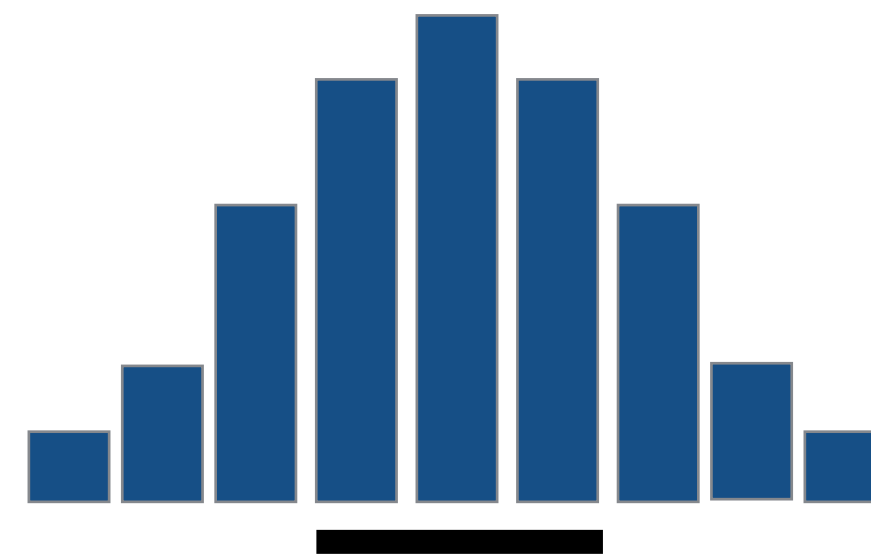
challenge many different axiomatizations

$x \sim \text{dist}$



challenge many different axiomatizations

$x \sim \text{dist}$

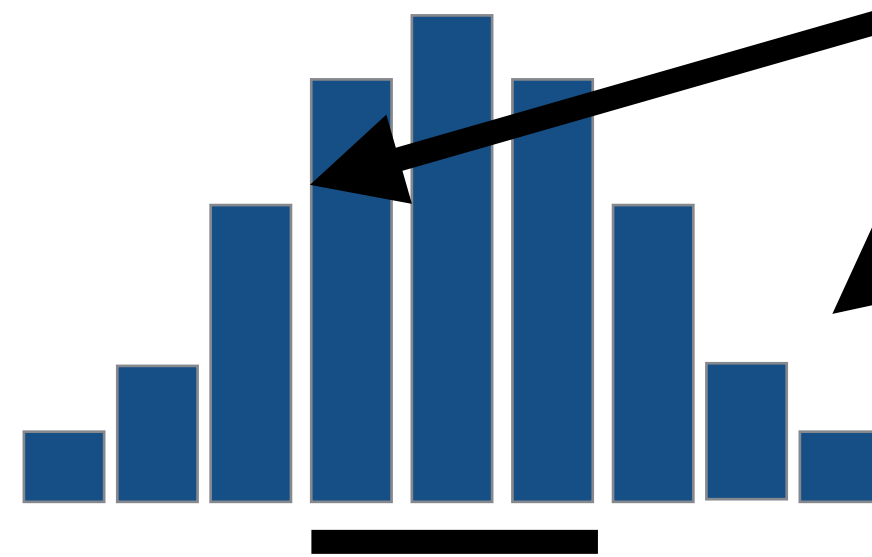


assume x is one of
those 3 values

challenge many different axiomatizations

$x \sim \text{dist}$

failure probability is

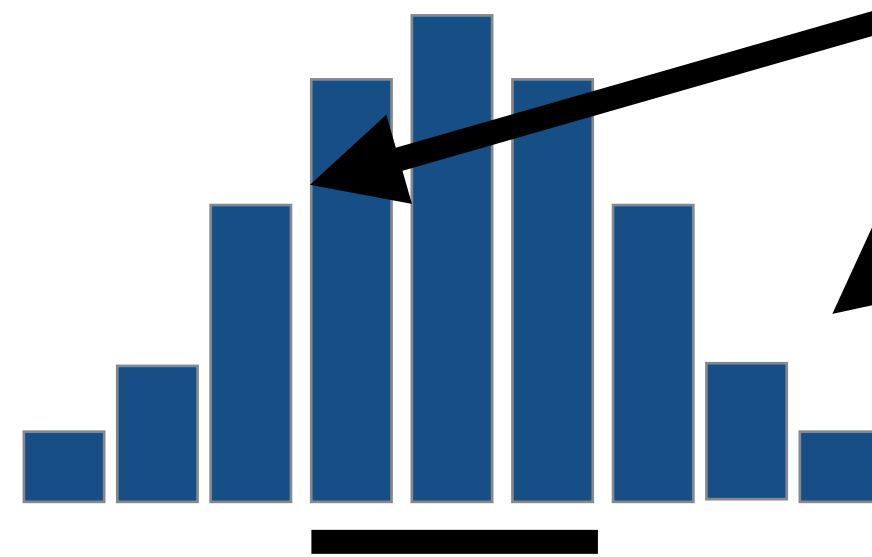


assume x is one of
those 3 values

challenge many different axiomatizations

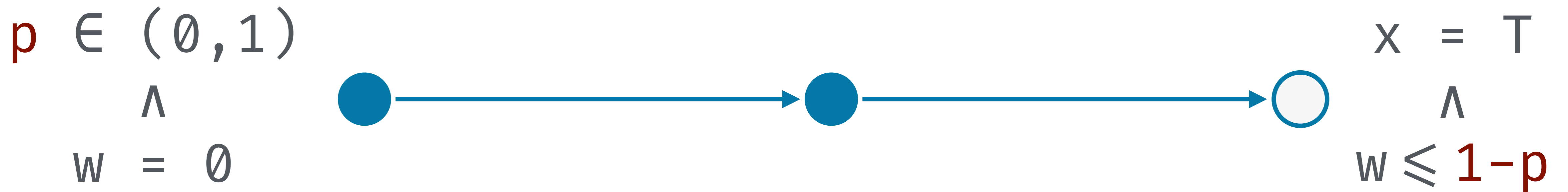
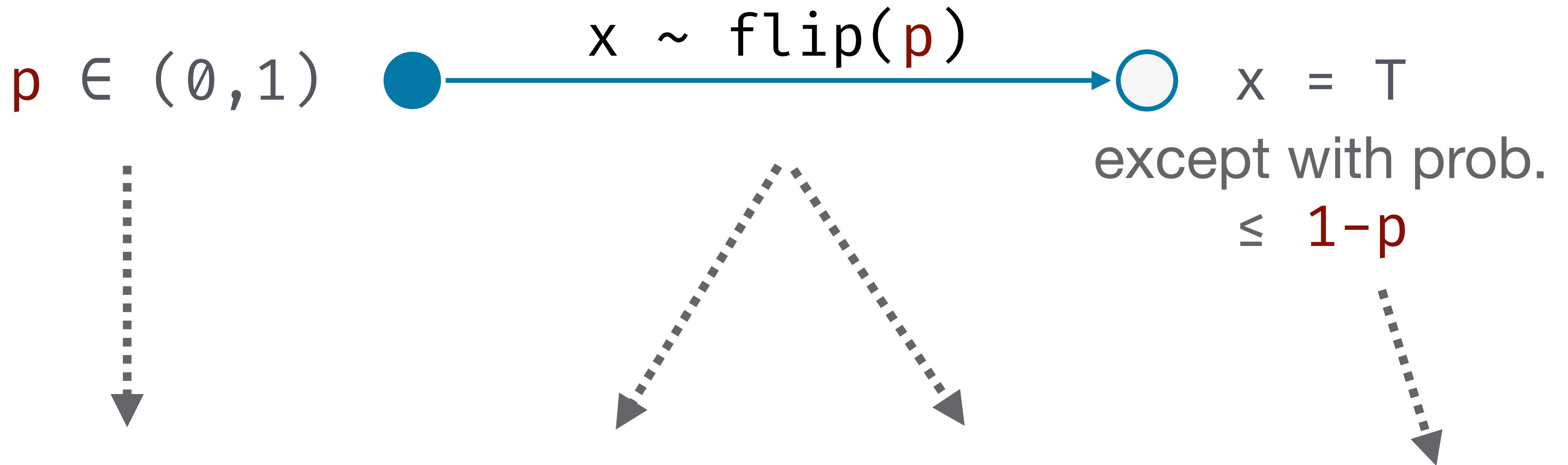
$x \sim \text{dist}$

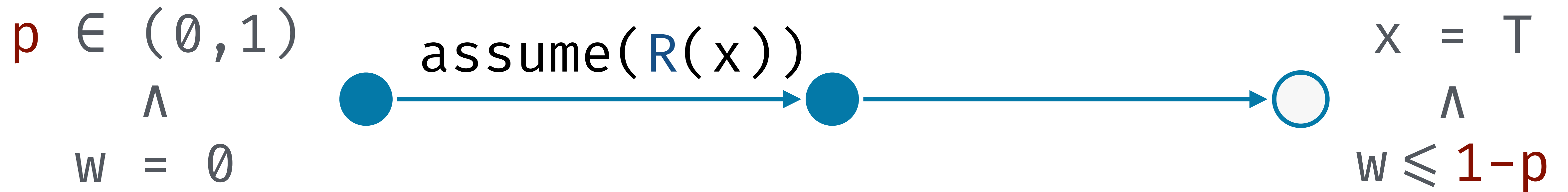
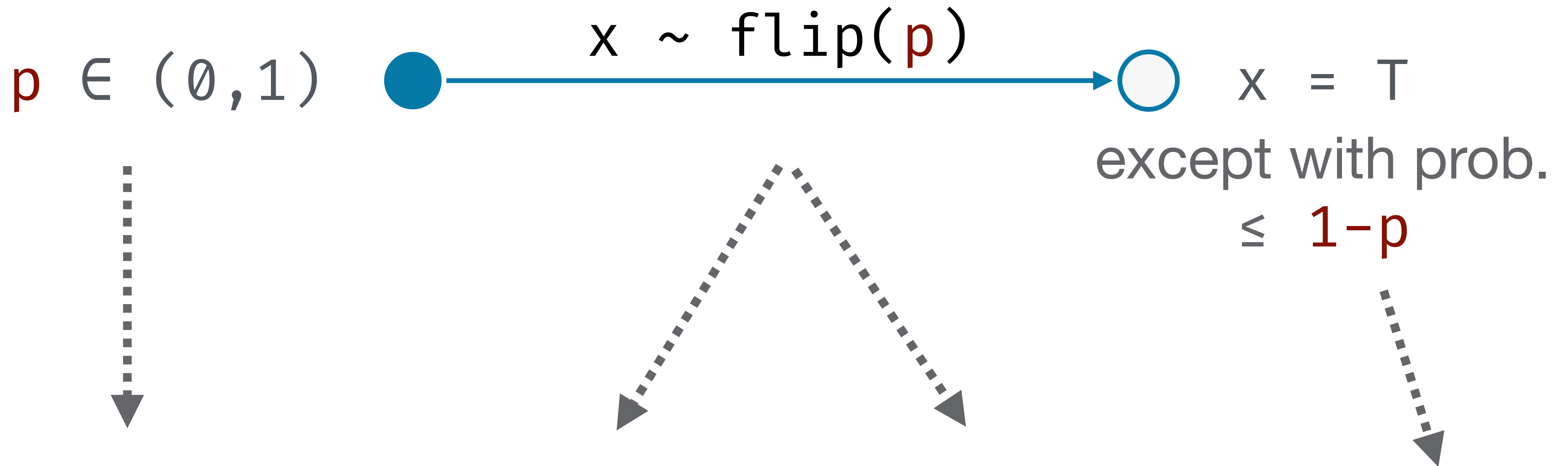
failure probability is

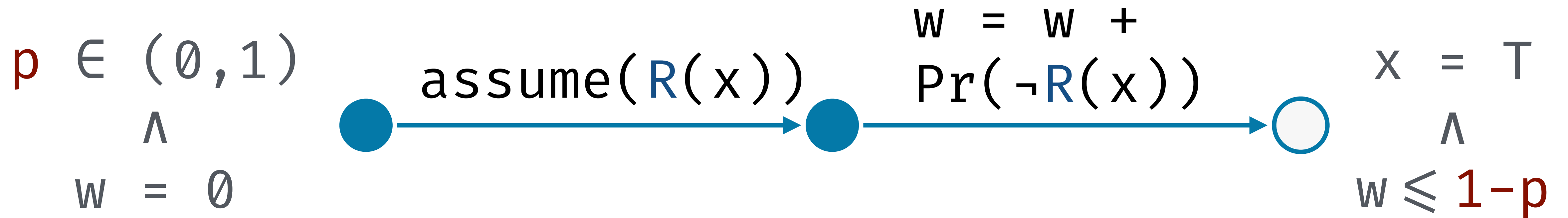
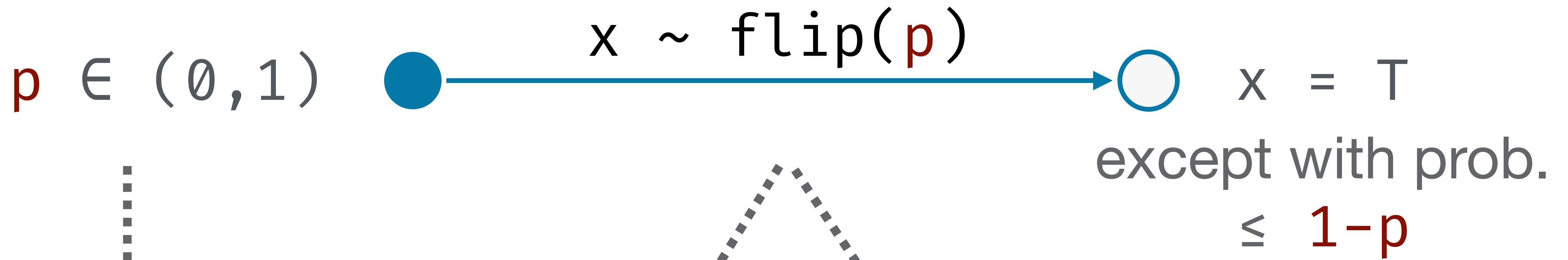


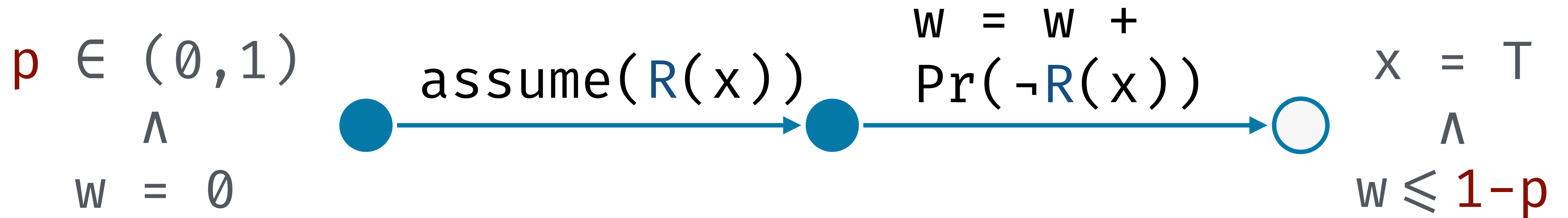
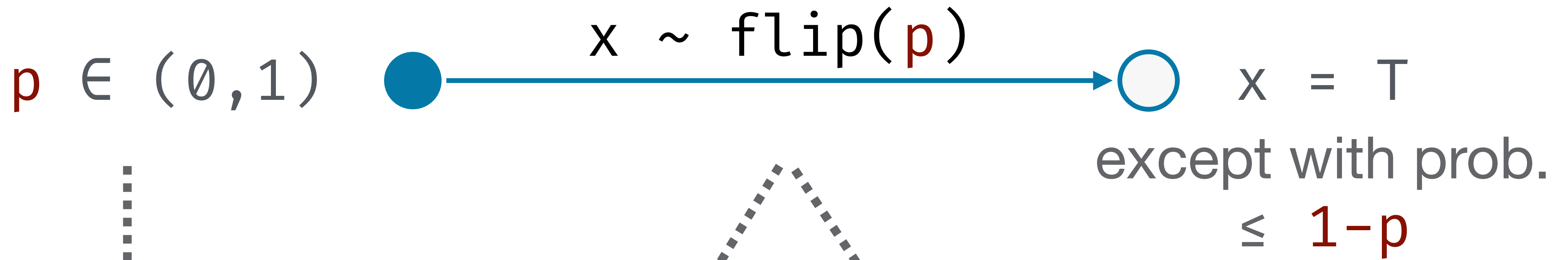
assume x is one of
those 3 values

challenge many different axiomatizations

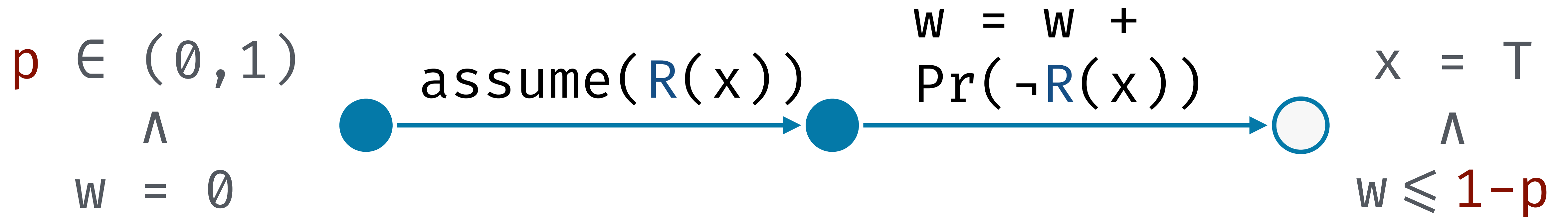
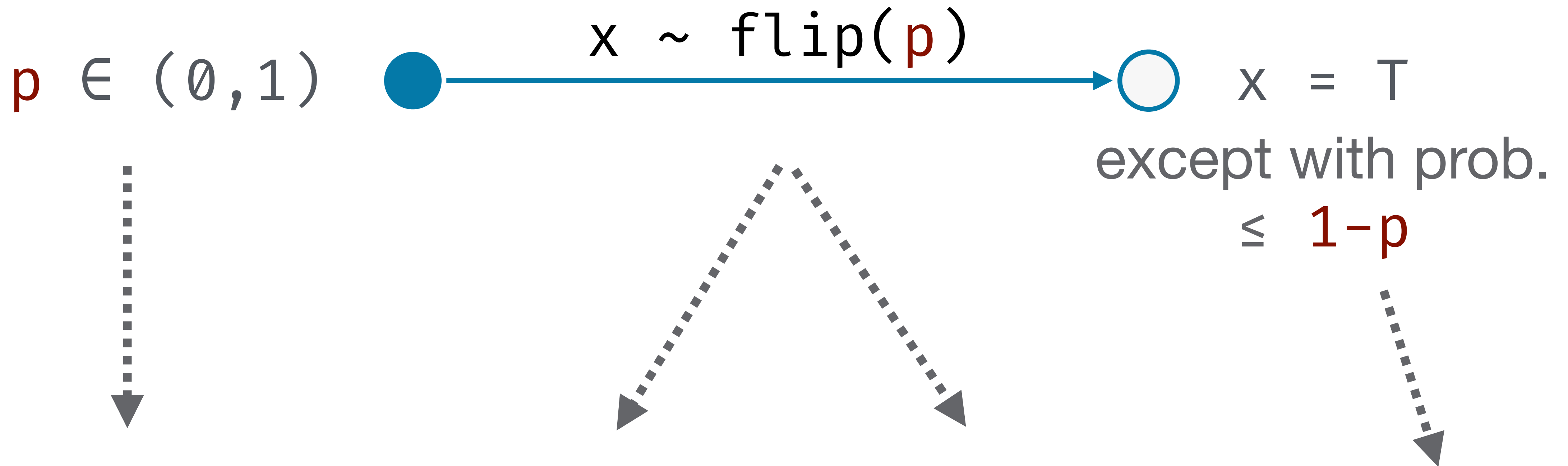






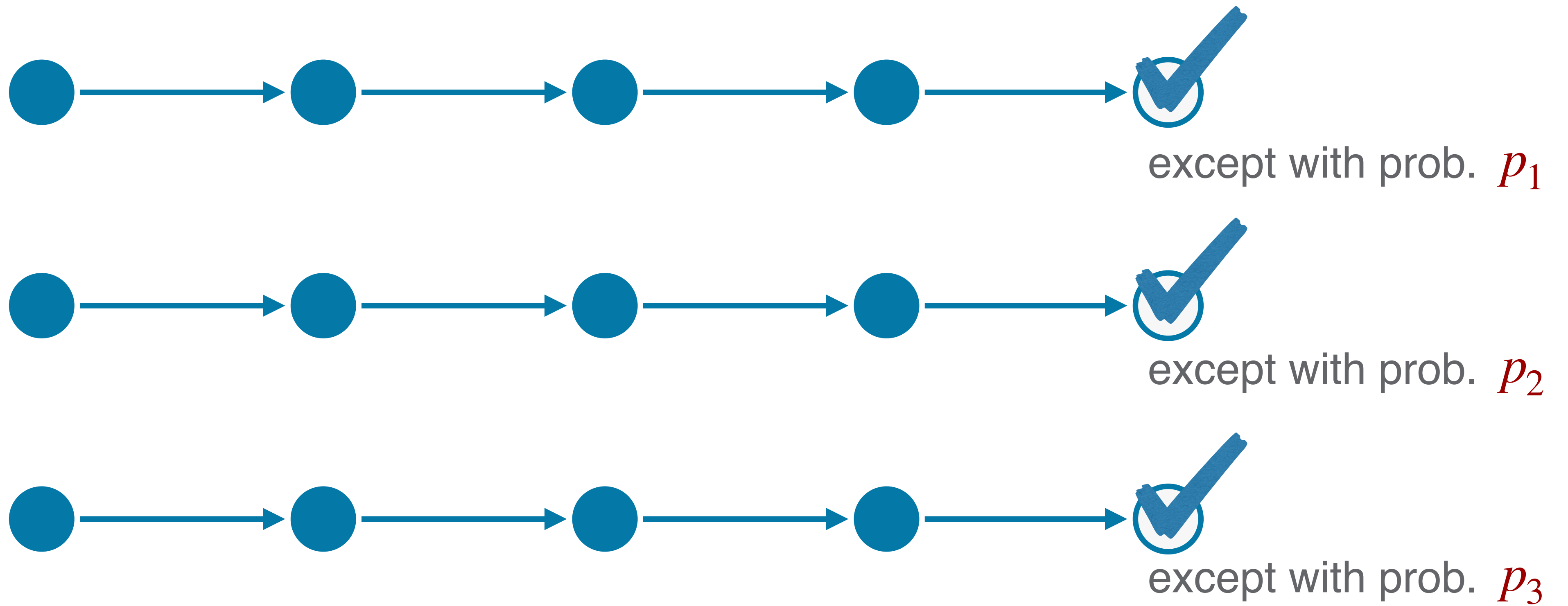


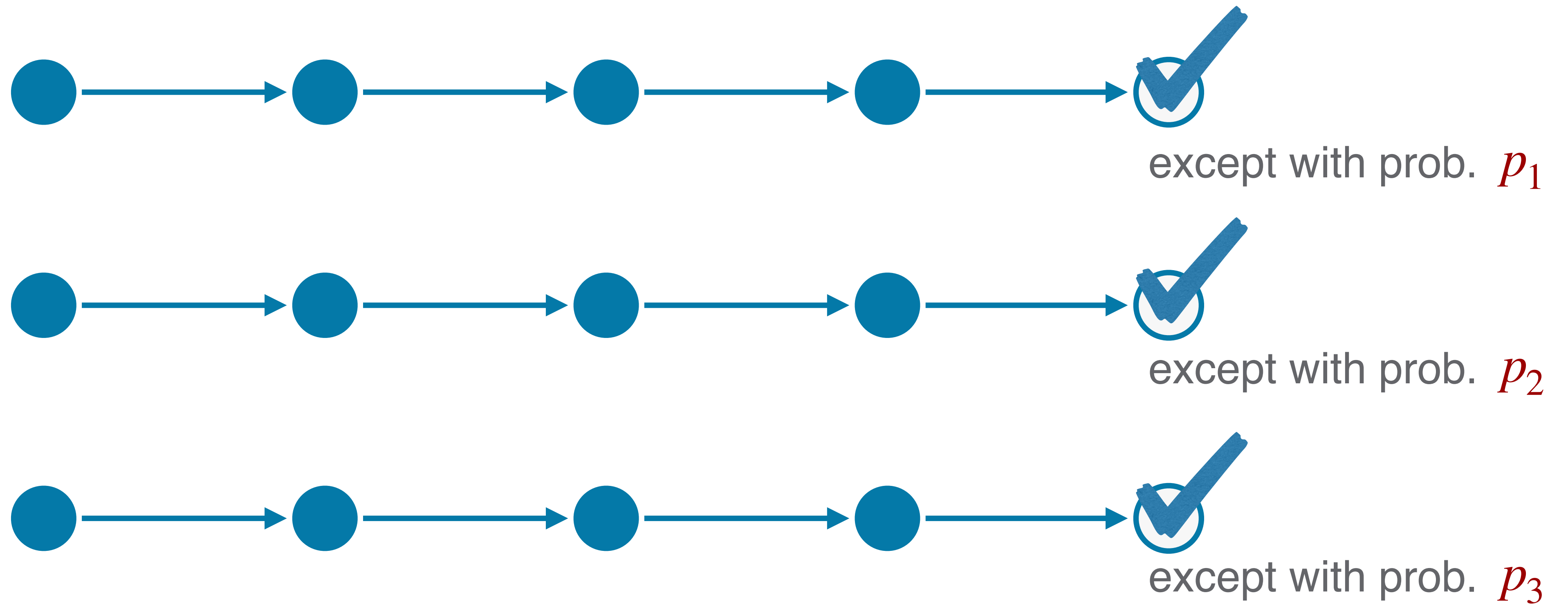
$\exists R. \forall w, w', x.$



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

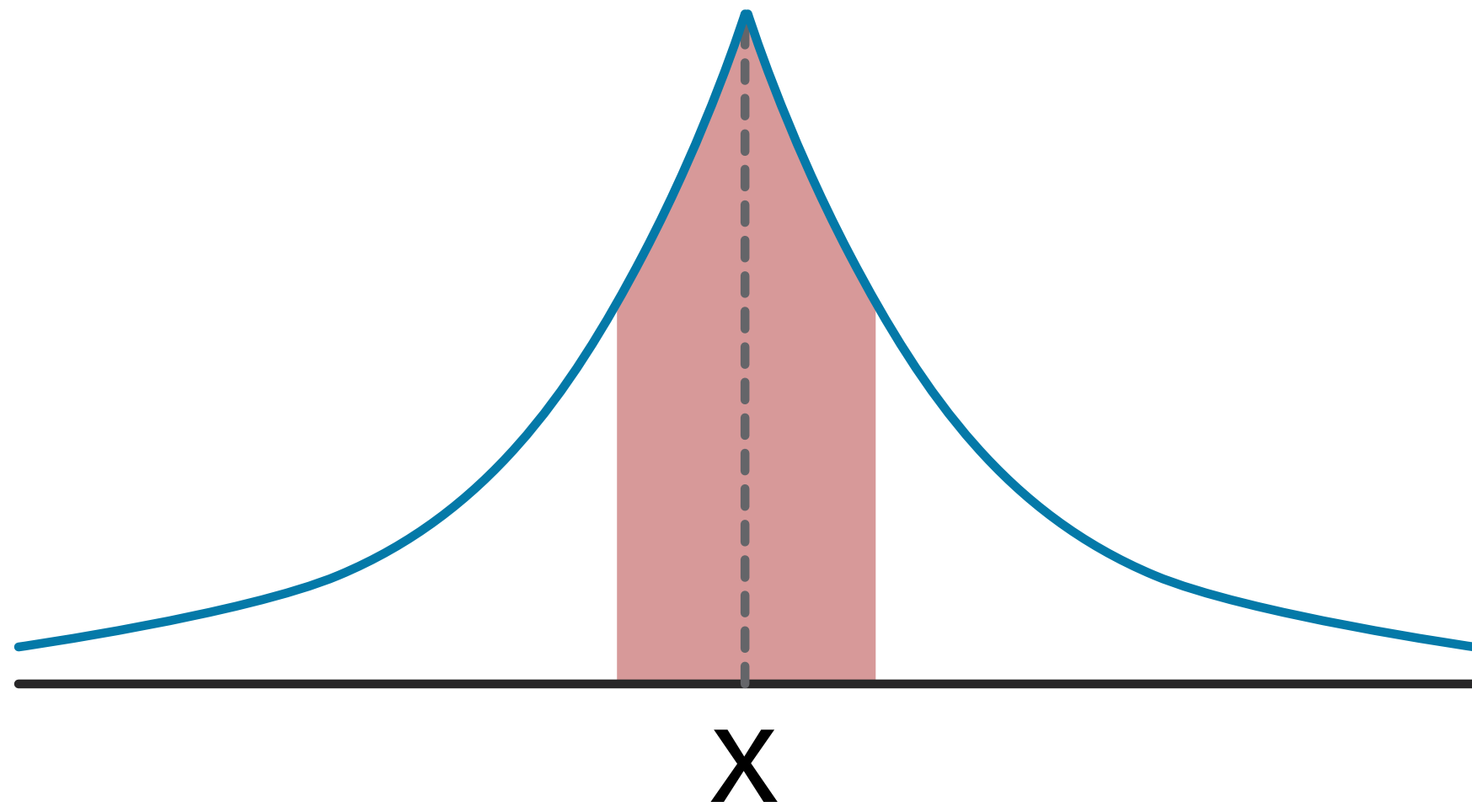
$$w = 0 \wedge R(x) \wedge w' = w + \text{Pr}(\neg R(x)) \implies x \wedge w' \leq 1 - p$$



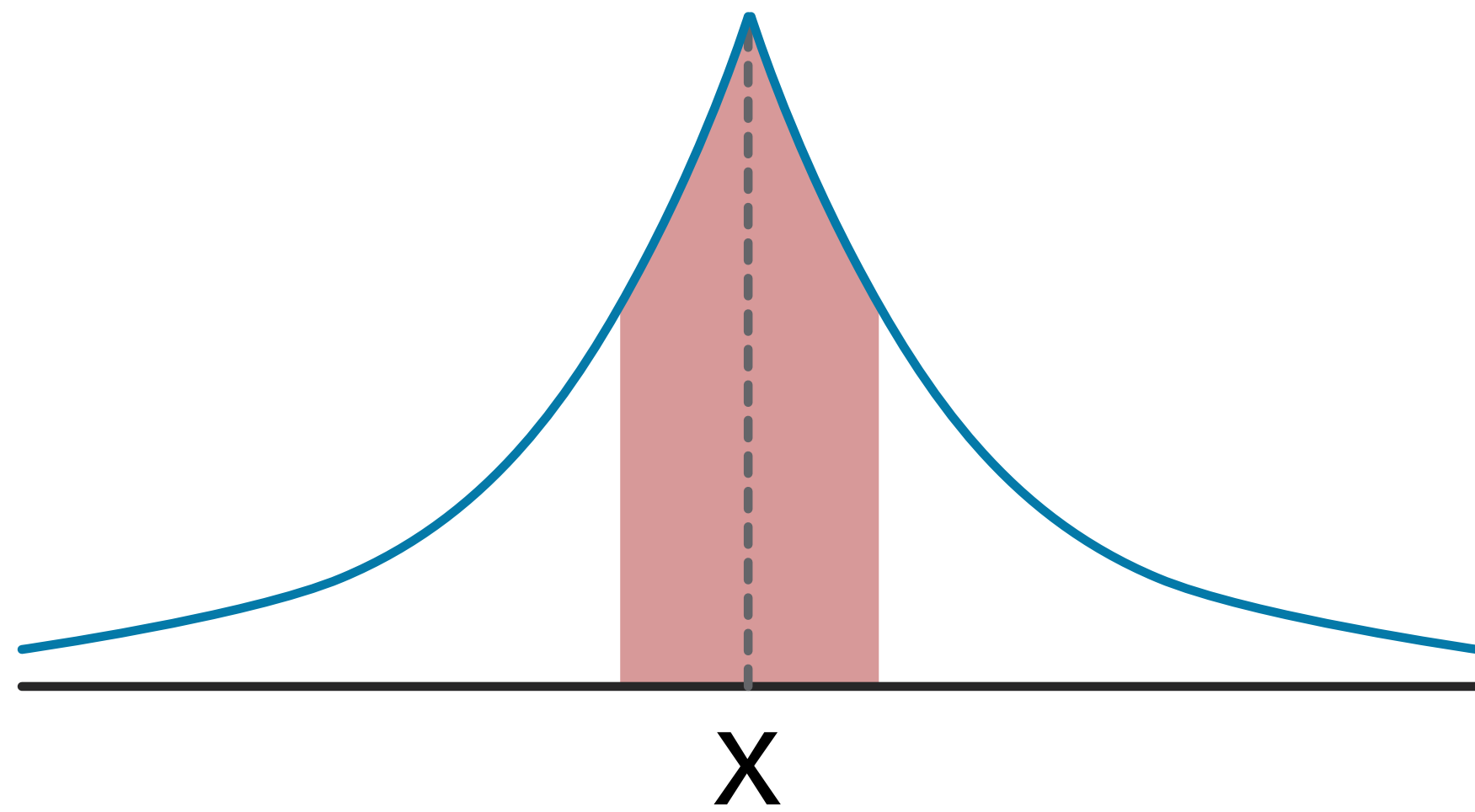


simply, total failure probability is $\sum_i p_i$

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



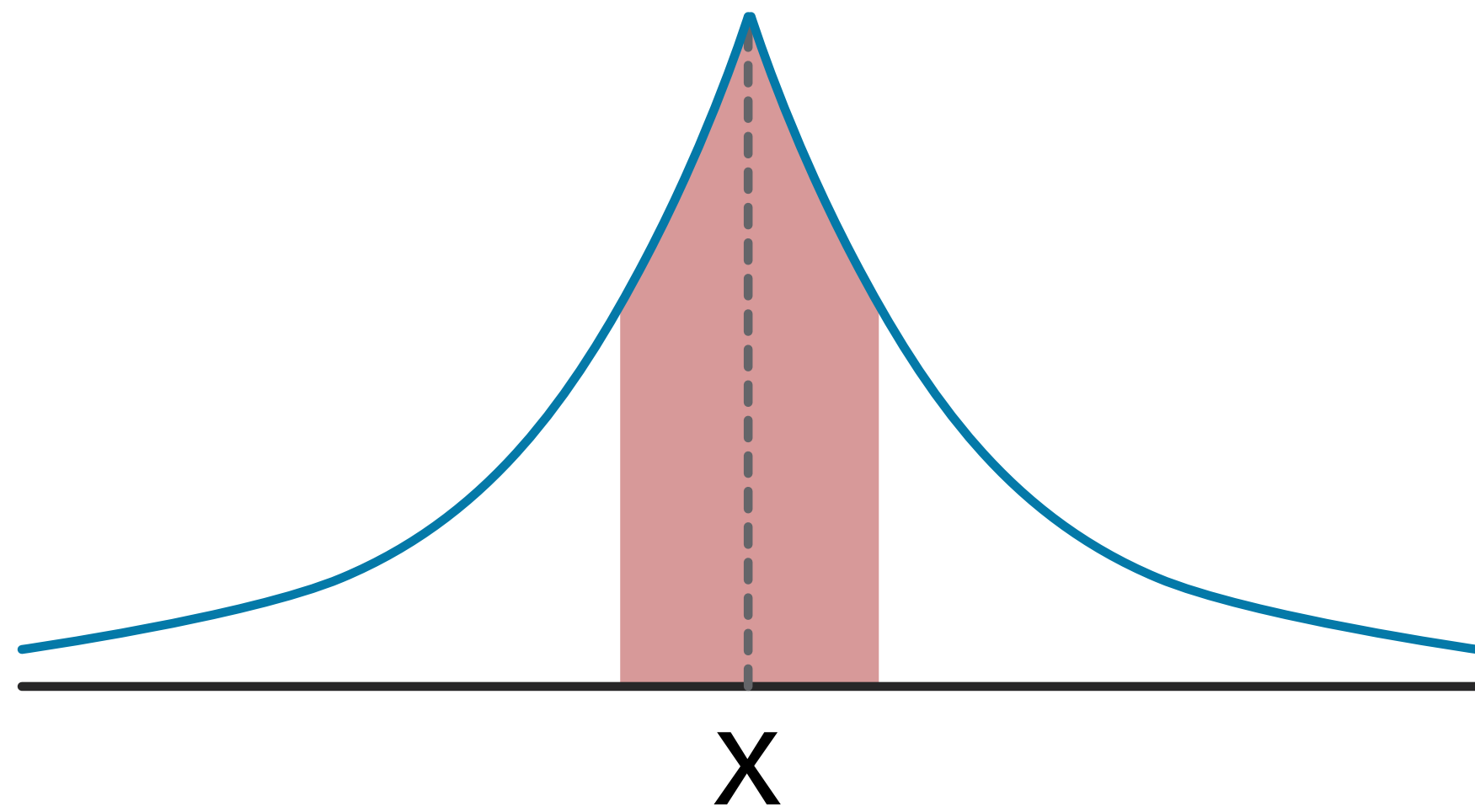
$$y \sim \text{Lap}(x, s)$$



axiom family

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

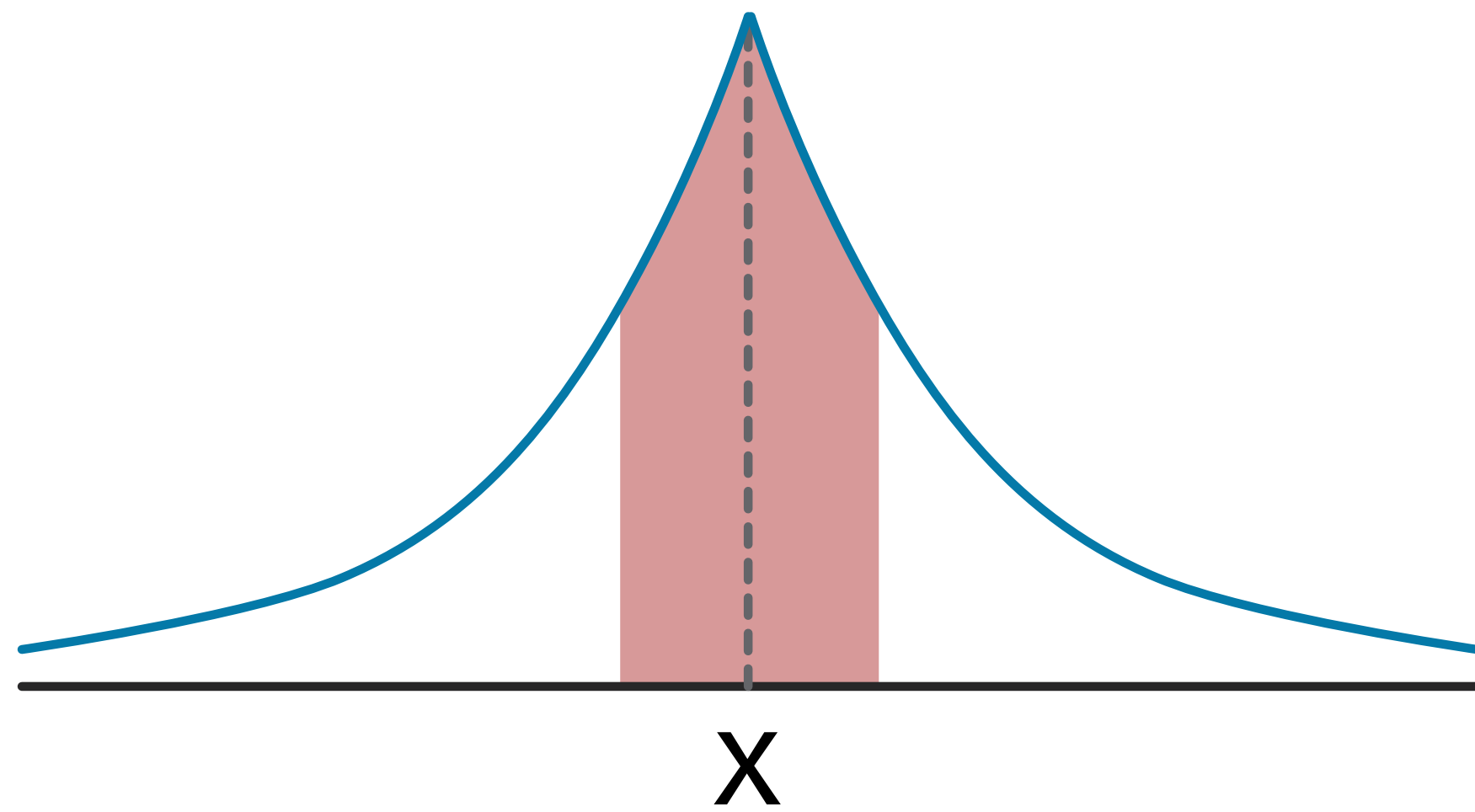
$$y \sim \text{Lap}(x, s)$$



axiom family

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

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



axiom family

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

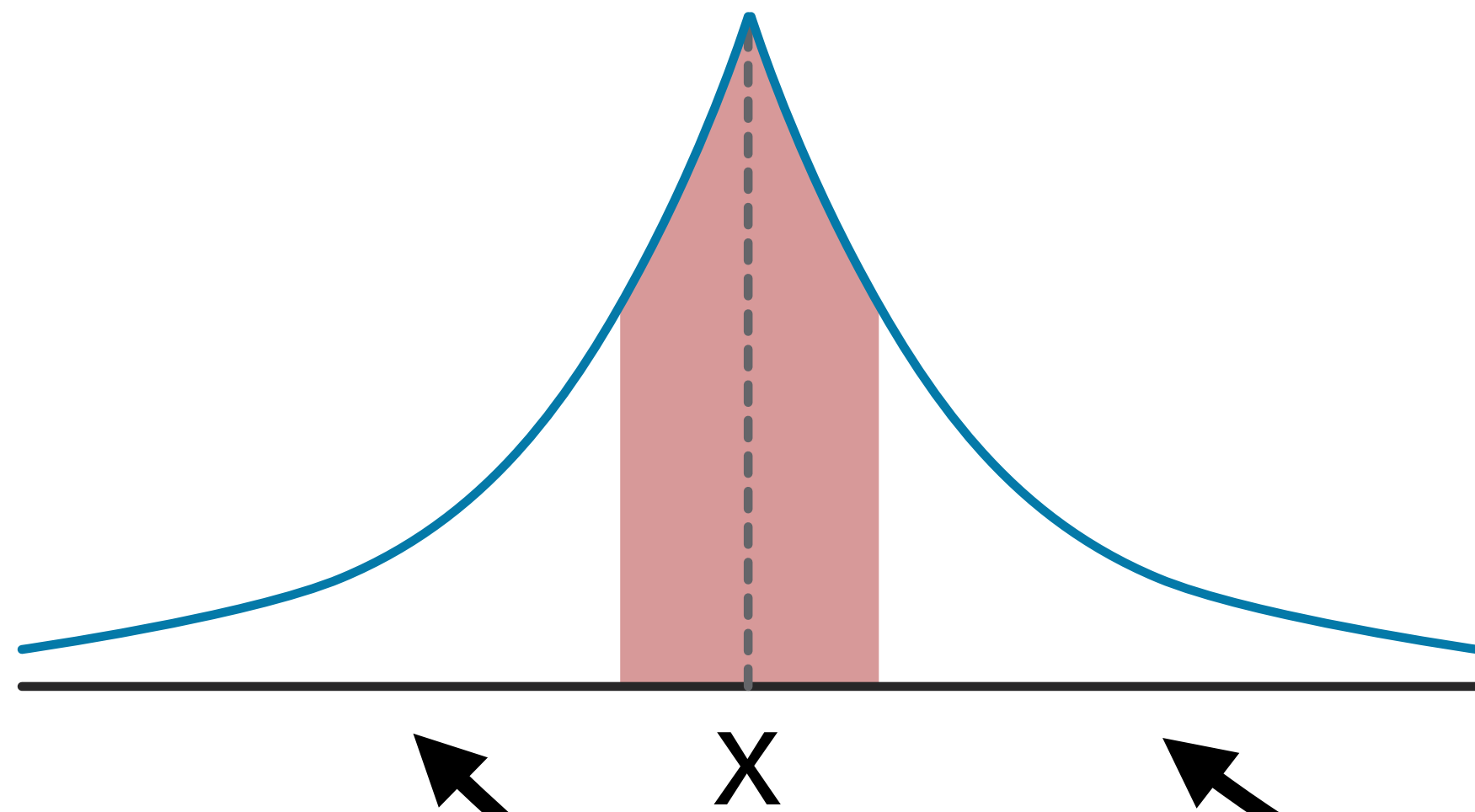
with failure probability

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

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

axiom family

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



with failure probability

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

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```

$p \in (0, 1)$

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```


$p \in (0, 1)$

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```

$\forall j. q[r] \geq q[j] - 4/\varepsilon * \log(|q|/p)$
except with prob. $\leq p$

$p \in (0, 1)$

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```



$\forall j. q[r] \geq q[j] - 4/\epsilon * \log(|q|/p)$
except with prob. $\leq p$

$p \in (0, 1)$

```
def rnm(q):  
    i, best, r = 0  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
    return r
```



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

with failure probability $\frac{p}{|q|}$

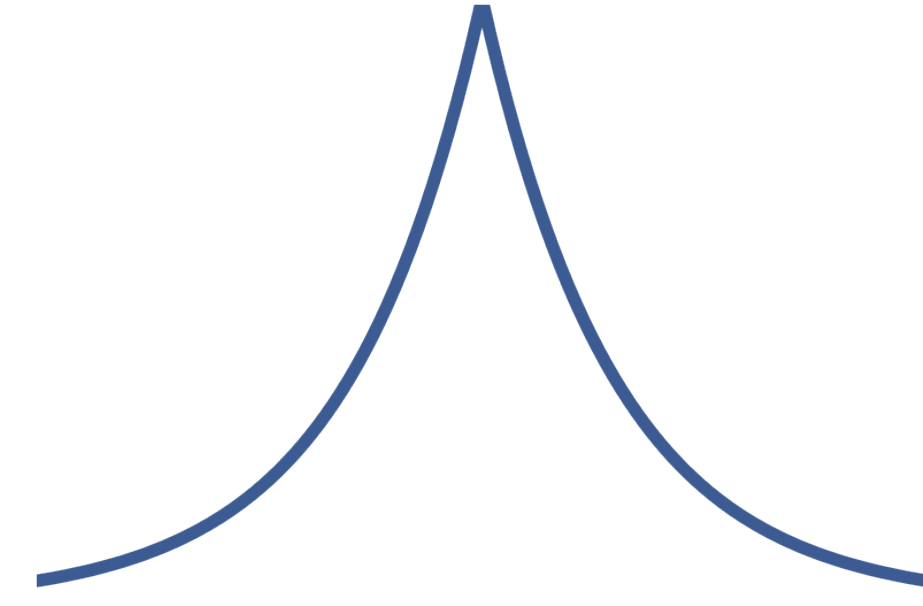
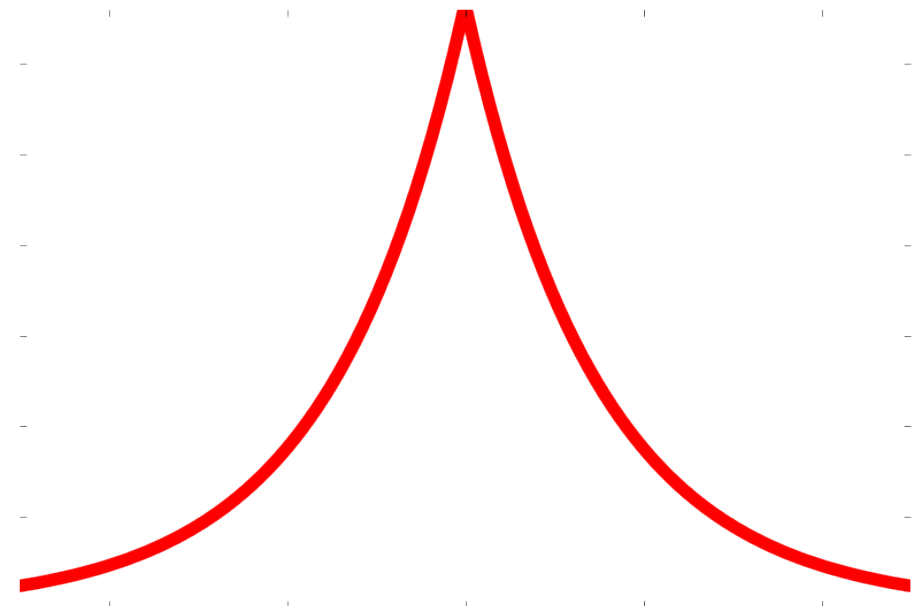
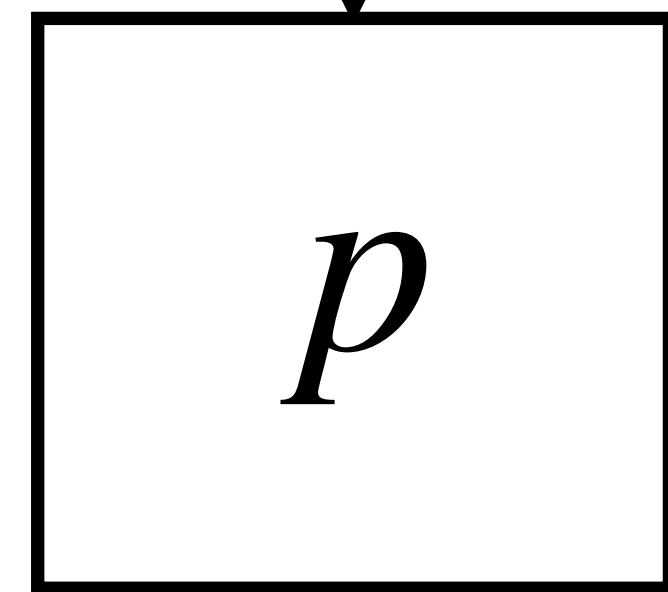
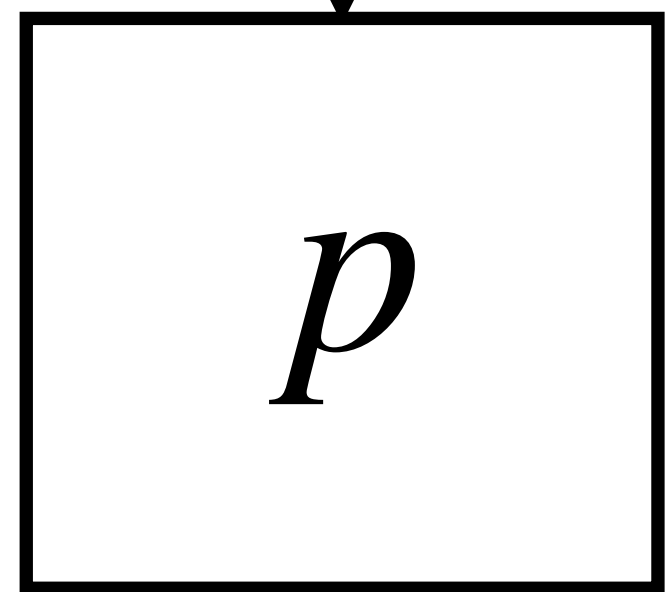
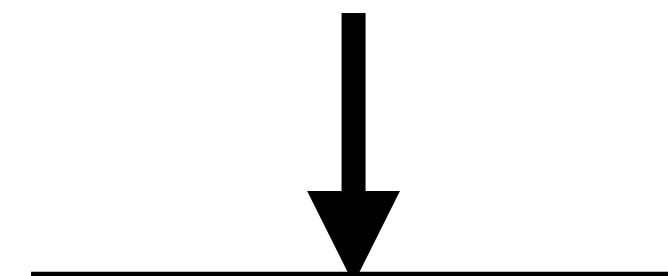
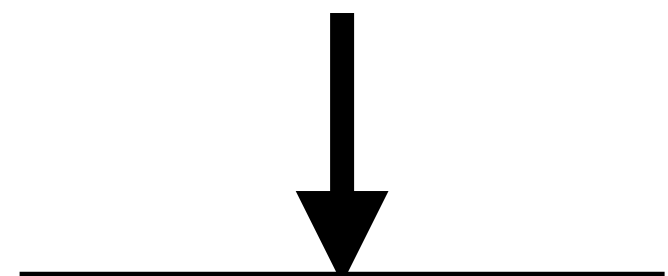
$\forall j. q[r] \geq q[j] - 4/\epsilon * \log(|q|/p)$
except with prob. $\leq p$

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

theme get rid of probability! long live logic!

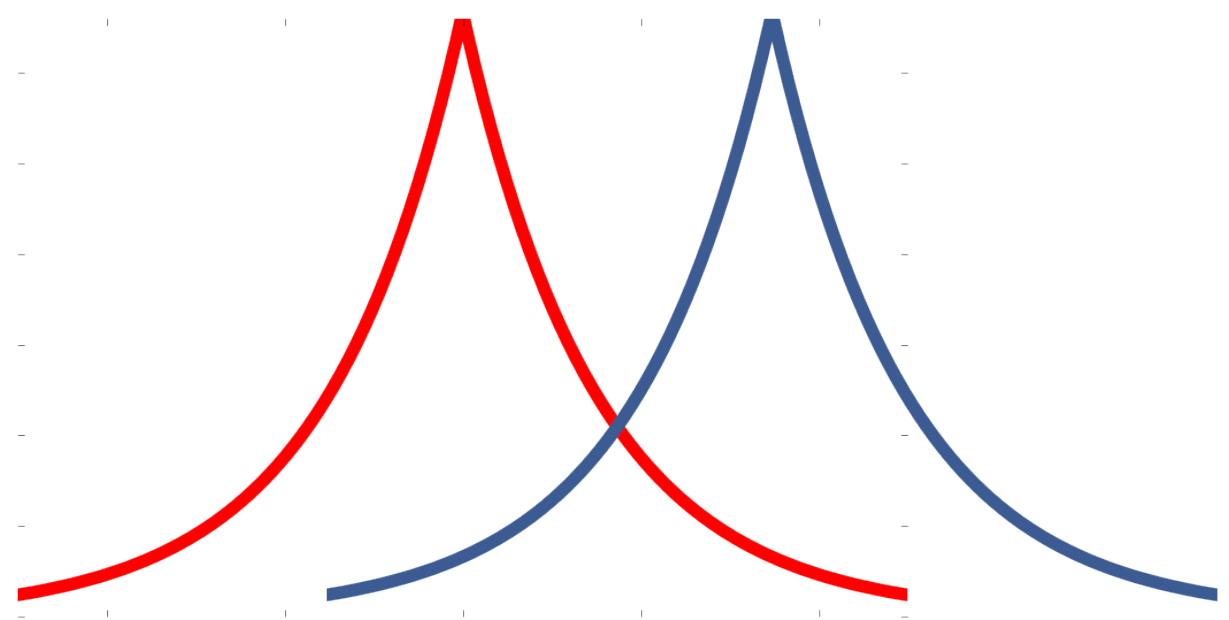
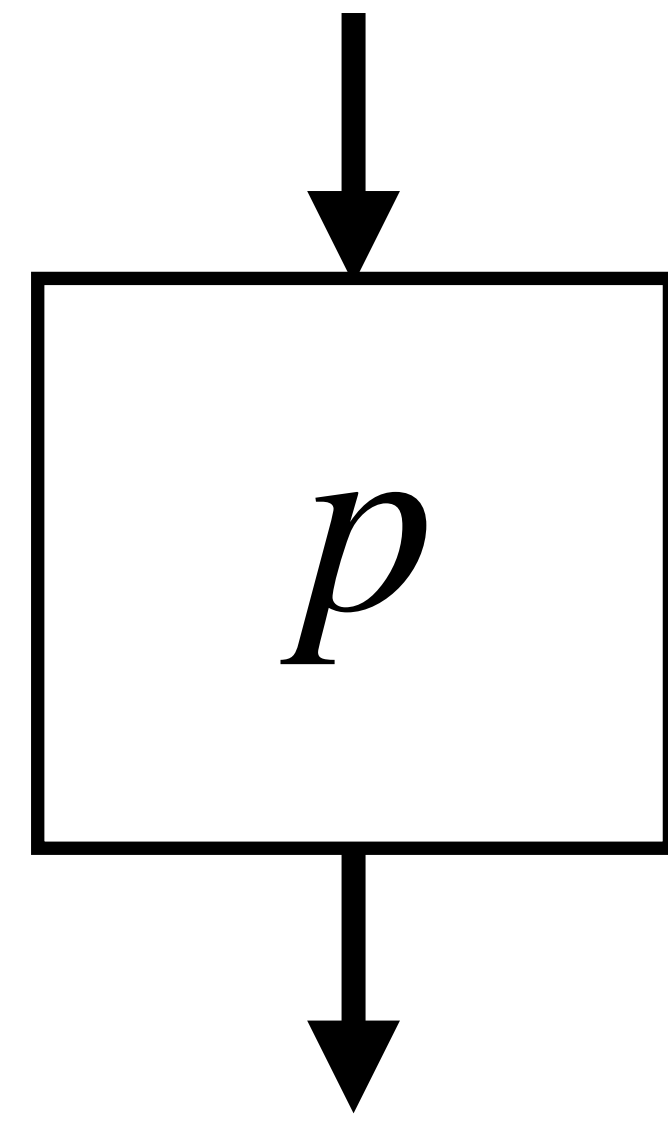
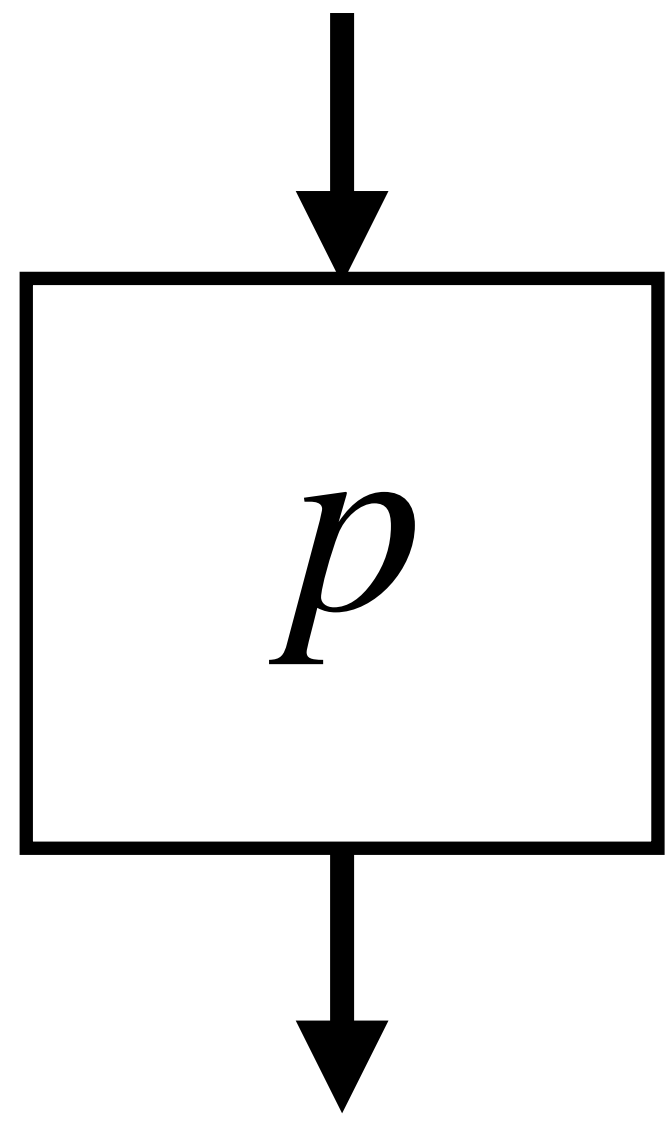
A	6
B	1
C	0

A	6
B	1
C	1

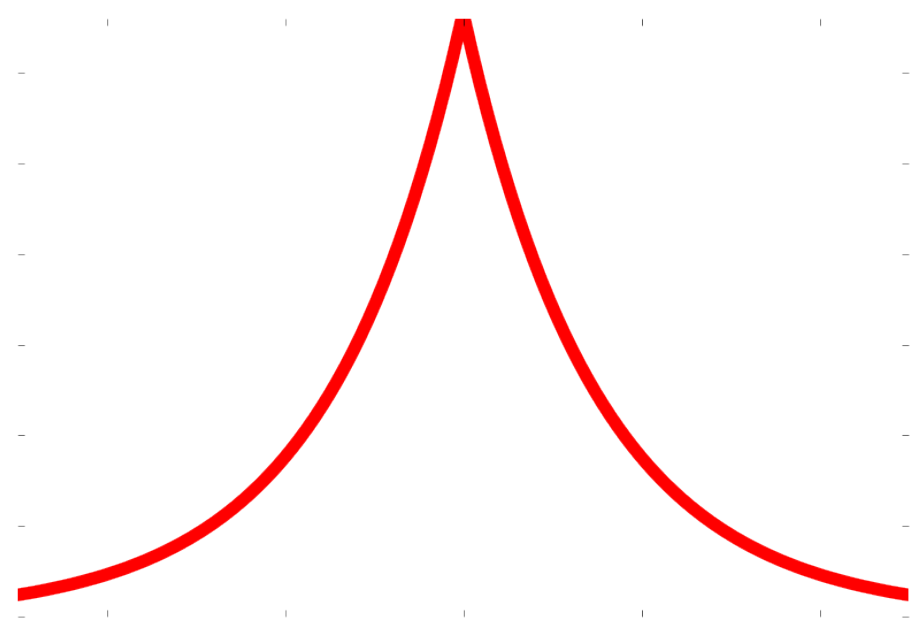
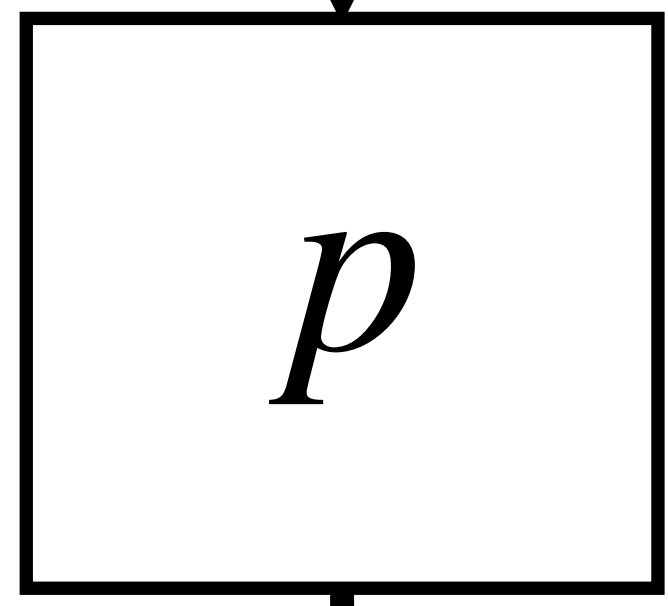
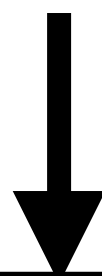


A	6
B	1
C	0

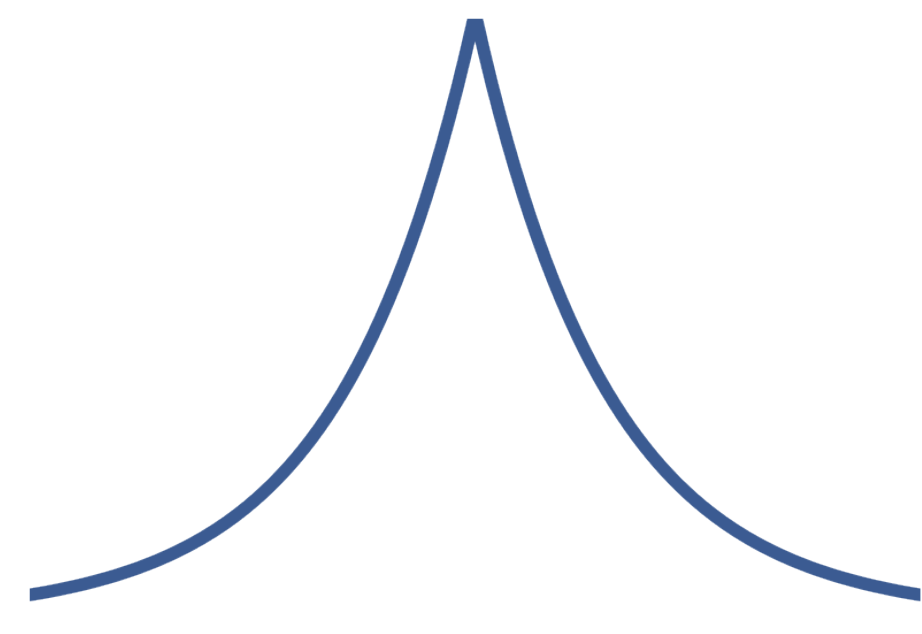
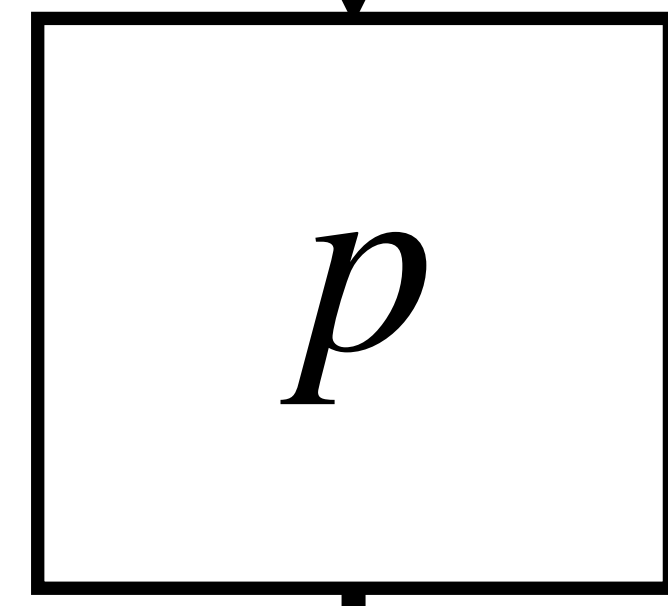
A	6
B	1
C	1



A	6
B	1
C	0



A	6
B	1
C	1



$$\forall d \sim d', a, \epsilon .$$

$$\forall d \sim d', a, \epsilon.$$

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

$$\forall d \sim d', a, \epsilon.$$

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

problems

problems

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

problems

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

existing automated techniques only work for simple algorithms

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

key ideas

view differential privacy coupling proofs as games

key ideas

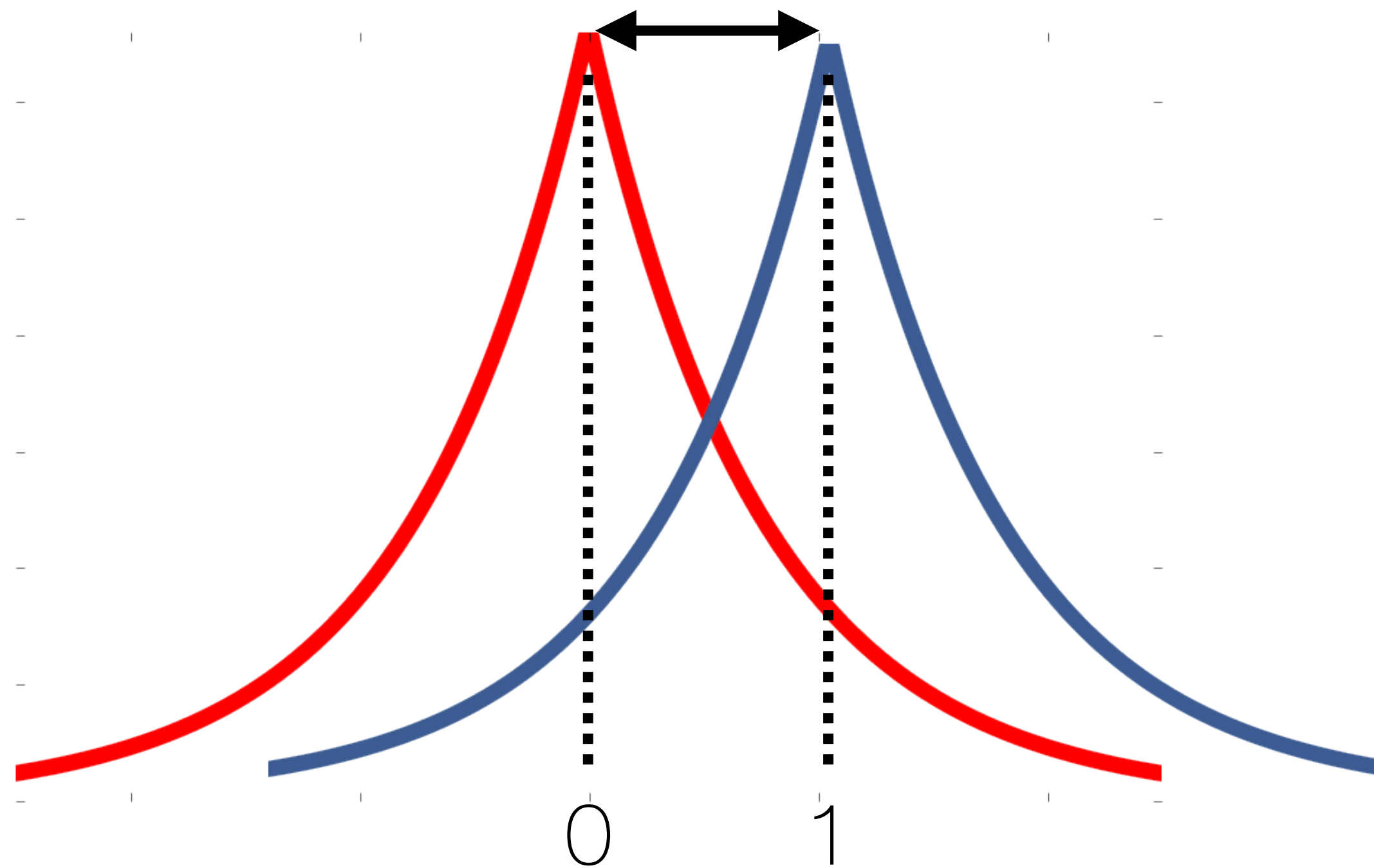
view differential privacy coupling proofs as games

solve a program **synthesis/verification problem**

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

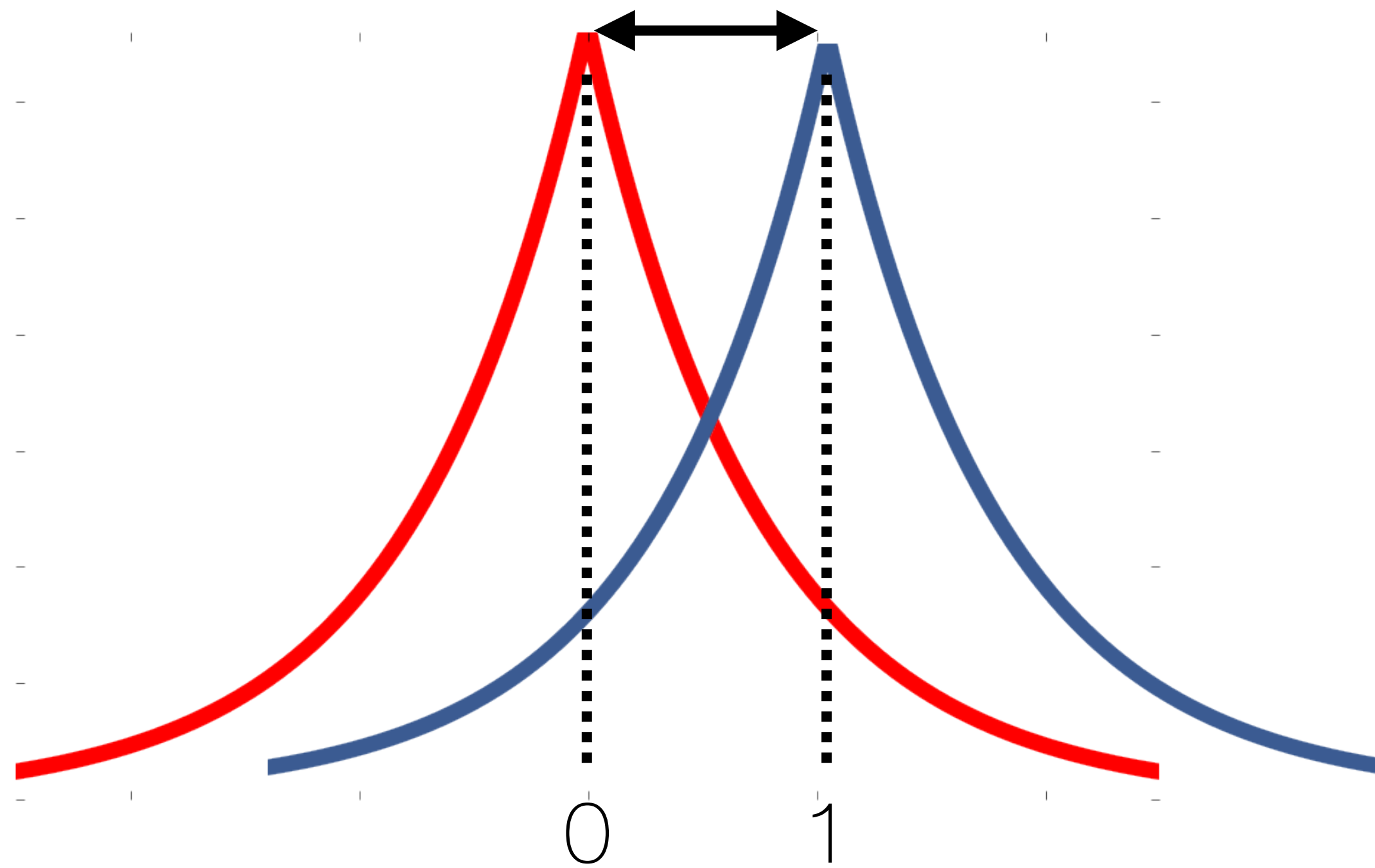
variable approximate couplings

scale of distributions is $1/y$



variable approximate couplings

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

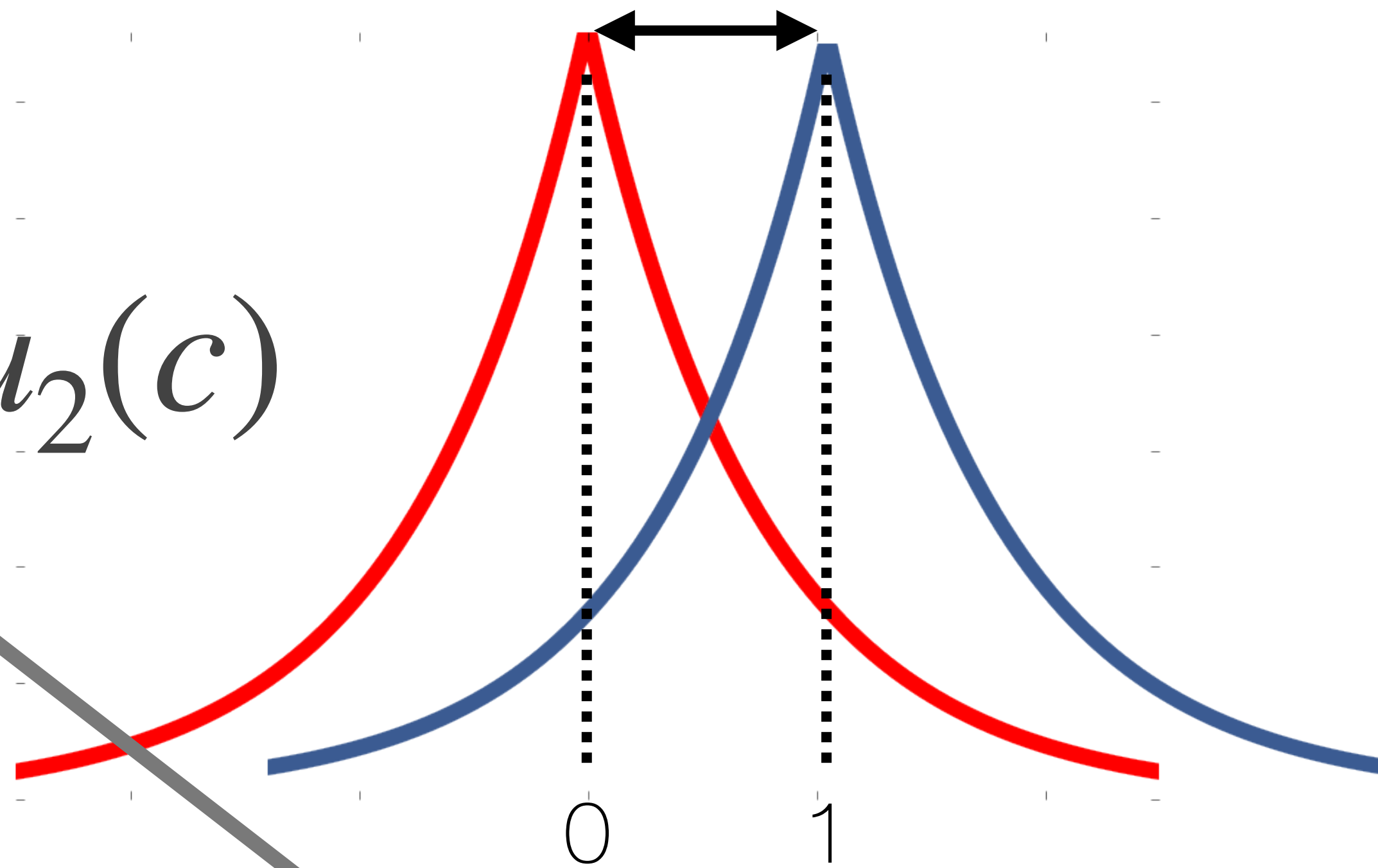


$$\{(c, c, y) \mid c \in \mathbb{Z}\}$$

variable approximate couplings

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

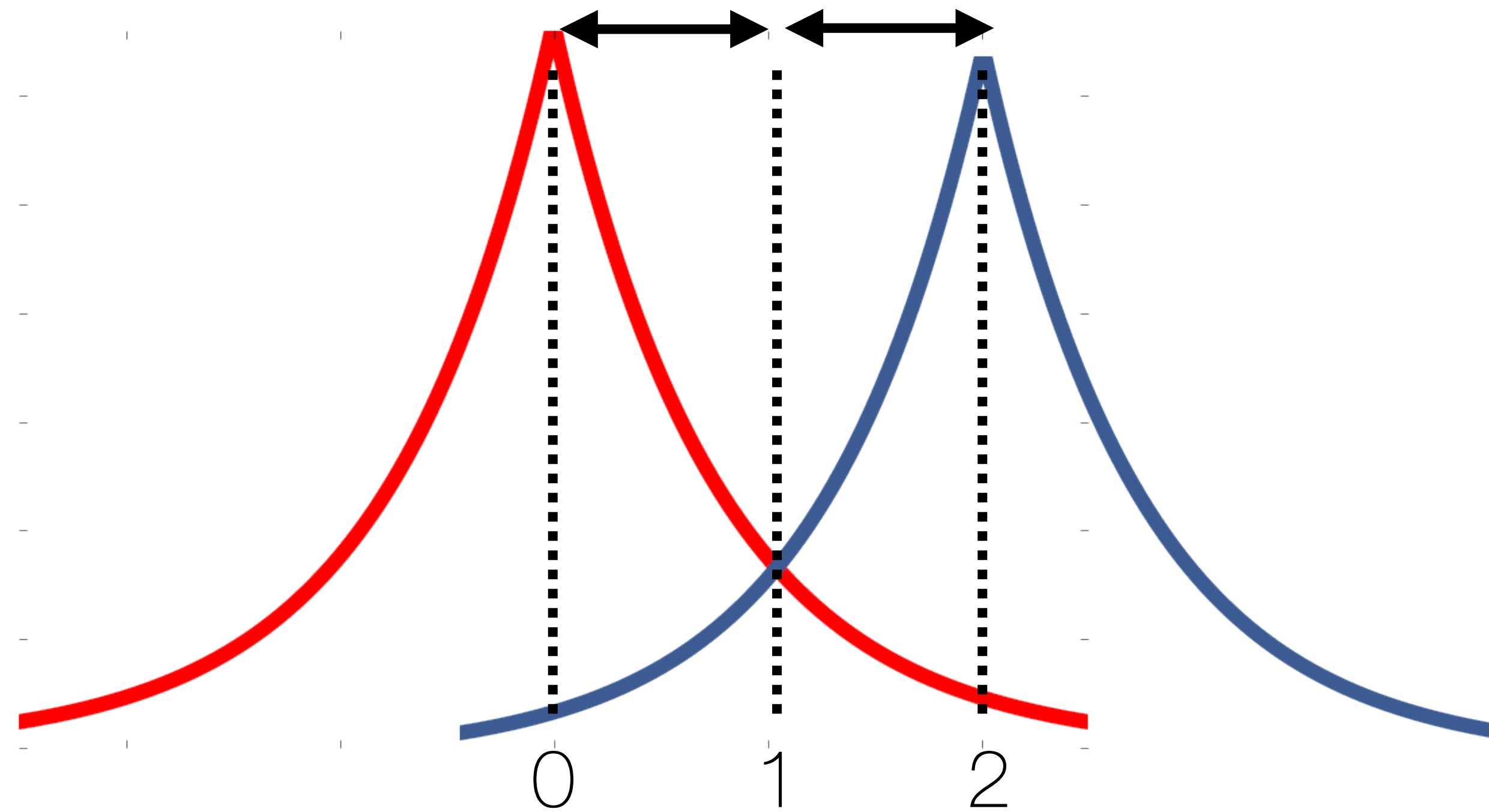
$$\mu_1(c) \leq e^y \cdot \mu_2(c)$$



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

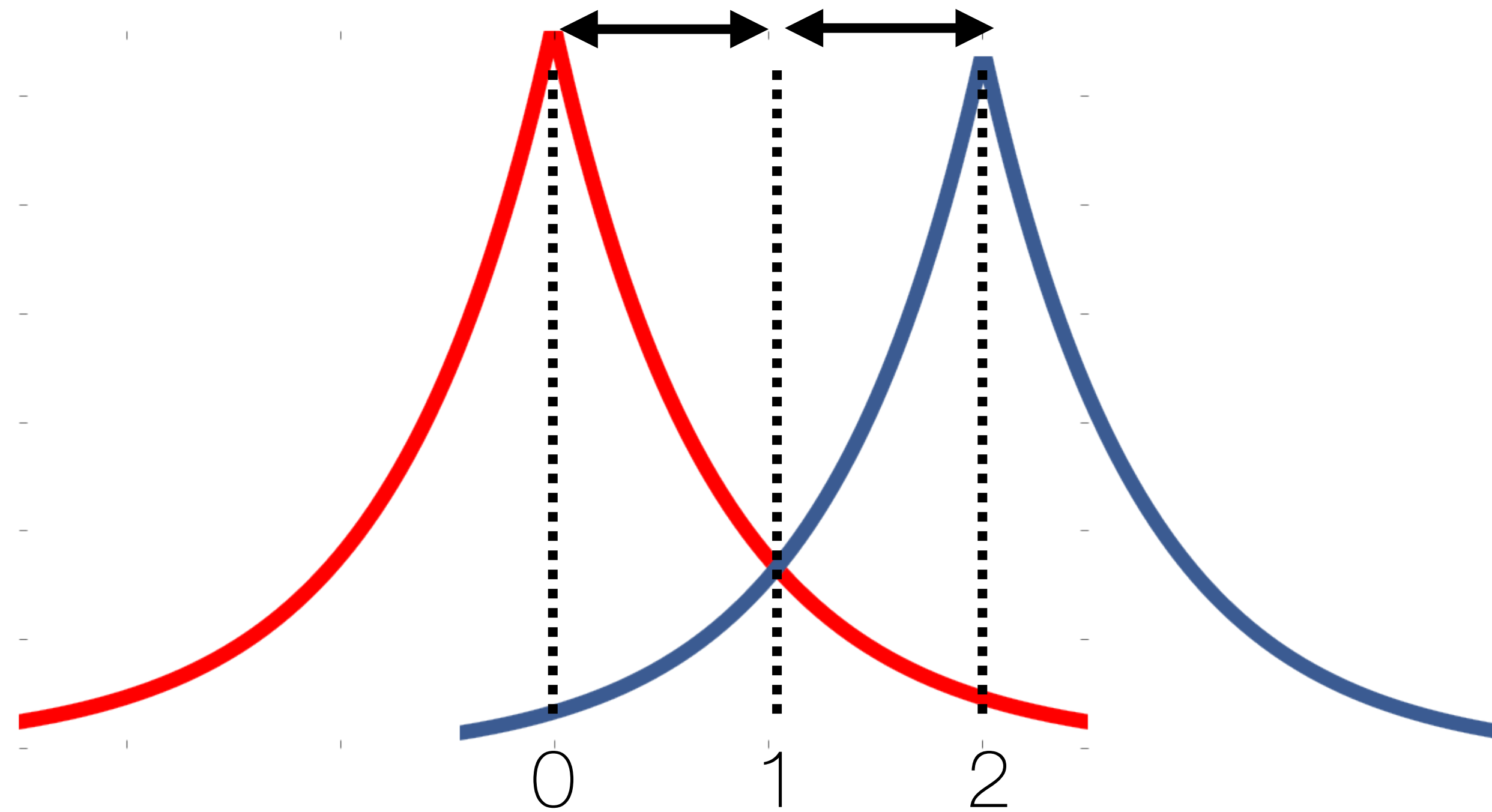
variable approximate couplings

scale of distributions is $1/y$



variable approximate couplings

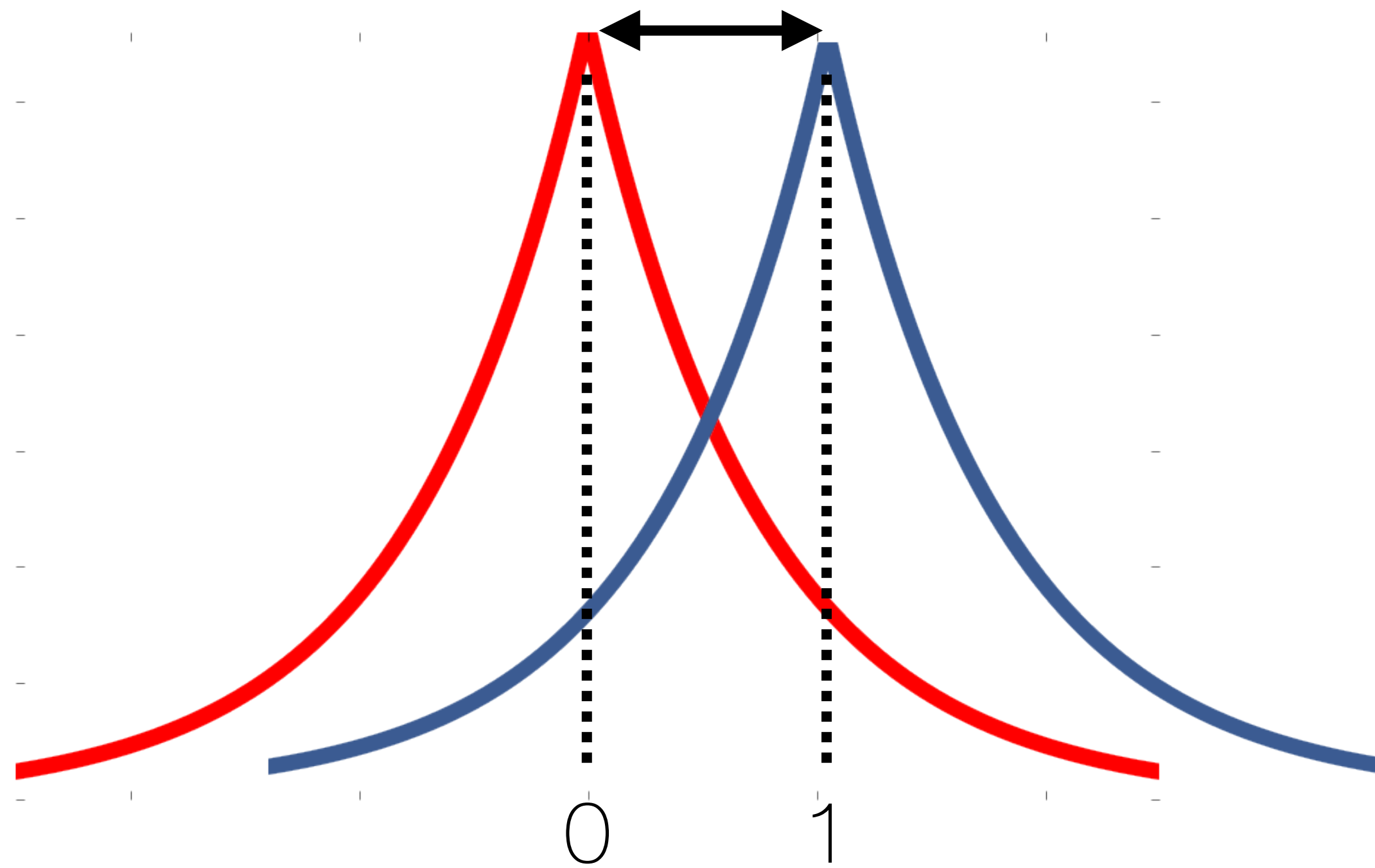
scale of distributions is $1/y$



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

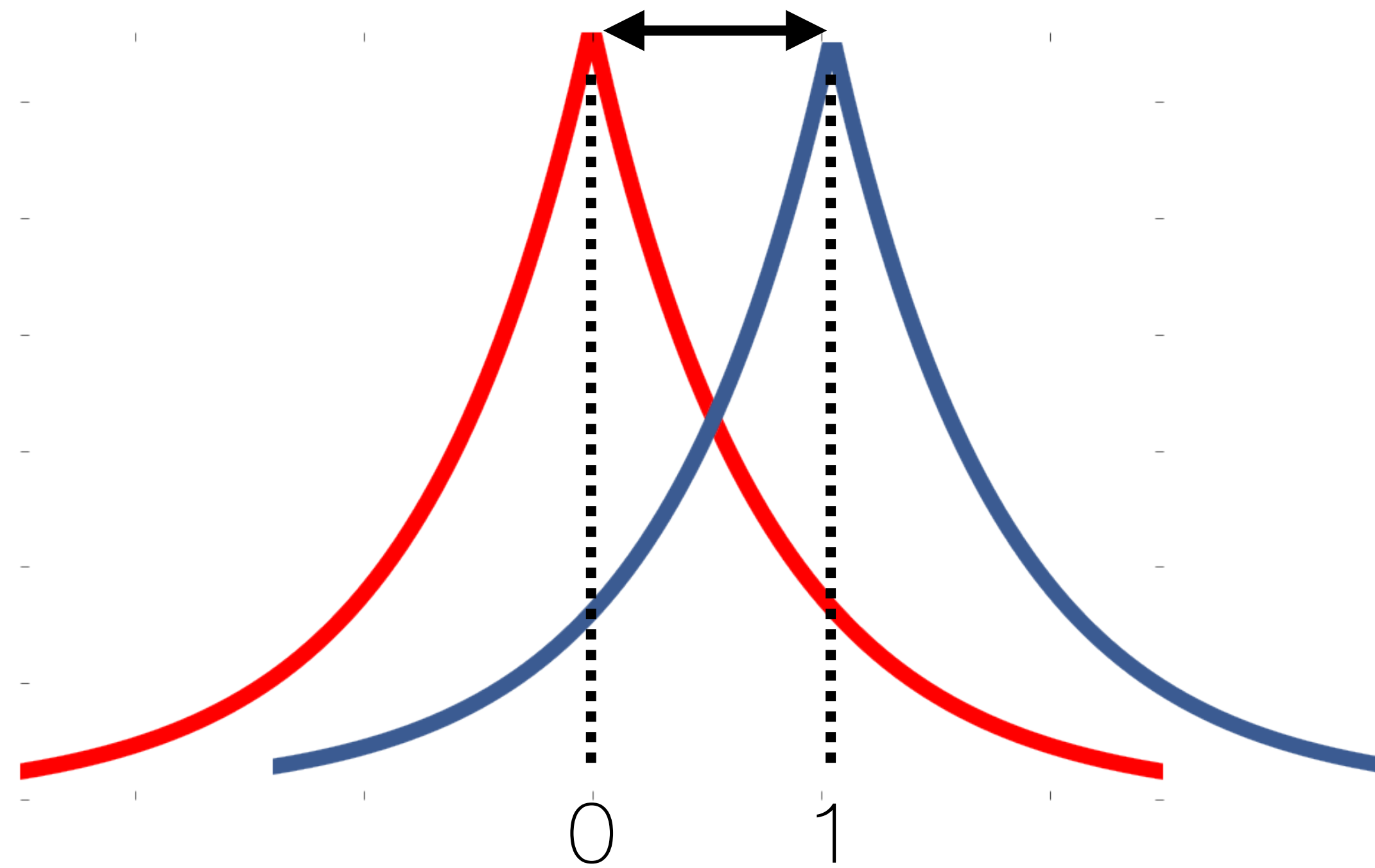
variable approximate couplings

scale of distributions is $1/y$



variable approximate couplings

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



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

proof rule

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

proof rule

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

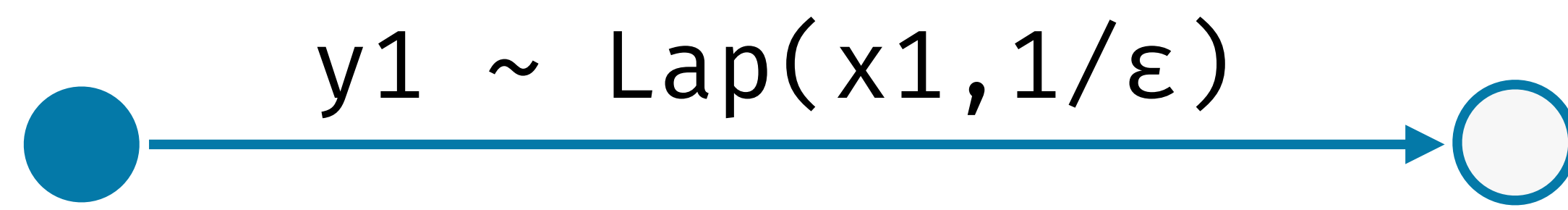
\mathcal{C} couples $p(d), p(d')$

proof rule

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

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

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



$y_1 \sim \text{Lap}(x_1, 1/\epsilon)$

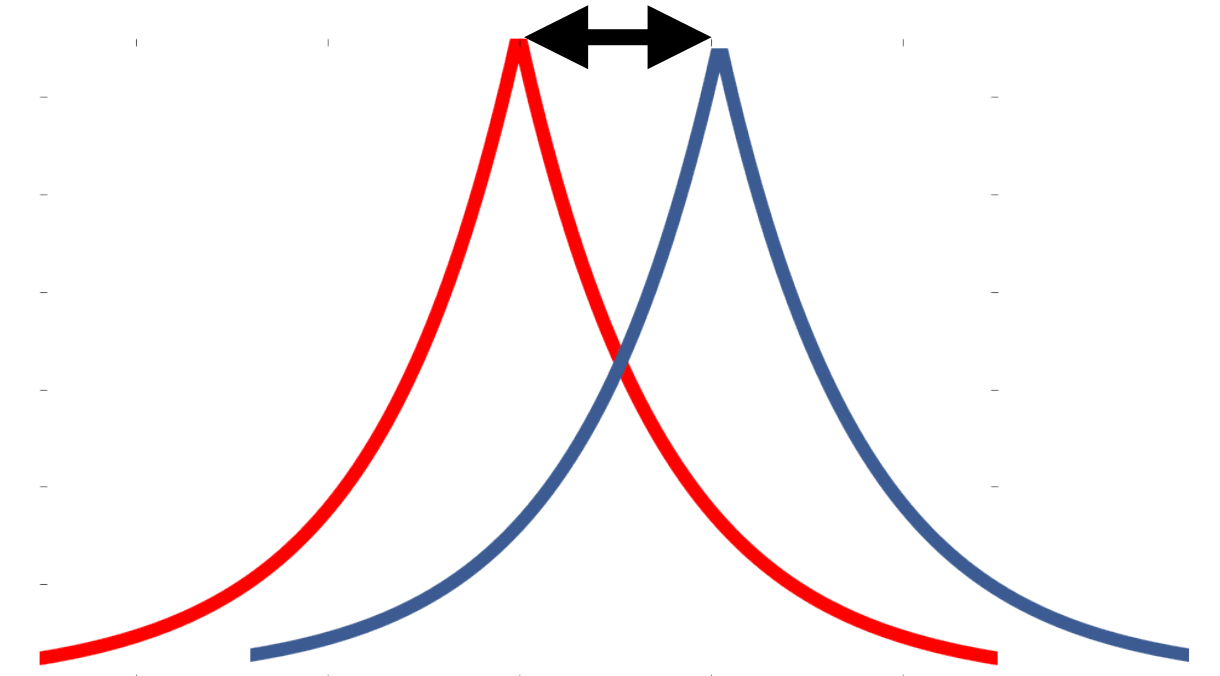
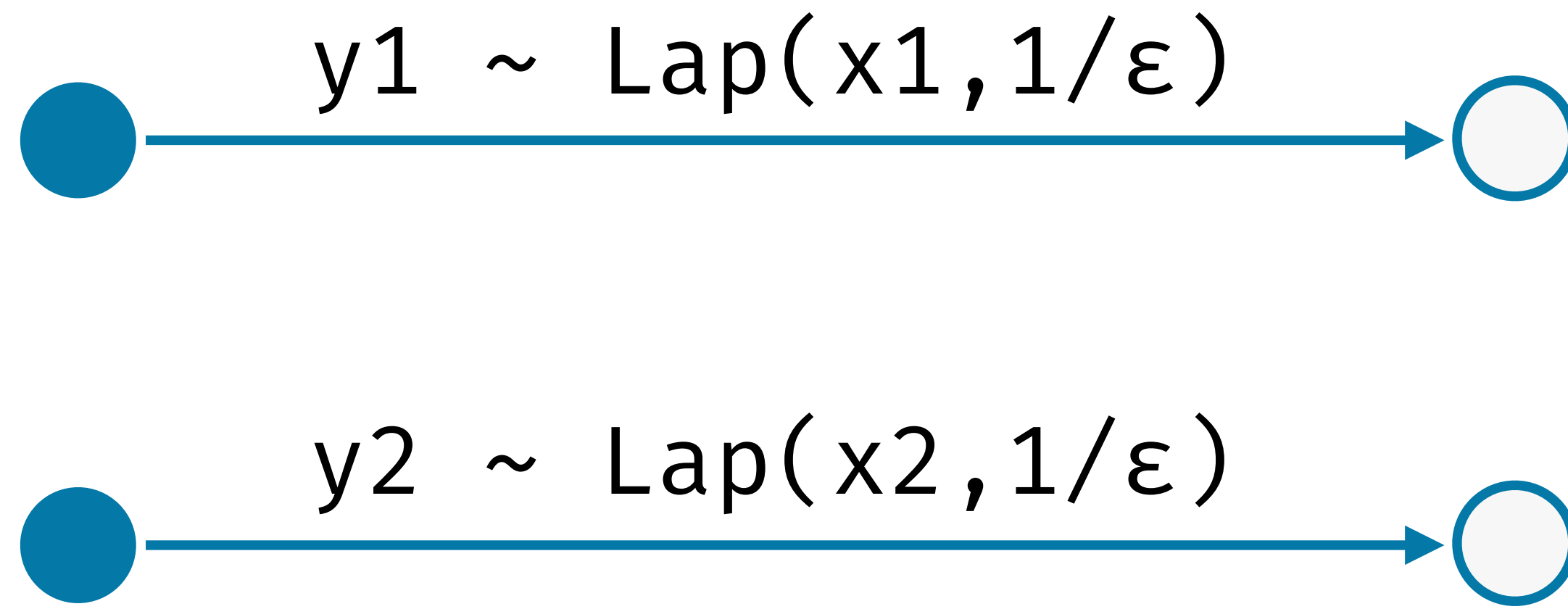


$y_2 \sim \text{Lap}(x_2, 1/\epsilon)$

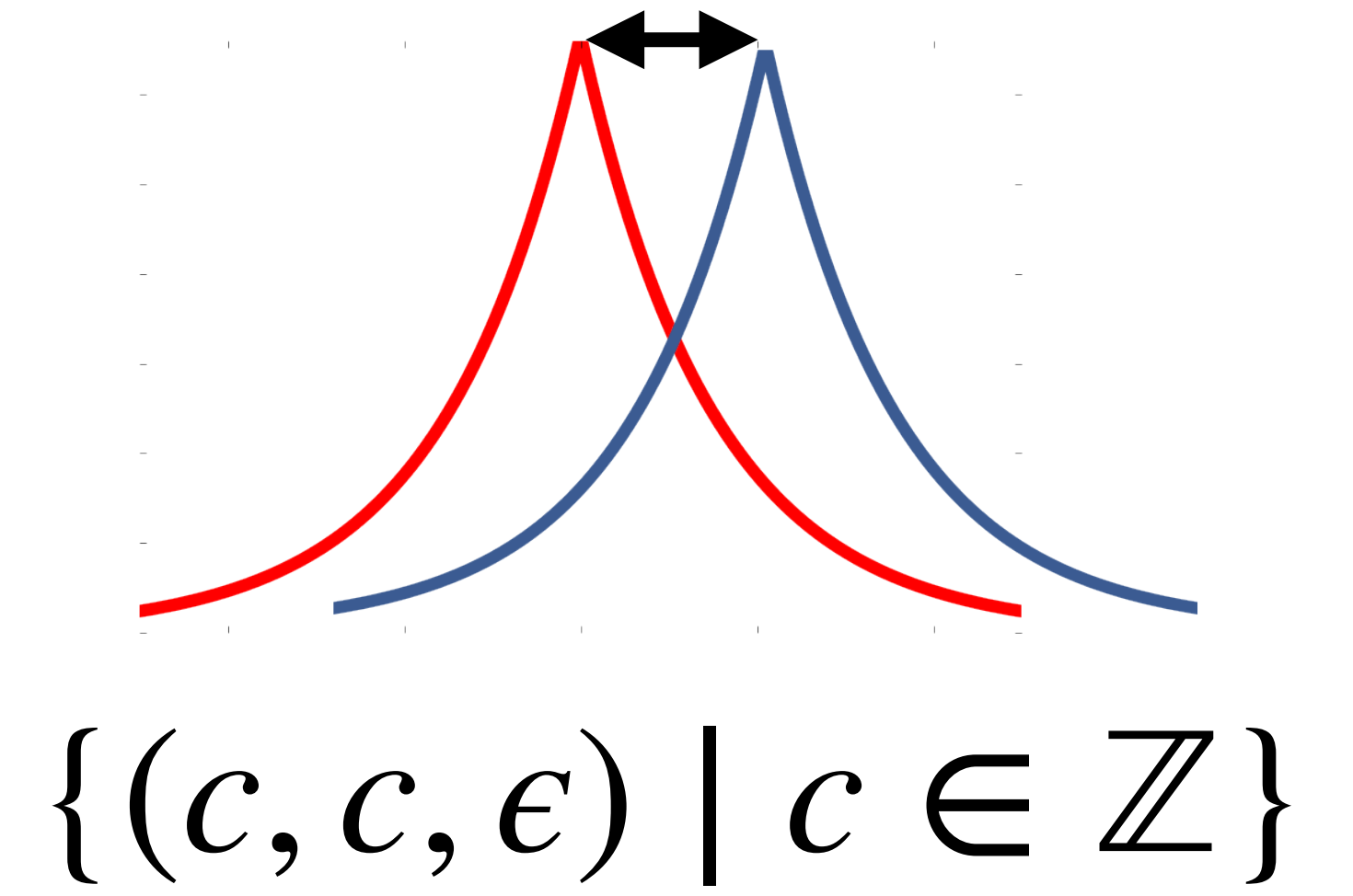
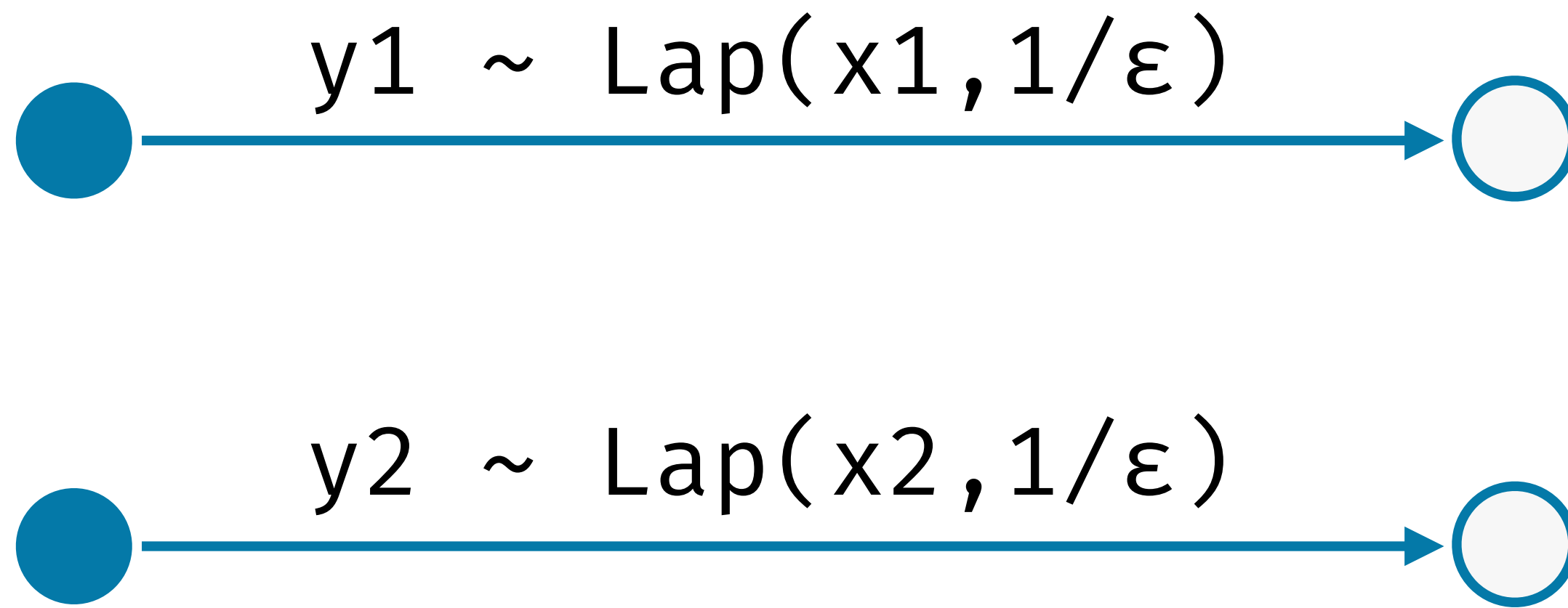


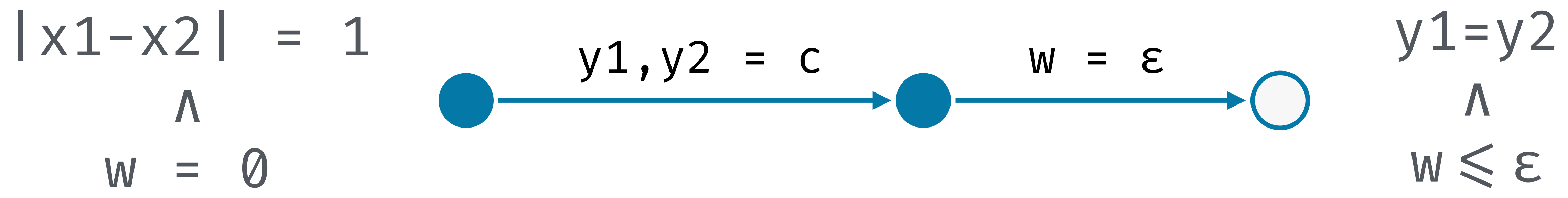
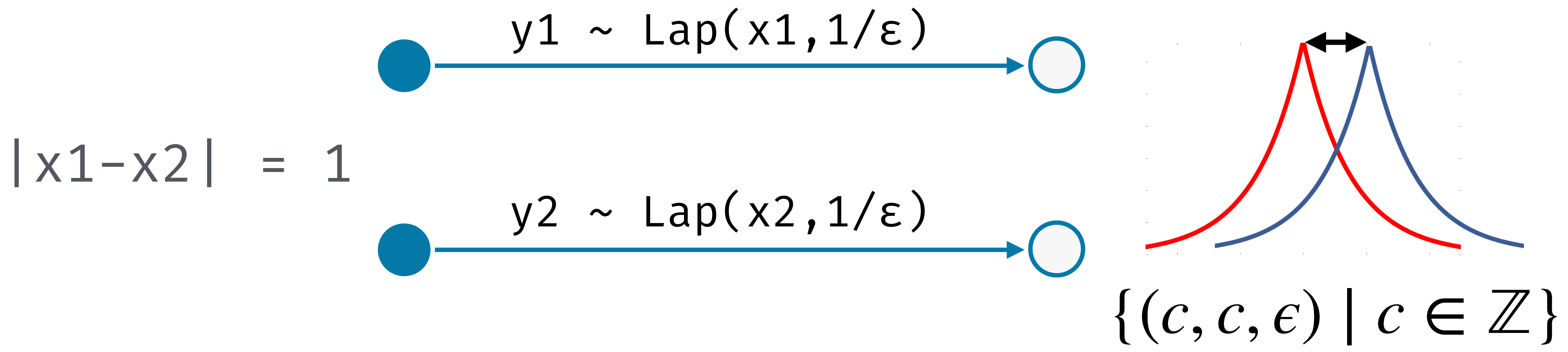
$|x_1 - x_2| = 1$

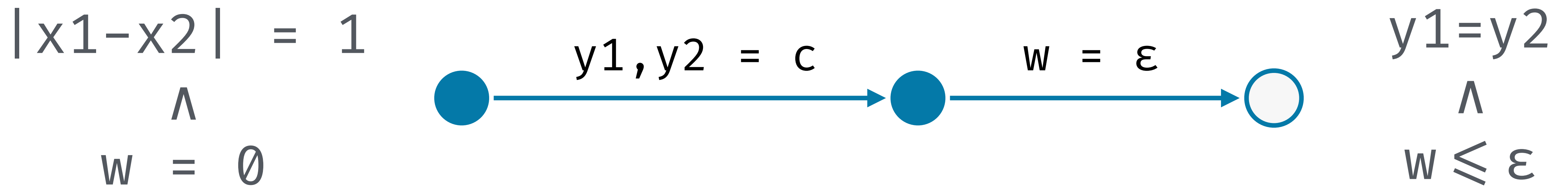
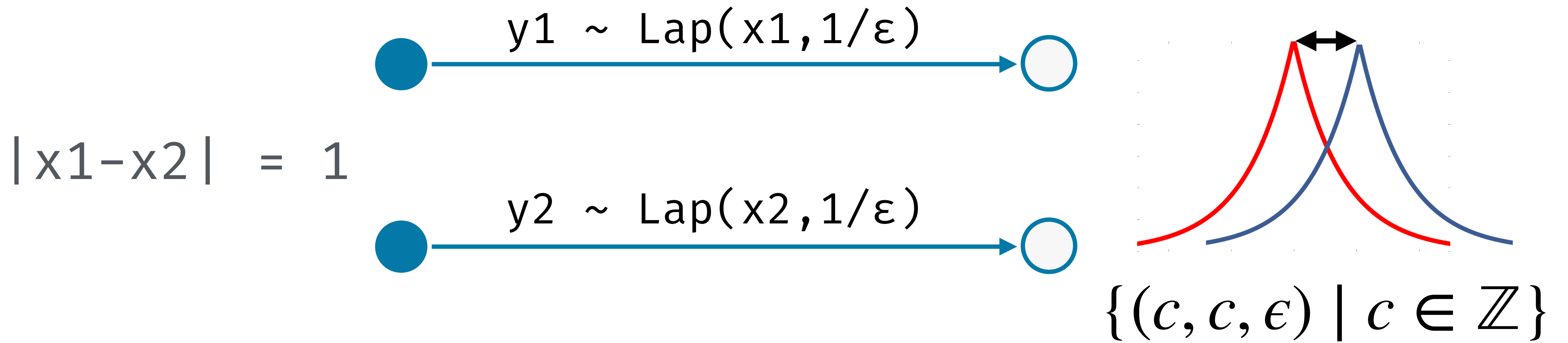
$$|x_1 - x_2| = 1$$



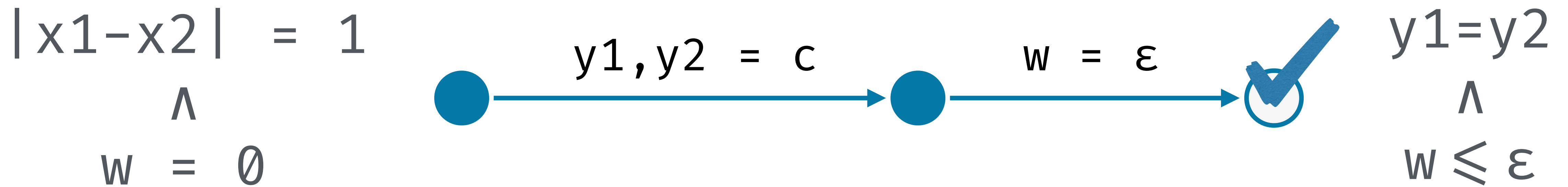
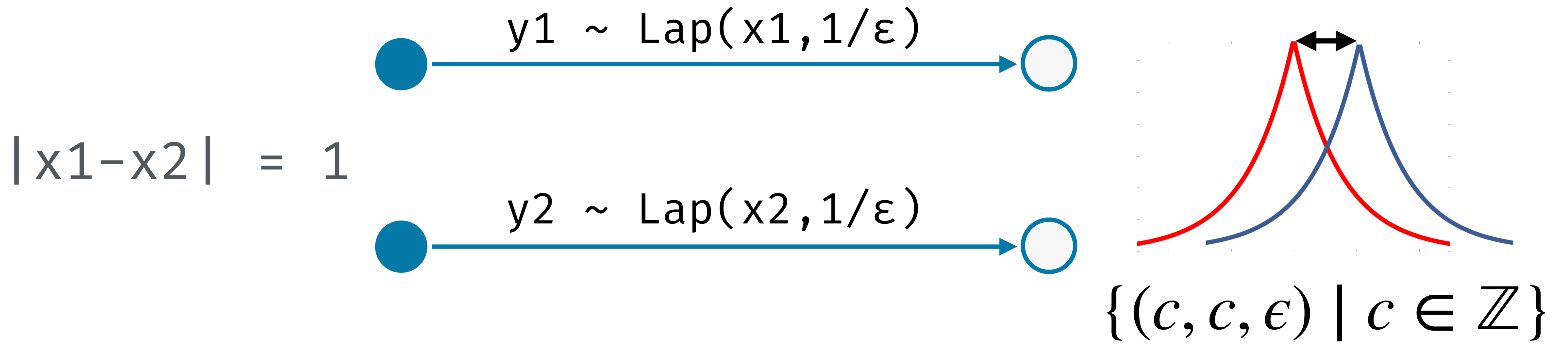
$$|x_1 - x_2| = 1$$







the triple **(y_1, y_2, w)** is a coupling!



the triple **(y_1, y_2, w)** is a coupling!

let's play!

```
def rnm(q):  
    i, best, r = 0  
  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
  
    return r
```

```
def rnm(q):  
    i, best, r = 0  
  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
  
    return r
```

q1 = [9, 0]

q2 = [10, 1]

```
def rnm(q):  
    i, best, r = 0  
  
    while i < |q|  
        d ~ Lap(q[i], 2/ε)  
  
        if d > best || i = 0  
            r = i  
            best = d  
  
        i = i + 1  
  
    return r
```

q1 = [9, 0]

q2 = [10, 1]

w = 0

```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

$q1 = [9, 0]$ $q2 = [10, 1]$
 $w = 0$

$r1 = r2 \wedge w \leq \epsilon$


```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

```

q1 = [9, 0]      q2 = [10, 1]
                w = 0

```

$r1 = r2 \wedge w \leq \epsilon$

```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

```

q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0

```

$r1 = r2 \wedge w \leq \epsilon$

```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

```

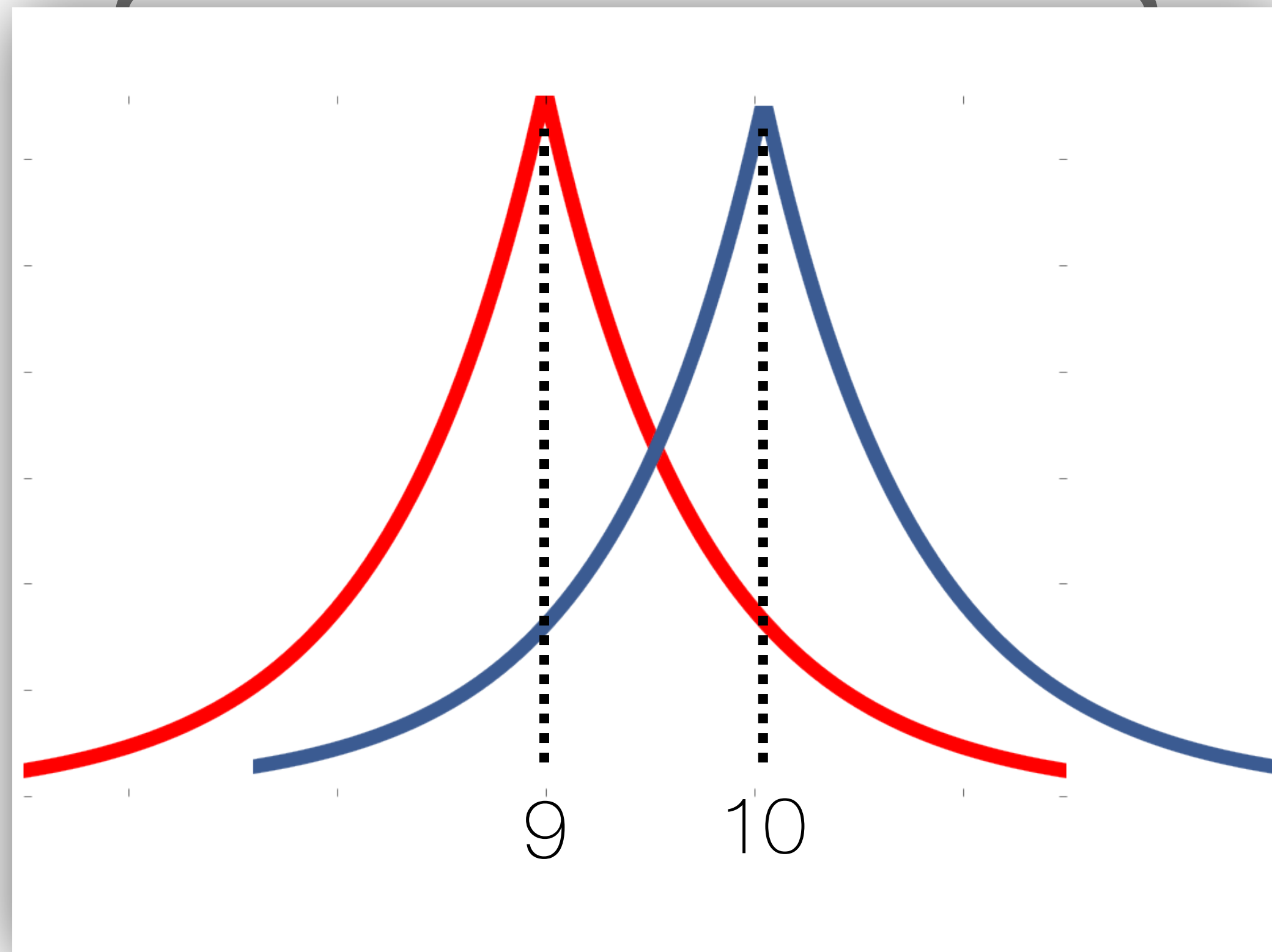
q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0

```

$r1 = r2 \wedge w \leq \epsilon$

```
def rnm(q):
    i, best, r = 0

    while i < |q|
```

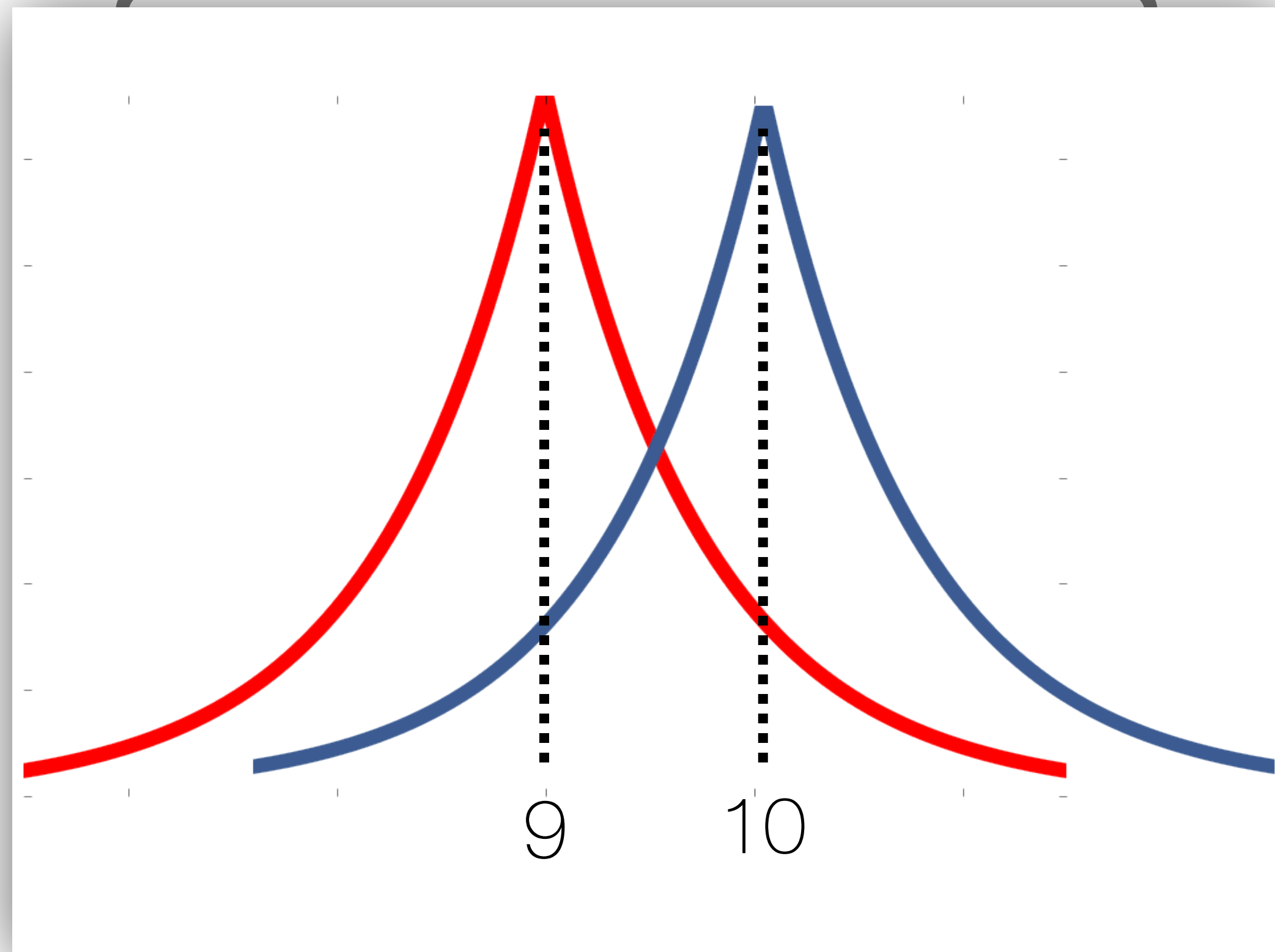


```
q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0
```

$$r1 = r2 \wedge w \leq \epsilon$$

```
def rnm(q):
    i, best, r = 0

    while i < |q|
```



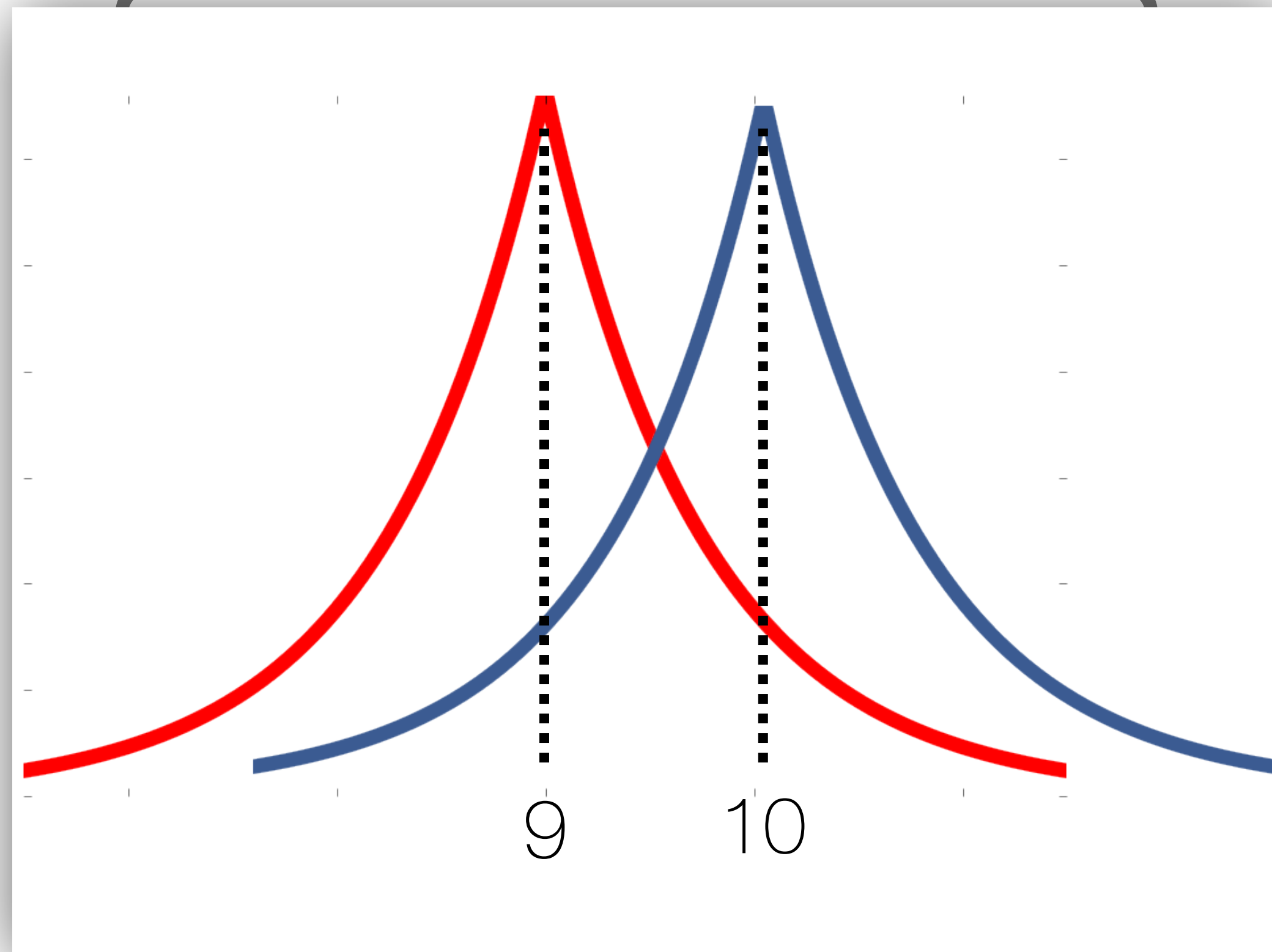
```
q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0
```

non-deterministically pick from
 $\{(c, c, \epsilon/2) \mid c \in \mathbb{Z}\}$

$$r1 = r2 \wedge w \leq \epsilon$$

```
def rnm(q):
    i, best, r = 0

    while i < |q|
```



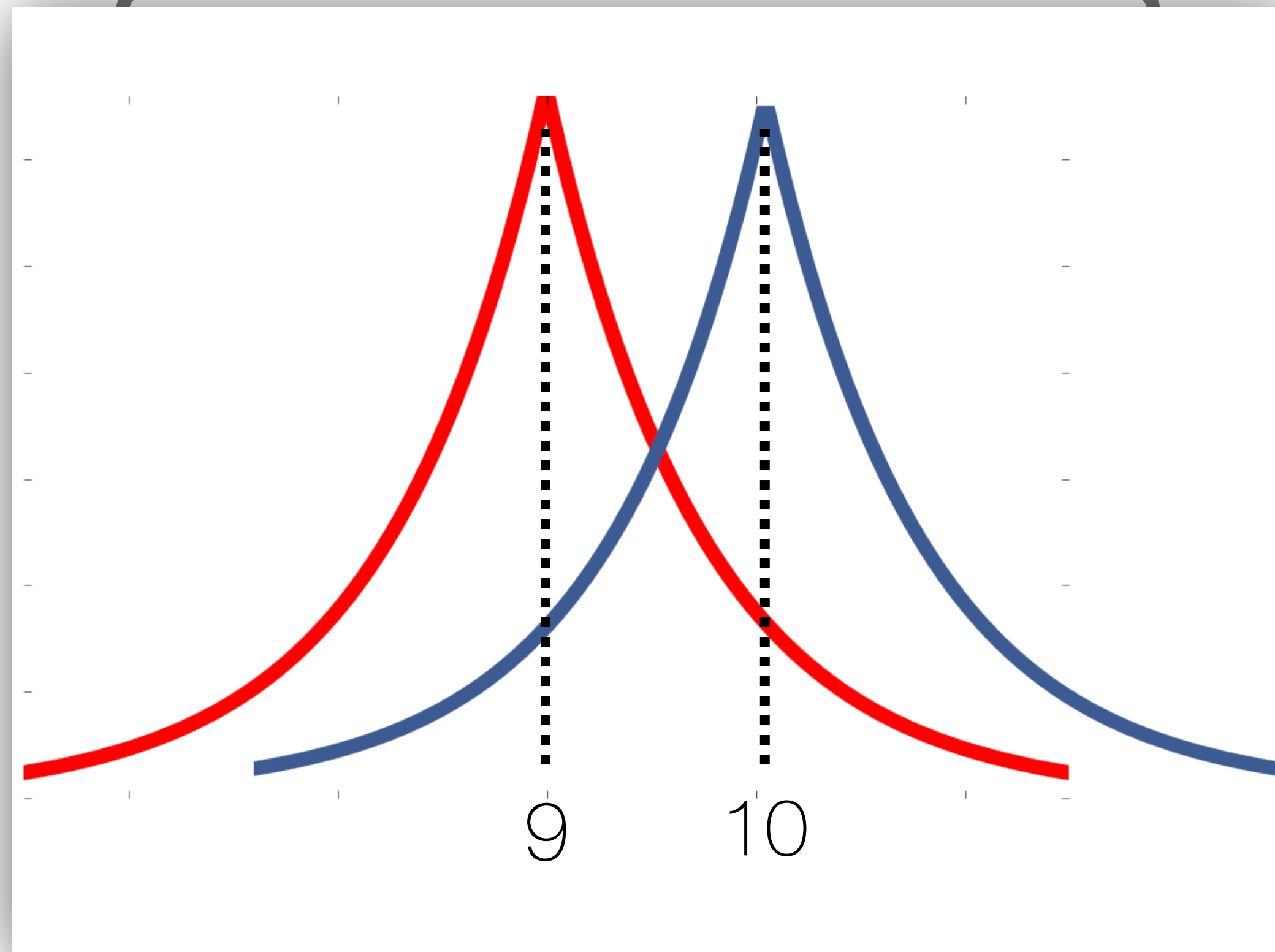
```
q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0
r1 = 0                r2 = 0
d1 = c                d2 = c
```

non-deterministically pick from
 $\{(c, c, \epsilon/2) \mid c \in \mathbb{Z}\}$

$$r1 = r2 \wedge w \leq \epsilon$$

```
def rnm(q):
    i, best, r = 0

    while i < |q|
```



```
q1 = [9, 0]          q2 = [10, 1]
```

```
w = 0
```

```
r1 = 0
```

```
r2 = 0
```

```
r1 = 0
```

```
r2 = 0
```

```
d1 = c
```

```
d2 = c
```

```
w = ε/2
```

non-deterministically pick from

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

$r1 = r2 \wedge w \leq \epsilon$

```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

```

q1 = [9, 0]          q2 = [10, 1]
                    w = 0
r1 = 0              r2 = 0

r1 = 0              r2 = 0
d1 = c              d2 = c

                    w = ε/2

```

$r1 = r2 \wedge w \leq \epsilon$


```

def rnm(q):
    i, best, r = 0

    while i < |q|
        d ~ Lap(q[i], 2/ε)

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

        i = i + 1

    return r

```

[dwork & roth 14]

```

q1 = [9, 0]           q2 = [10, 1]
                        w = 0
r1 = 0                r2 = 0

r1 = 0                r2 = 0
d1 = c                d2 = c

                        w = ε/2
                        ⋮
                        ⋮
                        ⋮
                        w = ε

```

$r1 = r2 \wedge w \leq \epsilon$

our game strategy

in every iteration, couple samples using

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

our game strategy

in every iteration, couple samples using

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

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

~~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

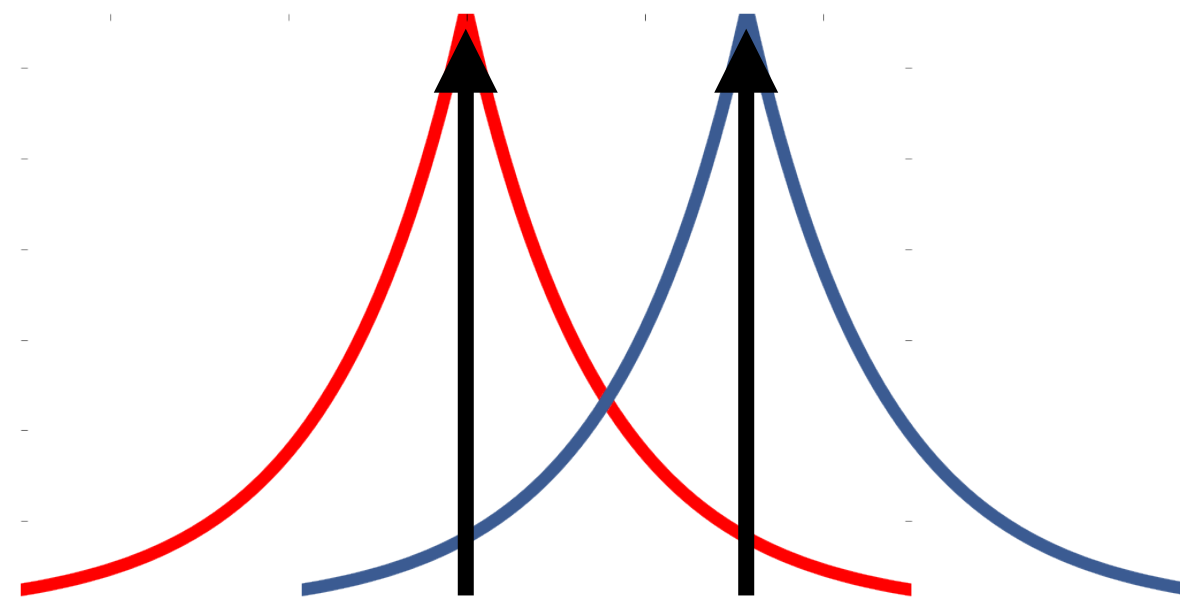
$$\{(c, c + 1, \epsilon) \mid c \in \mathbb{Z}\}$$

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

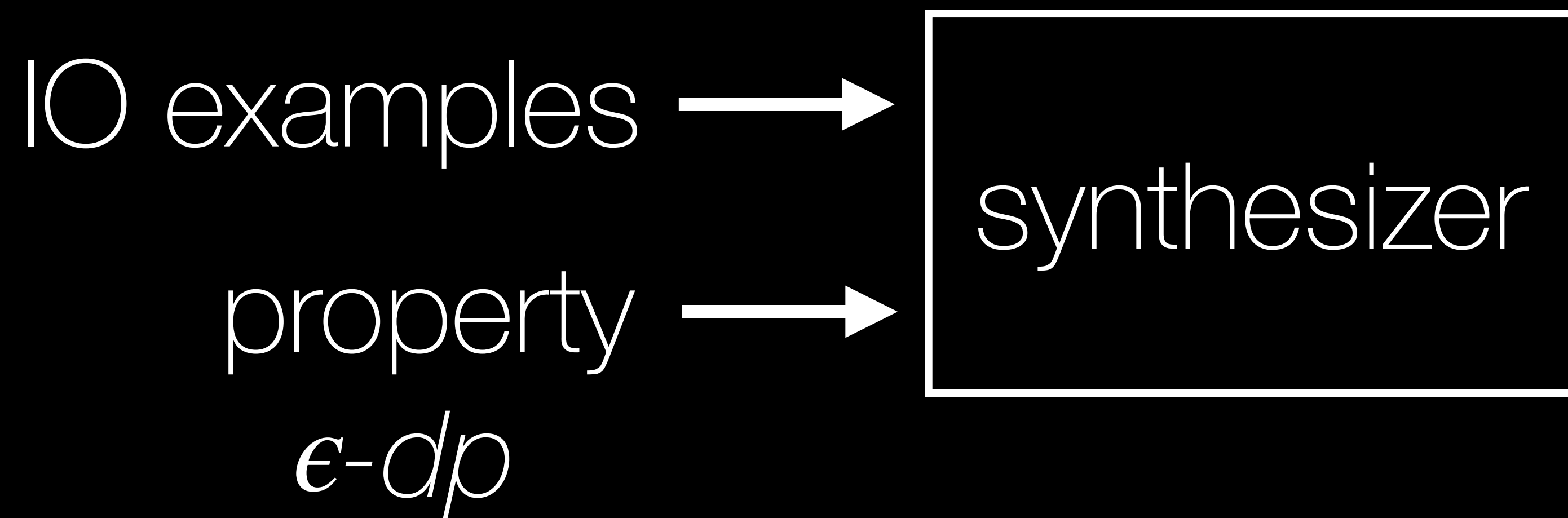
evaluation

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].

...and more!

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

theme get rid of probability! long live logic!





```

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]

```

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]