

- scribes?

- lecture recording

Exponential mechanism

if parameters are set appropriately

- For any scoring function, the mechanism is ϵ -D.P.
- W.h.p. the output $y \in Y$ satisfies

$$\text{score}(D, y) \geq \text{score}(D, y^*) - O\left(\frac{GS}{\epsilon} \cdot \log |Y|\right)$$

$$GS = \max_y \max_{D, D'} | \text{score}(D, y) - \text{score}(D', y) |$$

Application: outputting synthetic data

Given dataset D , given set of queries Q

For all $q \in Q$, $q(D) = \sum_i q(x_i)$, $D = (x_1, \dots, x_n)$

$$\text{Set } \alpha = O\left(\left(\frac{(\log |Q| \log |X|)^{1/3}}{\epsilon \cdot n}\right)\right)$$

Use exponential mech. to output synthetic dataset \hat{D}

S.t. w.h.p. for all $q \in Q$

$$|q(\hat{D}) - q(D)| \leq O(\alpha)$$

Use scoring function

$$\text{score}(D, \hat{D}) = - \max_{q \in Q} |q(D) - q(\hat{D})|$$

Set $m = O\left(\frac{\log |\mathcal{Q}|}{\alpha^2}\right)$ to the # of rows in output dataset

$\Rightarrow \exists \hat{D}^*$ s.t. for all $g \in \mathcal{Q}$
 $|g(\hat{D}^*) - g(D)| \leq O(\alpha)$

\Rightarrow w.h.p. the output \hat{D} satisfies

$$\begin{aligned} \text{score}(D, \hat{D}) &\geq \underbrace{\text{score}(D, \hat{D}^*)}_{-O(\alpha)} - \underbrace{O\left(\frac{1}{2} \cdot \log |\mathcal{X}|^m\right)}_{O(\alpha)} \\ &\geq -O(\alpha) \end{aligned}$$

PAC learning

Class \mathcal{C} of boolean functions $\mathcal{C} = \{c: X \rightarrow \{0,1\}\}$

For some $\underline{c} \in \mathcal{C}$, learning algorithm given $\underline{(x_1, c(x_1)), \dots, (x_n, c(x_n))}$,
where $x_i \in X$ are sampled from unknown distribution D .

\mathcal{L} should output some $\underline{c'} \in \mathcal{C}$ s.t. w.h.p.

$$\underline{\Pr_{x \in D} [c'(x) = c(x)] \text{ is high}}$$

Use exponential mechanism w/ scoring function

$$\underline{\text{score}(\{(x_i, y_i)\}, c')} = \underline{-|i: c'(x_i) \neq y_i|}$$

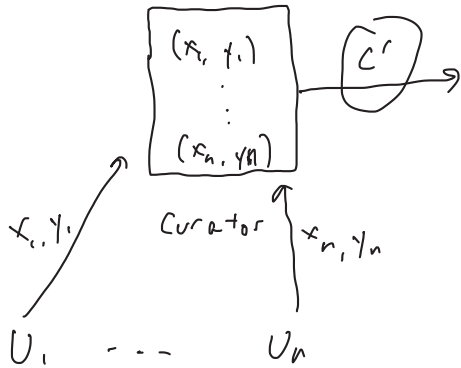
$\exists c$ s.t. $\underline{\text{score}(\{(x_i, y_i)\}, c) = 0}$

\Rightarrow output c' satisfies the following w.h.p.:

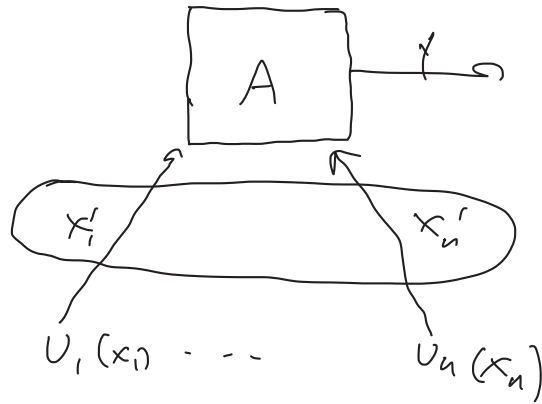
$$\underline{\text{score}(\underline{\mathcal{I}}, c')} \geq -\frac{1}{\epsilon} \log |\mathcal{C}|$$

$\Rightarrow \Pr_{x \leftarrow D} [c'(x) = c(x)]$ is high

Centralized model



Local diff. privacy



$$x'_i \leftarrow \underline{R(x_i)}$$

$$R: X \rightarrow X'$$

LDP definition: $\forall x, x', T \subseteq X'$:

$$\Pr [R(x) \in T] \leq e^\epsilon \cdot \Pr [R(x') \in T]$$

LDP version of Laplace mech:

$$\underline{R(x)} = x + \text{Lap}(\beta/\epsilon) = x'$$

$$x'_1 = x_1 + \text{Lap}(\beta/\epsilon)$$

\vdots

$$x'_n = x_n + \text{Lap}(\beta/\epsilon)$$

$$\sum x'_i = \sum x_i + \underbrace{\sum_{i=1}^n \text{Lap}(\beta/\epsilon)}$$

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

Randomized response

$$x \in \{0, 1\}$$
$$x' = \begin{cases} 0 & \delta/2 \\ 1 & \delta/2 \\ x & 1-\delta \end{cases}$$

Randomized response

$$x \in X$$
$$x' = \begin{cases} x & \text{w/ prob. } 1-\delta \\ x' \leftarrow X & \text{w/ prob. } \delta \end{cases}$$

$$\underbrace{E_{xp} [\sum x'_i]} = (1-\delta) \cdot \underbrace{E_{xp} [\sum x_i]} + \frac{1}{2} \cdot \delta$$

$$\rightarrow X' = (1-\delta) \cdot X + \frac{\delta}{2}$$

$$Pr [R(1) = 0] = \delta/2$$

$$Pr [R(0) = 0] = (1-\delta) + \delta/2 = 1 - \delta/2$$

$$\frac{\delta/2}{1 - \delta/2} \geq e^{-\epsilon}$$