

# Differential Privacy In Times Of Adversity

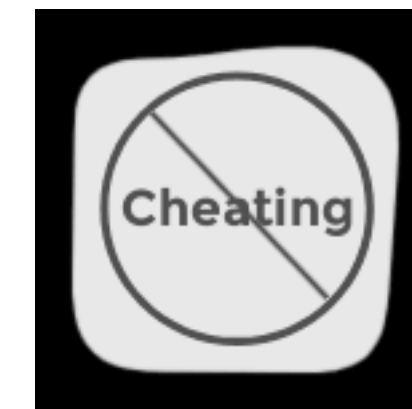


Ari Biswas + Graham Cormode

# Motivation

- A survey on sensitive topics where an estimate of the right answer is good enough.
- Each participant selects one out of  $M$  choices
- Let  $x_i$  represent the  $i$ 'th person's data
- **Want to know the average number of YES values in each category**

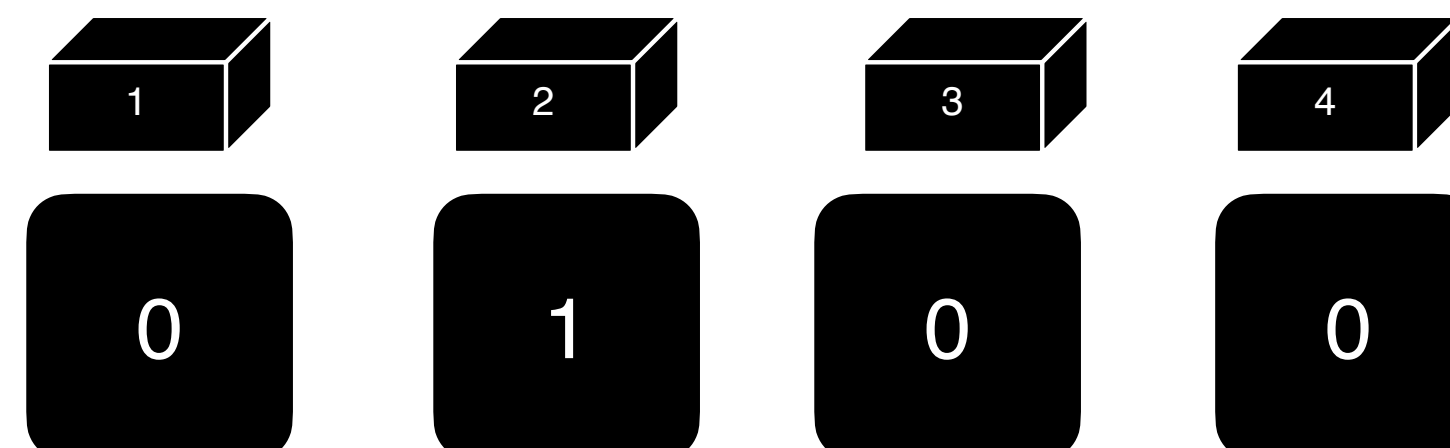
Binary Choice :  $x_i \in \{0,1\}$



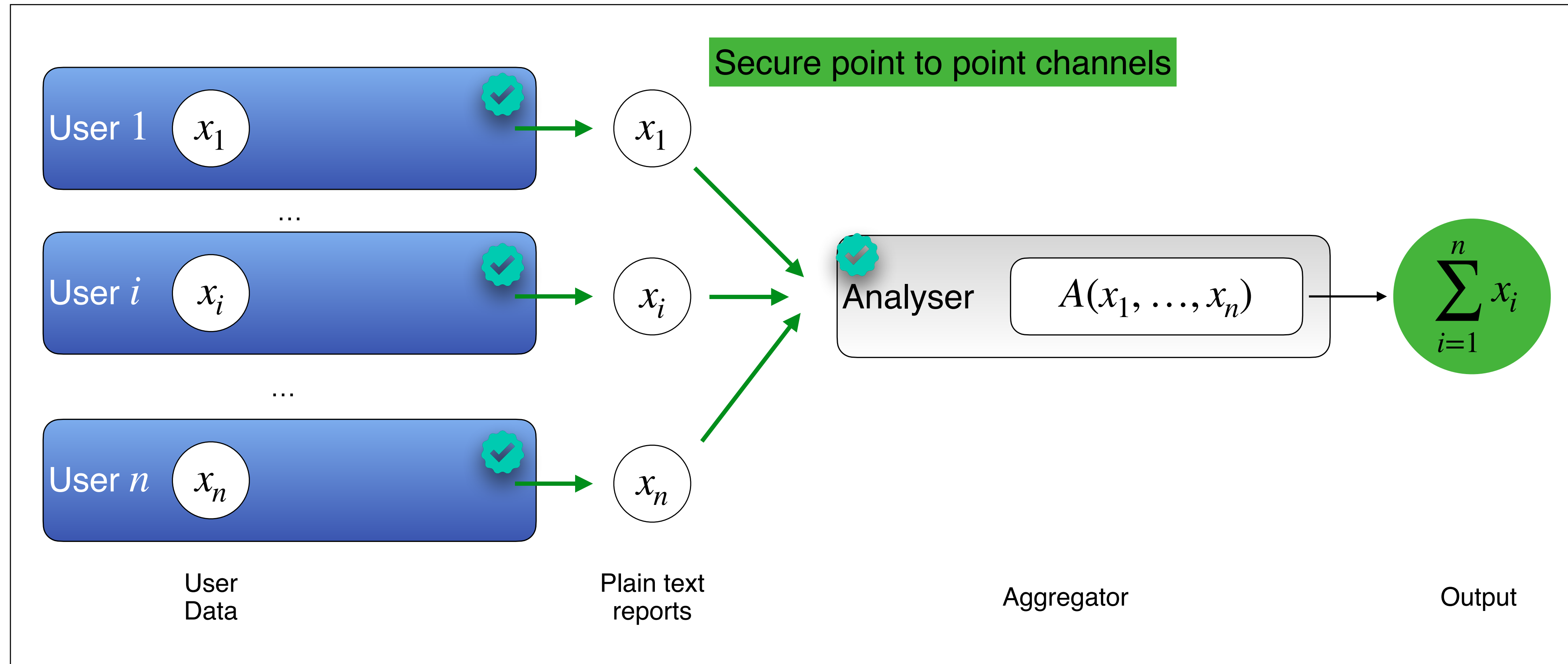
*Question: have you ever cheated on an exam ?*

$M$  choices:  $x_i \in \{1,2,\dots,M\}$

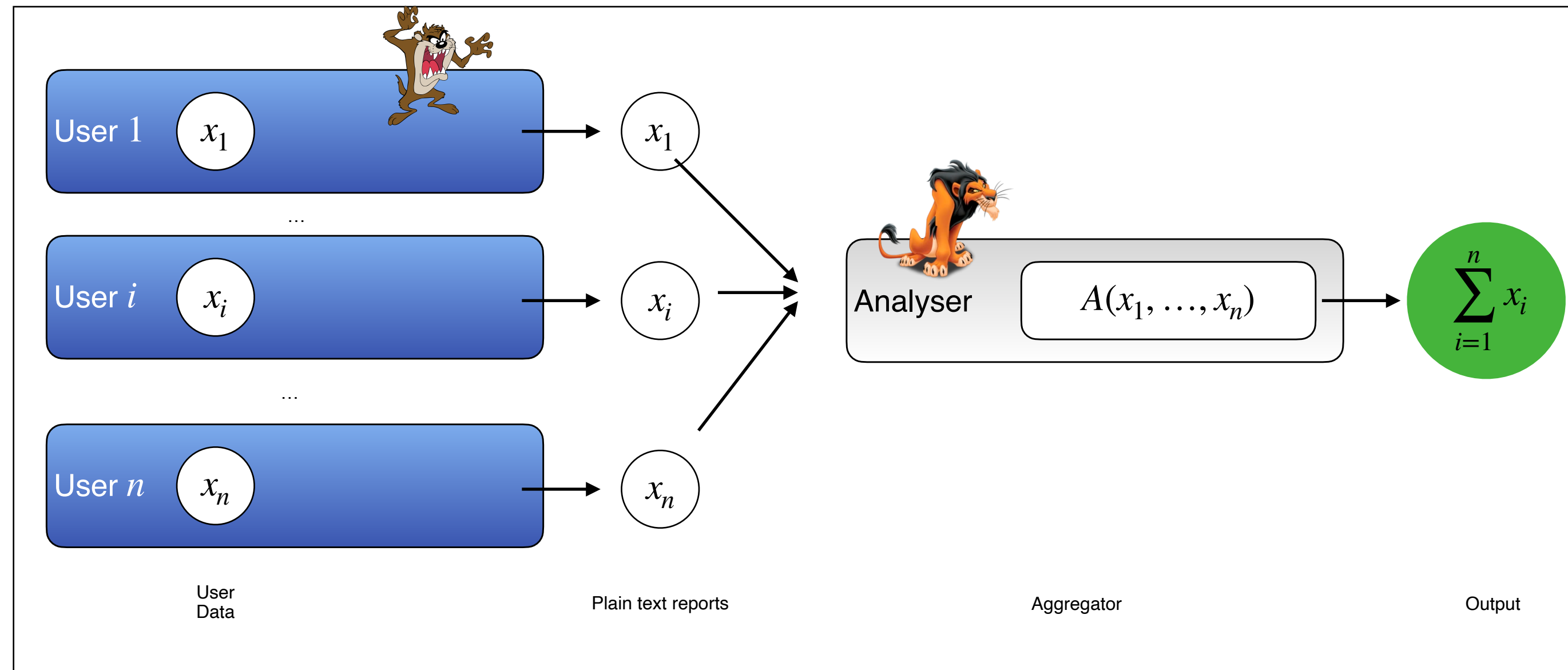
*Question: what is the highest grade of felony you have been convicted of?*



# Ideal solution



# Notations and Assumptions



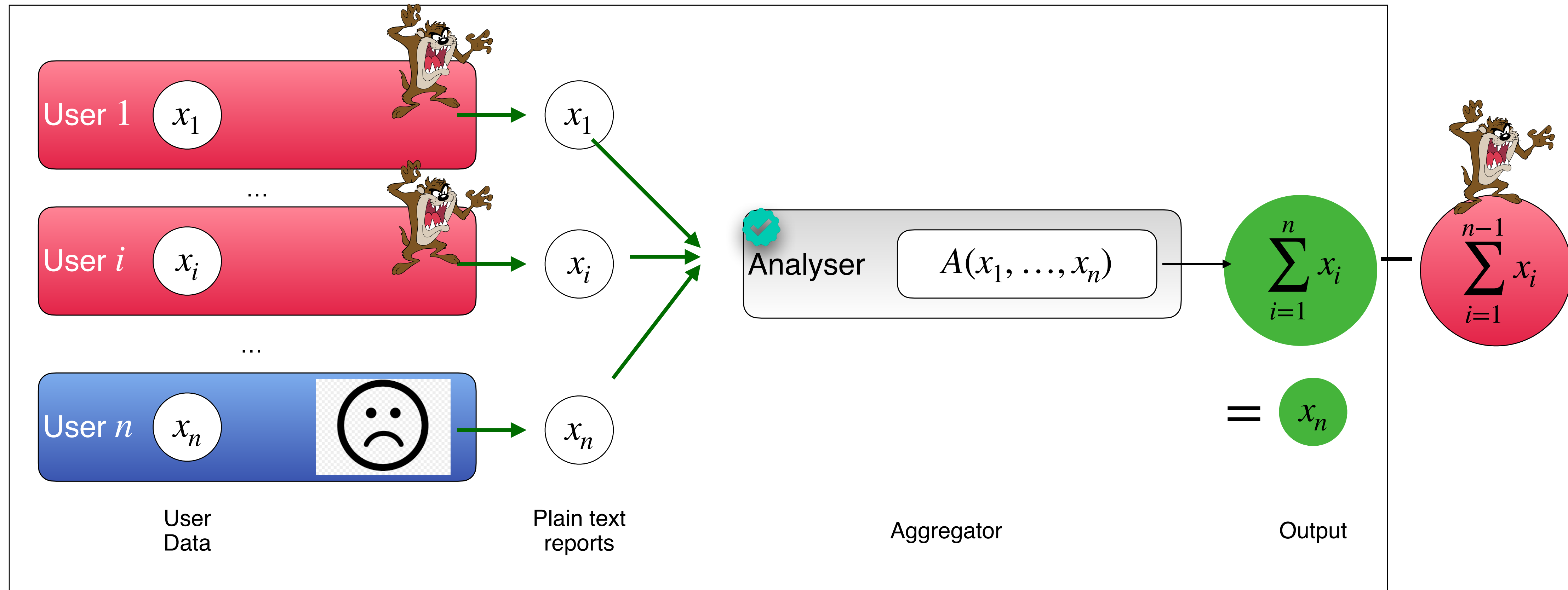
Deviates from prescribed protocol arbitrarily: **Active Adversary**



Follow all prescribed protocols but try and learn as much additional information from protocol transcript:  
**Passive Adversary/Honest but curious/ Semi honest**

Will always assume secure point to point and broadcast channels.

# Adversary controls $n - 1$ users

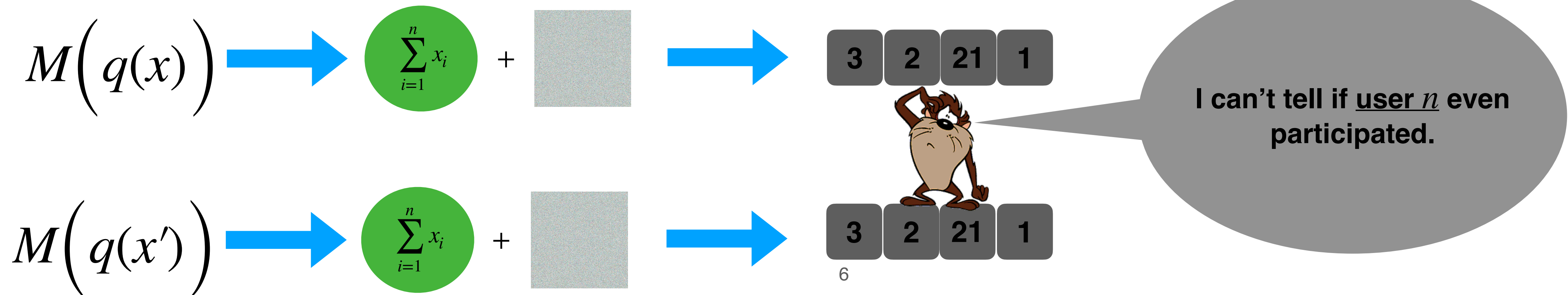


# Differential Privacy

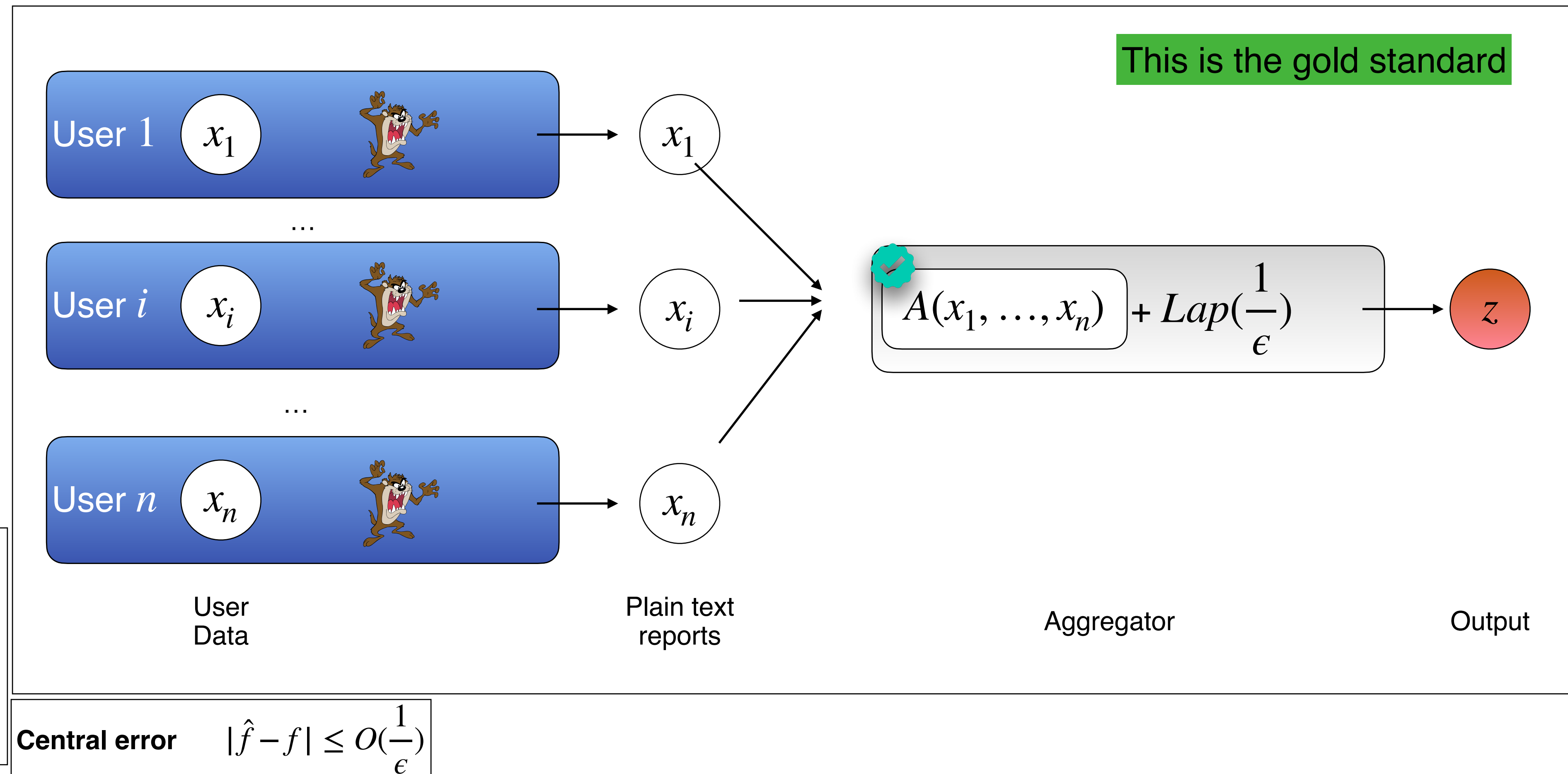
An algorithm  $M : (X^n \times Q) \rightarrow Z$  satisfies  $(\epsilon, \delta)$  differentially private if for every two neighbouring datasets  $x \sim x' \in X^n$  and for every query  $q \in Q$  we have

$$\forall T \subseteq Z, \mathbb{P}[M(x, q) \in T] \leq e^\epsilon \mathbb{P}[M(x', q) \in T] + \delta$$

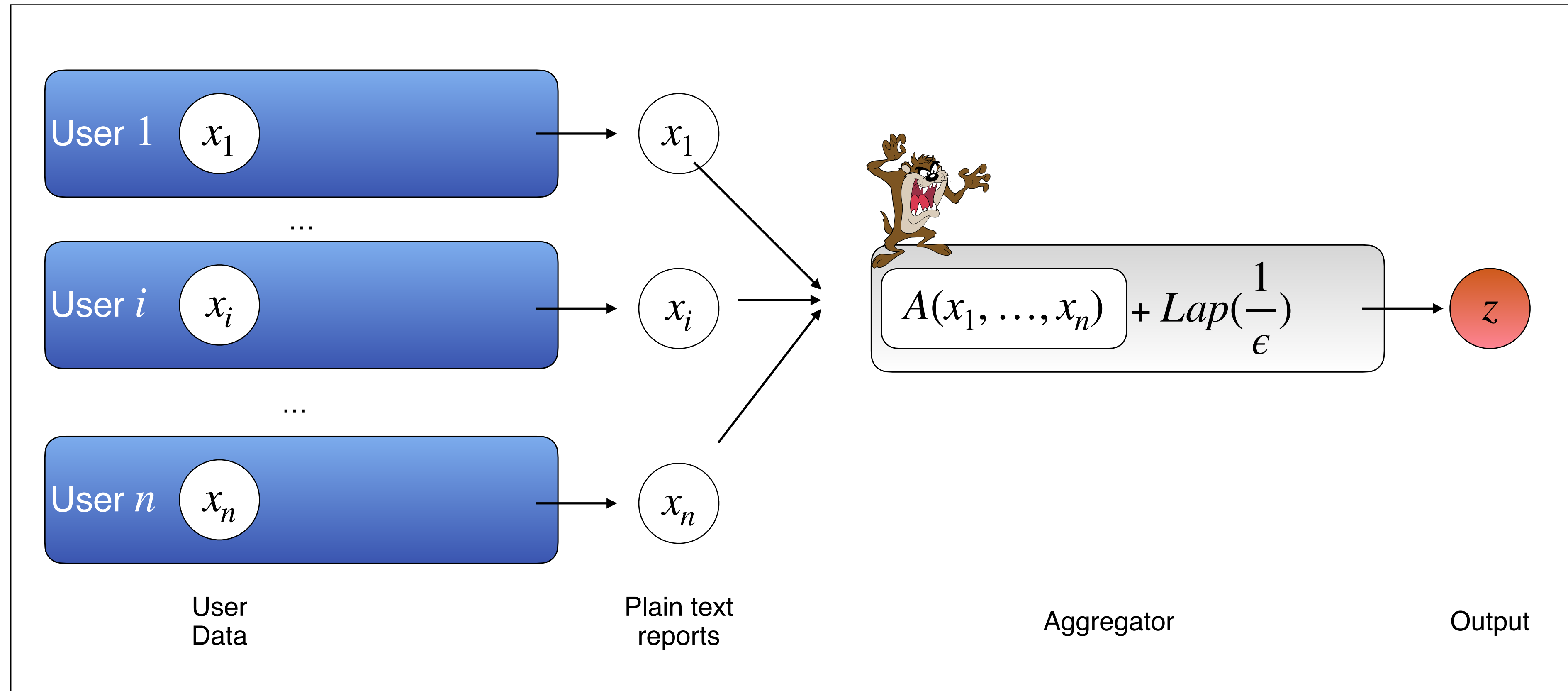
Random Noise blanket



# Laplace Mechanism

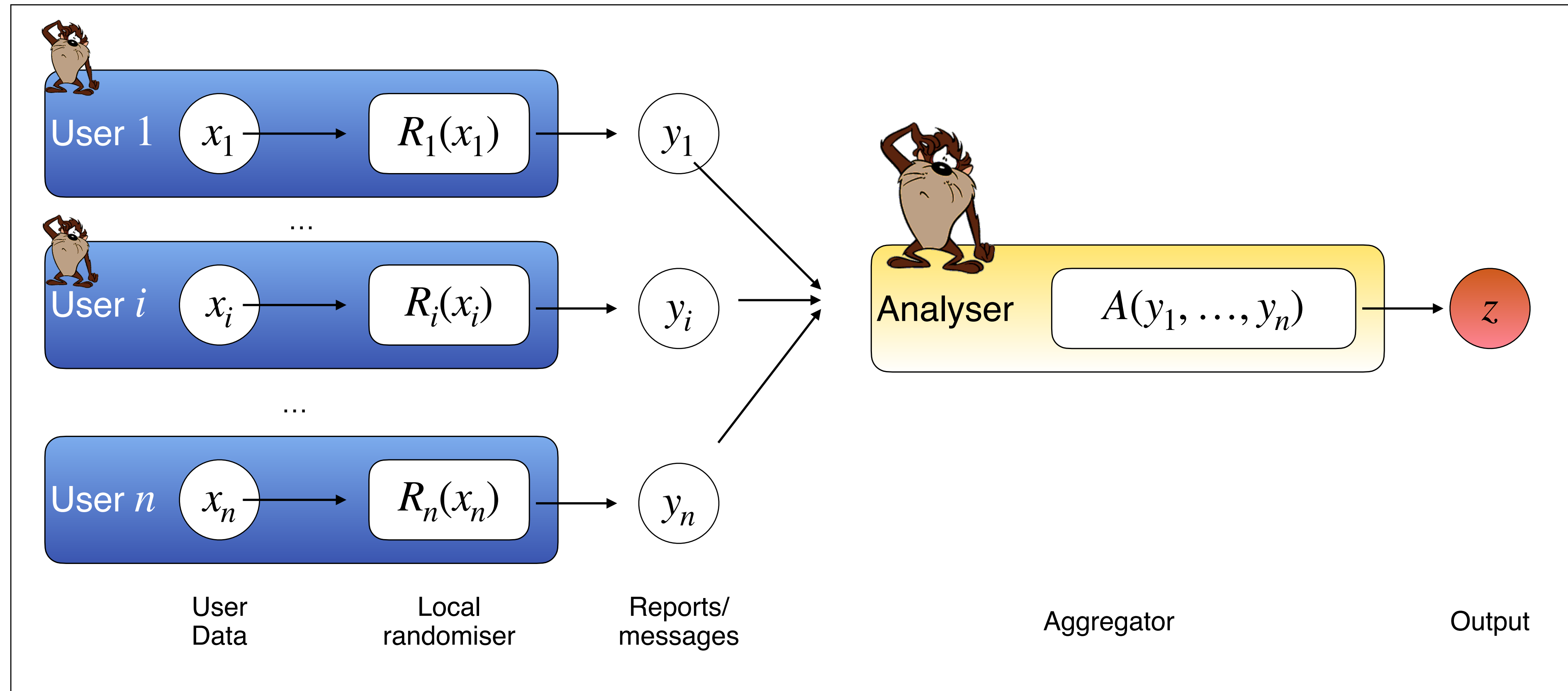


# What If I cannot trust the curator ?





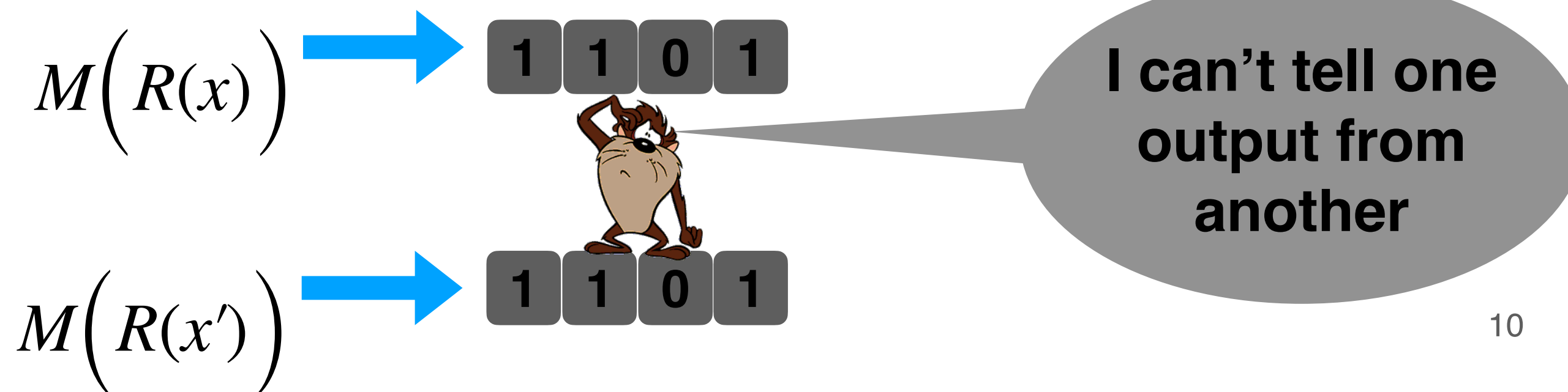
# Local Differential Privacy: Noisify at the other end



When not mentioned specifically we assume  $|x_i| = |y_i|$

# Local Differential Privacy

An algorithm  $R : X \rightarrow Y$  satisfies  $(\epsilon, \delta)$  local differential privacy if for every two users  $x, x' \in X$   
 $\forall T \subseteq Y, \mathbb{P}[R(x) \in T] \leq e^\epsilon \mathbb{P}[R(x') \in T] + \delta$



# Randomised Response: A way to get local DP

Let  $p \in (0, 1/2)$

$$y_i = \begin{cases} x_i & \text{with pr. } \frac{1}{2} + p \\ 1 - x_i & \text{with pr. } \frac{1}{2} - p \end{cases}$$

$$f = \sum_{i=1}^n x_i \quad \text{What we want to estimate}$$

$$\hat{f} = \sum_{i=1}^n \left[ \frac{1}{2p} (y_i - 1/2 + p) \right] \quad \text{What we estimate}$$

$$\mathbb{E}[\hat{f}] = f$$

(In expectation they are the same)

$$\text{LDP error} \quad |\hat{f} - f| \leq O\left(\frac{\sqrt{n}}{\epsilon}\right) \leftarrow \text{Unavoidable}$$

$$\text{Central error} \quad |\hat{f} - f| \leq O\left(\frac{1}{\epsilon}\right)$$

## Randomised Response is optimal in LDP

Duchi, Jordan, and Wainwright, 'Local Privacy, Data Processing Inequalities, and Statistical Minimax Rates'.

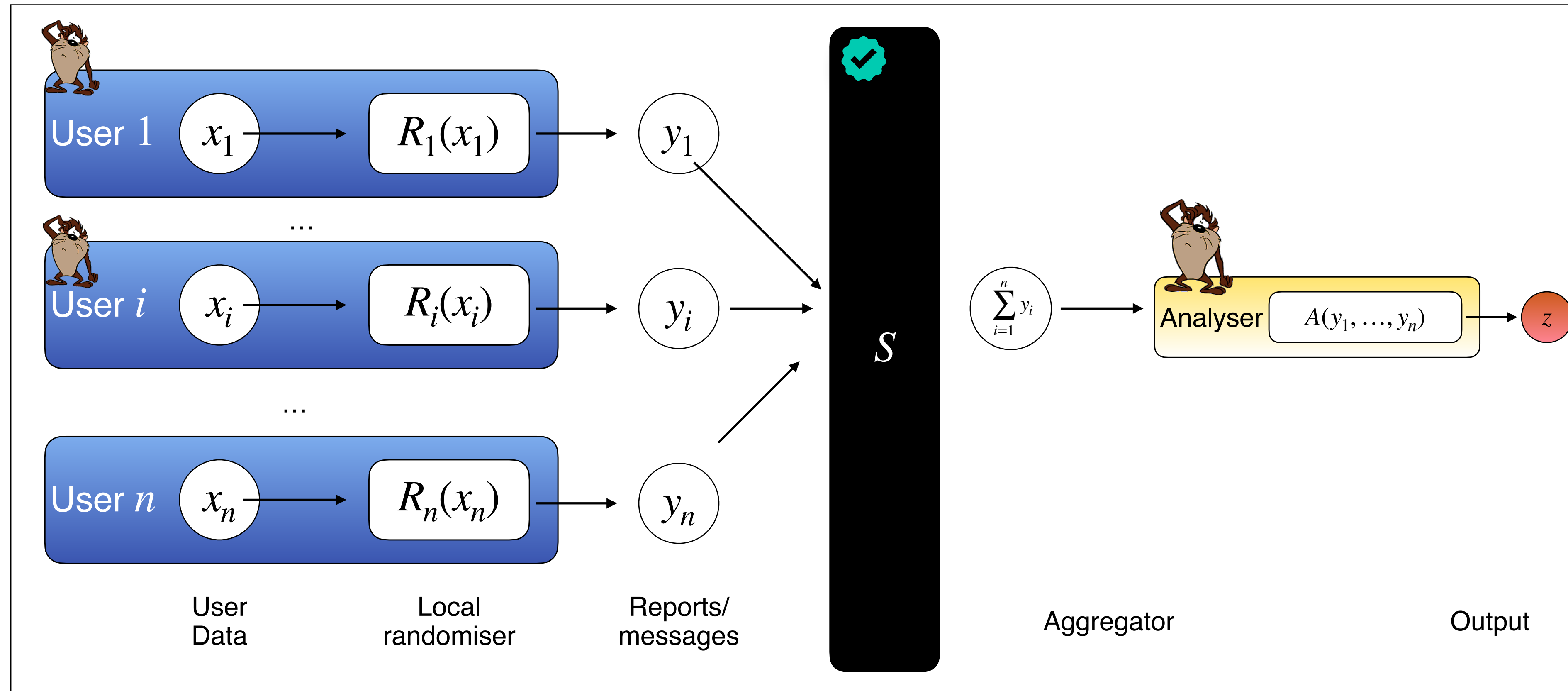
## If you can attack Randomised Response, you can attack all LDP algorithms

Cheu, Smith, and Ullman, 'Manipulation Attacks in Local Differential Privacy'.

**Comparison is unfair** — LDP imposes stricter privacy constraints

Each user has to generate enough noise to hide himself as opposed to each user has to generate enough noise to hide amongst the crowd.

# Shuffle Privacy



**Randomised Response gives near central error**

Balle et al., 'The Privacy Blanket of the Shuffle'

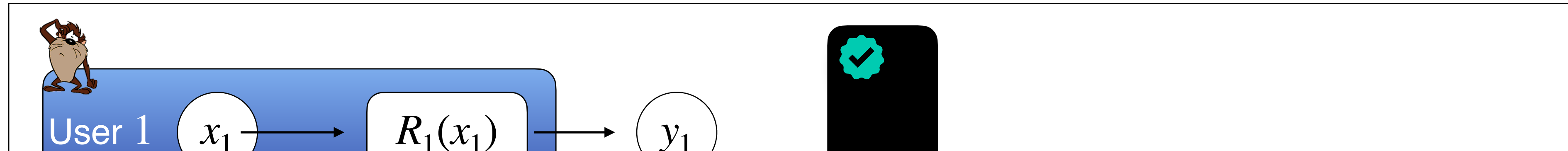
**If we do not restrict  $|x| = |y|$  we can do just as well as central**

Balcer and Cheu, 'Separating Local & Shuffled Differential Privacy via Histograms'. 12

**If we do not restrict  $|x| = |y|$  we can do just as well as central**

Ghazi et al., 'Differentially Private Aggregation in the Shuffle Model'.

# Shuffle Privacy



Rich history of research and improvements but all this work has been done under the semi honest model.

**Randomised Response gives near central error**

Balle et al., 'The Privacy Blanket of the Shuffle

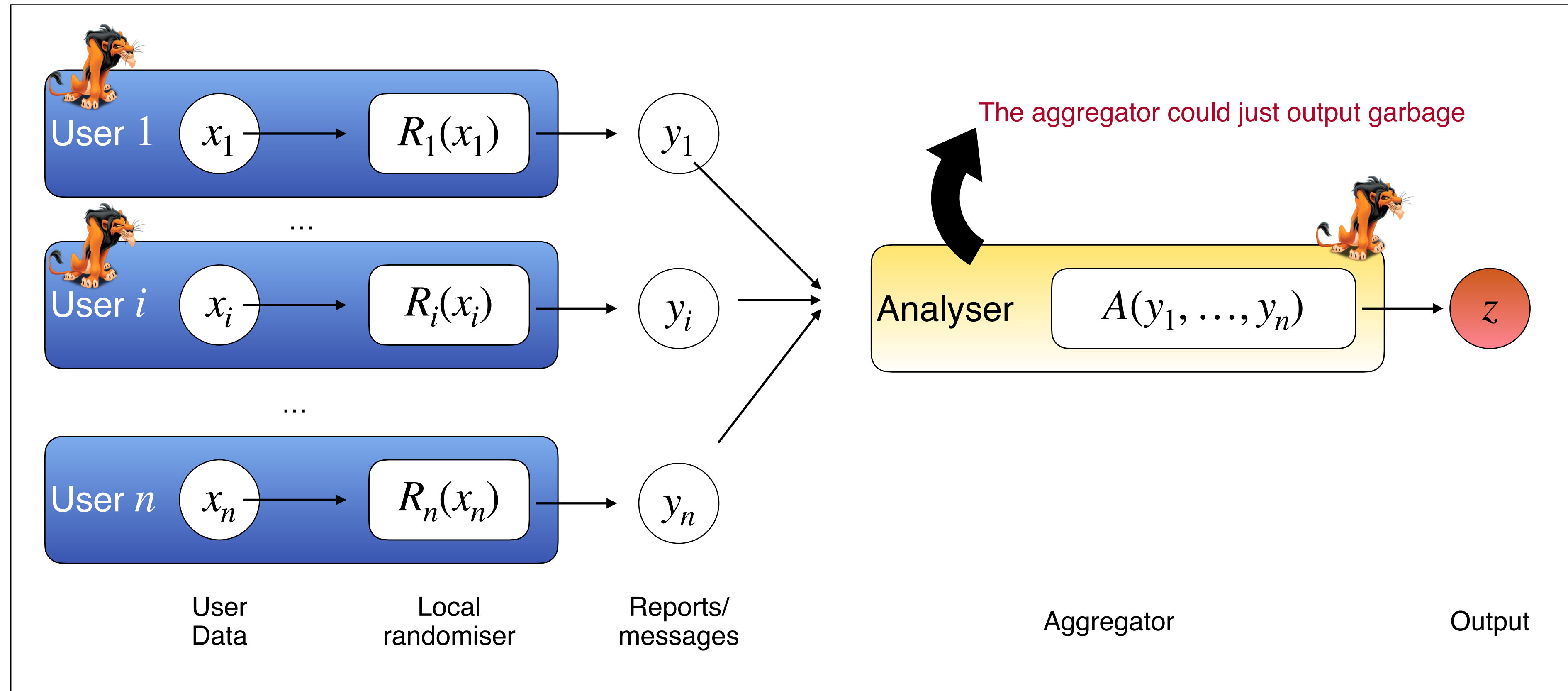
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# What happens when the curious become dishonest?



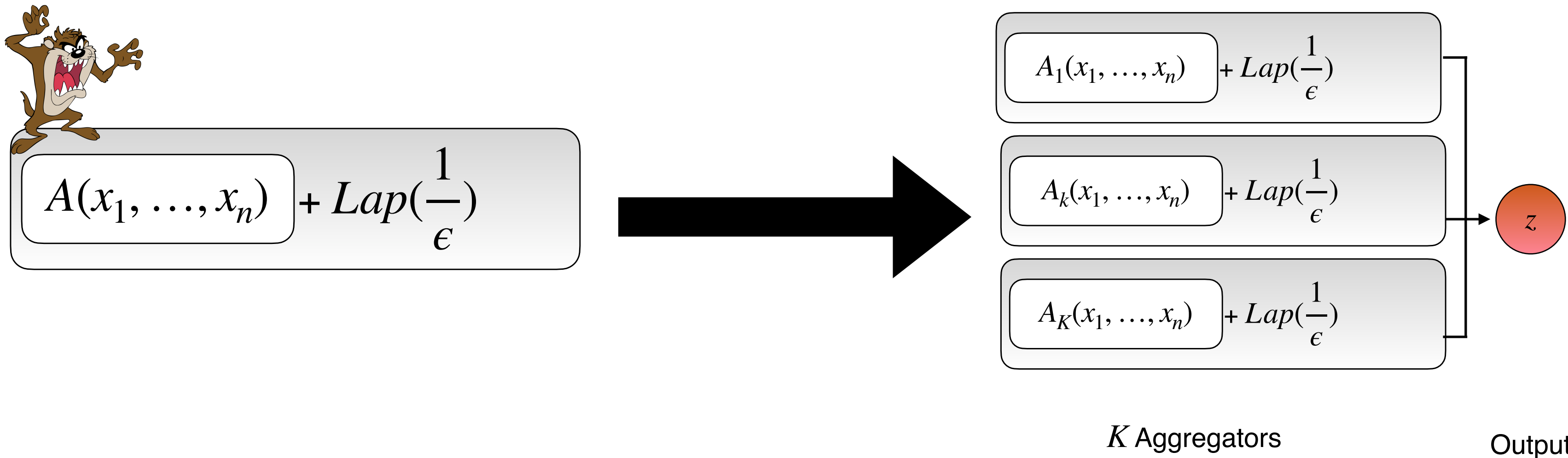
Derive bounds for how many users have to be corrupted for randomised response utility to be indistinguishable from  $\text{Bin}(n, \frac{1}{2})$



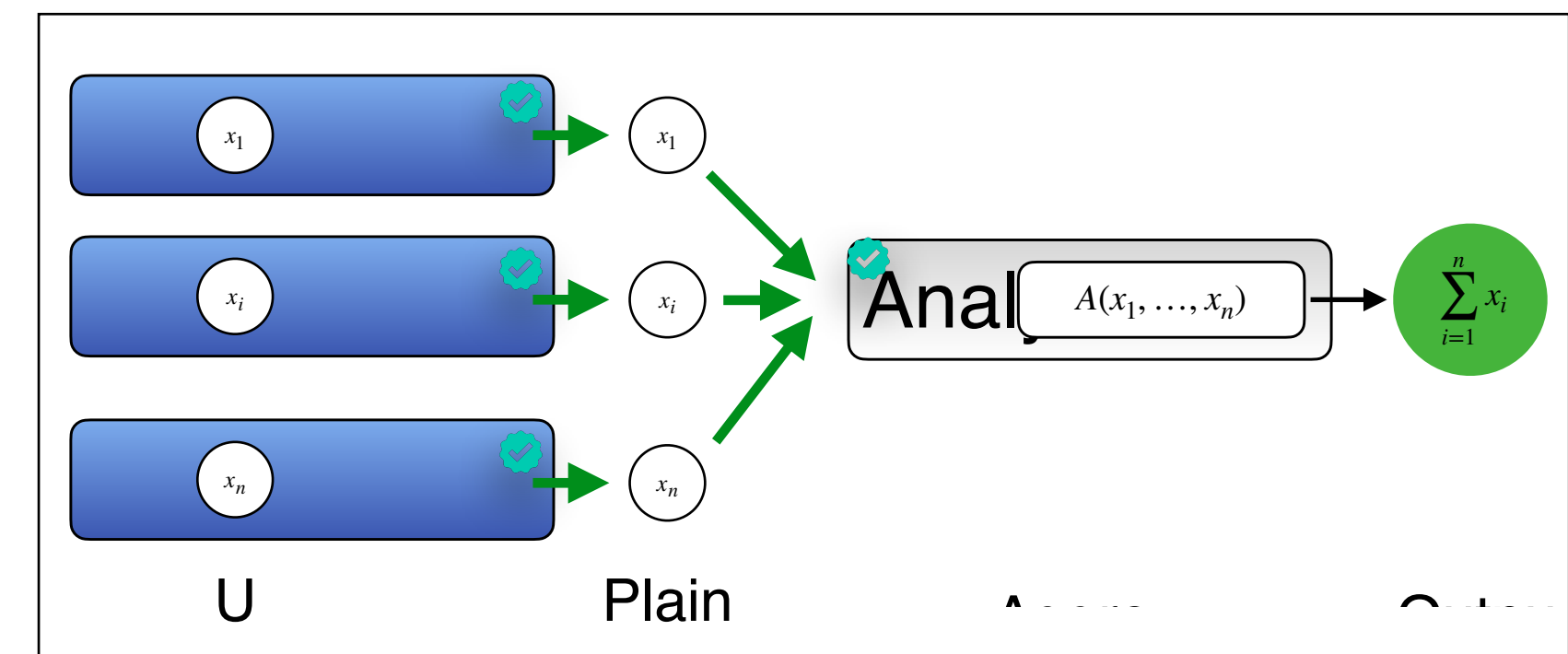
# Relax the ideal world to allow for more curators

What does it mean to be fine ?

**IMPORTANT  
NOTICE**



Don't have enough money to corrupt all  $K$  curators. Let's hope that as long as at least **1** server is semi honest we will be fine



# What we consider to be fine\*

\* Fine is determined by assumptions that  $K$  curators and only guaranteed that 1 server is semi honest

- Perfect Privacy of inputs + Differential privacy + Output is meaningful
- Perfect Privacy of inputs + Differential privacy + Output is not guaranteed to be meaningful
- Computational privacy of inputs + differential privacy + output is “guaranteed” to be meaningful
  - If an adversary violates any of this, the honest server detects this and tells everyone that they cheated and voids the protocol.

## Not possible

Ben Or, Goldwasser and Widgerson, ‘Completeness theorems for non cryptographic fault tolerant distributed computation’

## Poplar: The focus is on lightweight protocols and the emphasis is on privacy

Boneh et al., ‘Lightweight Techniques for Private Heavy Hitters’.

## Our work: Lightweight-ish but focus on reliability



# Linear Secret Sharing

- Two algorithms share and reconstruct s.t  $s \in \mathbb{Z}_q$
- $\text{Share}(s) = [s]_1, \dots, [s]_K$  such that  $[s]_i \xleftarrow{R} \mathbb{Z}_q$  for  $i \in [K-1]$  and
 
$$[s]_K = s - \sum_{i=1}^{K-1} [s]_i$$
- $\text{Reconstruct}([s]_1, \dots, [s]_K) = \sum_{i=1}^K [s]_i = s$

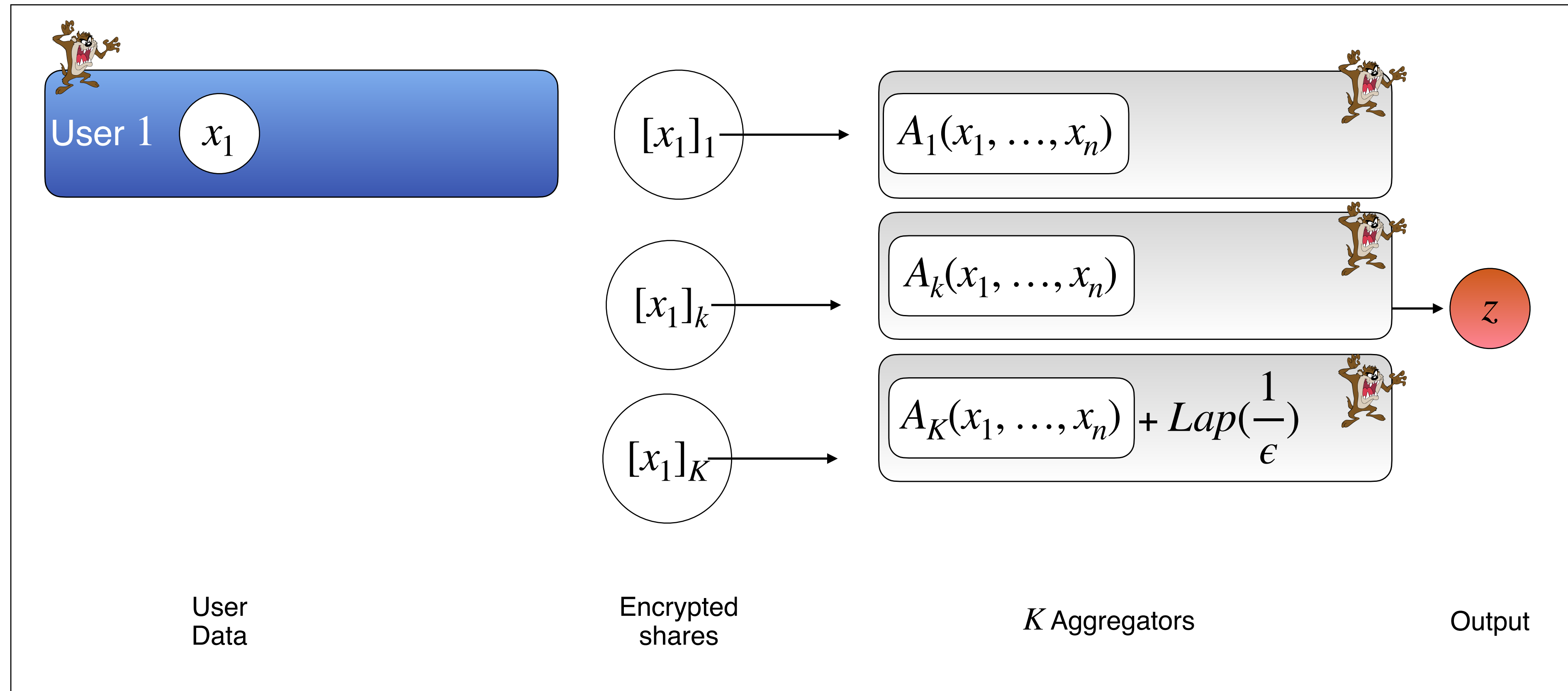
Example in  $\mathbb{Z}_{11}$  and  $K = 3$

Secret  $s = 7$

$$\begin{aligned} [s]_1 &= 4 \\ [s]_2 &= 5 \\ [s]_3 &= 9 \end{aligned}$$

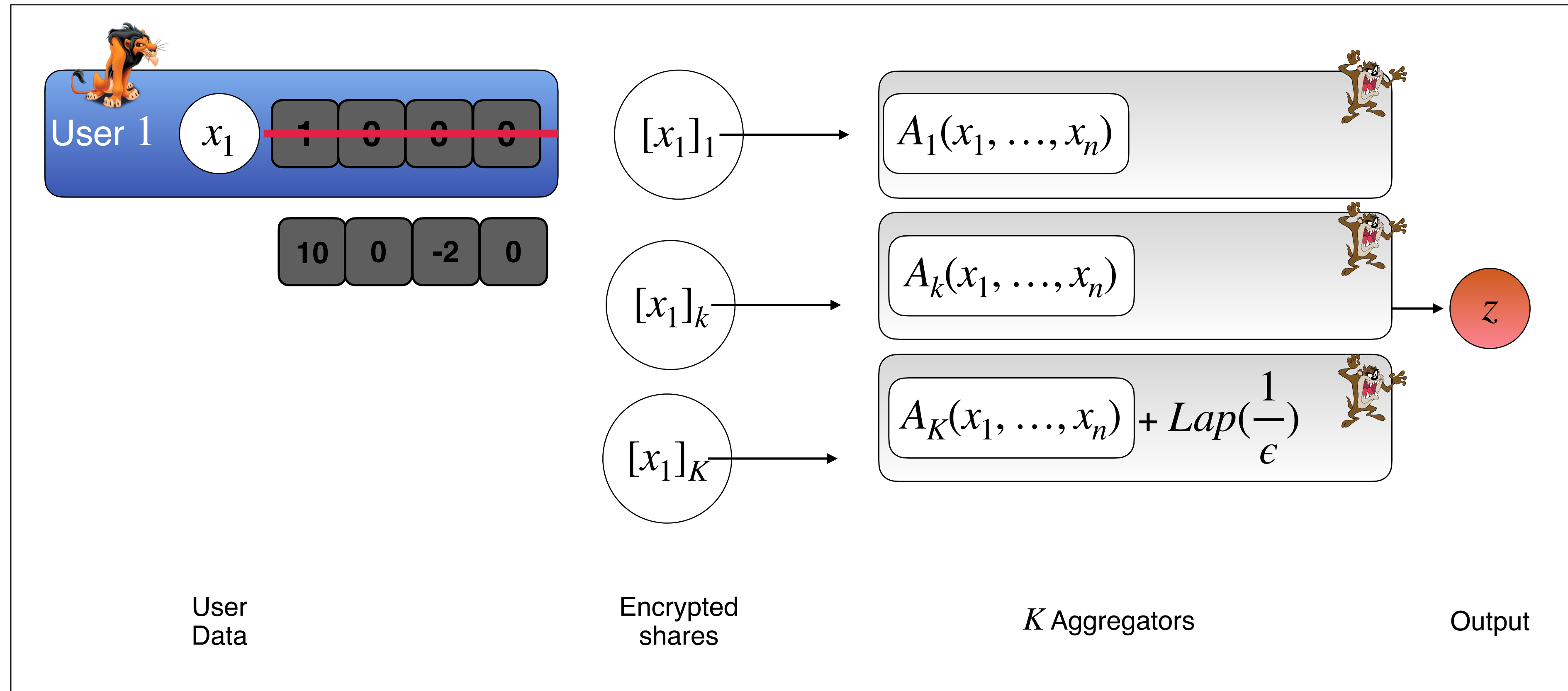
$$\sum_{i=1}^3 [s]_i = (4 + 5 + 9) \bmod 11 = 7$$

# PRIO



**Correctness:** 
$$\sum_{i=1}^n \sum_{k=1}^K [x_i]_k = \sum_{i=1}^n x_i$$

# Ballot stuffing



# Sketching protocol



$$[x]_1 \in \mathbb{Z}_q^M$$



$$[x]_3 \in \mathbb{Z}_q^M$$



$$[x]_2 \in \mathbb{Z}_q^M$$

**Sketching protocol from work in 2016 on function secret sharing**

Boyle, Gilboa, and Ishai, 'Function Secret Sharing'.

# Sketching protocol



$$[x]_1 \in \mathbb{Z}_q^M$$



$$[x]_3 \in \mathbb{Z}_q^M$$



$$[x]_2 \in \mathbb{Z}_q^M$$

1. Server 1 samples  $r_1, \dots, r_M$  where  $r_i \xleftarrow{R} \mathbb{Z}_q$  independently and broadcasts it to other servers

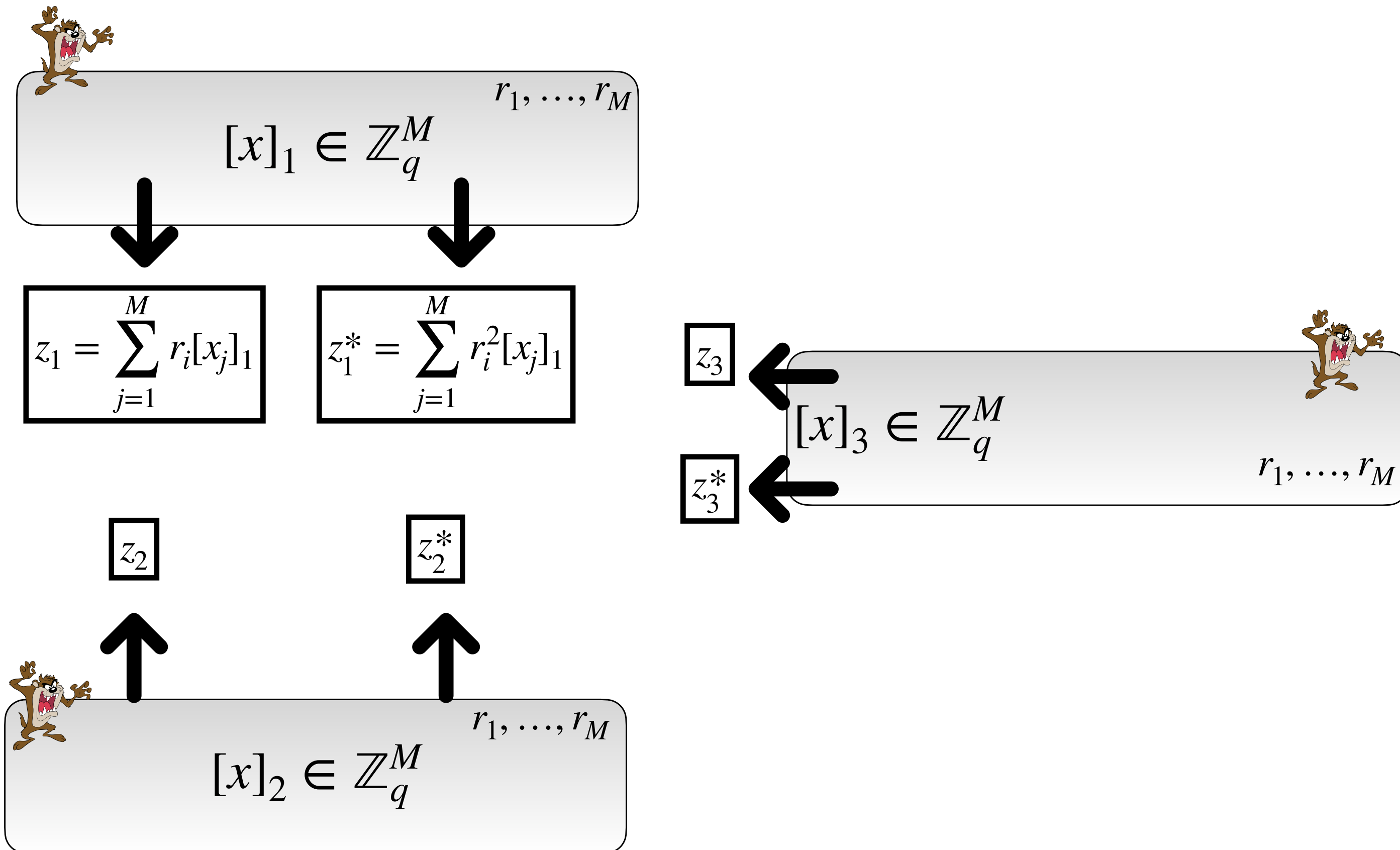
## INTUITION:

We will create a random  $p(\vec{r})$  degree two polynomial. If sampled  $\vec{r}$  is not a root, then the only way to 0 out this polynomial is to have a single non zero entry equal to 1

The cheating client does not know the values of  $\vec{r}$  thus with

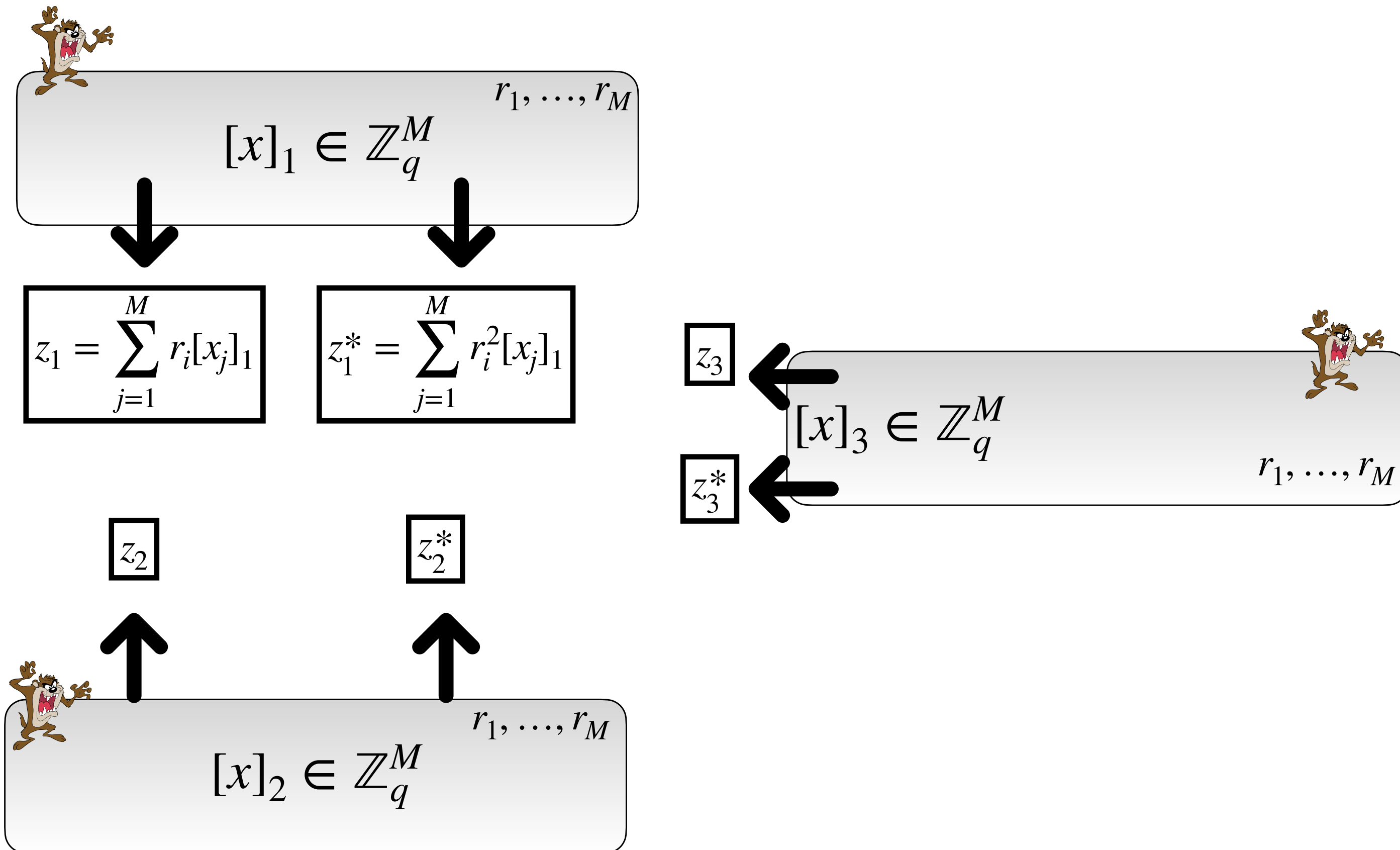
probability  $\frac{2}{q}$  fails to pass to the test

# Sketching protocol



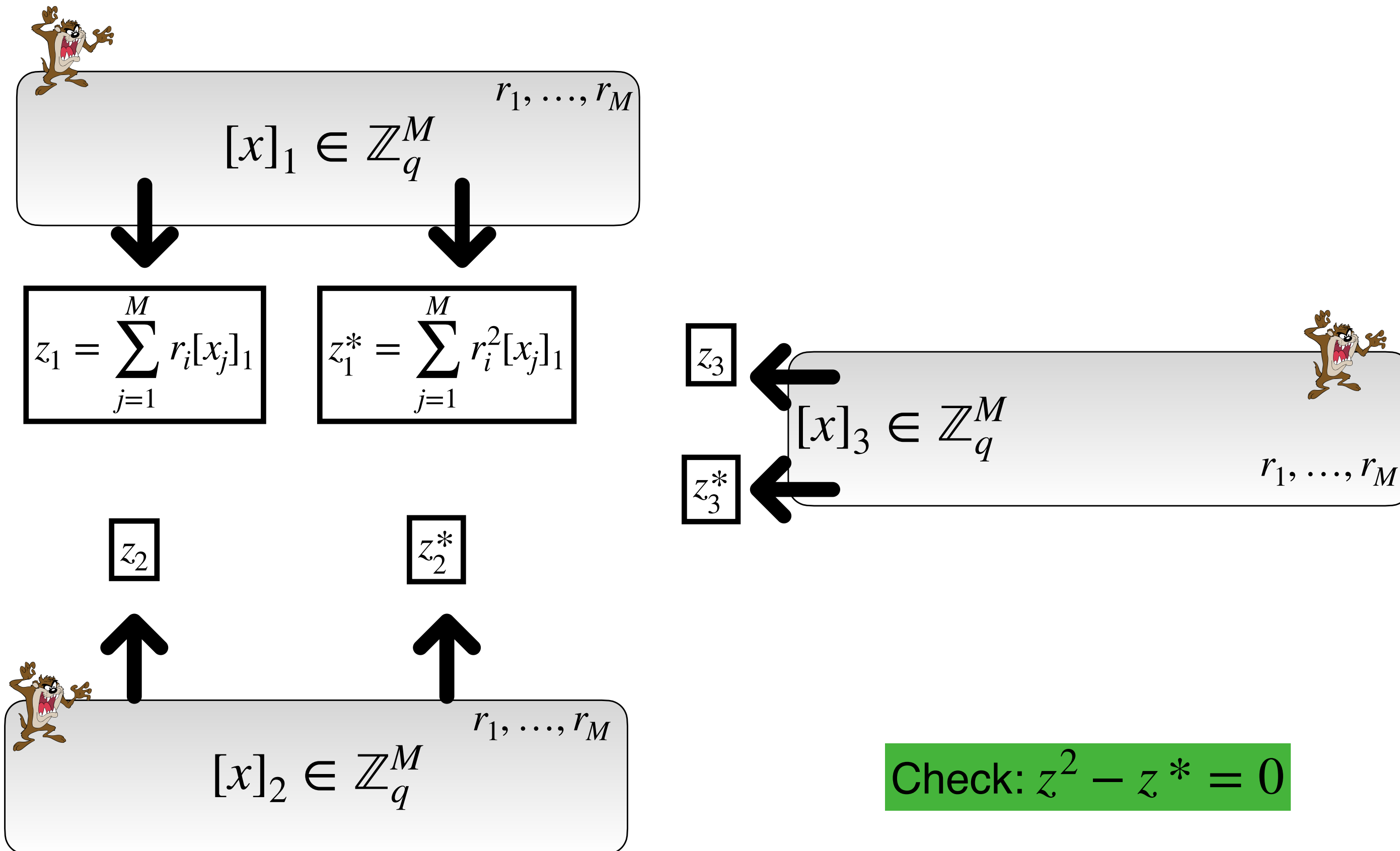
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2. Server k broadcasts  $z_k = \sum_{j=1}^M r_j [x_j]_k$  and  $z_k^* = \sum_{j=1}^M r_j^2 [x_j]_k$

# Sketching protocol



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4. Each server computes  $z = \sum_{i=1}^3 z_i$  and  $z^* = \sum_{i=1}^3 z_i^*$

# Sketching protocol

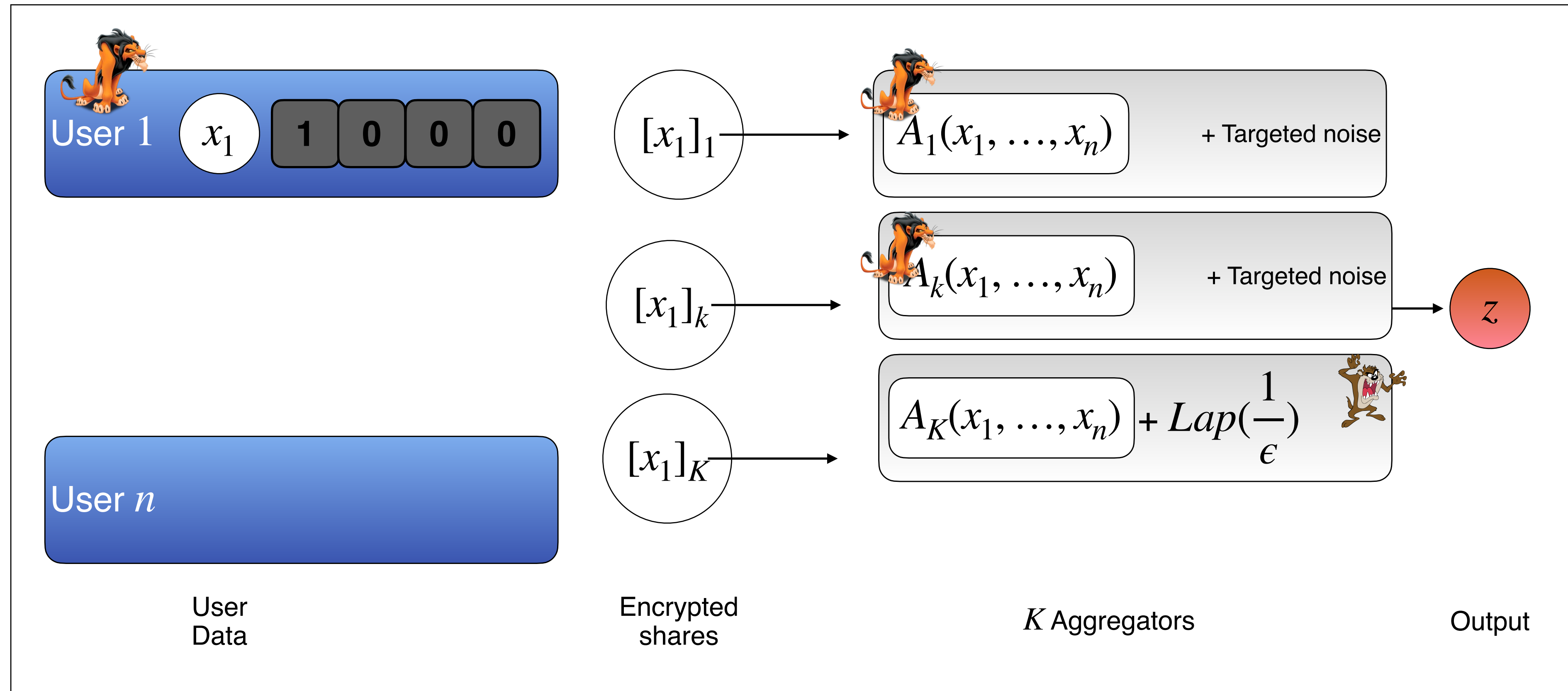


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4. Each server computes  $z = \sum_{i=1}^3 z_i$  and  $z^* = \sum_{i=1}^3 z_i^*$

$$\begin{aligned}
 z^2 - z^* &= \left( \sum_{i \in [M]} r_i v_i \right)^2 - \sum_{i \in [M]} r_i^2 v_i \\
 &= \sum_{i \in [M]} r_i^2 v_i (v_i - 1) + 2 \sum_{i, j: i \neq j} r_i r_j v_i v_j
 \end{aligned}$$



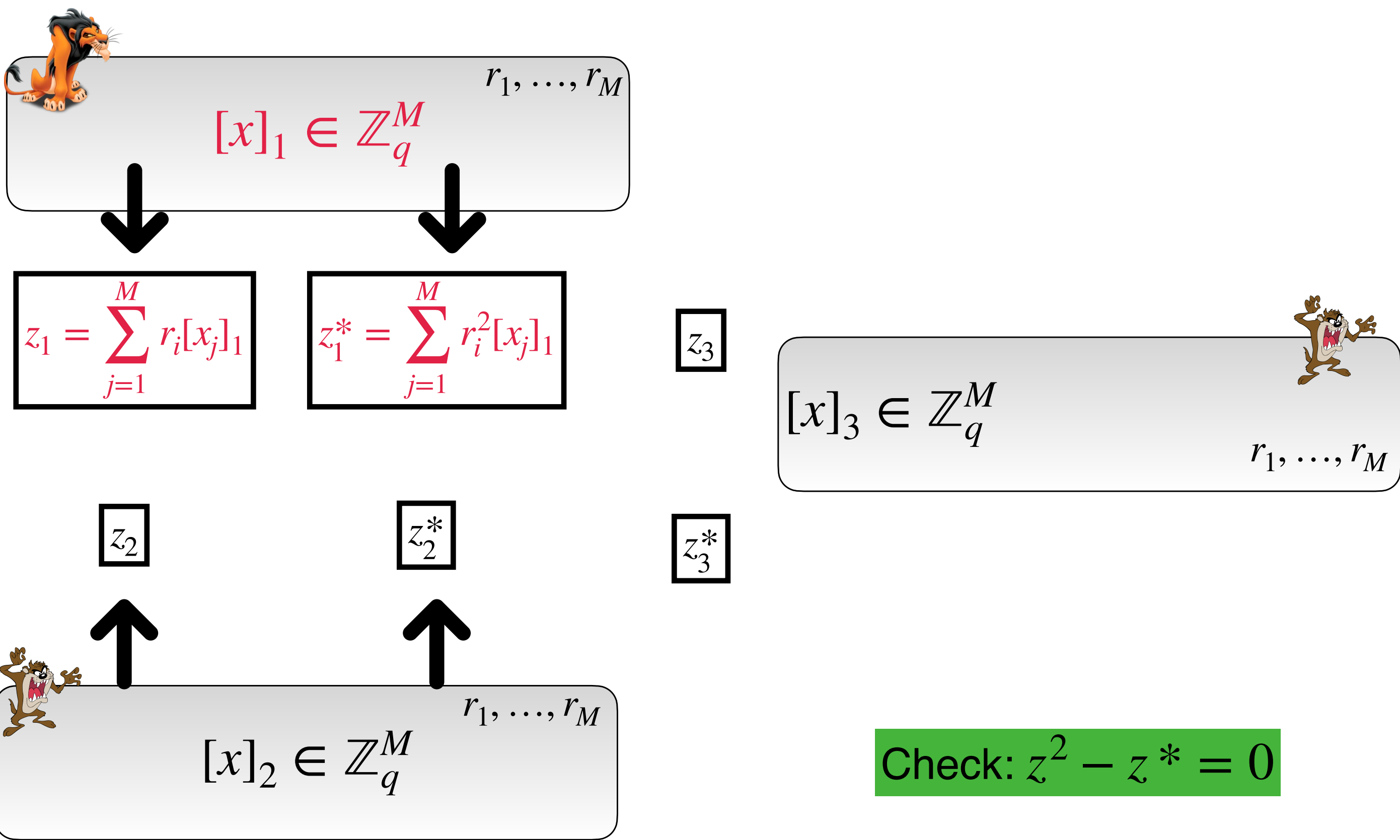
# K-1 corrupt servers




Is sketching still secure ?

# Sliding Attack on honest client

Adds +1 at some index and subtracts -1



  $x =$  0 1 0 0

Leaks 1 bit of information.

# Malicious Sketching



$$\kappa[x]_1, [x]_1 \in \mathbb{Z}_q^M$$

Only the honest client knows  $\kappa$

Servers now also broadcast

$$z_k^{**} = \sum_{i=1}^M r_i(\kappa[x_i]_k)$$



$$\kappa[x]_3, [x]_3 \in \mathbb{Z}_q^M$$

$$\text{Check: } (z^2 - z^*) + (\kappa z - z^{**}) = 0$$



$$\kappa[x]_2, [x]_2 \in \mathbb{Z}_q^M$$

**Show that the protocol is zero knowledge and a dishonest server does not learn any new information**

Boneh et al., 'Lightweight Techniques for Private Heavy Hitters'.

**The secrecy of  $\kappa$  prevents a sliding attack.**

We are abstracting details of implementation: In reality the client also has to supply beaver triples or Shares of  $\kappa$

# Collusions break Sketching protocols



$$\kappa[x]_1, [x]_1 \in \mathbb{Z}_q^M$$

Only the honest client knows  $\kappa$

Servers now also broadcast

$$z_k^{**} = \sum_{i=1}^M r_i(\kappa[x_i]_k)$$



$$\kappa[x]_3, [x]_3 \in \mathbb{Z}_q^M$$

$$\text{Check: } (z^2 - z^*) + (\kappa z - z^{**}) = 0$$

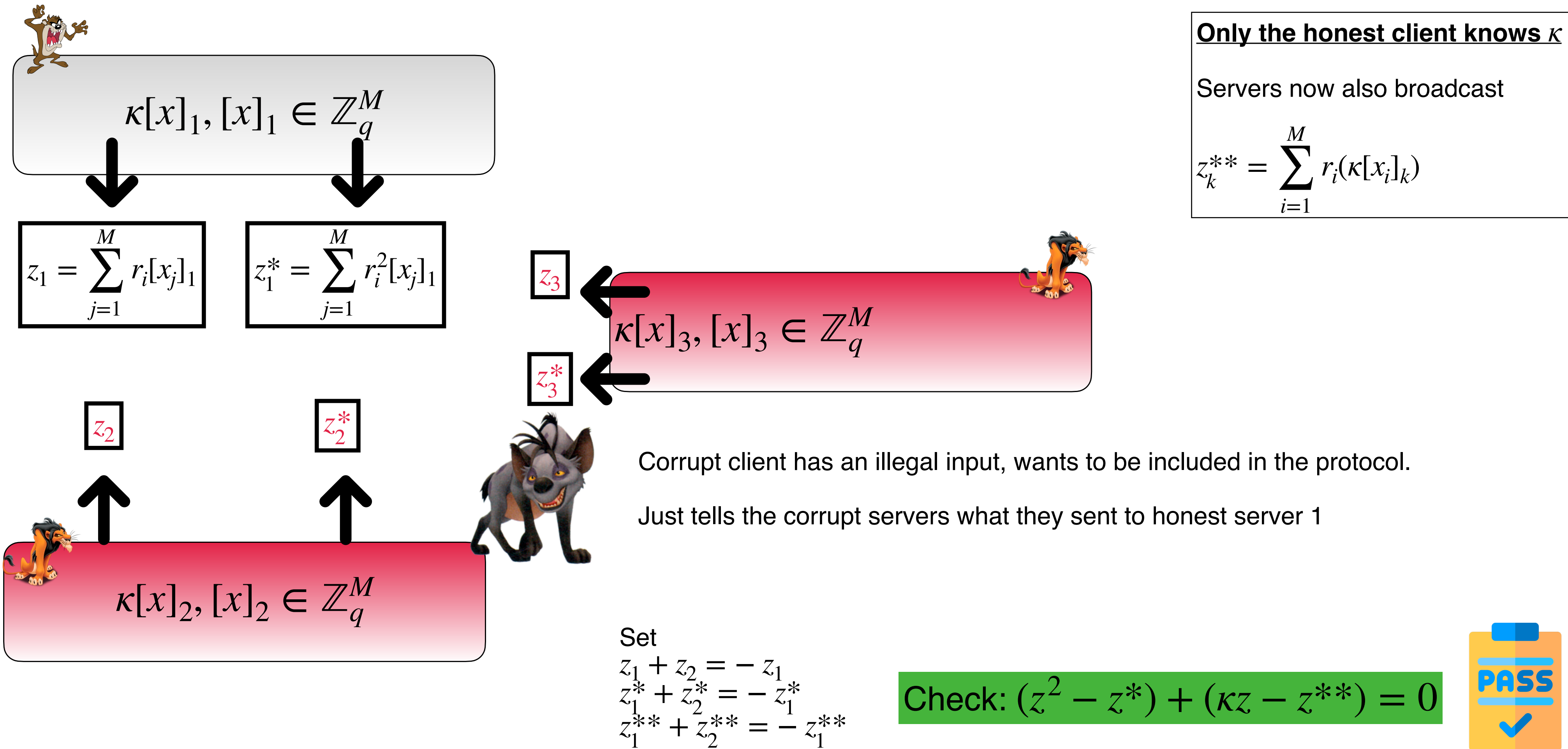


$$\kappa[x]_2, [x]_2 \in \mathbb{Z}_q^M$$

Corrupt client has an illegal input, wants to be included in the protocol.

Just tells the corrupt servers what they sent to honest server 1

# Collusions break Sketching protocols



# Our contribution

- We want the same trust model as PRIO/POPLAR
- We want central privacy error guarantees
- **If any party deviates from the protocol, the honest party can detect it as such and prove it to a court of law that this party deviated from the protocol.**
- Thus the output of the our protocol is either ABORT or valid
- This comes at the cost of 1-bit leak of information and some lightweight public key cryptography

## Formalised as Covert Security

Aumann and Lindell, 'Security Against Covert Adversaries'.

# Contributions

**Theorem 6.1.** *A collusion between a dishonest client and  $K - 1$  servers cannot include an illegal input with a success probability any greater than their advantage in the discrete log game.*

**Theorem 6.2.** *If a corrupt client can force honest servers to abort the protocol, then they have a non negligible advantage in the DLOG game.*

**Theorem 6.3.** *If a corrupt server tampers with input shares of an honest client, then the honest server always detects such tampering and aborts the protocol with non negligible probability.*

**Theorem 6.4.** *(Informal) If the output of the protocol is not ABORT, then the output is guaranteed to be differentially private and preserve near central accuracy guarantees of semi honest protocols.*

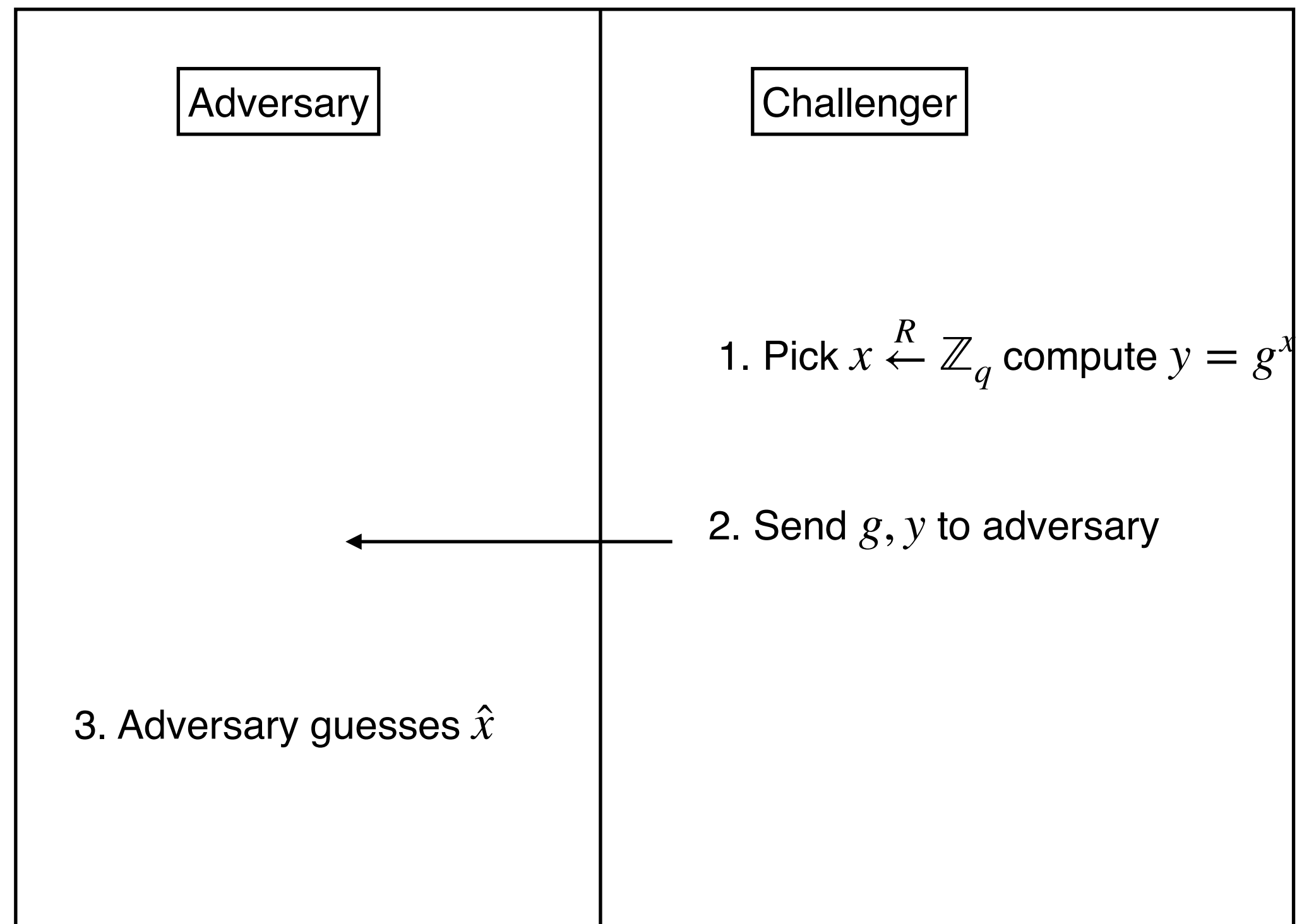


# Pederson Commitments

- Let  $\mathbb{G}_q$  be a sub group of  $\mathbb{Z}_p^*$  with order  $q$  where  $p$  and  $q$  are large primes such that  $q \mid p - 1$
- We have a secret  $s \in \mathbb{Z}_q$  and we want to commit to it. Then a Peterson commitment to  $s$  is given by  $c = \text{Com}(s, t) = g^s h^t$  where  $t \xleftarrow{R} \mathbb{Z}_q$  and  $g, h$  are randomly selected generators for  $\mathbb{G}_q$
- Given  $c$ , a computationally unbounded adversary  $\mathcal{A}$  cannot infer any information about  $s$  (**Perfectly Hiding**)
- Given  $c$ , if adversary  $\mathcal{A}$  that can find  $(s', t') \neq (s, t)$  such that  $\text{Com}(s, t) = \text{Com}(s', t')$ , then  $\mathcal{A}$  can solve the DLOG attack game (**Computationally Binding**)



# Discrete Log Attack Game



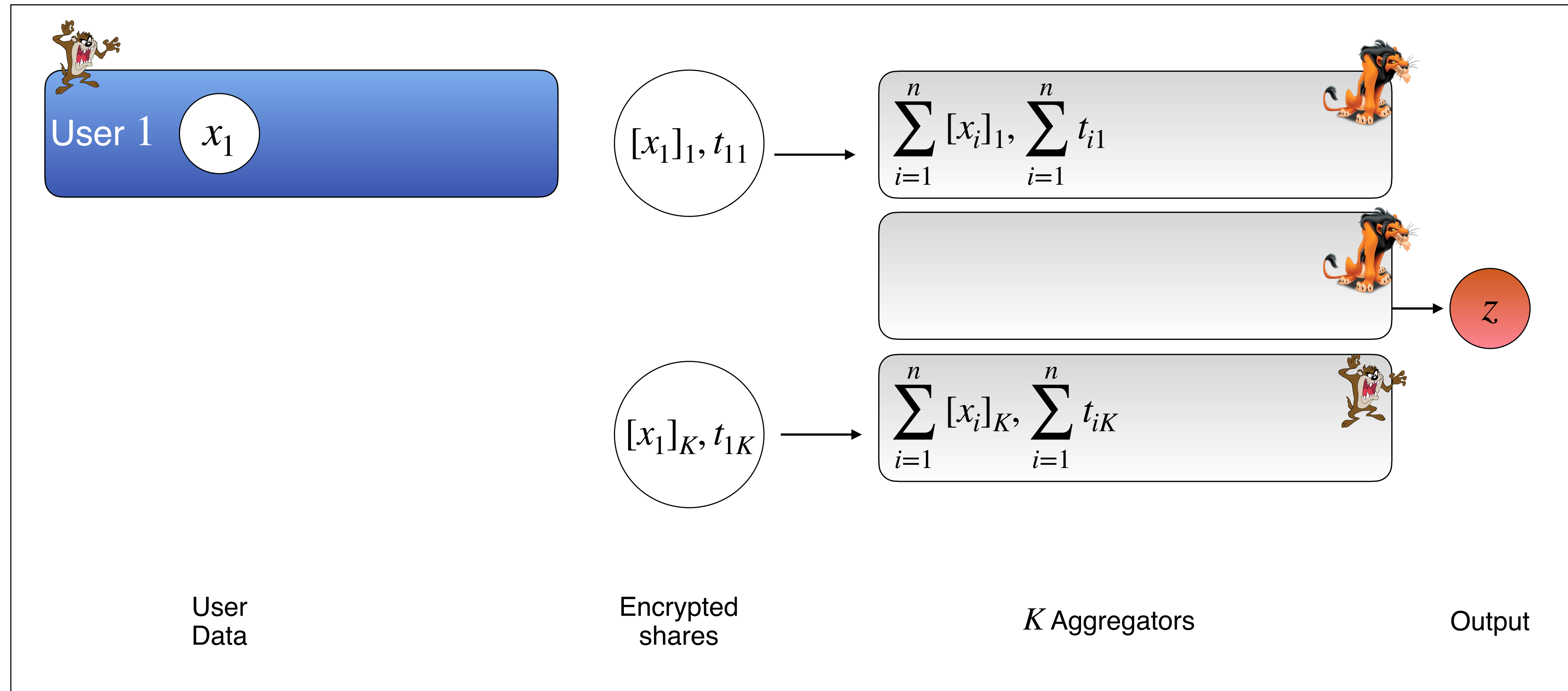
$$\text{Advantage}(\mathcal{A}, \mathbb{G}_q) := \Pr[\hat{x} = x]$$

We do not know any PPT algorithm that has non negligible advantage in guessing  $x$  for large enough  $q$ .

# Linearity trick — very useful

- Given  $c_1 = \text{Com}(s_1, t_1)$  and  $c_2 = \text{Com}(s_2, t_2)$ , then
- $c_1 c_2 = \text{Com}(s_1 + s_2, t_1 + t_2)$
- Addition in secret space is multiplication in commitment space

# Committed Input sharing



Public board for everyone to see

$$Com([x_i]_k, t_{ik}) \text{ for all } i \in [n], k \in [k]$$

# Distributed and verifiable noise generation

- Key idea if the algorithm is linear — then we will use commitments to our advantage and not allow the corrupt parties to deviate
- Binomial noise can be generated using a distributed and linear protocol.

See Dwork et al., 'Our Data, Ourselves'.

# Binomial Mechanism

- Given a bit  $b_i \in \{0,1\}$  from any arbitrary distribution
- And given  $c_i \sim \text{Bernoulli}(1/2)$
- $z_i = c_i \oplus b_i$  is guaranteed to be  $z_i \sim \text{Bernoulli}(1/2)$
- Use this along with commitments to get what we want

# Future work

- Can we lose that 1 bit leakage?
- Non linear protocols — could we leverage non-malleable codes for secret sharing ?
- Can we add bias to the noise sampler ?