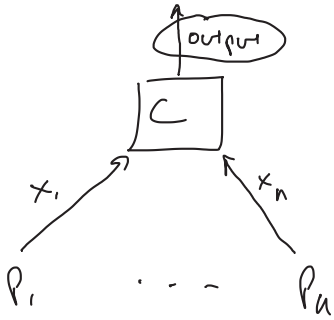
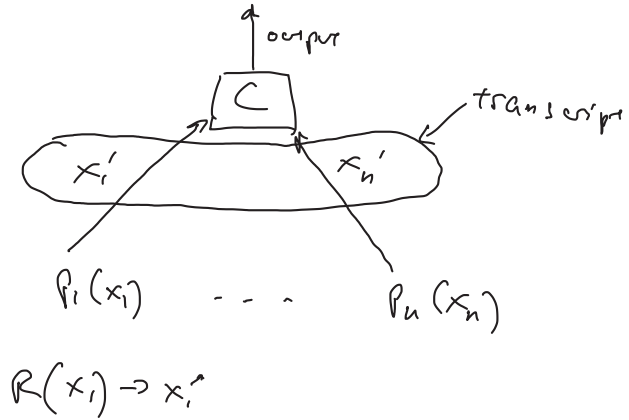


- exam
- scribes?
- lecture recording

Centralized model:



Local model:



$x_i \in \{0,1\}$

want to estimate $\sum x_i$

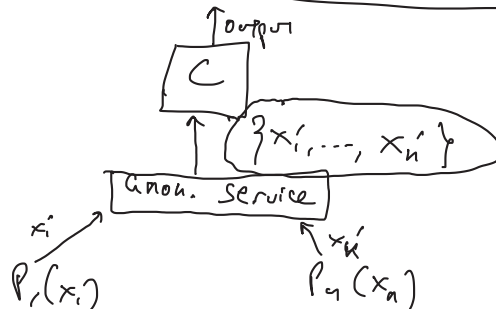
Centralized model: Laplace mechanism $\sum x_i + \text{Lap}(1/\epsilon)$

- ϵ -differential private
- noise $O(1/\epsilon)$

Local model: local Laplace mechanism: each party sends $x'_i = x_i + \text{Lap}(1/\epsilon)$
Curator releases $\sum x'_i$

- ϵ -differential private
- noise $O(\sqrt{n}/\epsilon)$ - optimal

= Shuffle model



I.e., to generate a noisy histogram:

- each party applies randomized response
 w/ prob. $1-\delta$, $x_i' = x_i$
 w/ prob δ , $x_i' \leftarrow \{1, \dots, K\}$
- each party sends x_i' to anonymous bulletin board
- curator gets $\{x_1', \dots, x_n'\}$ & generates histogram from that

In expectation, δ -fraction of the parties replace their inputs by random value

Consider changing input of P_i

Case 1 P_i sends uniform value in $\{1, \dots, K\}$
 view is independent of P_i 's input

Case 2 P_i sends its input (either x_i or \hat{x}_i)
 Still a privacy benefit in shuffle model,
 b/c w/ some probability, other parties send x_i/\hat{x}_i due to
 randomized response

Fix any view of the curator - including bit-vector indicating which parties sent random values

Let V denote the values sent by P_i & the values sent by the parties sending random values

$$\Pr[M(x_1, \dots, x_n) = V] = \binom{|B|}{n_1, n_2, \dots, n_K} \cdot \Pr[|B| \text{ parties send random values}]$$

$$\Pr[M(x_1, x_2, \dots, x_n) = V] = \binom{|B|}{n_1, n_2, \dots, n_K} \cdot \Pr[|B| \text{ parties send random values}]$$

$$\binom{|B|}{n_1, n_2, \dots, n_K} = \binom{|B|}{n_1} \cdot \binom{|B| - n_1}{n_2} \cdot \binom{|B| - n_1 - n_2}{n_3} \dots$$

$$\binom{|B|}{n_1, n_2, \dots, n_K} = \binom{|B|}{n_1} \cdot \binom{|B| - n_1}{n_2 - 1} \cdot \binom{|B| - n_1 - n_2 + 1}{n_3} \dots$$

$$\begin{aligned}
 \frac{P_C(M(x_1, x_2, \dots, x_n) = v)}{P_C(M(x_2, x_3, \dots, x_n) = v)} &= \frac{\binom{B}{n_1-1} \cdot \binom{|B|-n_1+1}{n_2}}{\binom{|B|}{n_1} \cdot \binom{|B|-n_1}{n_2-1}} \\
 &= \frac{\cancel{|B|!} \cdot \cancel{(|B|-n_1+1)!}}{(n_1-1)! \cdot \cancel{(|B|-n_1)!} \cdot n_2! \cdot \cancel{(|B|-n_1-n_2+1)!}} \\
 &= \frac{\cancel{|B|!} \cdot \cancel{(|B|-n_1)!}}{n_1! \cdot \cancel{(|B|-n_1)!} \cdot (n_2-1)! \cdot \cancel{(|B|-n_1-n_2+1)!}} \\
 &= \frac{n_1! \cdot (n_2-1)!}{n_2! \cdot (n_1-1)!} = \frac{n_1}{n_2}
 \end{aligned}$$

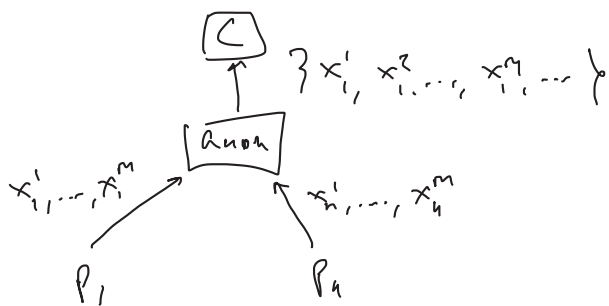
Application to summation

- use this protocol to generate a histogram
- compute the sum of the contributed values

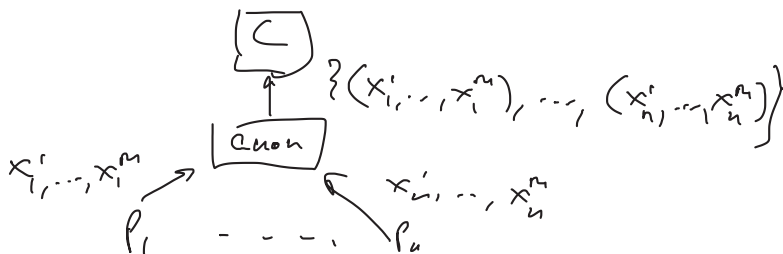
⇒ noise $O(n^{1/3})$

Amplification result: take any R that is ϵ_0 -LDP and run it through the shuffle mechanism, the result is $O(\min\{\epsilon_0, \epsilon\} \cdot e^{\epsilon_0} \cdot \sqrt{\frac{\log(1/\delta)}{n}})$ -DP
 ← assuming $\epsilon_0 = O(\log(\frac{n}{\log(1/\delta)}))$

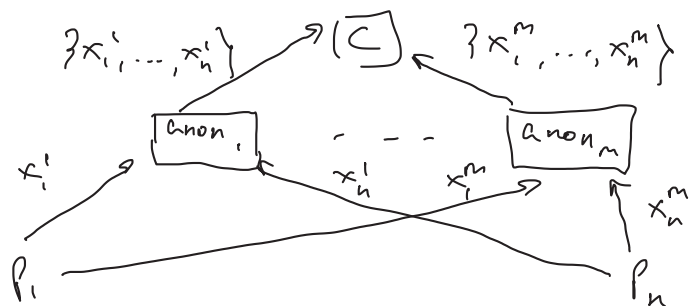
Multi-message shuffle model



Single-msg shuffle model



parallel multi-message shuffling



Exact summation using anonymization layer

- want to learn the sum exactly, w/o revealing parties inputs

View(\vec{x}) \approx View(\vec{x}') for any \vec{x}, \vec{x}' w/ the same sum

Protocol: each party P_i w/ input x_i chooses m values $\underbrace{x_i^1, \dots, x_i^m}_{\text{uniformly subject to } \sum_j x_i^j = x_i \pmod q}$

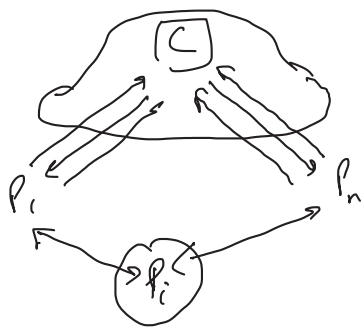
send x_i^1, \dots, x_i^m to the anon. service

Curator gets $\{x_1^1, \dots, x_1^m, \dots, x_n^1, \dots, x_n^m\}$ and outputs the sum

To achieve differential privacy, apply this protocol to $x_i + \text{noise}_i$

$$\text{Final result: } \sum x_i + \underbrace{\sum \text{noise}_i}_{O(\sqrt{\epsilon})}$$

Interactive local model



General protocols

