

Lecture 10

— Selection Problem Continued

Exponential Mechanism.

Announcement:

- HW2 due in two weeks 10/17 (Sunday)
- HW1 Solution will be posted.
- Next week No Class on 10/13 Weds.
Optional Bonus Guest lecture on Zoom. (?)
- Make-up class on 10/15 Friday.
during Recitation Time.

Selection Problem

Heavy Hitter

Example. A set of websites $\{1, \dots, d\}$

Each user submits $x_i \subseteq \{1, \dots, d\}$

Winner: website with the highest score: $\forall j \in \{1, \dots, d\}$

$$f(j; x) = |\{i \mid j \in x_i\}|$$

Proposed solution: ① Laplace Mech. + Report the noisy max.
GS := d.

② Exponential Mech.

Example 2: Pricing a digital good.

- Selling an app; what price?
- n people's valuations: "How much are they willing to pay?"

Revenue: $f(p; x) = p \cdot \# \{i : x_i \geq p\}$.

price
↓

$x_i :=$ private value.

Error: $\underbrace{\max_p f(p; x)}_{\text{optimal Revenue.}} - f(\underbrace{A(x)}_{\substack{\uparrow \\ \text{Price returned by} \\ \text{your algorithm } A.}}, x)$

Formulation: Selection Problem

Y : possible outcomes (e.g. websites, prices).

$f: \underline{Y} \times \underline{X}^n \rightarrow \mathbb{R}$ "score" function (e.g., #hits, revenue)
measures how good y is on dataset X .

f is Δ -sensitive if $\forall y \in Y$
 $f(y; \cdot)$ has $GS_f \leq \Delta$.

Exponential Mechanism. $A_{EM}(x, f, \varepsilon, \Delta)$

Output an outcome y with probability proportional to $\exp\left(\frac{\varepsilon}{2\Delta} f(y; x)\right)$.

For this class, assume outcome space Y is finite.

$$\mathbb{P}[A_{EM}(x, f, \varepsilon, \Delta) = y] = \frac{1}{C_x} \cdot \exp\left(\frac{\varepsilon}{2\Delta} f(y; x)\right)$$

"Normalization factor" $C_x = \sum_{y' \in Y} \exp\left(\frac{\varepsilon}{2\Delta} f(y'; x)\right)$.

Privacy Proof.

Theorem. For every Δ -sensitive g ,
 $A_{EM}(\cdot, g, \varepsilon, \Delta)$ is ε -DP.

Proof. Sketch. Fix neighbors x, x' , any outcome $y \in Y$

Goal:
$$\frac{\mathbb{P}[A(x)=y]}{\mathbb{P}[A(x')=y]} \leq e^\varepsilon$$

$$\frac{\mathbb{P}[A(x)=y]}{\mathbb{P}[A(x')=y]} = \underbrace{\frac{C_{x'}}{C_x}}_{\text{show } \leq e^{\varepsilon/2}} \cdot \underbrace{\frac{\exp(\frac{\varepsilon}{2\Delta} g(y;x))}{\exp(\frac{\varepsilon}{2\Delta} g(y;x'))}}_{\leq e^{\varepsilon/2}}$$

Claim: For any $y' \in Y$,

$$\exp\left(\frac{\varepsilon}{2\Delta} g(y'; x)\right) \leq e^{\varepsilon/2} \exp\left(\frac{\varepsilon}{2\Delta} g(y'; x')\right).$$

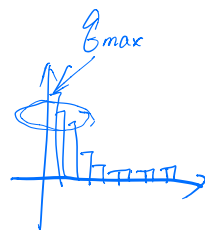
$$\Rightarrow \text{Set } y' = y = \frac{\exp(\frac{\varepsilon}{2\Delta} g(y;x))}{\exp(\frac{\varepsilon}{2\Delta} g(y;x'))} \leq e^{\varepsilon/2}$$

$$\begin{aligned} \Rightarrow C_{x'} &= \sum_{y'} \exp\left(\frac{\varepsilon}{2\Delta} g(y'; x)\right) \\ &\leq \sum_{y'} \exp\left(\frac{\varepsilon}{2\Delta} g(y'; x')\right) \cdot e^{\varepsilon/2} \\ &\leq C_x \cdot e^{\varepsilon/2} \end{aligned}$$

How useful is EM?

Compare $g_{\max}(x) = \max_y f(y; x)$

$$\text{error} := \underbrace{g_{\max}(x) - f(A_{\text{EM}}(x); x)}_{\text{minimize.}}$$



Theorem. (Y is finite) Let $|Y| = d$

$$\text{Then. } \mathbb{E}_{\hat{y} \sim A_{\text{EM}}} [g_{\max}(x) - f(\hat{y}; x)] \leq \frac{2\Delta}{\epsilon} (\ln(d) + 1)$$

$$\forall t > 0, \underbrace{\mathbb{P}_{\hat{y} \sim A_{\text{EM}}} [g_{\max}(x) - f(\hat{y}; x) \geq \underbrace{\frac{2\Delta}{\epsilon} (\ln(d) + t)}_{\text{threshold / error bound}}]}_{\text{Tail Bound on the error.}} < \underbrace{e^{-t}}_{\text{"failure probability" 1\%}}$$

Proof. Fix any data set $x \in \mathcal{X}^n$.

$$B_t = \{y \in Y \mid f(y; x) < \underbrace{g_{\max} - \frac{2\Delta}{\epsilon} (\ln(d) + t)}_{\text{err bound}}\}$$

"Bad set of outcomes"

For any $y \in B_t$,

$$P[A(x) = y] = \frac{1}{C_x} \exp\left(\frac{\epsilon}{2\Delta} f(y; x)\right)$$

$$\begin{aligned} &< \frac{1}{C_x} \exp\left(\frac{\epsilon}{2\Delta} \left(g_{\max} - \frac{2\Delta}{\epsilon} (\ln(d) + t)\right)\right) \\ &= \underbrace{\frac{1}{C_x} \exp\left(\frac{\epsilon}{2\Delta} g_{\max}\right)}_{P[A(x) = \text{Best}] \leq 1} \underbrace{\exp(-\ln(d)) \cdot \exp(-t)}_{\frac{1}{d}} \end{aligned}$$

plug in

$$\text{Our goal: } P[A(x) \in B_t] < e^{-t}$$

$$P[A(x) \in B_t] \leq \frac{P[A(x) \in B_t]}{P[A(x) = \text{Best}]}$$

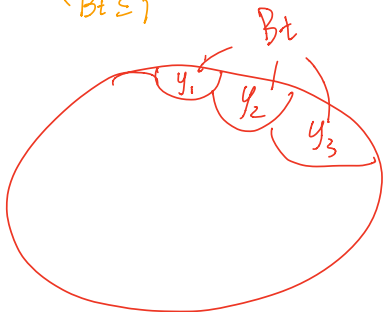
($P[A(x) = \text{Best}] \leq 1$)

(Union Bound)

$$< \frac{|B_t| \cdot \{P[A(x) = \text{Best}] \cdot \frac{1}{d} \cdot \exp(-t)\}}{P[A(x) = \text{Best}]}$$

Upper Bound
on prob.
for each
 $y \in B_t$

$$\left(\begin{array}{l} |B_t| \leq d \\ B_t \subseteq Y \end{array} \right) \leq d \cdot \frac{1}{d} \exp(-t) = \exp(-t).$$



Selection Problem Example

Heavy Hitter

Example. A set of websites $\{1, \dots, d\}$

Each user submits $x_i \in \{1, \dots, d\}$

Winner: website with the highest score: $\forall j \in \{1, \dots, d\}$

$$f(j; x) = |\{i \mid j \in x_i\}|$$

$$\text{Error} = \underbrace{\max_j f(j; x)}_{f_{\max}} - f(A(x); x) \quad \text{"# users visiting"}$$

Error Bounds:

$$\text{Set } t = \ln\left(\frac{1}{100}\right)$$

① Exp Mech.

$$\hat{y} \sim A_{\text{EM}} \quad \mathbb{P}\left[\underbrace{f_{\max}(x) - f(\hat{y}; x)}_{\text{error}} \geq \underbrace{\frac{2\Delta}{\epsilon} (\ln(d) + t)}_{\text{threshold / error Bound}} \right] < \underbrace{\left\{ e^{-t} \right\}}_{\text{"failure probability"}} e^{-t} = 1\%$$

W. p. 99%,

error <

$$\boxed{\frac{2 \ln(100d)}{\epsilon}}$$

$$\forall y \in Y, \quad |f(y, x) - f(y, x')| \leq \Delta, \quad \Delta = 1.$$

② Laplace Mech.

$$\text{Release } f(y; x) + \text{Lap}\left(\frac{GS_f}{\epsilon}\right) \quad \forall y.$$

$$GS_f = \max_{x, x'} \sum_{j=1}^d |f(j; x) - f(j; x')| = d.$$

$$\text{Error} \geq \underbrace{\left\lceil \left(\frac{d}{\epsilon} \right) \right\rceil}$$