

To Appear In CCS 2023

Interactive Proofs For Differential Privacy

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Motivating Problem: Counting



The local government of Wolvercote, a small village in Oxfordshire want to know if they should change public healthcare policy.

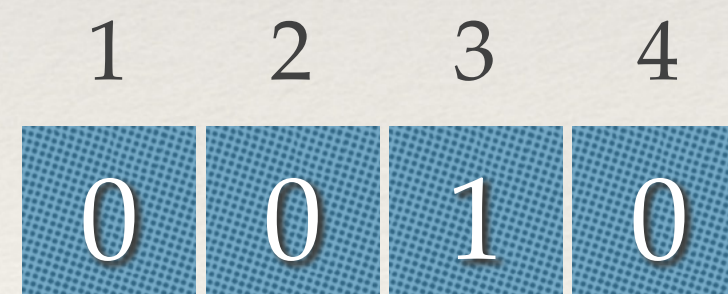
In order to gauge public opinion they conduct a survey over the population of the village.

Survey Question

Each resident is asked to vote for a single policy only



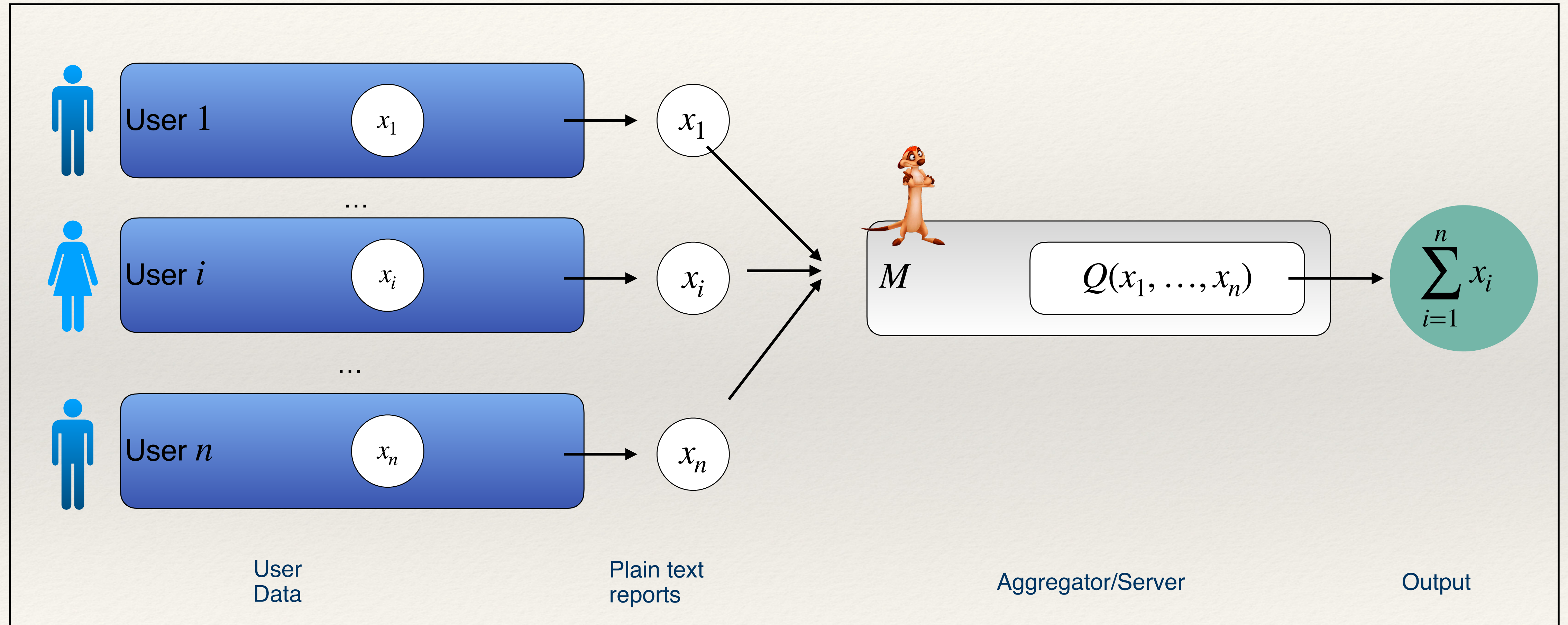
i



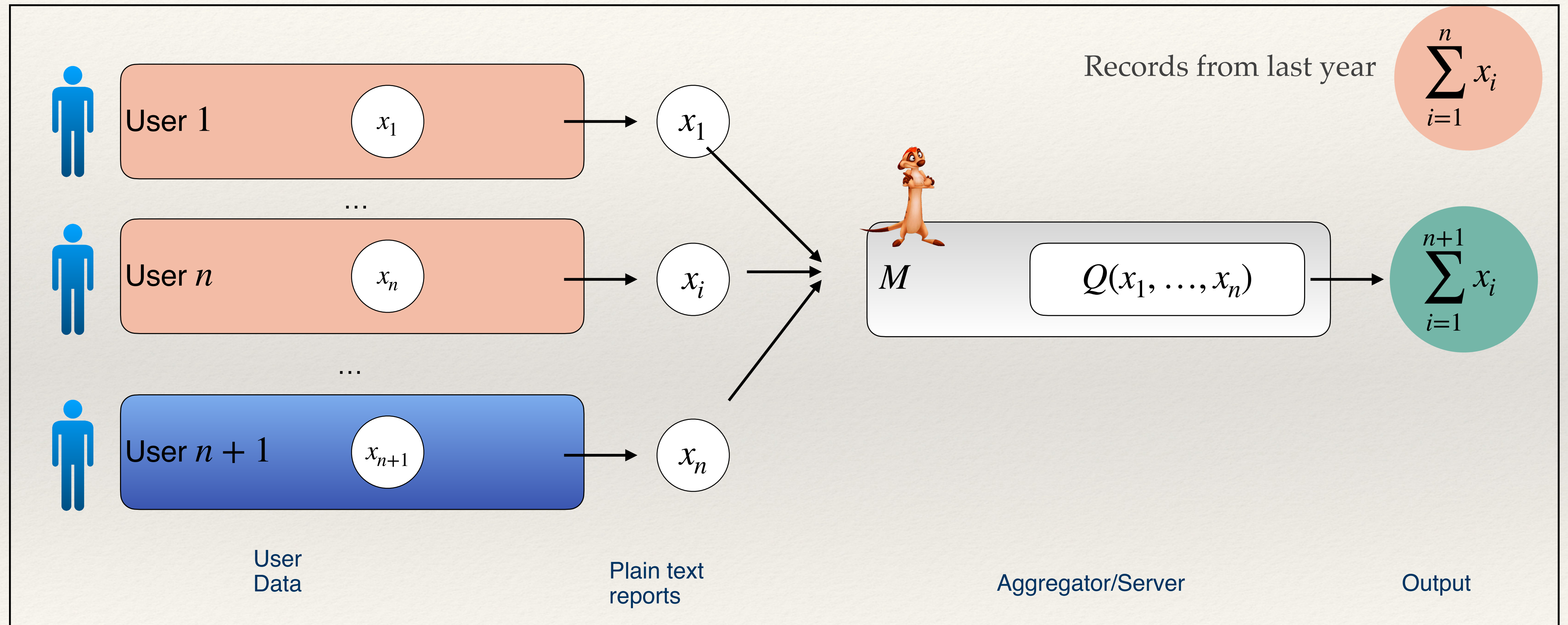
x_i

- 1: Mandatory Vaccination
- 2: Increase Pay Towards Healthcare workers
- 3: Decrease Taxes Towards Healthcare
- 4: Increase Taxes Towards Healthcare

An Ideal Solution



A New Person Moves in

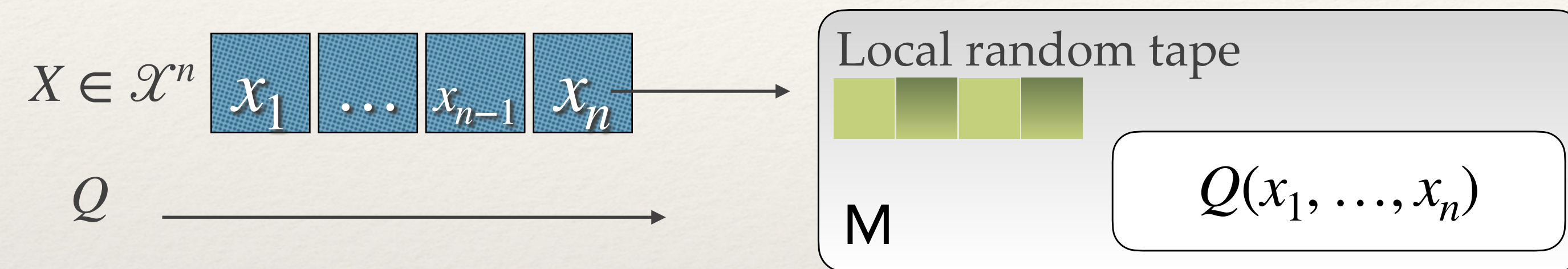


Randomness To The Rescue

- ❖ In this scenario, there is no deterministic algorithm that can help prevent information leakage about the n 'th user's value.
- ❖ Thus we **MUST** randomness to obfuscate information about the new user.

(ϵ, δ) -Differential Privacy (DP)

An algorithm $M : \mathcal{X}^n \times \mathcal{Q} \rightarrow \mathcal{Y}$ for releasing $Q(X)$

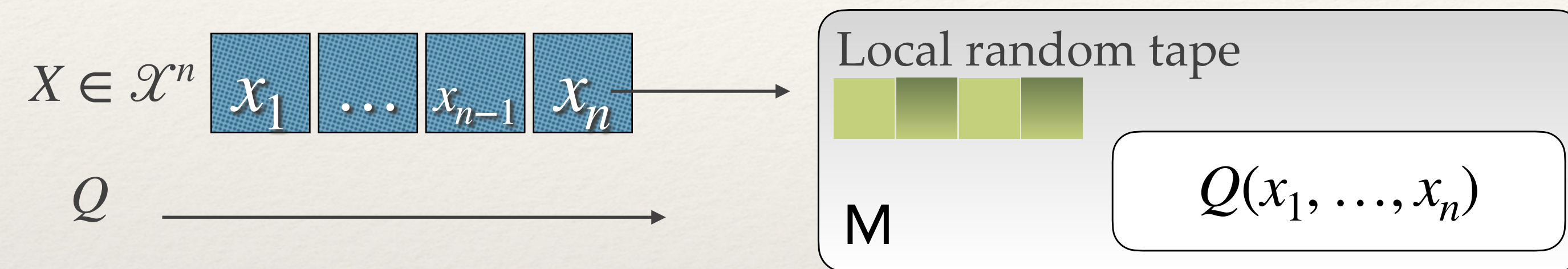


The output of M is a random value sampled according to $M(X, Q)$, where the randomness comes from the M 's private local randomness.

Thus $M(X, Q)$ defines a probability distribution over \mathcal{Y}

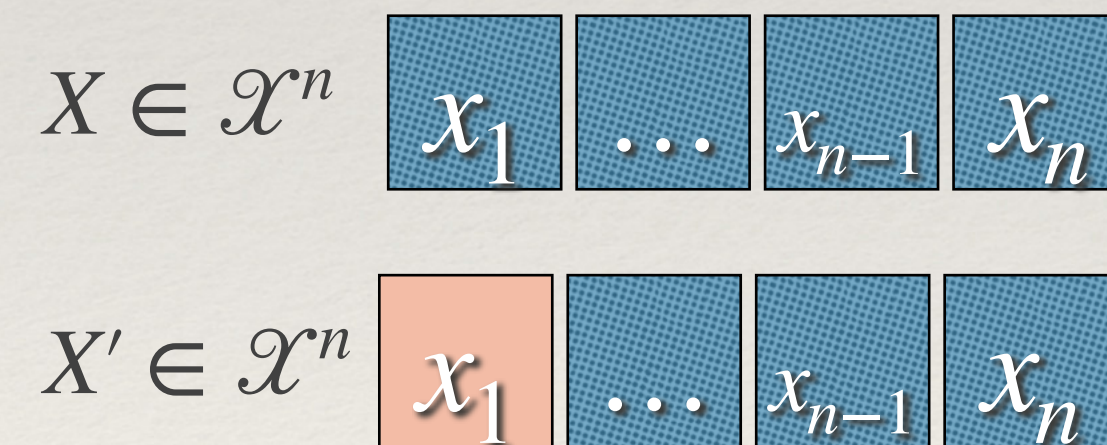
(ϵ, δ) -Differential Privacy (DP)

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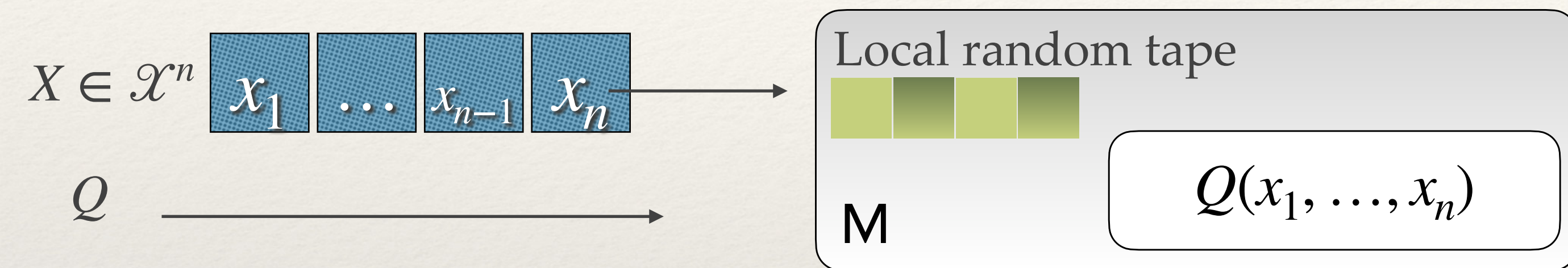
M is said to be (ϵ, δ) -Differentially Private if for any subset $T \subseteq \mathcal{Y}$

For **any** neighbouring datasets $X \sim X'$ i.e datasets that differ by just one element



(ϵ, δ) -Differential Privacy (DP)

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For **any** neighbouring datasets $X \sim X'$ i.e datasets that differ by just one element

$X \in \mathcal{X}^n$ $x_1 \dots x_{n-1} x_n$

$X' \in \mathcal{X}^n$ $x_1 \dots x_{n-1} x_n$

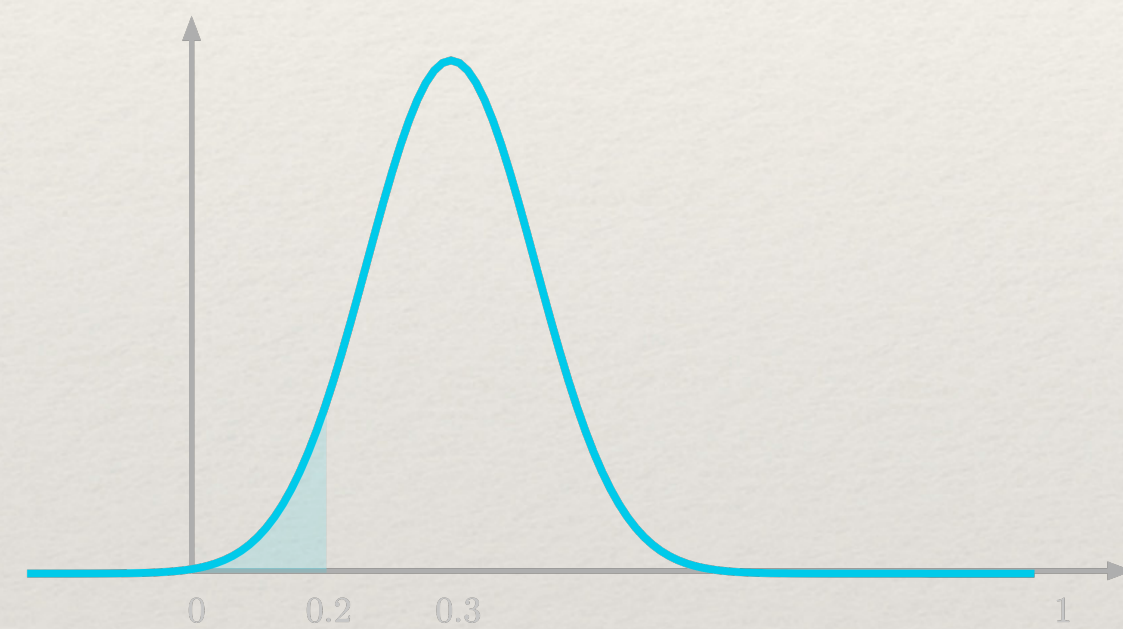
$$\Pr_{y \leftarrow M(X, Q)} [y \in T] \leq e^\epsilon \Pr_{y \leftarrow M(X', Q)} [y \in T] + \delta$$

Understanding The Definition: Bayesian Perspective

$$X' \in \mathcal{X}^n \quad \boxed{x_1} \quad \boxed{\dots} \quad \boxed{x_{n-1}} \quad \boxed{x_n}$$

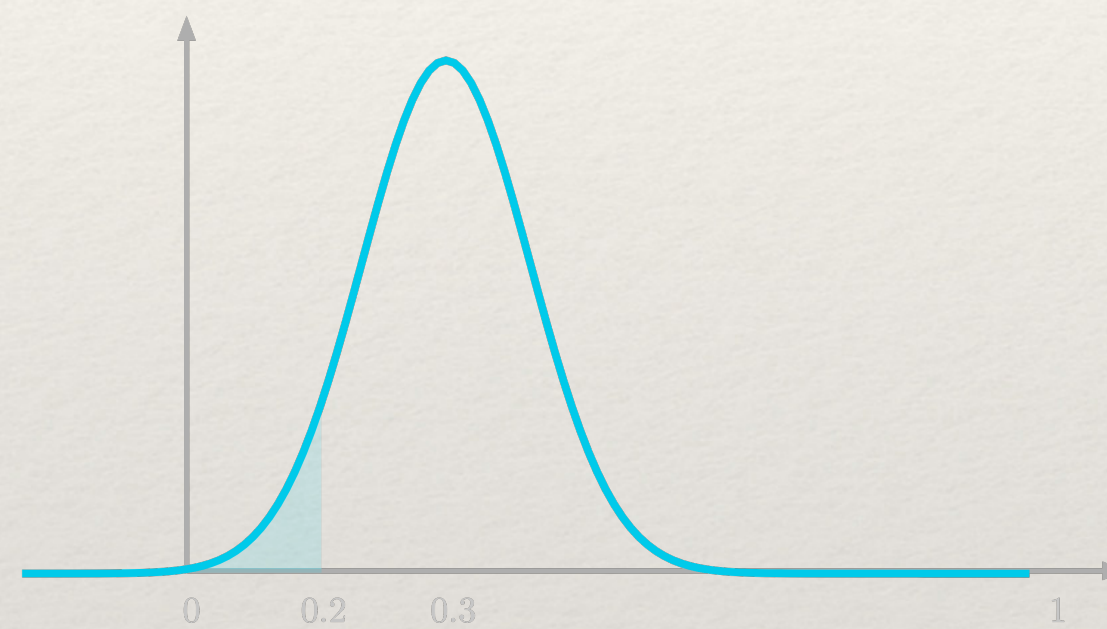


Computationally
unbounded algorithm, that
knows all values in X
except x_1



$$\Pr[x_1 = x]$$

Adversaries prior belief about x_1



$$\Pr[x_1 = x \mid M(X, Q) = y]$$

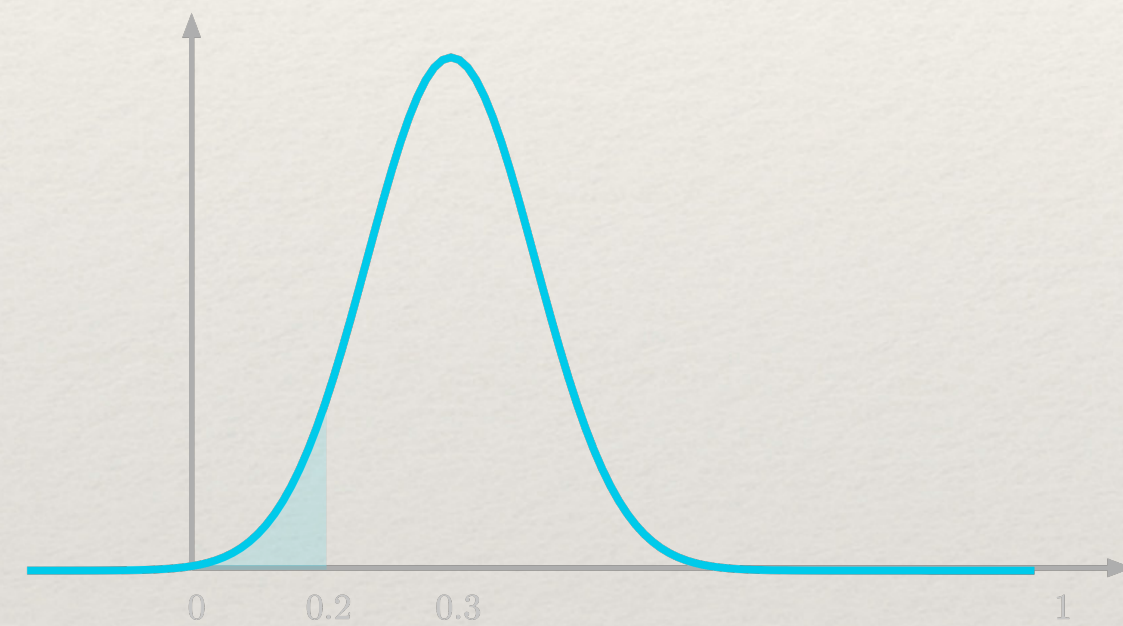
Adversaries updated posterior
about x_1 now that it has seen a
sample y from $M(X, Q)$

Understanding The Definition: Bayesian Perspective

$$X' \in \mathcal{X}^n \quad \boxed{x_1} \quad \boxed{\dots} \quad \boxed{x_{n-1}} \quad \boxed{x_n}$$

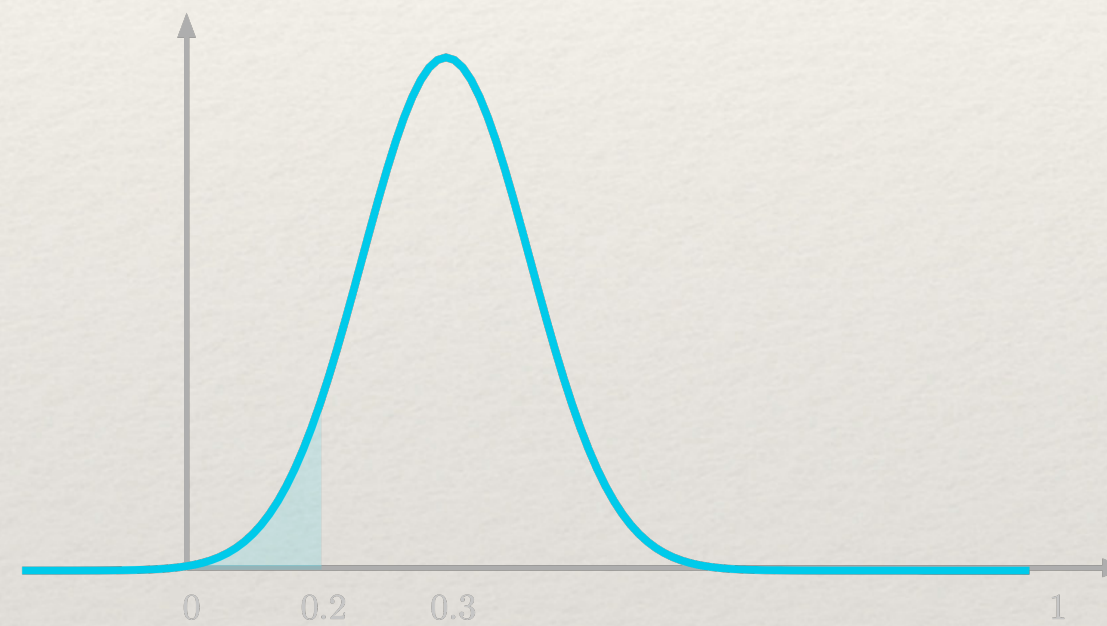


Computationally
unbounded algorithm, that
knows all values in X
except x_1



$$\Pr[x_1 = x]$$

Adversaries prior belief about



$$\Pr[x_1 = x \mid M(X, O) = v]$$

If M is (ϵ, δ) -DP, then with probability atleast $1 - \delta$
$$\text{TV}(D_1, D_2) \leq \epsilon$$

Utility Of A DP Algorithm

An algorithm $M : \mathcal{X}^n \times Q \rightarrow \mathcal{Y}$ for releasing a DP version of $y = Q(X)$ where (\mathcal{Y}, d) is a metric space we define utility

$$\text{Error} = \mathbb{E}_{\hat{y} \leftarrow M(X, Q)} [d(\hat{y}, y)]$$

Candidate metrics

$$\mathcal{Y} = \mathbb{R}^d \quad d(x, y) = \|x - y\|_1$$

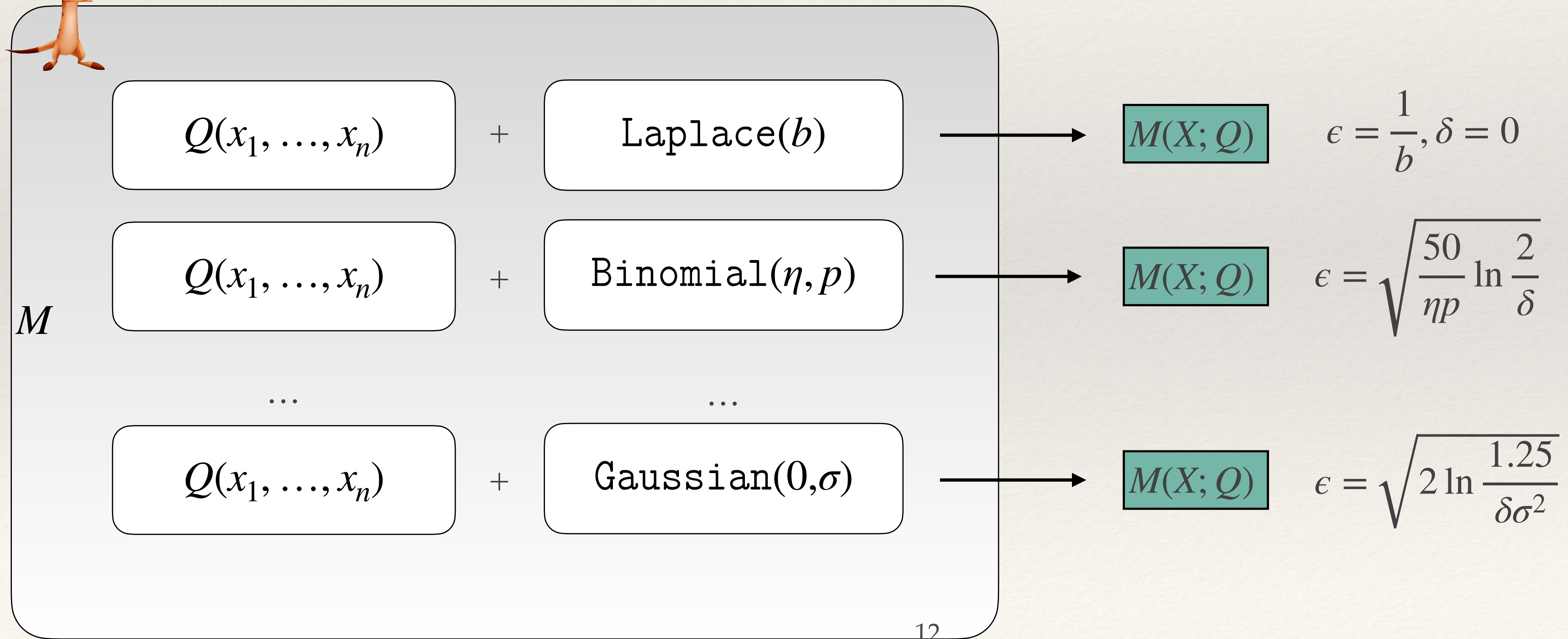
$$\mathcal{Y} = \mathbb{Z}_q^d \quad d(x, y) = \|x - y\|_2$$

$$d(x, y) = \|x - y\|_\infty$$

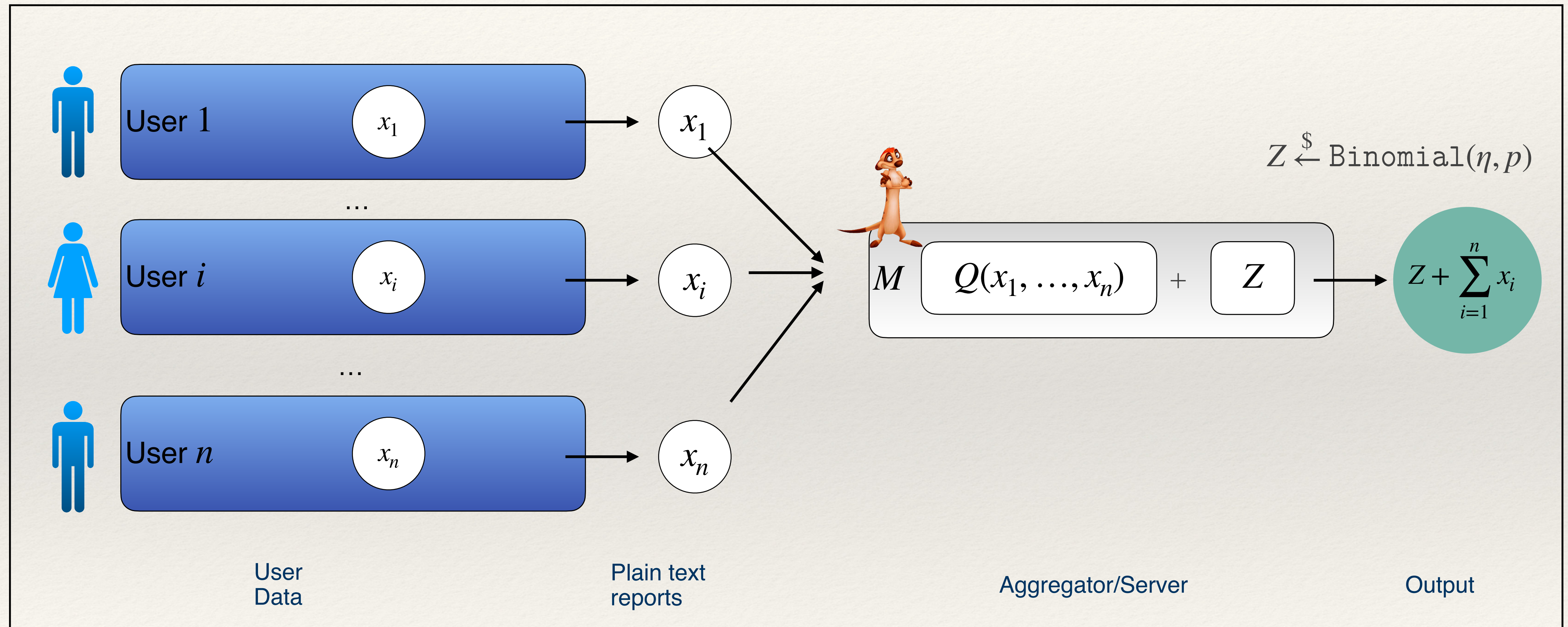
If we draw a sample from $M(X, Q)$, then on average how far is that sample from the true untampered answer.

DP Counting

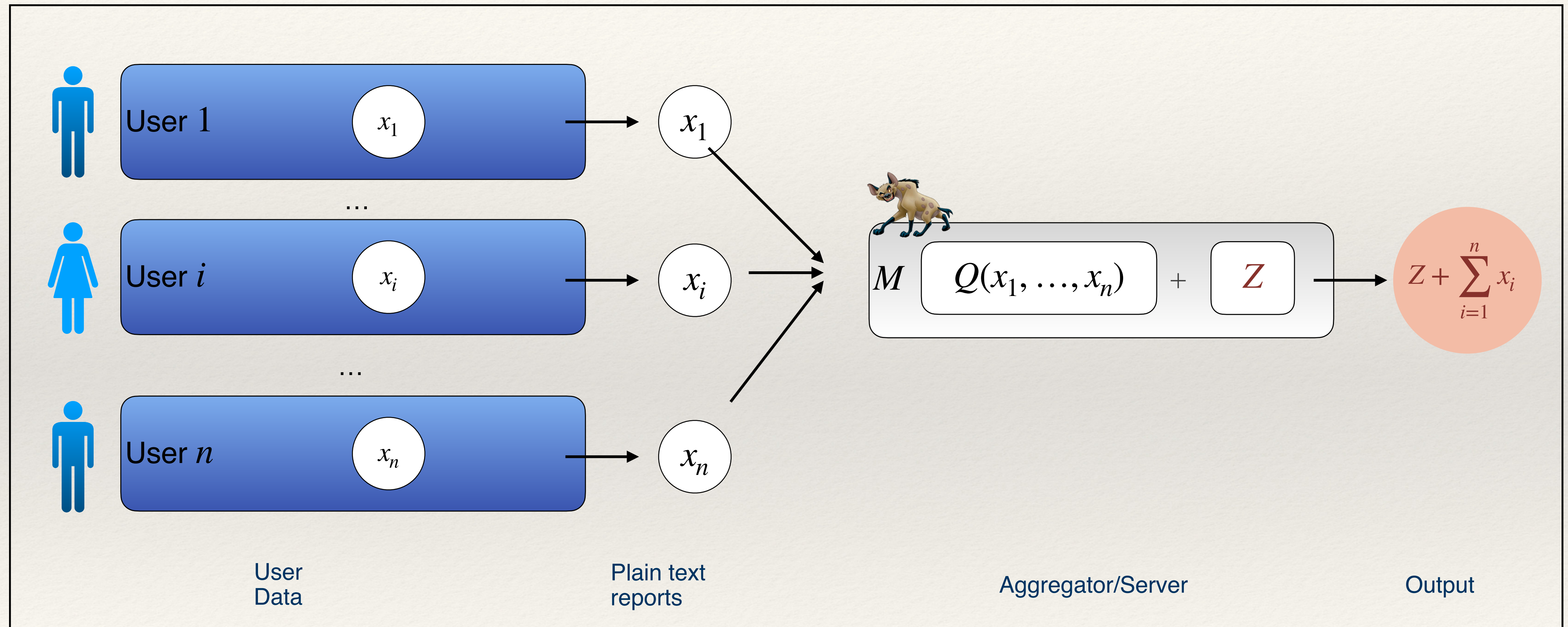
$$Q(x_1, \dots, x_n) = \sum_{i=1}^n x_i$$



Back To Our Ideal World



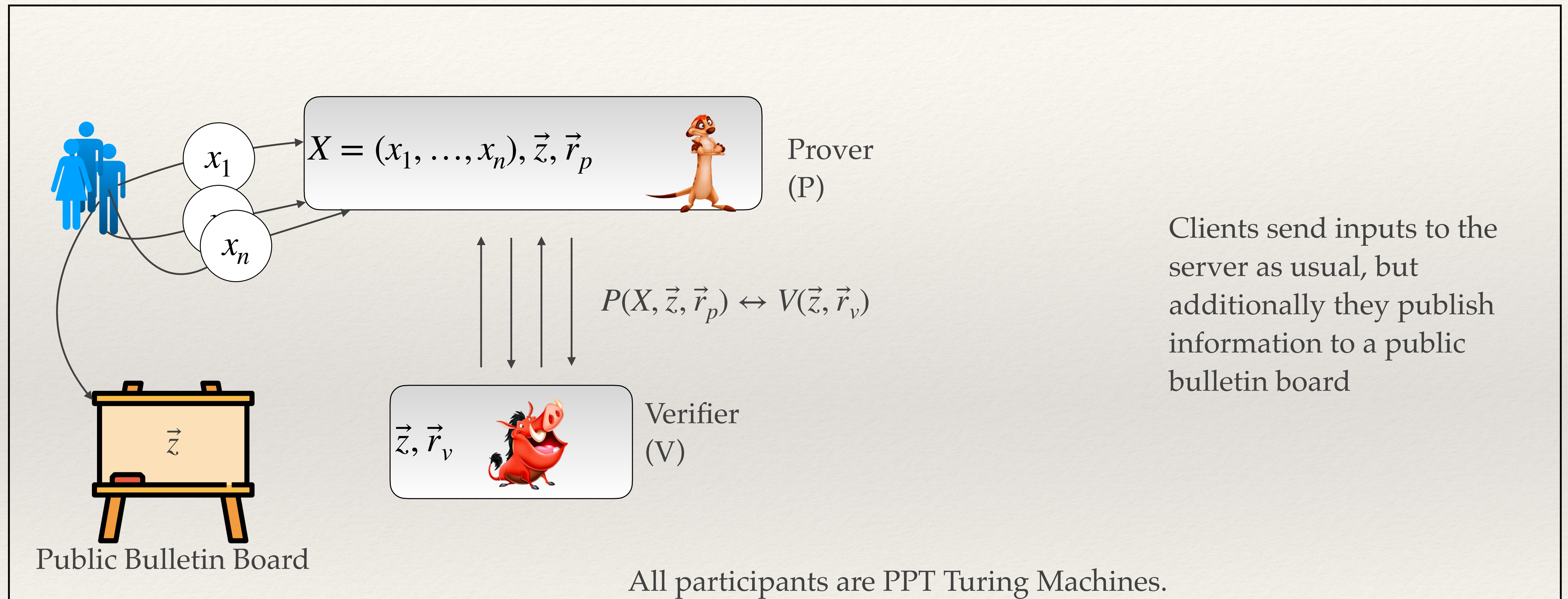
What If We Cannot Trust The Server ?



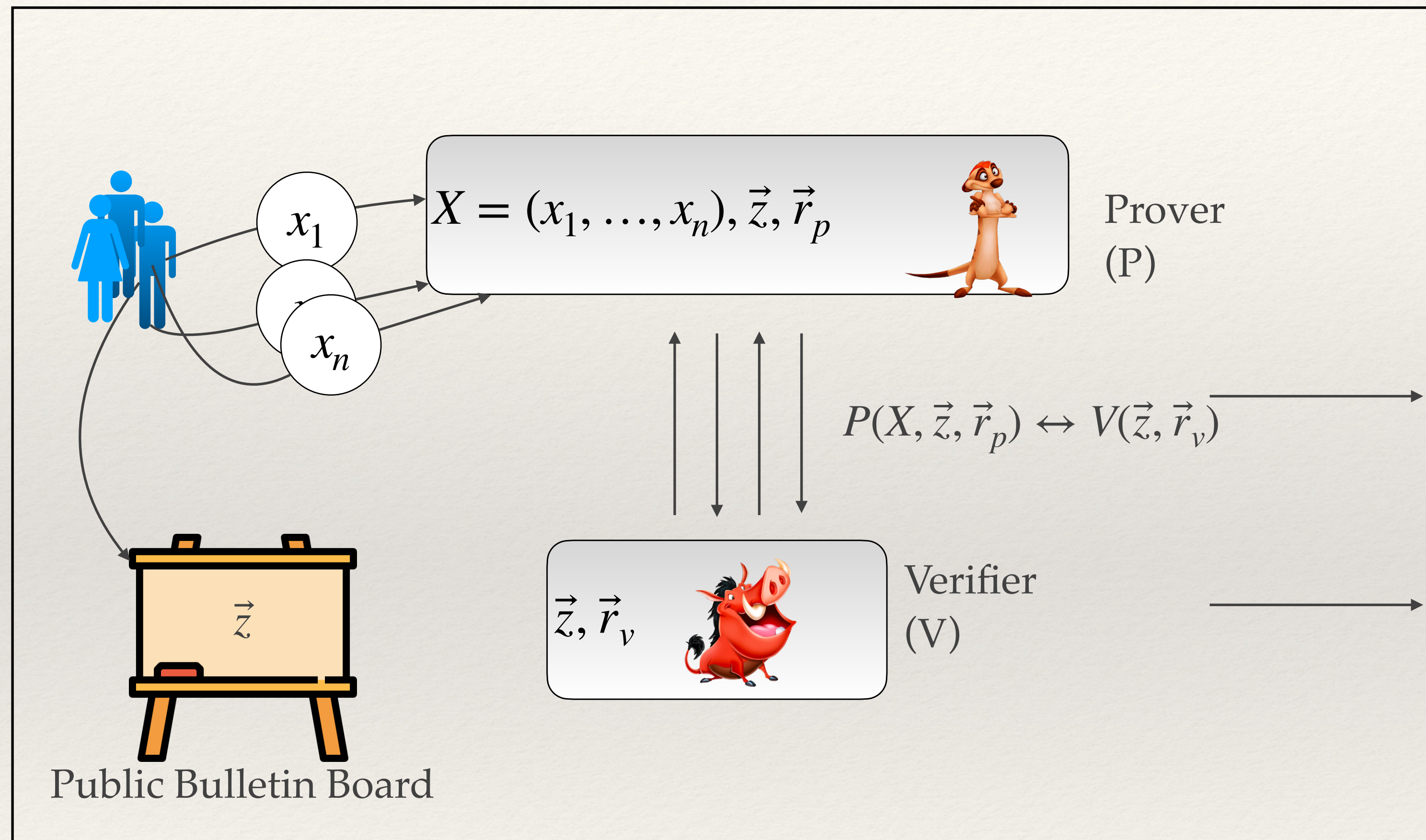
What Do We Want

- ❖ We want outputs to be differentially private
- ❖ However, we also want the output to be reliable i.e, by that we mean any error in the output must come as a result of DP noise and that only.

Client Server Verifiable DP



Verifiable DP



Security Parameter

$$\kappa \in \mathbb{N}$$

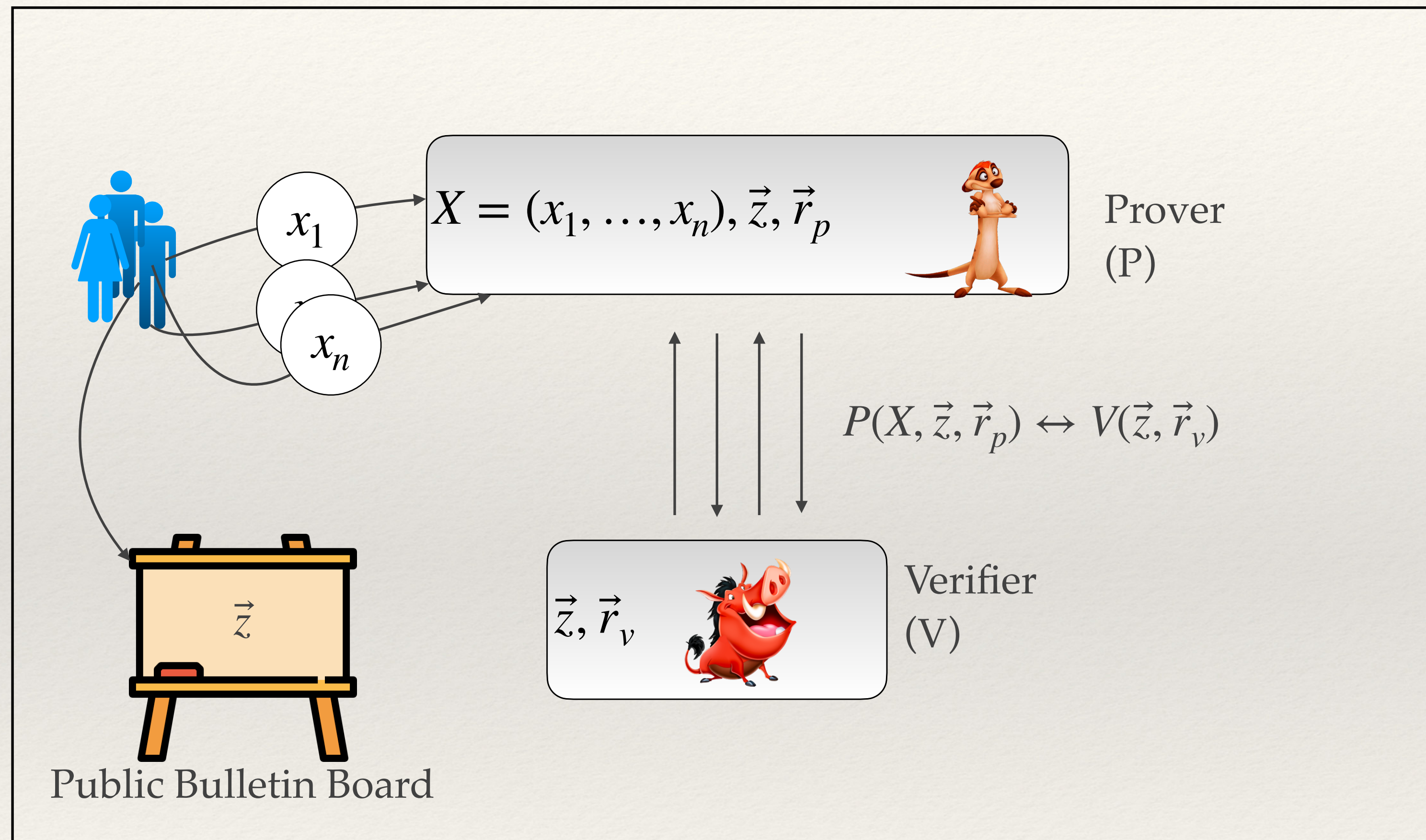
Typically, the size of the input in bits.

Prover interacts with the verifier over multiple rounds and **finally outputs** y .

The verifier looks at the board and the messages either **accepts or rejects the claim** that $y \stackrel{\$}{\leftarrow} M(X, Q)$

$$\text{Verify}(P \leftrightarrow V) \in \{0,1\}$$

Verifiable DP

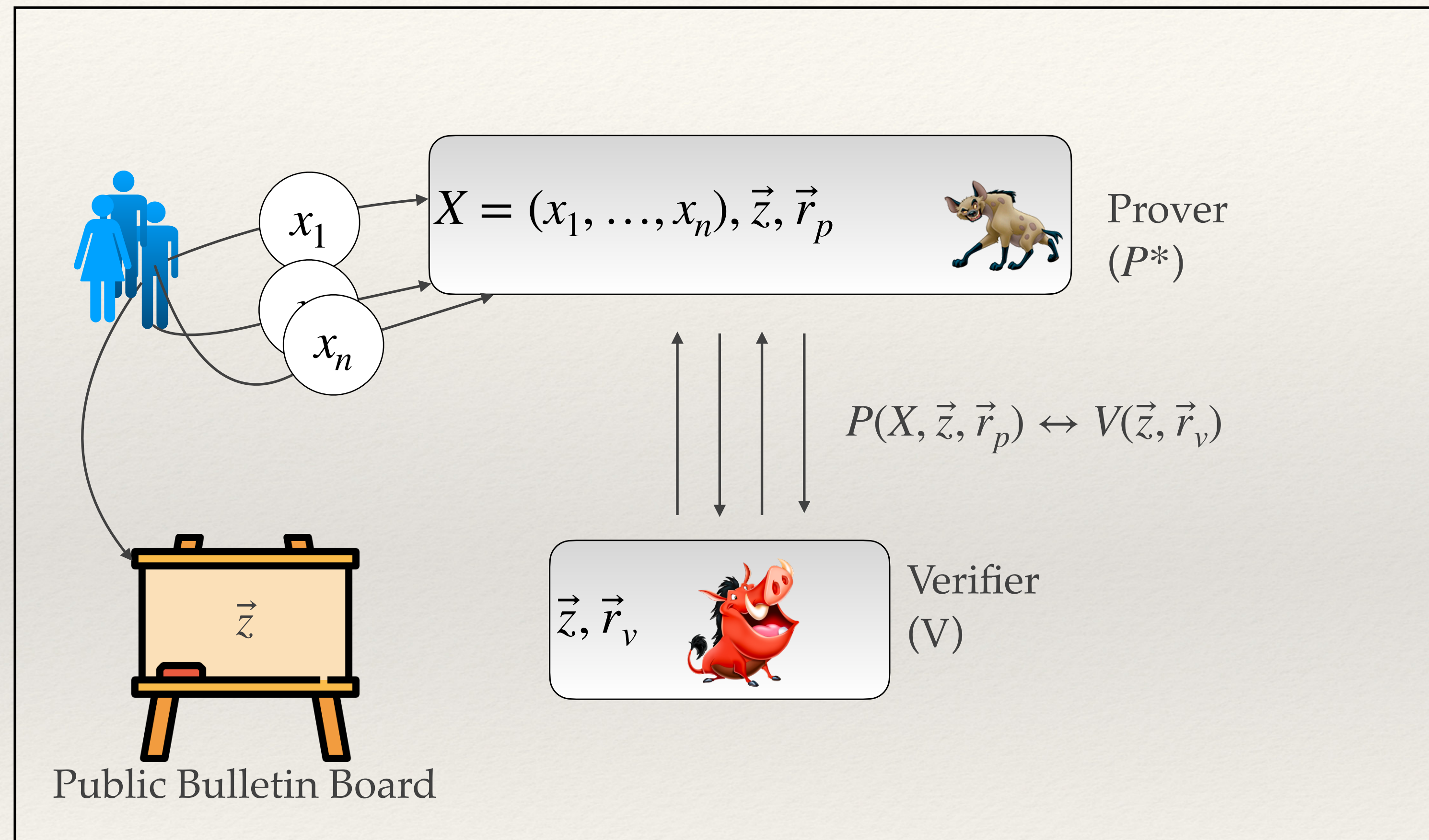


Completeness:

If both the prover and the verifier are honest, then $y \stackrel{\$}{\leftarrow} M(X, Q)$ and

$$\Pr[\text{Verify}(P \leftrightarrow V) = 1] = 1$$

Verifiable DP

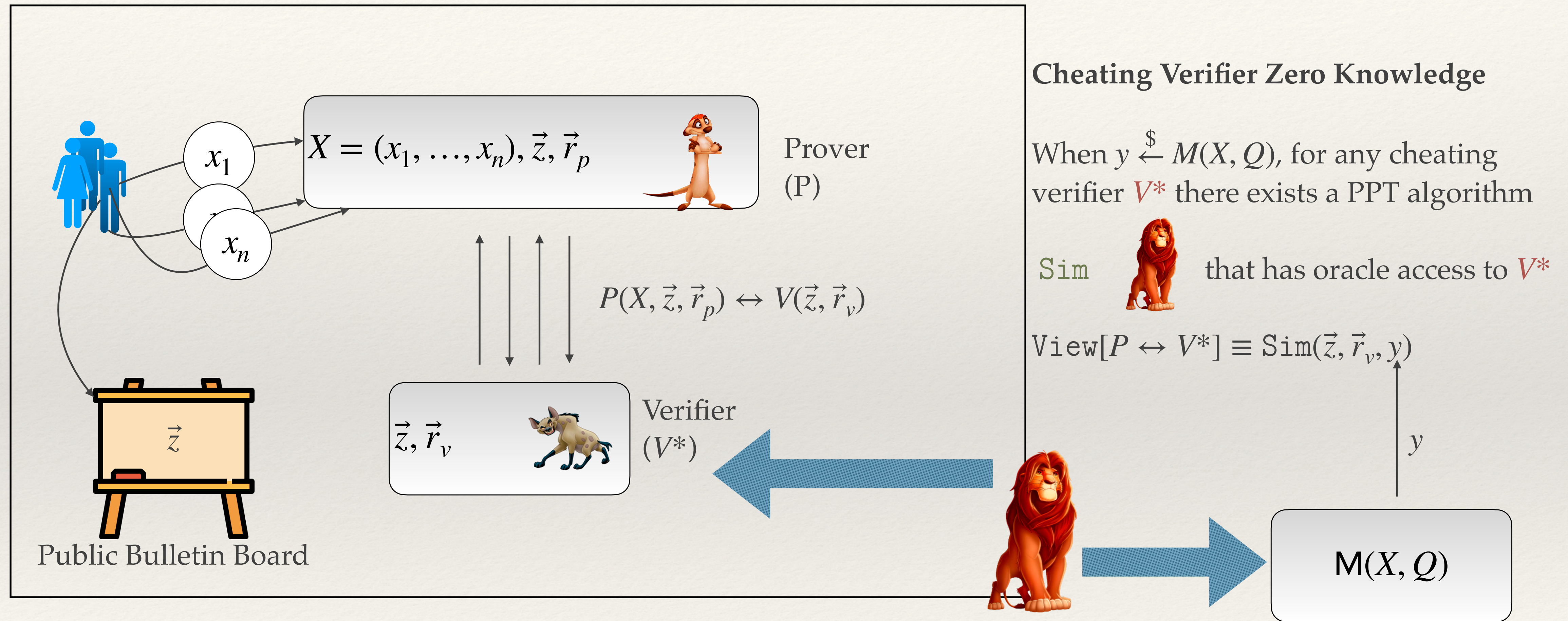


Soundness

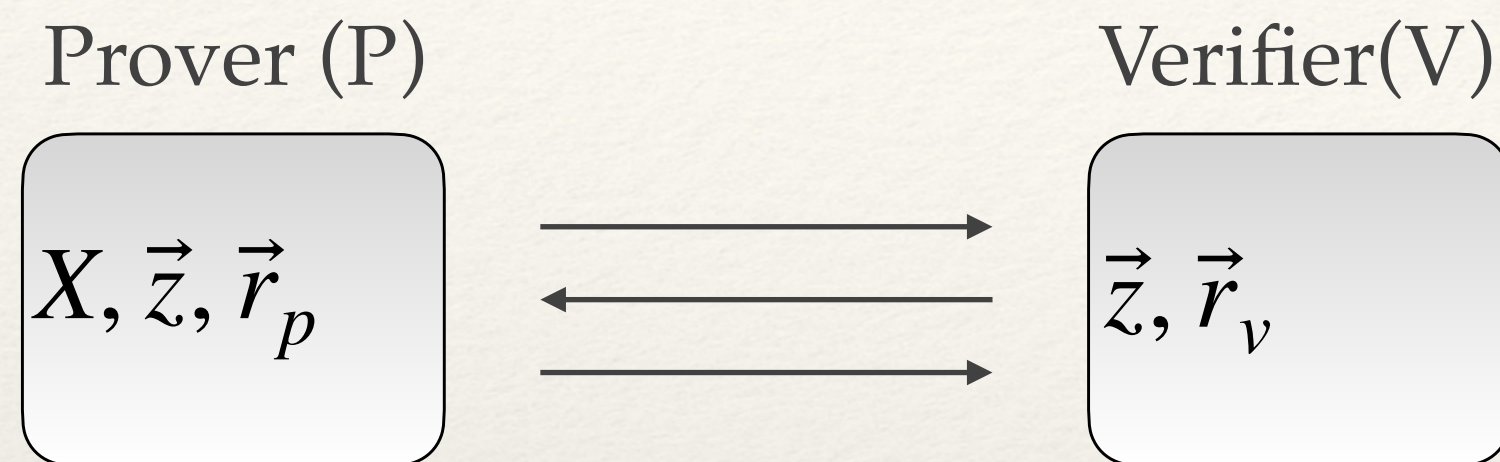
For any cheating prover P^* that samples y from a distribution \mathcal{D} such that $\text{TV}(\mathbf{M}(X, Q), \mathcal{D}) > 0$

$$\Pr[\text{Verify}(P^* \leftrightarrow V) = 1] \leq 1/3$$

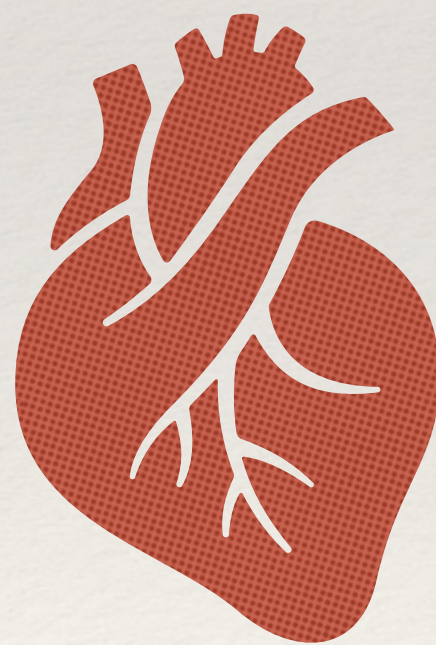
Verifiable DP



The Soundness/ZK conflict



THE HEART OF THE PROBLEM



*Not to be confused with Proof Of Knowledge

** The noise used is not **pseudorandom** noise either

$$y = \boxed{Q(x_1, \dots, x_n)} + \boxed{Z} \longrightarrow \boxed{M(X; Q)}$$

$Z \xleftarrow{\$} \text{Binomial}(\eta, \frac{1}{2})$

The output is a function of the provers local randomness. However the prover cannot ever reveal this randomness to the verifier as it would compromise DP.

The prover must find a way to prove that Z was sampled from the right distribution without ever revealing any information about Z .

However, we also need some shared information (like say public randomness) for the verifier to be able to confident that Z is sampled correctly.

Some Crypto Prelims

Commitments

Two stage interactive protocol between a Committer and a Receiver



Committer

Commit Phase

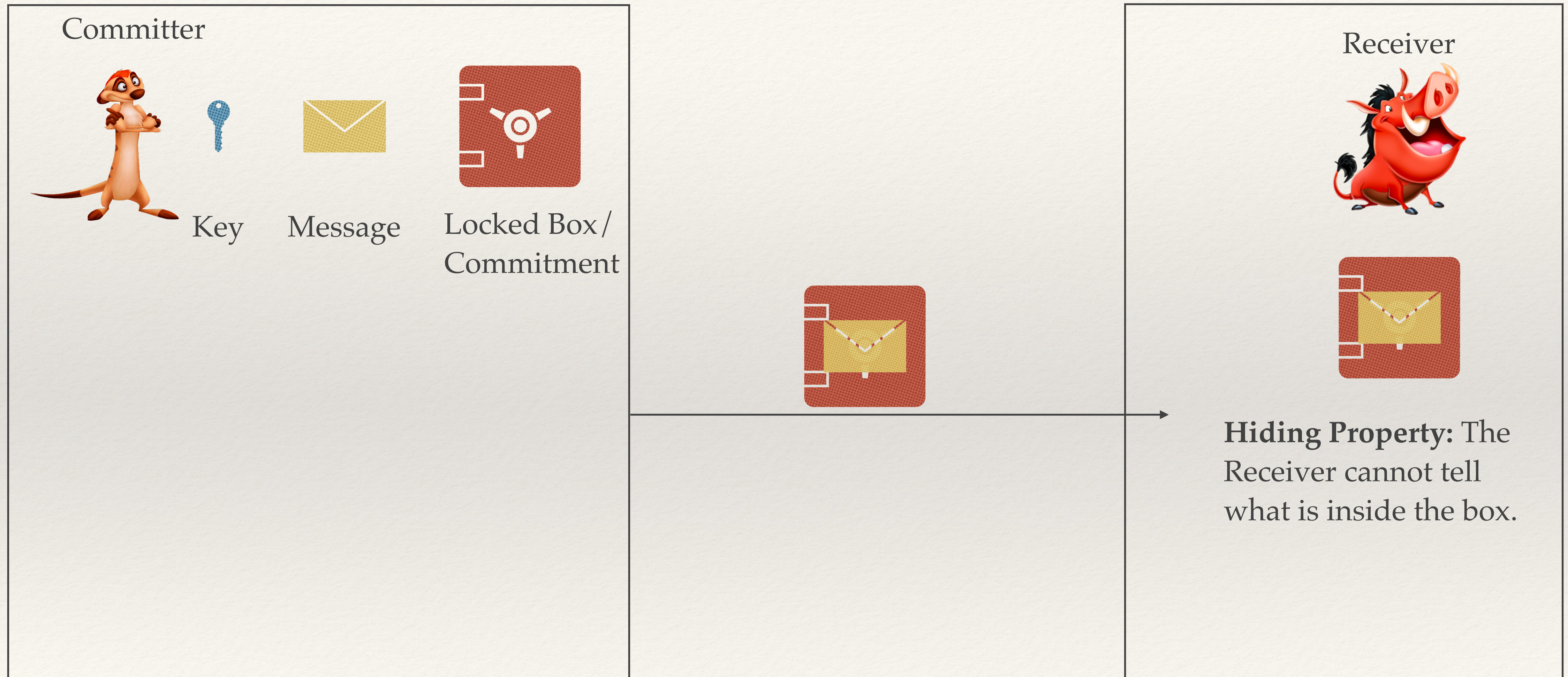


Receiver

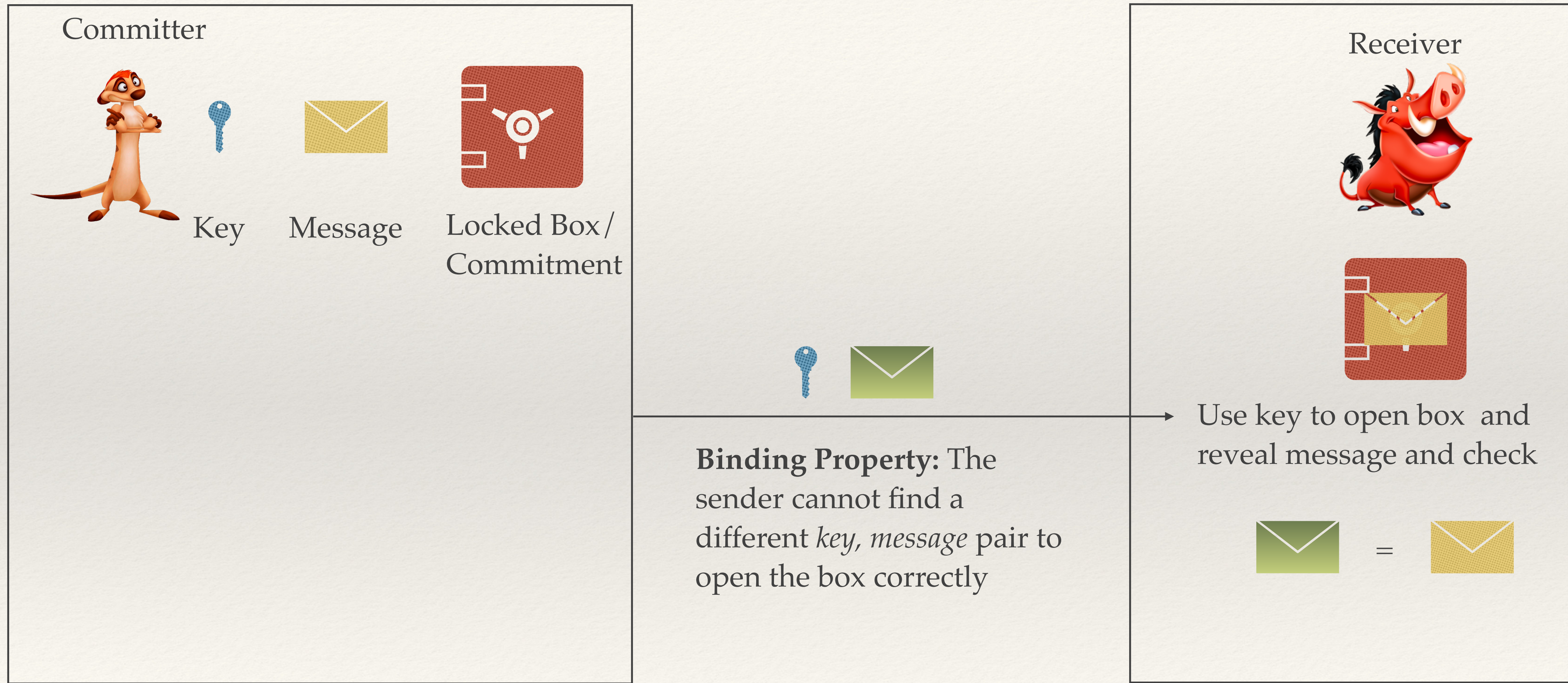
Reveal Phase



Commit Phase



Reveal Phase



Example: Pedersen Commitments



Key



Message



Locked Box/
Commitment

Let \mathbb{G}_q be a prime order cyclic group with operation $+$ and $g \in \mathbb{G}_q$ and $h \in \mathbb{G}_q$ be generators.

$$r \xleftarrow{\$} \mathbb{Z}_q$$

$$x \in \mathbb{Z}_q$$

$$c = g^x h^r$$

c is statistically hiding and computationally binding

Homomorphic Commitments



Key



Message



Locked Box/
Commitment



Key



Message



Locked Box/
Commitment



+



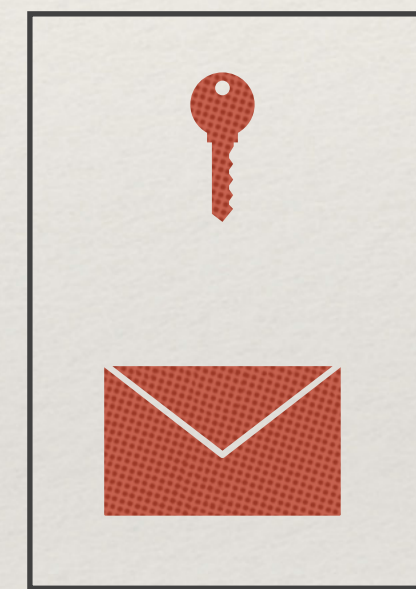
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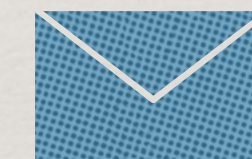
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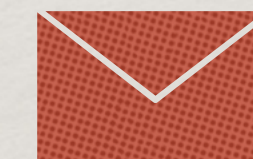
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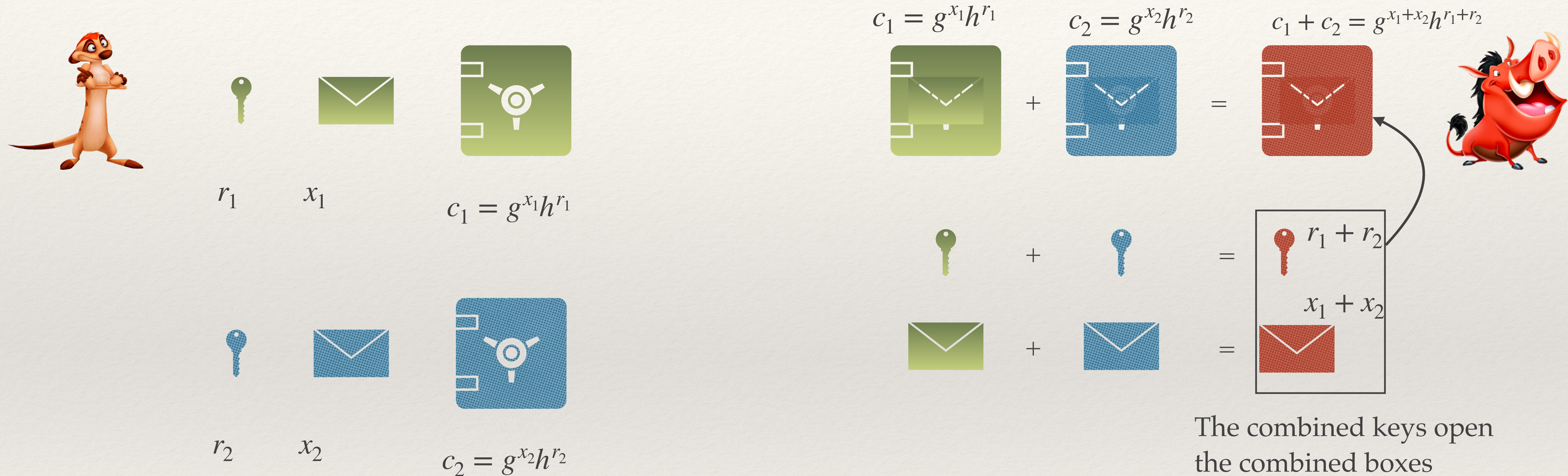
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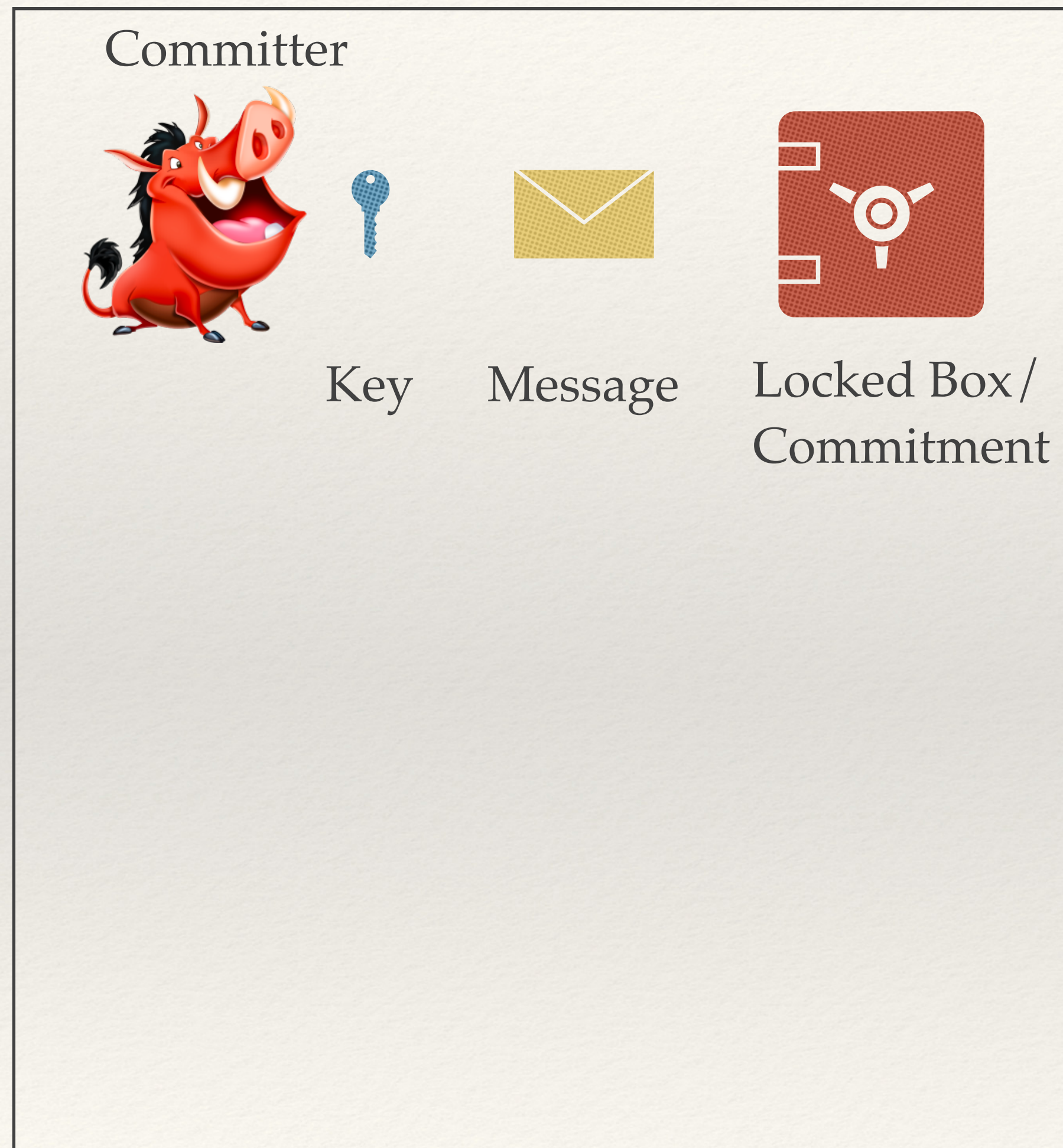
The combined keys open
the combined boxes



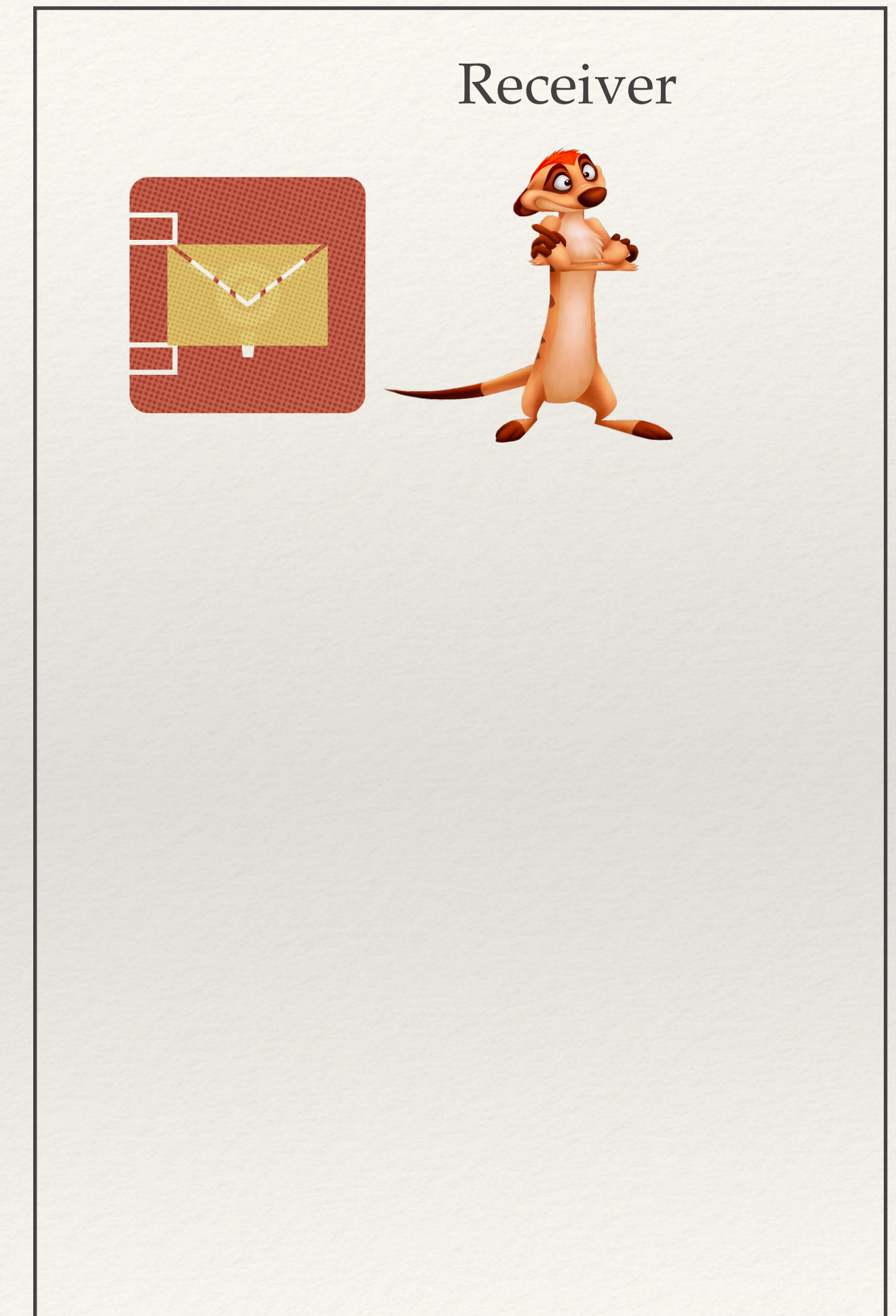
Pedersen Commitments Are Homomorphic



Disjunctive OR Arguments



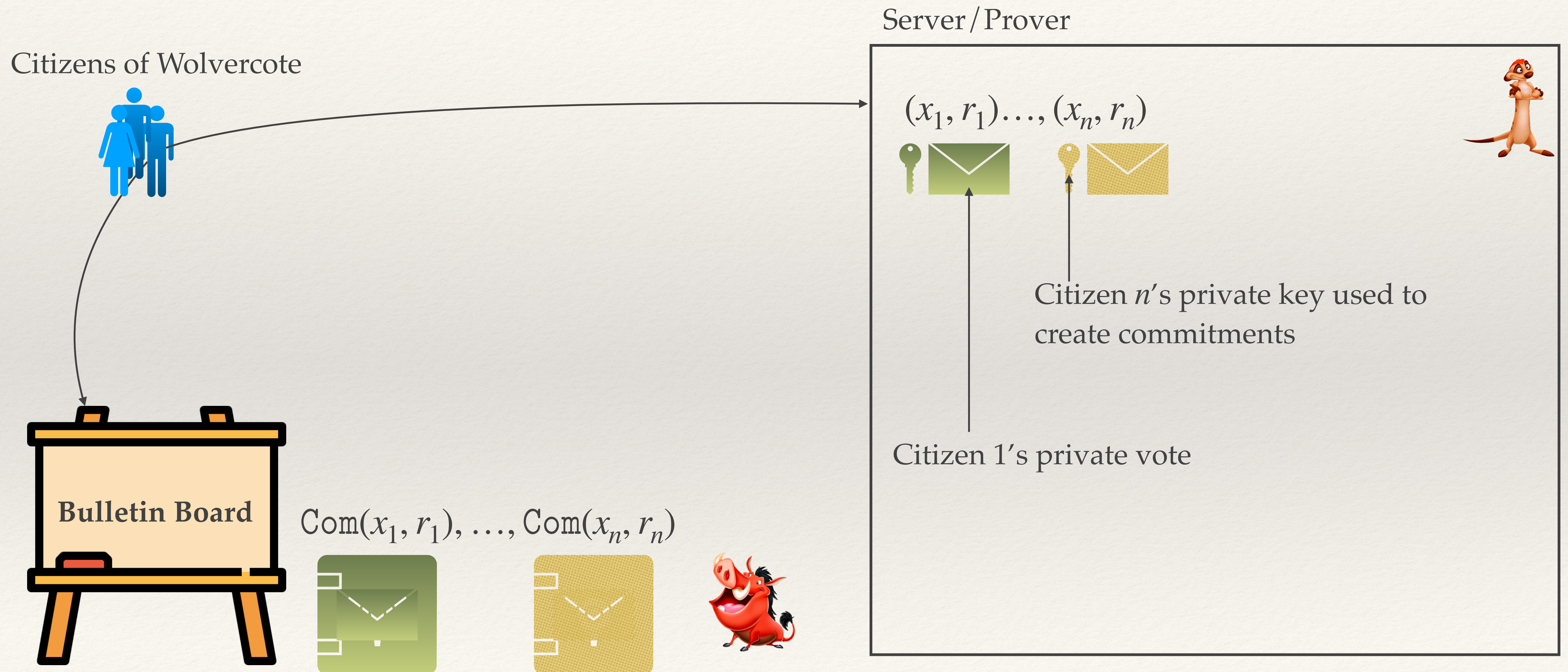
The prover can convince the receiver that the message is either 0 or 1 without revealing which one it is



Quick Recap

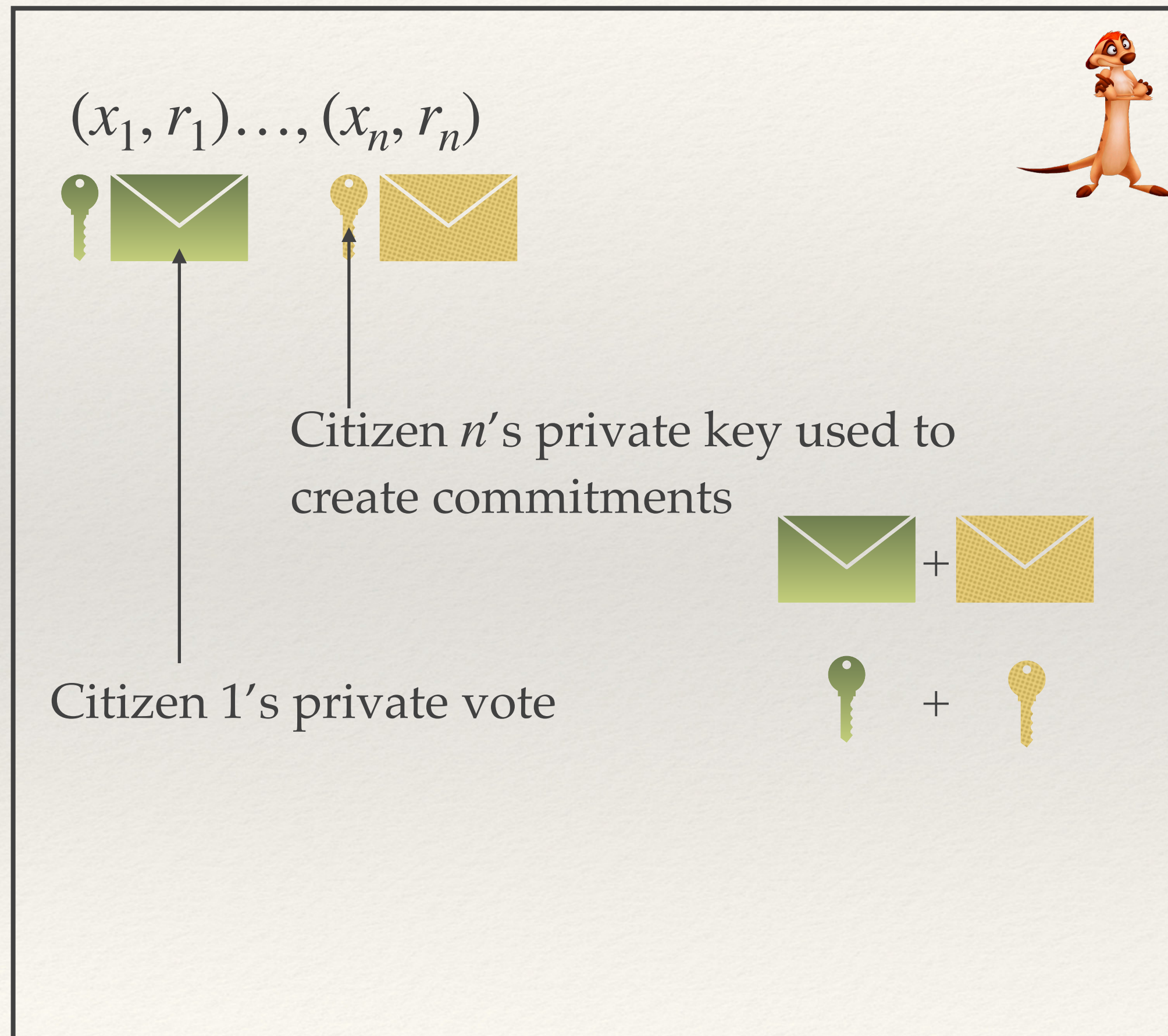
- ❖ We have commitments that are homomorphic and support OR arguments.

Main Protocol



Non Private Counting Is Was

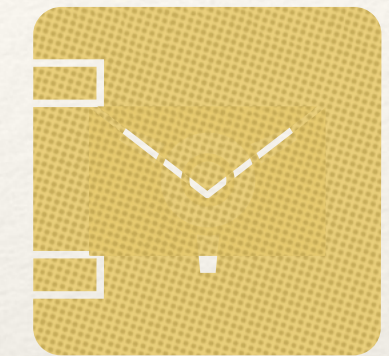
Server / Prover



$\text{Com}(x_1, r_1), \dots, \text{Com}(x_n, r_n)$

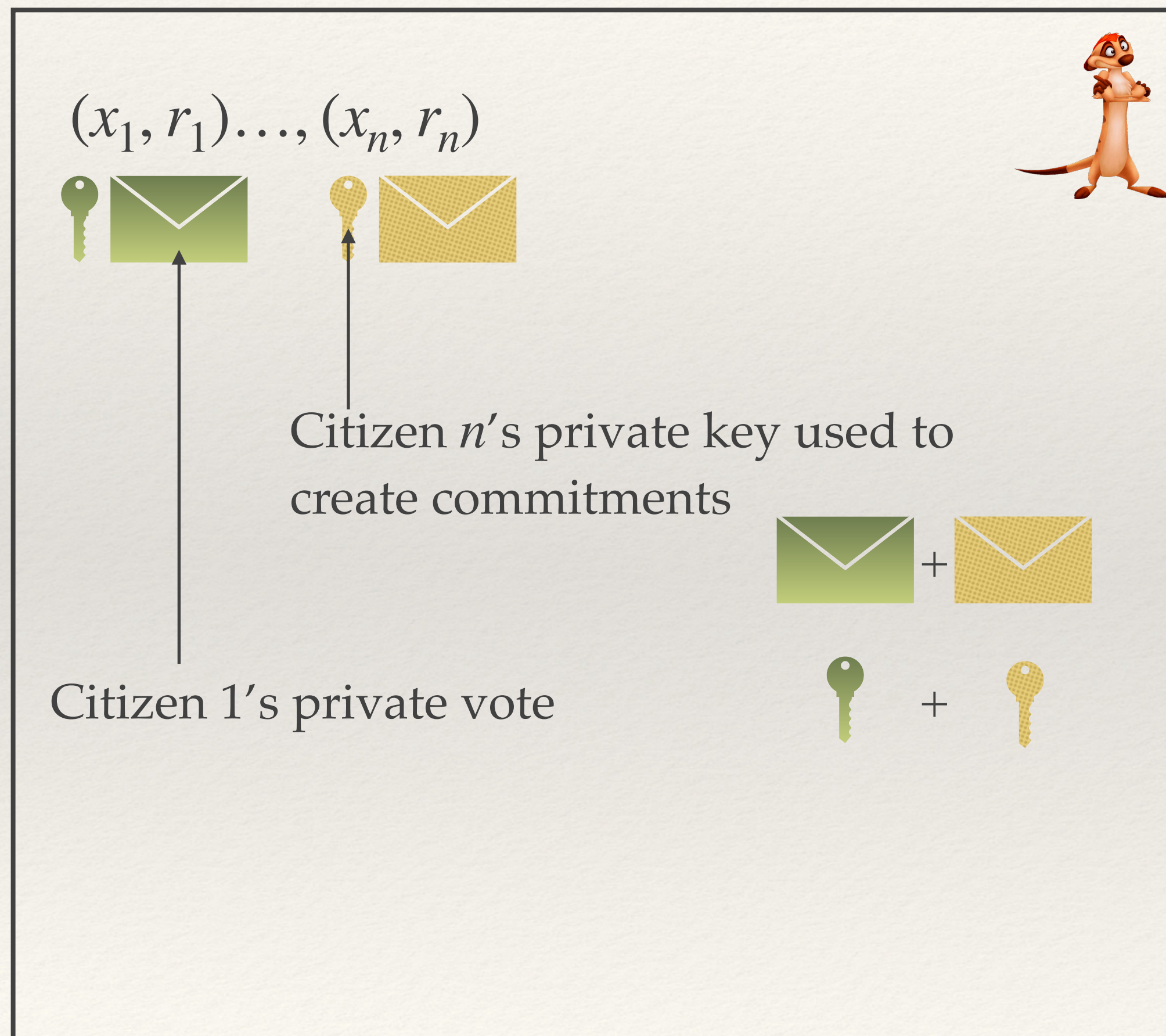


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Non Private Counting Is Was

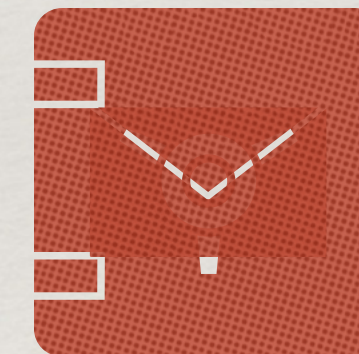
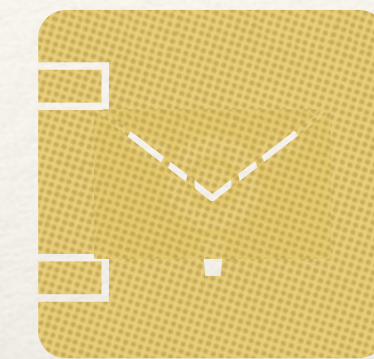
Server / Prover



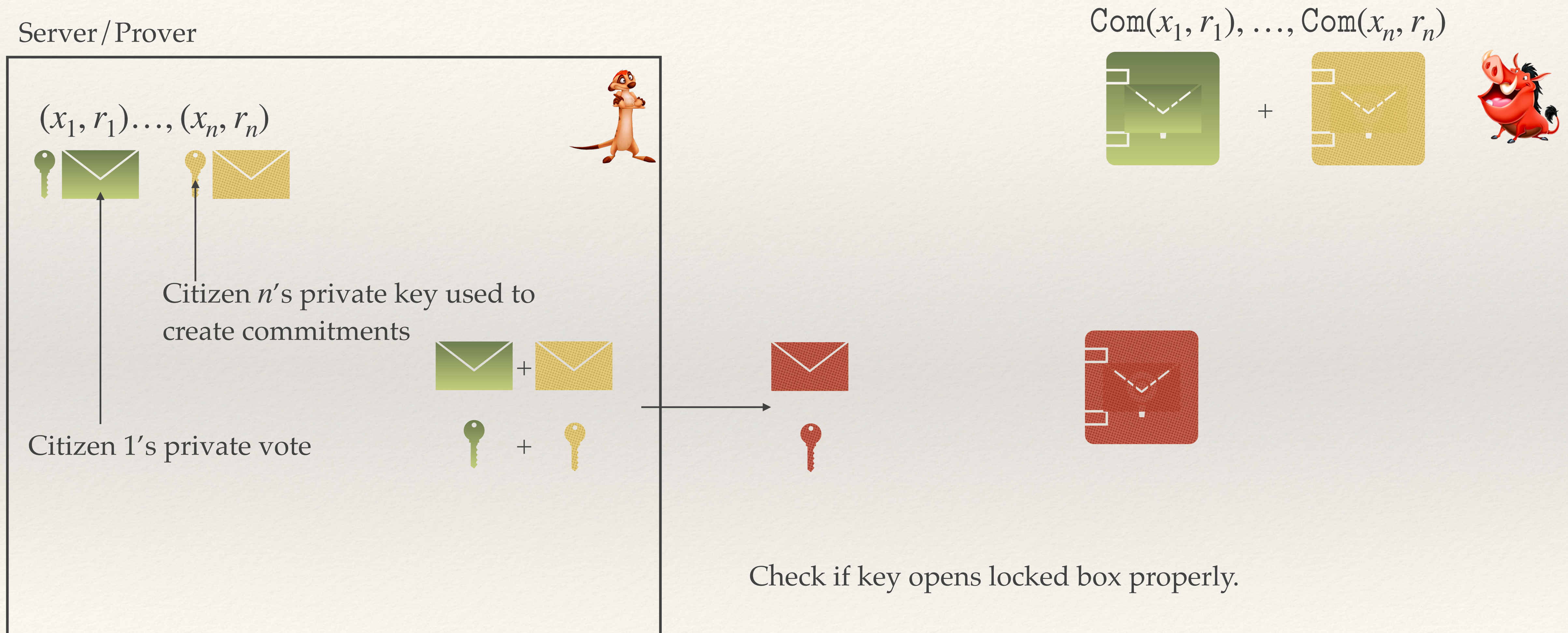
$\text{Com}(x_1, r_1), \dots, \text{Com}(x_n, r_n)$



+



Non Private Counting Is Was



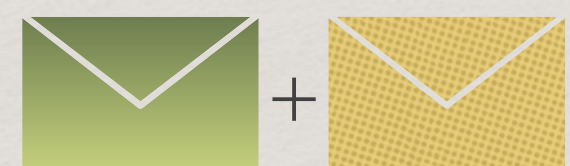
Verifiable DP counting - Essence

Server / Prover

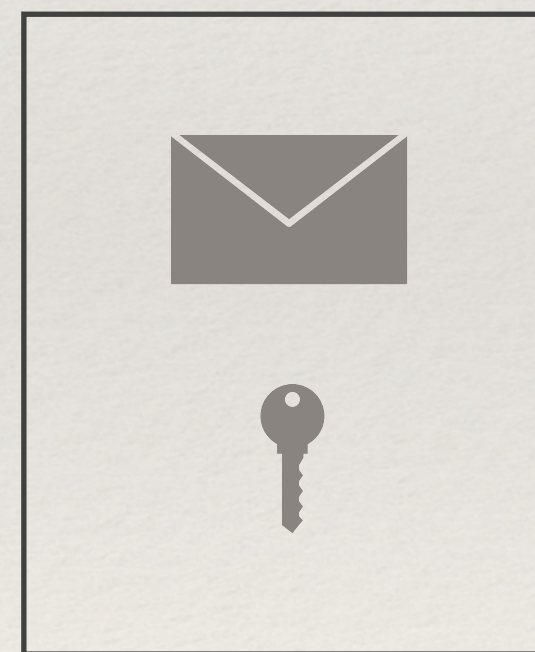
$(x_1, r_1), \dots, (x_n, r_n)$



$Z \xleftarrow{\$} \text{Binomial}(\eta, \frac{1}{2})$



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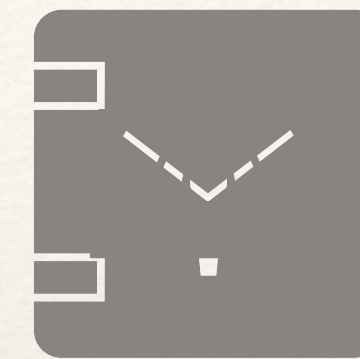


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Check if key opens locked box properly.

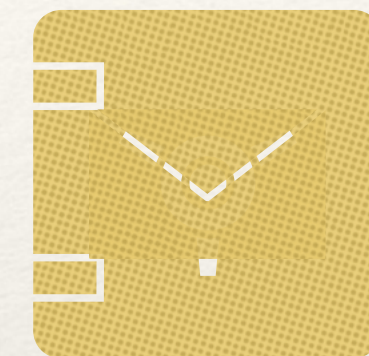
$\text{Com}(x_1, r_1), \dots, \text{Com}(x_n, r_n)$



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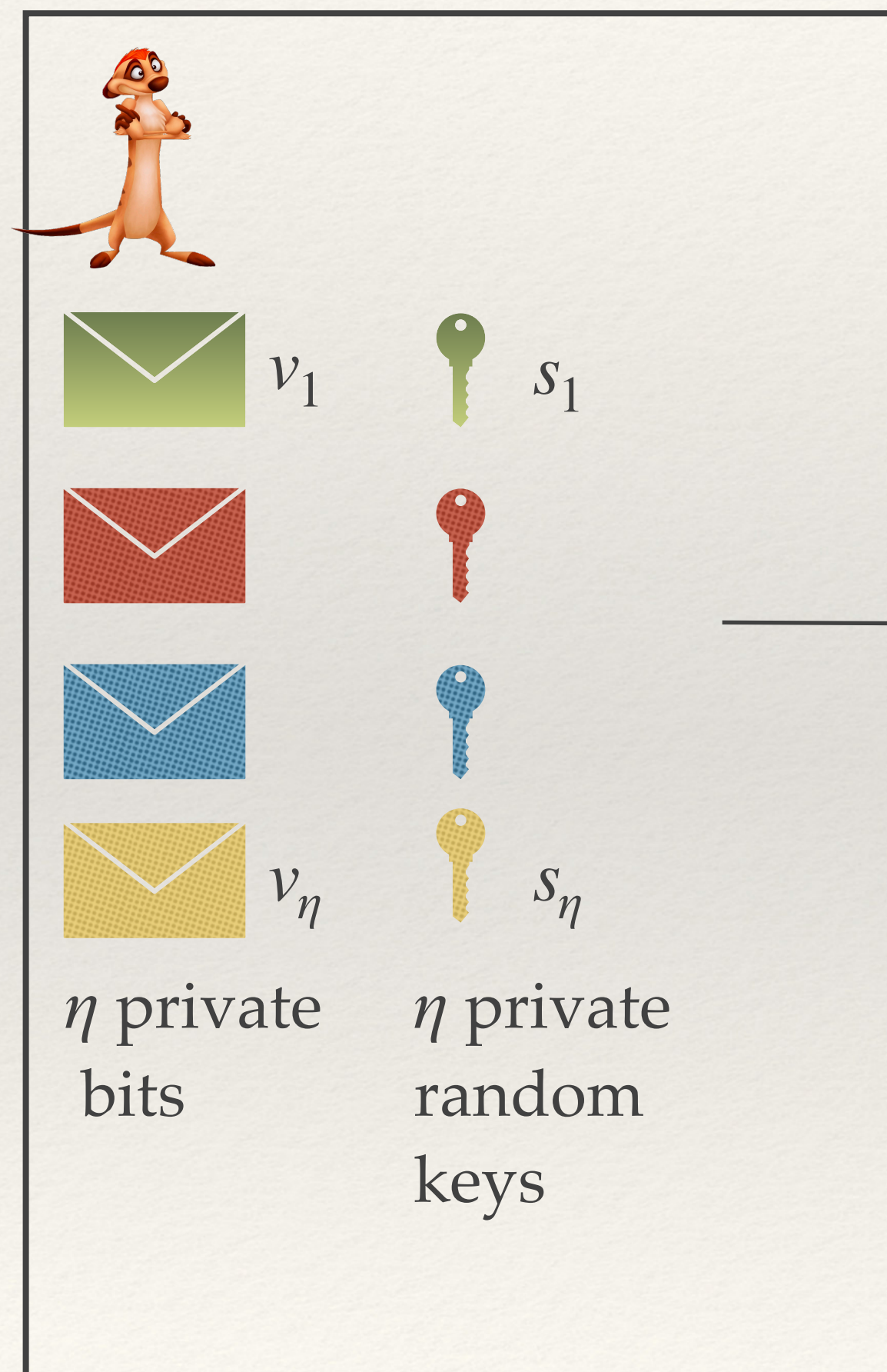


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A Simple Trick

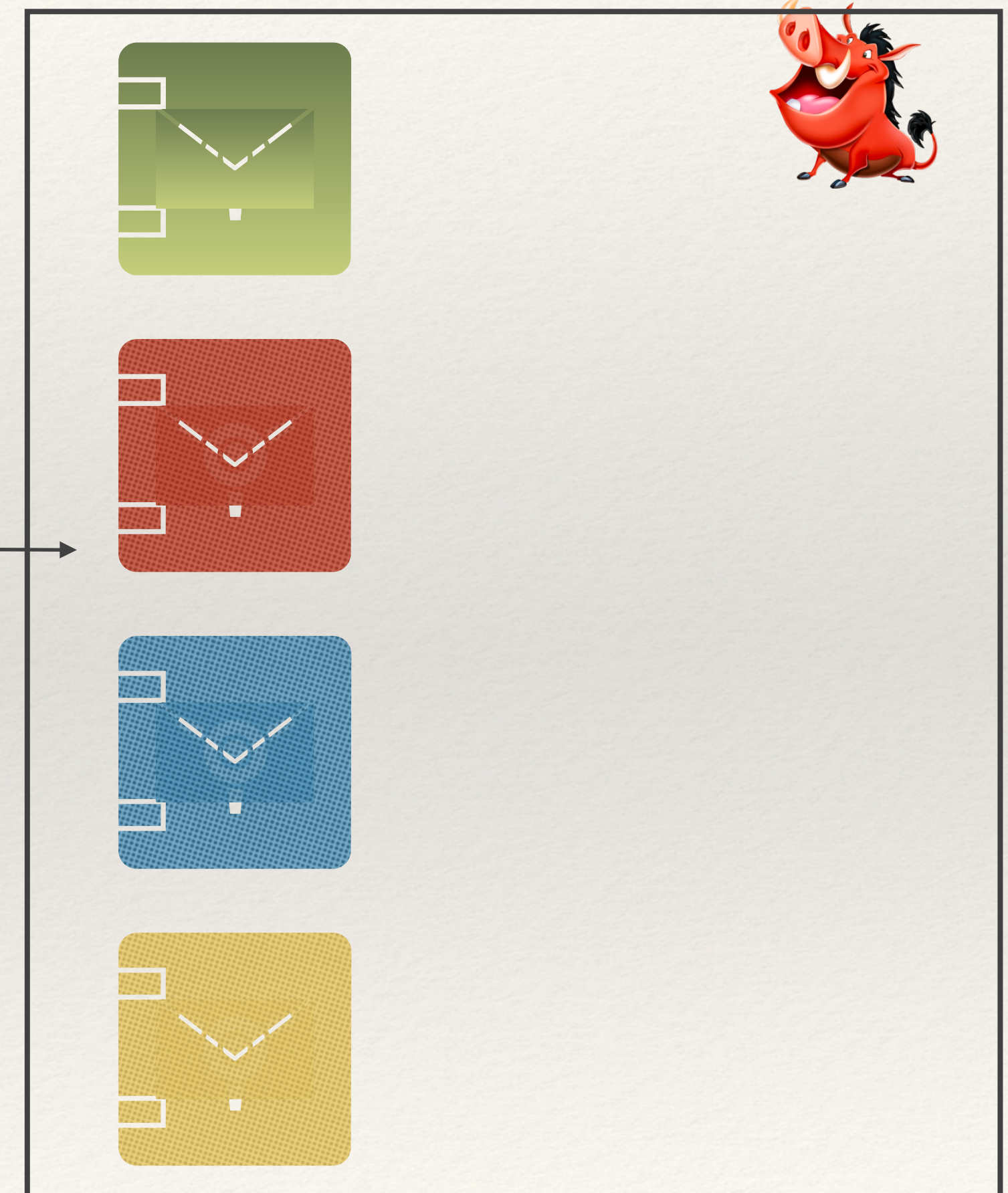
Server / Prover



Note we cannot say anything about the distribution from which these bits are being sampled.

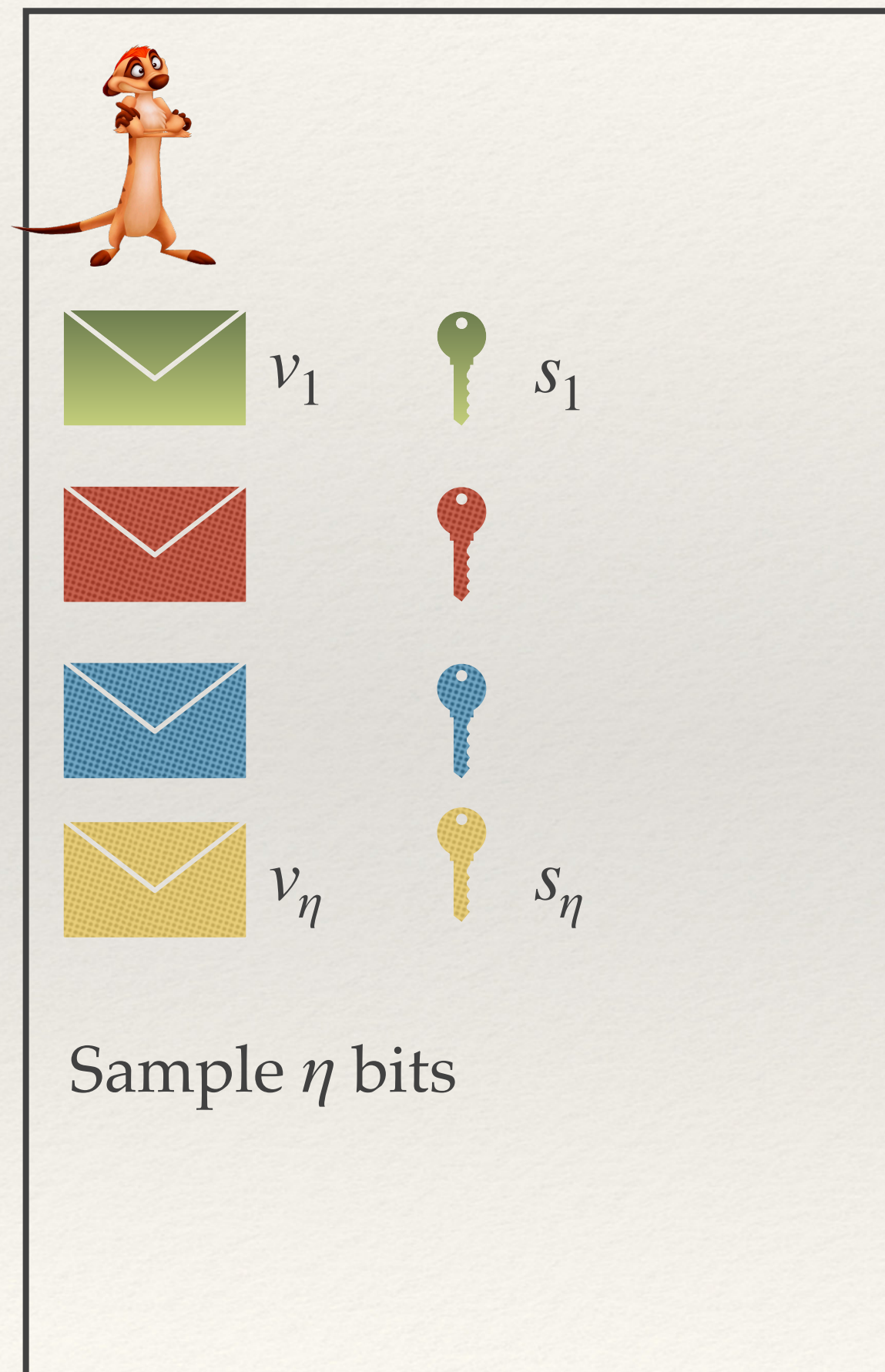
All the verifier knows is that these boxes are a commitment to a bit.

Verifier

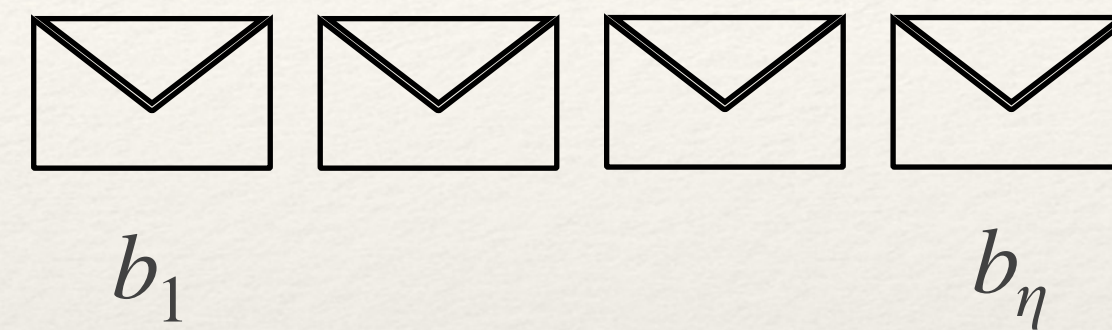


A Simple Trick

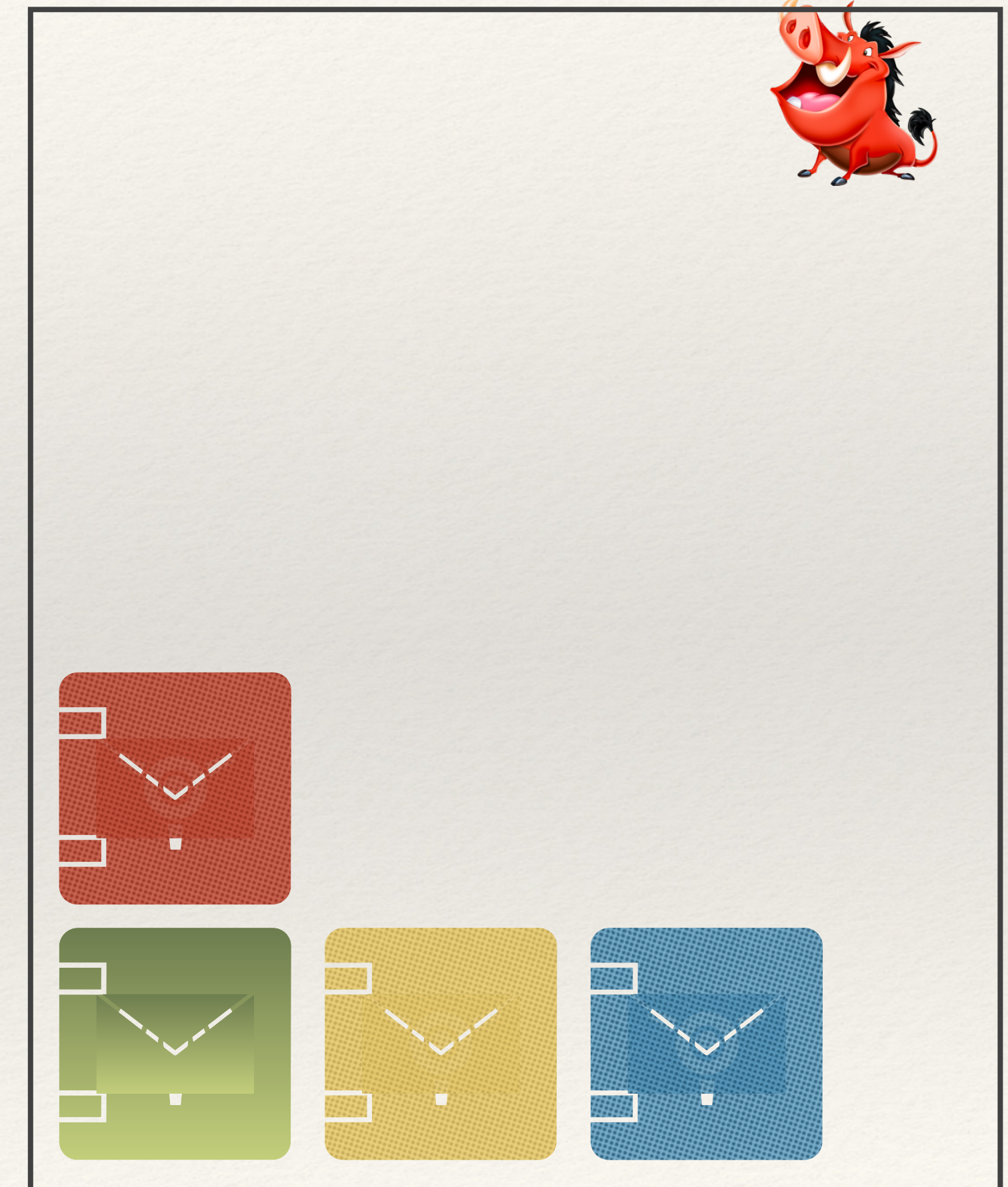
Server / Prover



Verifier generates η public unbiased coins

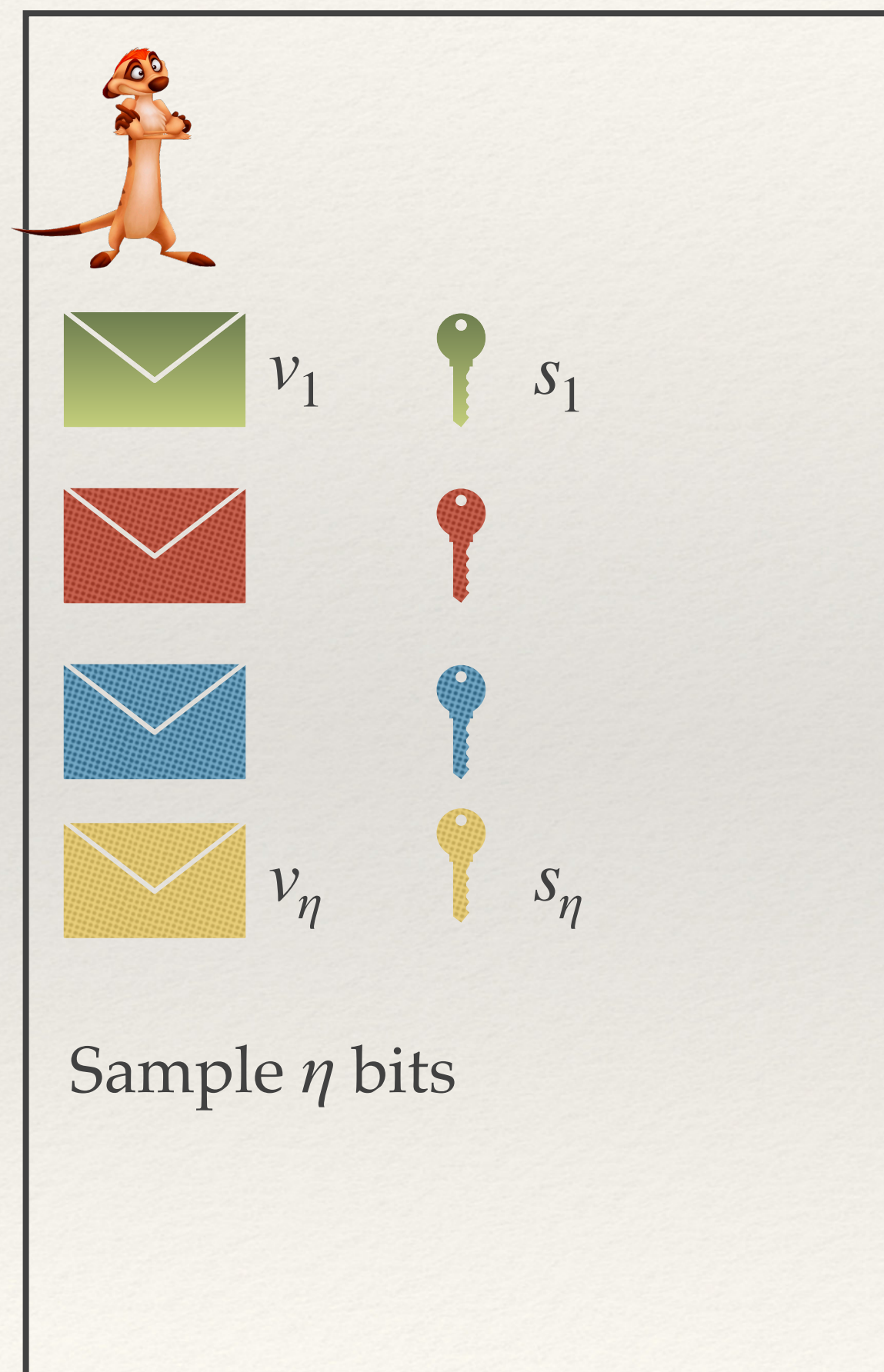


Verifier

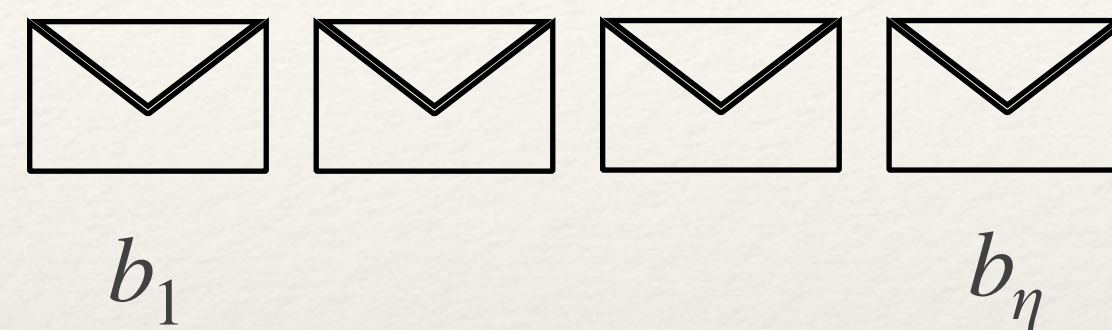


The Final Trick

Server / Prover

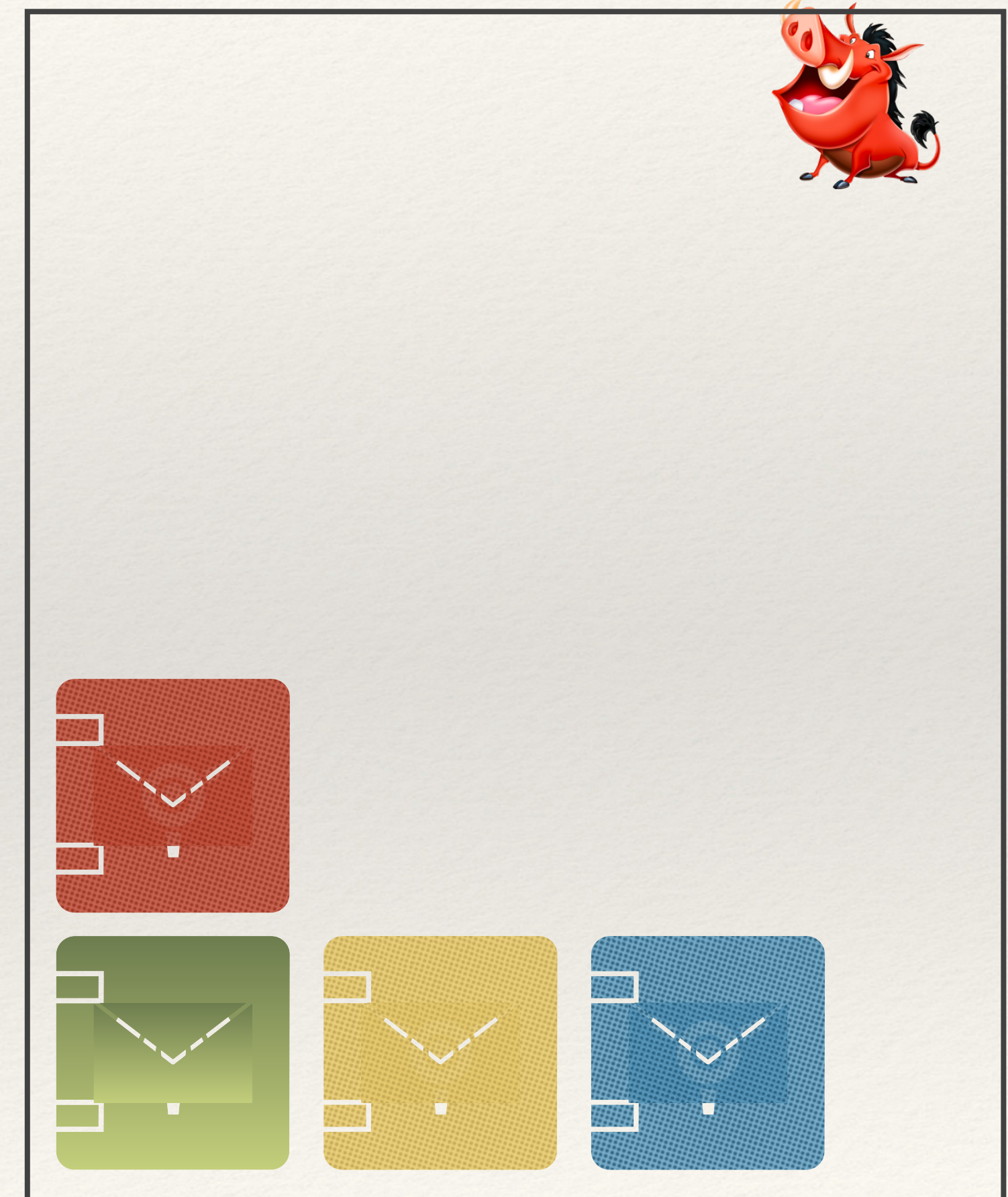


Verifier generates η public unbiased coins



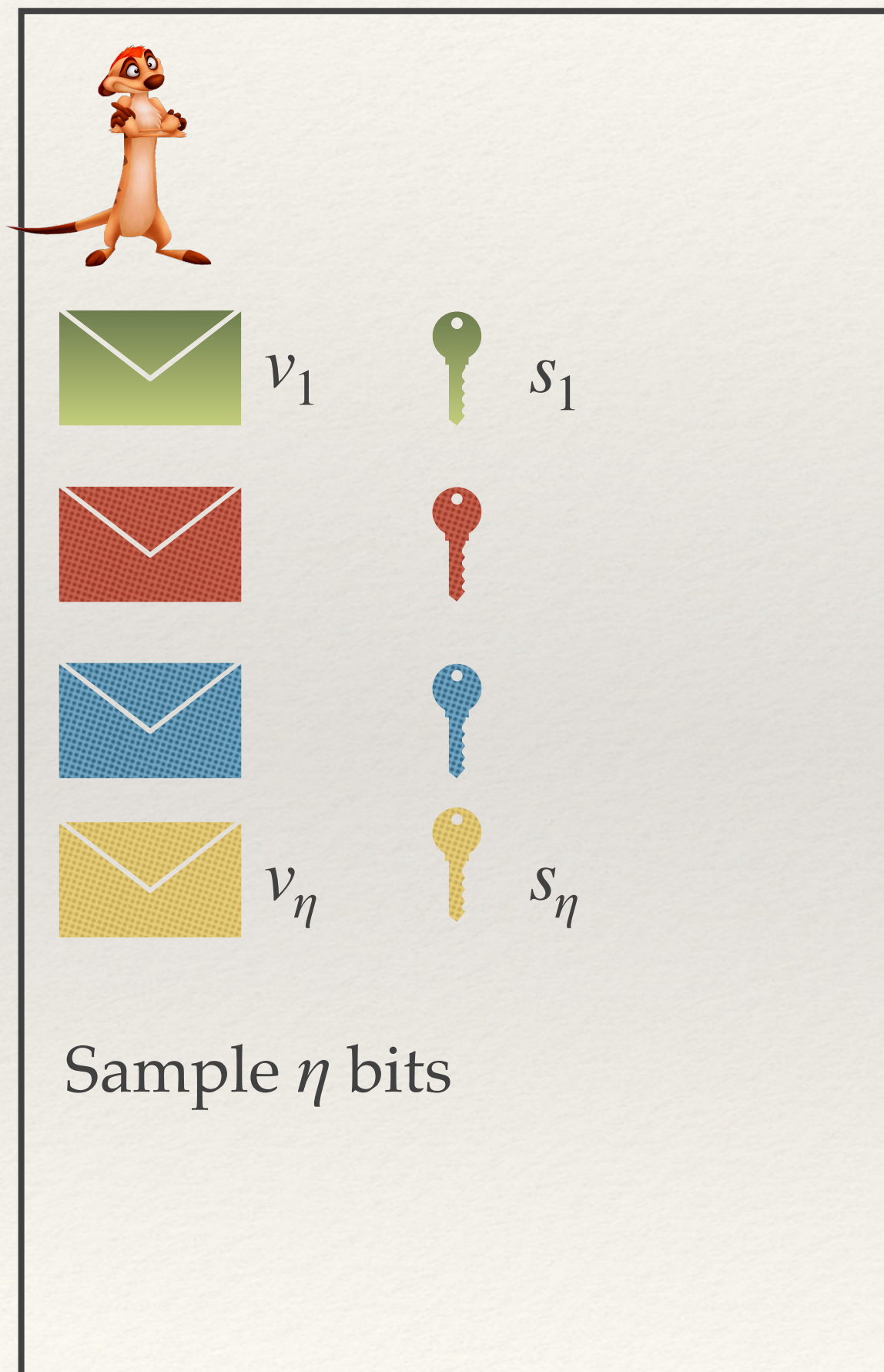
If $b_i = 1$ then set $v_i = 1 - v_i$
Otherwise, leave v_i unchanged.

Verifier

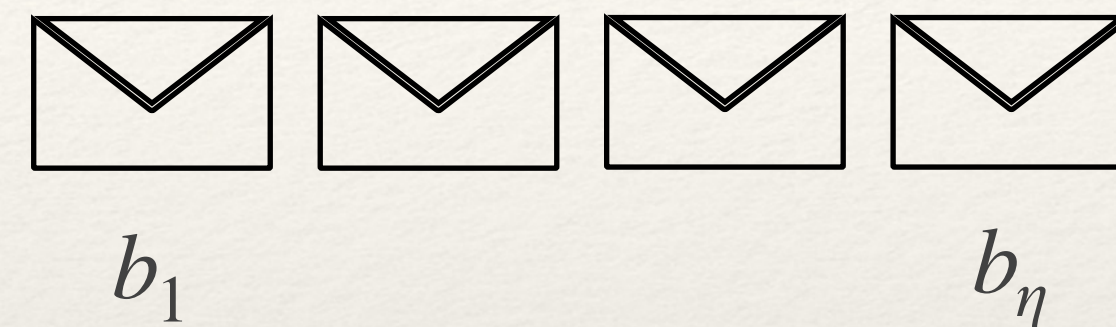


The Final Trick

Server / Prover



Verifier generates η public unbiased coins



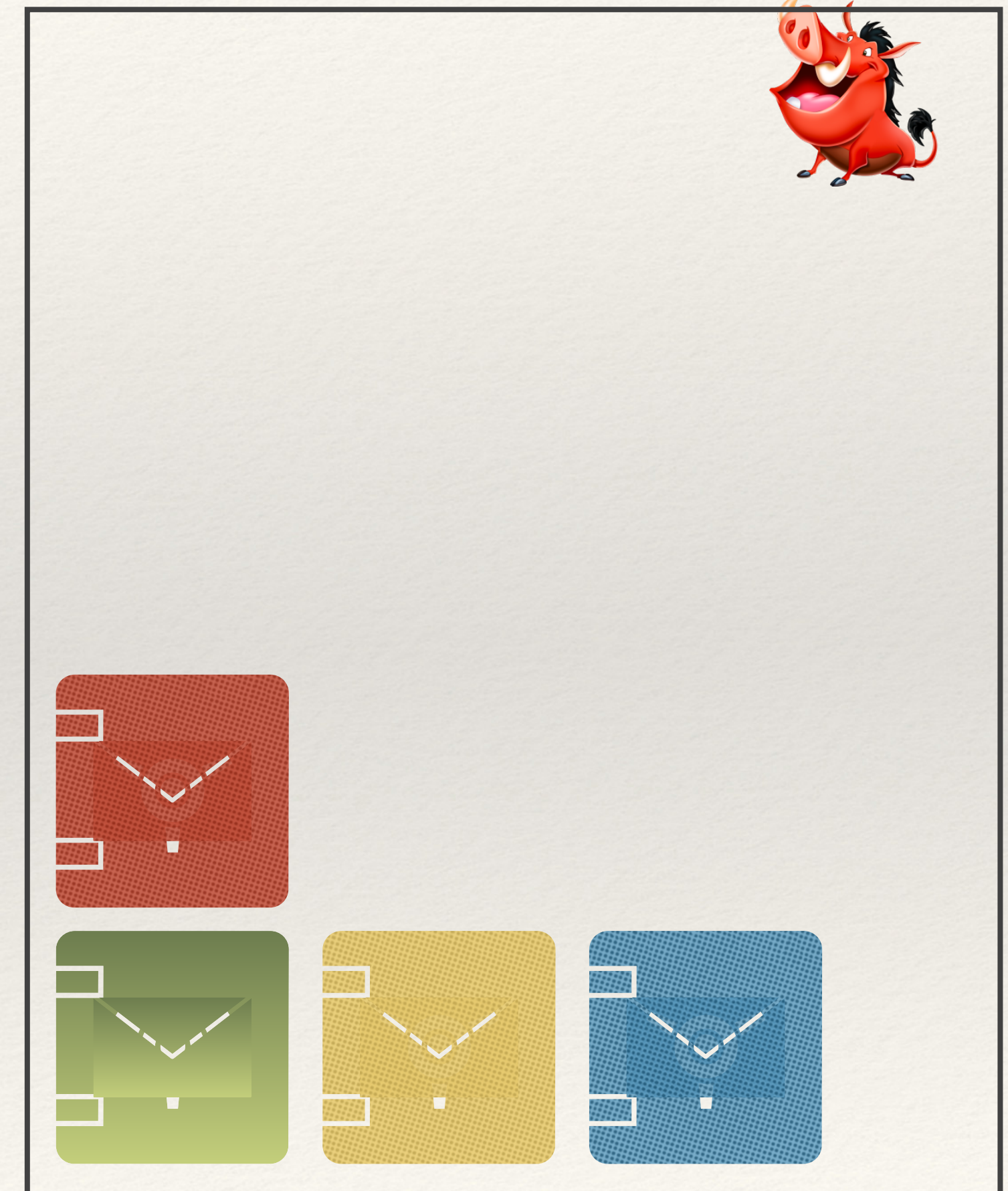
If $b_i = 1$ then set $v_i = 1 - v_i$ and $s_i = 1 - s_i$

Otherwise, leave v_i and s_i unchanged.

Observation 1:
The updates are LINEAR conditioned on b_i

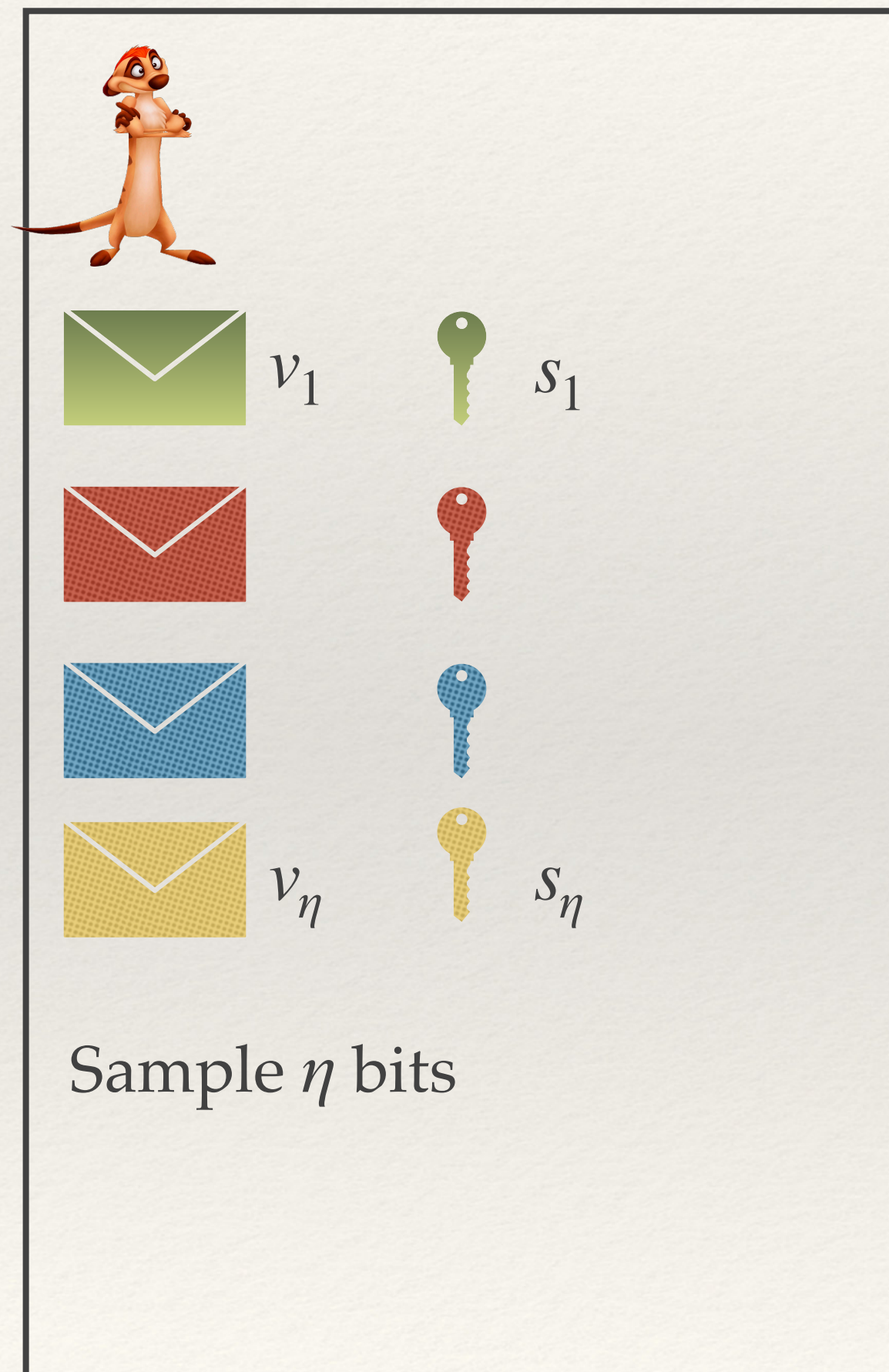
Without ever seeing v_i the verifier
can update
 $\text{Com}(v_i, s_i) = \text{Com}(1, 1) - \text{Com}(v_i, s_i)$

Verifier

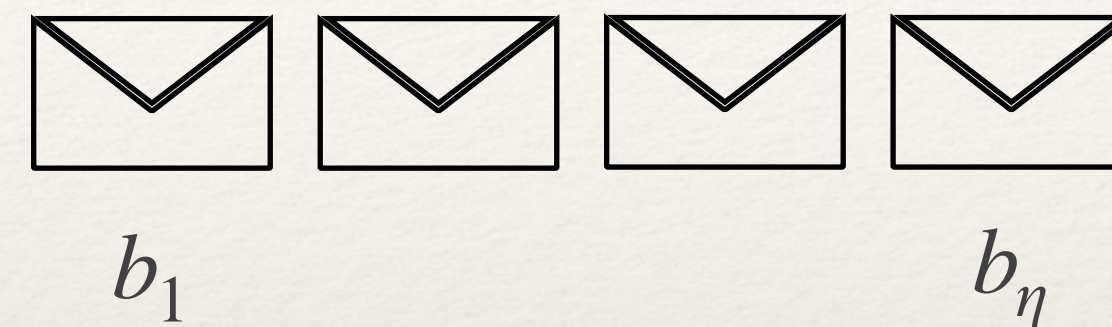


The Final Trick

Server / Prover



Verifier generates η public unbiased coins



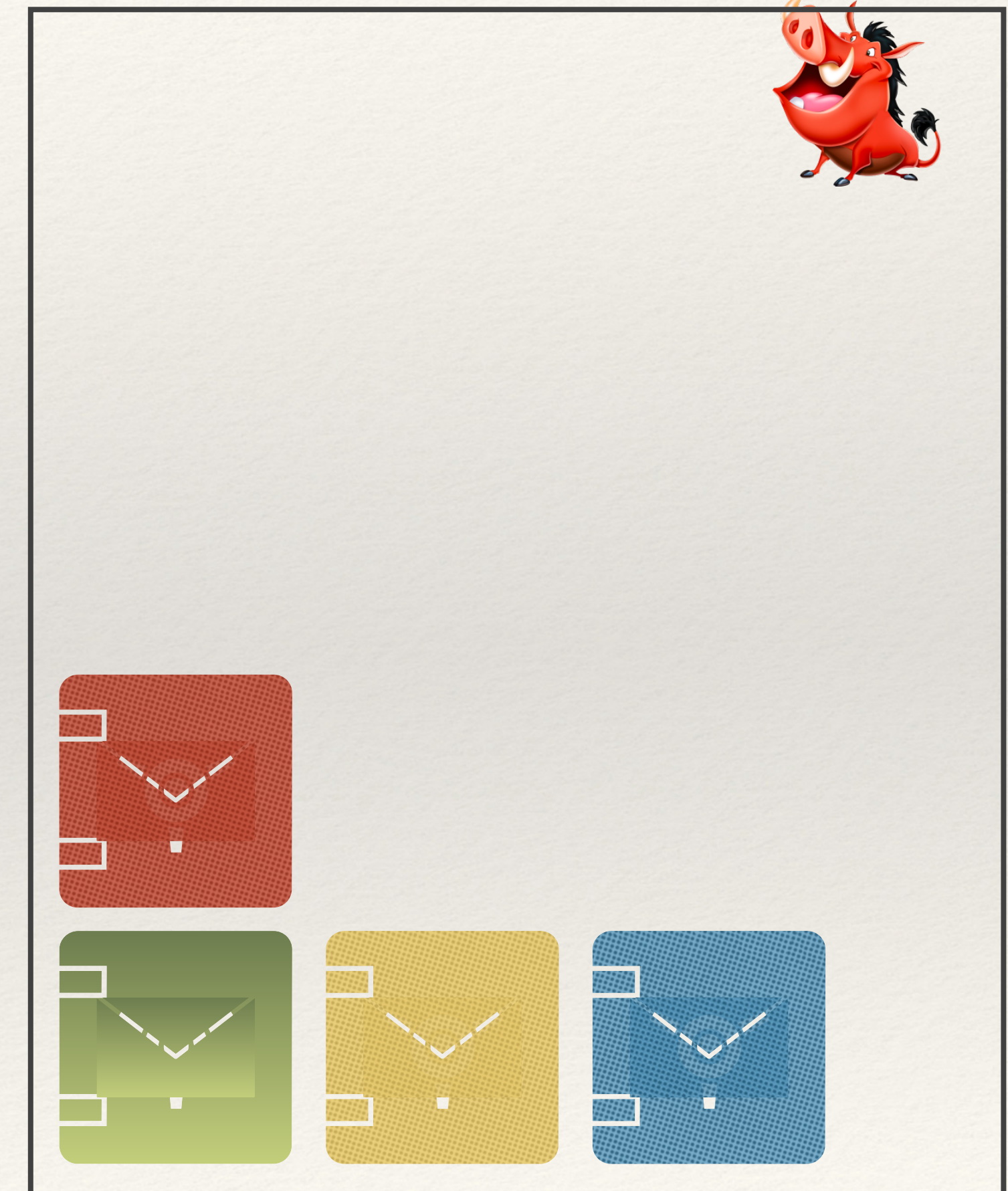
If $b_i = 1$ then set $v_i = 1 - v_i$

Otherwise, leave v_i unchanged.

Observation 2:
The above conditional statement is equivalent to
 $v_i = v_i \oplus b_i$

This forces the provers bit to have the correct distribution.

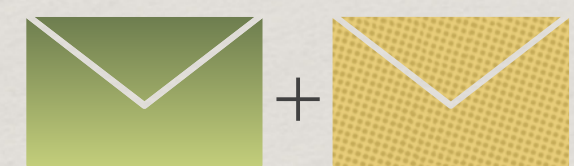
Verifier



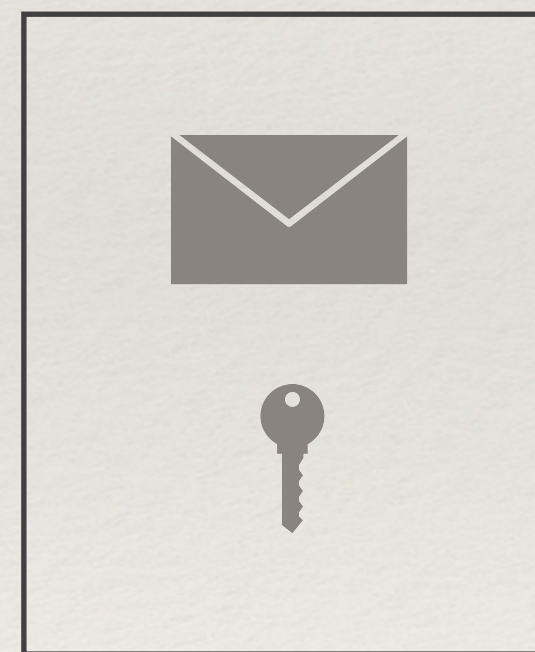
Final Check

Server / Prover

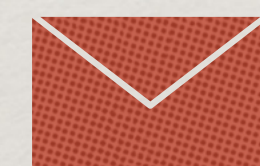
$(x_1, r_1), \dots, (x_n, r_n)$



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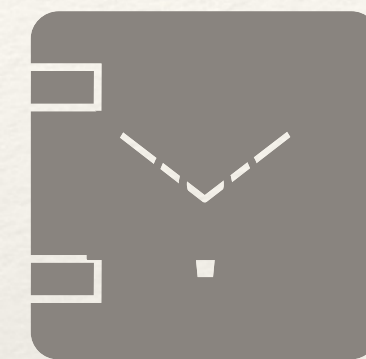


$\sum_{i=1}^{\eta} v_i$
 $\sum_{i=1}^{\eta} s_i$



Check if key opens locked box properly.

$\text{Com}(\sum_{i=1}^{\eta} v_i, \sum_{i=1}^{\eta} s_i)$

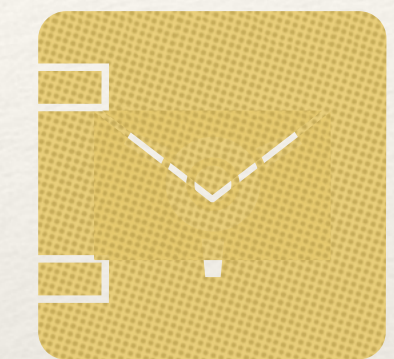


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$\text{Com}(x_1, r_1), \dots, \text{Com}(x_n, r_n)$



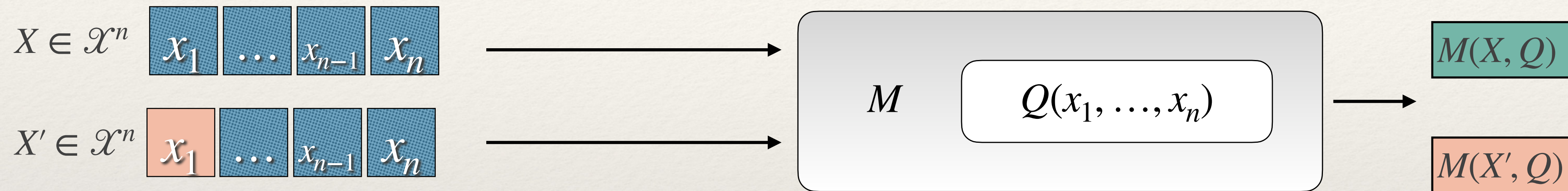
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Verifier

(ϵ, δ) -Computational DP

For **any** neighbouring datasets $X \sim X'$ i.e datasets that differ by just one element



M is said to be (ϵ, δ) -Differentially Private if for any subset $T \subseteq \mathcal{Y}$

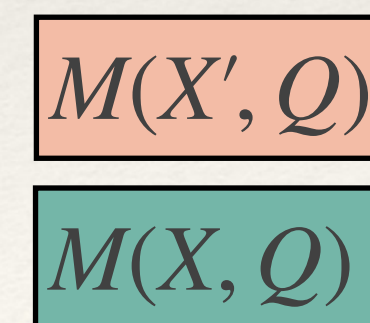
$$\Pr[D(M(X, Q)) \in T] \leq e^\epsilon \Pr[D(M(X', Q)) \in T] + \delta$$



Polynomially bounded algorithm D

OPEN PROBLEM

Is there a significant advantage if we relaxed this to be computational indistinguishability instead of statistical ?



????

Was X released or was it X' ?

Prior Separation Attempts

An algorithm $M : \mathcal{X}^n \times \mathcal{Q} \rightarrow \mathcal{Y}$ for releasing $Q(X)$

If $\mathcal{Y} \subseteq \mathbb{R}^d$ and utility is measured in terms of the L_p norm then there is NO advantage to relaxing privacy.

$$u(X, M(X, Q)) = \|M(X, Q) - Q(X)\|_p$$

GKY11- TCC

Limits of computational differential privacy in the client server setting

Thus \mathcal{Y} needs to be a more complex structure like a circuit, a graph or a proof.

GIKKM23-Arxiv

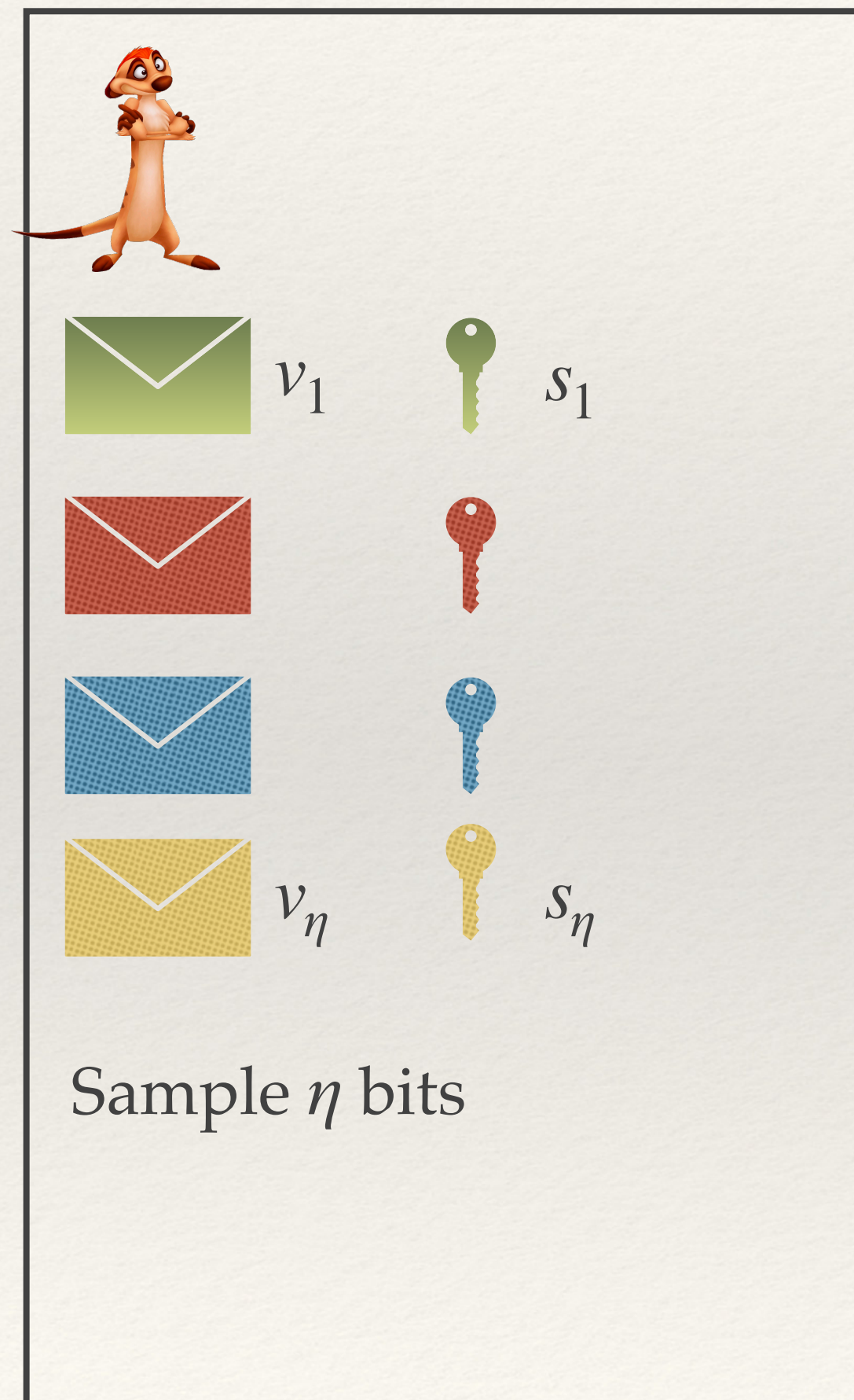
Separating Computational and Statistical Differential Privacy (Under Plausible Assumptions)

BV16 - TCC

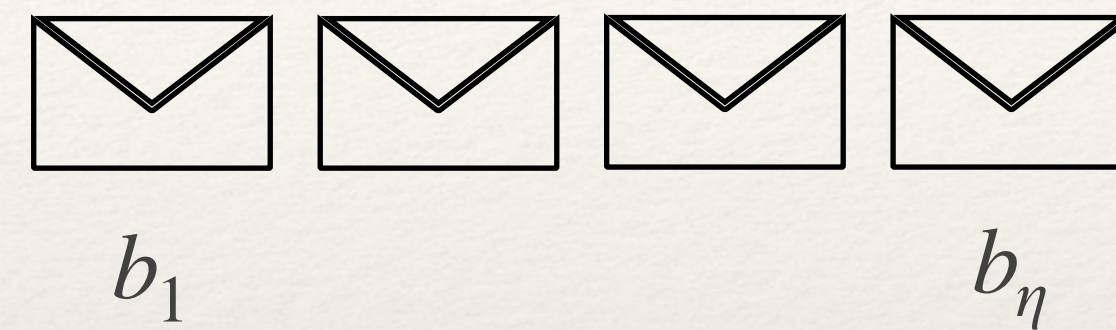
Separating Computational and Statistical Differential Privacy in the Client-Server Model

Where's the Separation ?

Server / Prover



Generate η public unbiased coins by playing Morra



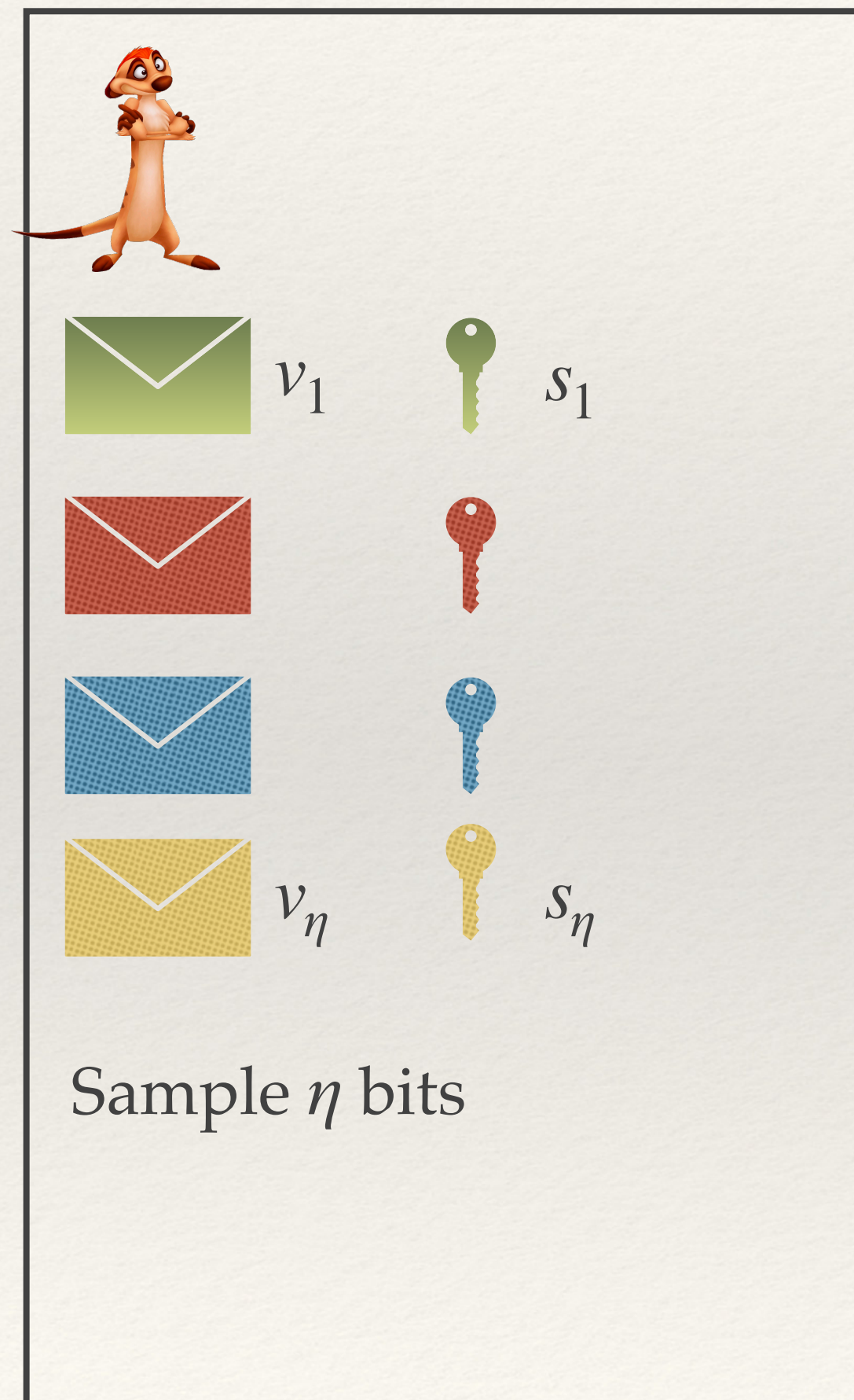
A key component in verifying the servers DP noise was to generate unbiased public randomness.

Verifier

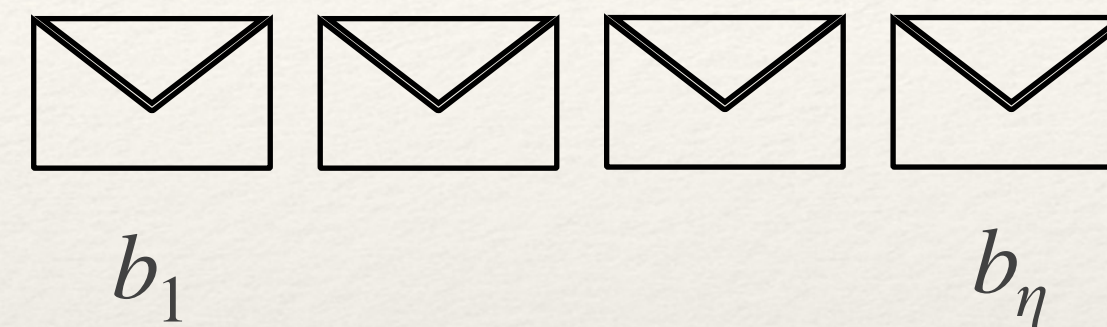


Where's the Separation ?

Server / Prover



Generate η public unbiased coins by playing Morra



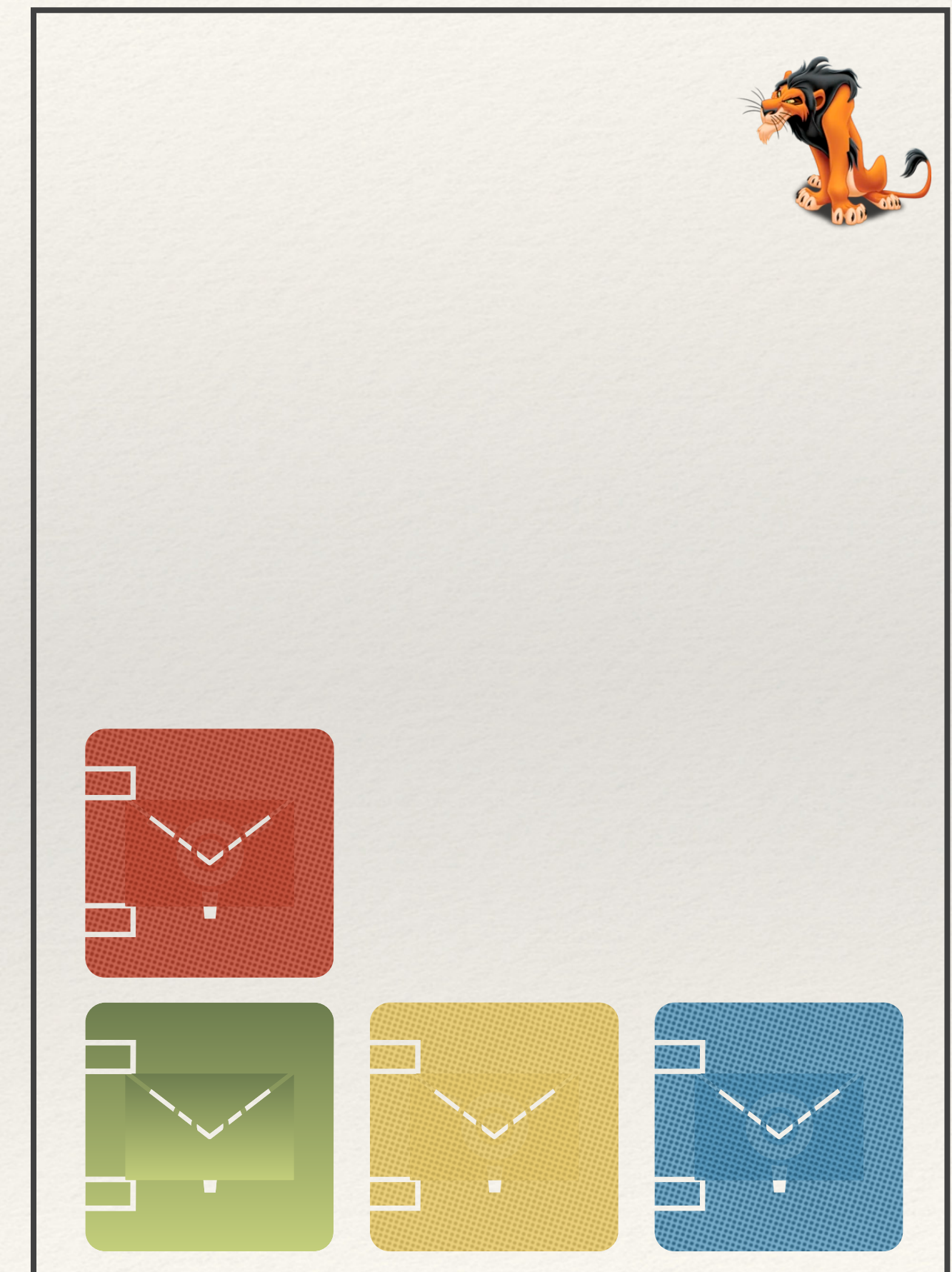
A key component in verifying the servers DP noise was to generate unbiased public randomness.

Coin-flipping \implies One way Functions \implies Commitments

Coin Flipping with Constant Bias Implies One way Functions - HO14

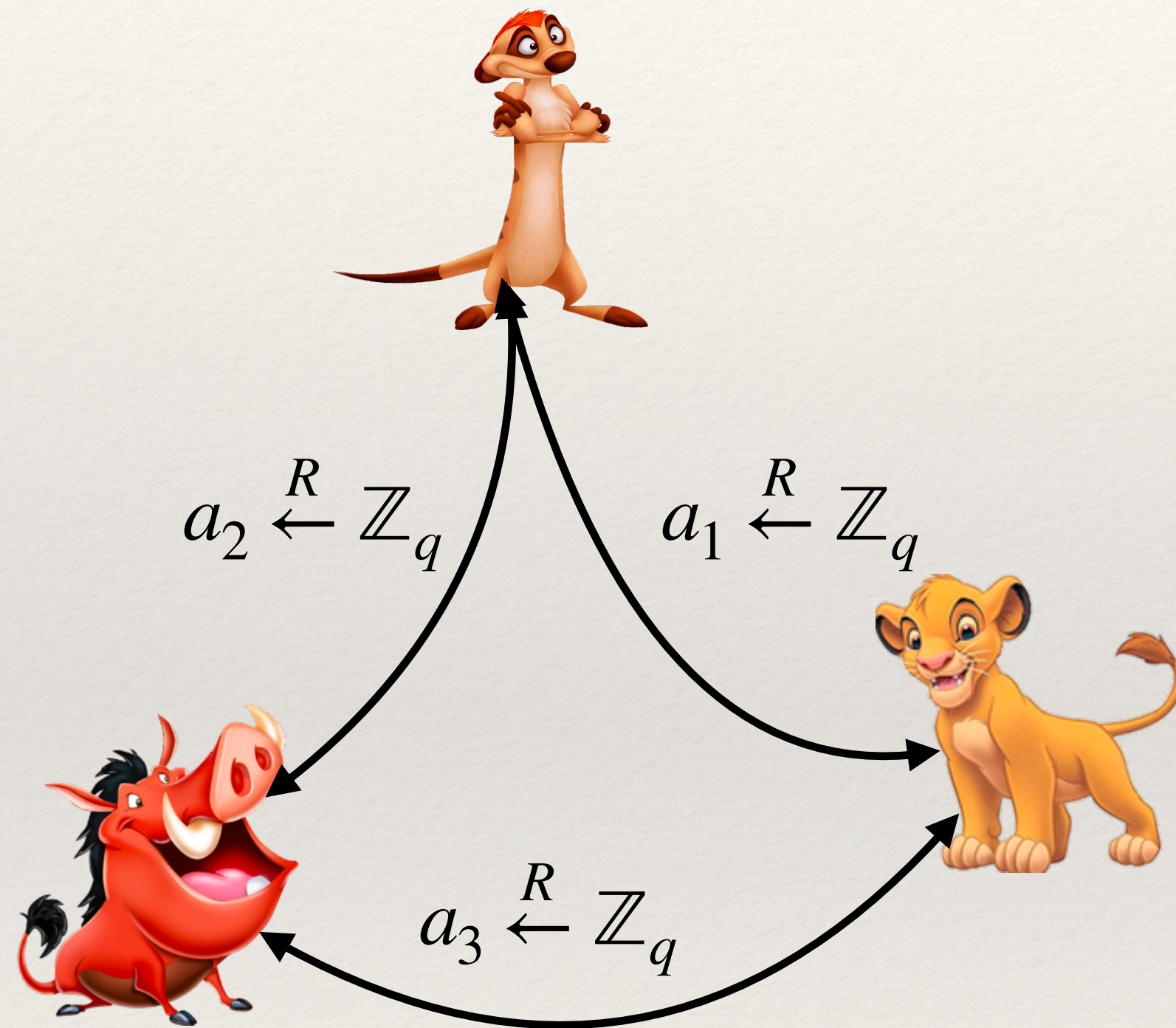
Coin Flipping with *any* Constant Bias Implies One way Functions - BHT21

Verifier



Questions

Public Coin Flipping (Morra)



1. Each party samples a random value from \mathbb{Z}_q
2. Each party broadcasts a commitment to the value.
3. Each party opens their commitments in the reverse order in which they broadcasted commitments.
4. Everyone checks all the opens are good.
5.
$$\tilde{b} = \sum_{i=1}^K a_i \mod q$$
6. If $\tilde{b} \leq \frac{q}{2}$, we set $b = 1$
7. Else $b = 0$

As long as a single party is honest, this protocol generates an unbiased bit b