

Lecture 5

- Recap

Definition of Differential Privacy

Randomized Response

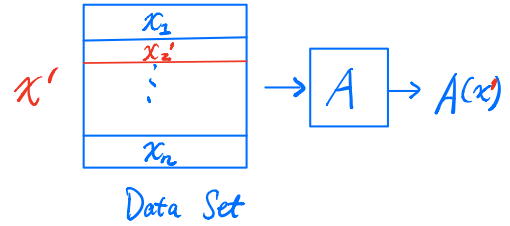
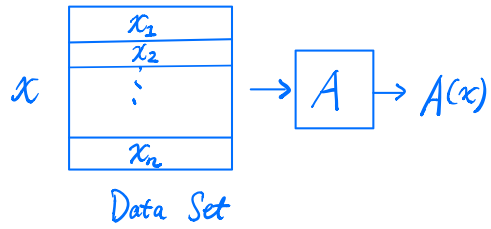
- Laplace Mechanism.

- HW1 is posted; due on Sep 26
Sunday

- Recitation on Friday.

No Problem set; DP Review
+ Randomized Response
+ Laplace Mech.

Neighboring datasets



x' is a neighbor of x
if they differ in one data point.

Definition. (Differential Privacy).

A is ϵ -differentially private if

for all neighbors x and x'

for all subsets E of outputs

$$\mathbb{P}[A(x) \in E] \leq e^\epsilon \mathbb{P}[A(x') \in E]$$

Definition. (Differential Privacy).

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$\approx (1+\epsilon)$

ϵ = Privacy (Loss) parameter

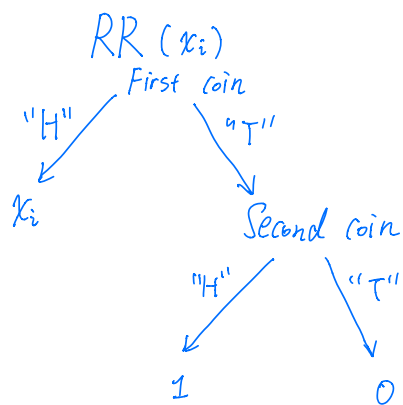
Small constant = $\frac{1}{10}, 1$, but not $\frac{1}{2^{80}}$ or 100

Example : Randomized Response (In lecture 1)

Each person has a secret bit $x_i = 0$ or $x_i = 1$
(Have you ever done XZ?)

Input : x_1, \dots, x_n

Output : y_1, \dots, y_n



Theorem. RR is (ϵ, δ) -differentially private

Basic Proof Strategy :

for all neighbors x and x'
for all subsets E of outputs ($E \subseteq Y$).

$$P[A(x) \in E] \leq e^\epsilon P[A(x') \in E]$$



$$P[A(x) = y] \leq e^\epsilon P[A(x') = y] \quad (*)$$

for all y in Y
output space.

\uparrow
we prove.

How to construct an estimate?

Input = $(x_1, x_2, \dots, x_n) \in \{0, 1\}^n$

For $i = 1, \dots, n$:

$$Y_i = \begin{cases} x_i & \text{with probability } \frac{3}{4} \\ 1-x_i & \text{with prob. } \frac{1}{4}. \end{cases}$$

Return: (Y_1, \dots, Y_n) .

Goal: want to estimate $p = \frac{1}{n} \sum_{i=1}^n x_i$

Observe: $\hat{y} = \frac{1}{n} \sum_{i=1}^n Y_i$.

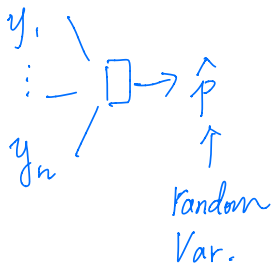
Estimation: $\hat{p} = a \hat{y} + b$

Question: What should a & b be?

"Implicit" Goal: Find a & b ,

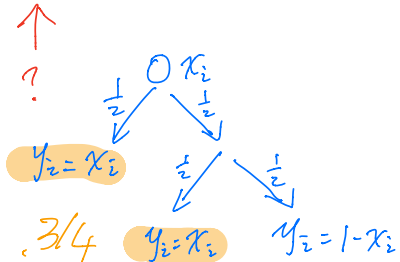
$$\mathbb{E}[\hat{p}] = p. \quad \leftarrow \text{Unbiased estimate}$$

Trials
(a, b)
= $(2, -\frac{1}{2})$? ✓



$$\mathbb{E}[\hat{p}] = \mathbb{E}\left[\frac{1}{n} \sum_i (a Y_i + b)\right]$$

Linearity of Expectation $\rightarrow = a \cdot \frac{1}{n} \sum_i \mathbb{E}[Y_i] + b.$

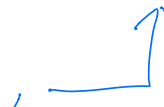


$$\begin{aligned}\mathbb{E}[Y_i] &= \frac{3}{4} x_i + \frac{1}{4} (1 - x_i) \\ &= \frac{x_i}{2} + \frac{1}{4}.\end{aligned}$$

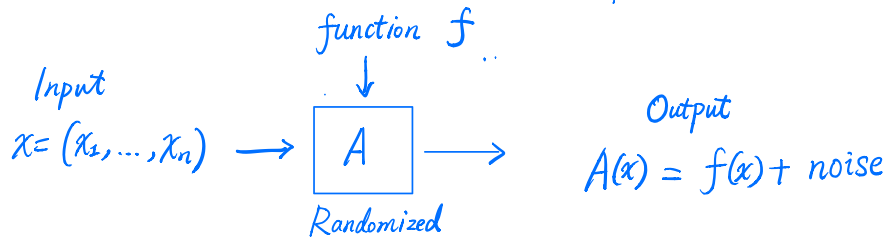
$$\begin{aligned}\mathbb{E}[\hat{p}] &= a \cdot \frac{1}{n} \left(\sum_i \left(\frac{x_i}{2} + \frac{1}{4} \right) \right) + b \\ &= \frac{a}{2} \underbrace{\left(\frac{1}{n} \sum_i x_i \right)}_p + \frac{a}{4} + b = p\end{aligned}$$

↑
unbiased
condition

$$\Rightarrow a=2, \quad b=-\frac{1}{2}.$$

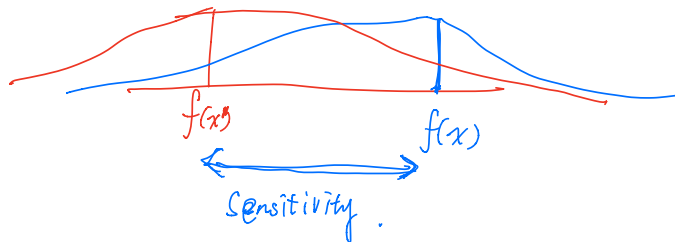
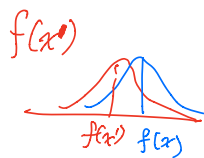
\bar{I}_n HW1, 
Generalization

Noise addition (Laplace Mechanism).



- Goal = Release approximation to $f(x) \in \mathbb{R}^d$
eg., # ppl wearing socks,
- Intuition: $f(x)$ can be released accurately if f is *insensitive* to the change of individual examples x_1, \dots, x_n

$f(x)$



Sensitivity.

- Intuition: $f(x)$ can be released accurately if f is *insensitive* to the change of individual examples x_1, \dots, x_n

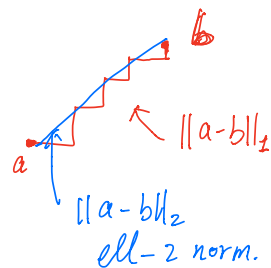
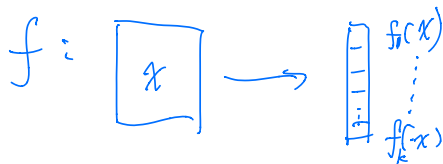
Global Sensitivity:

$$GS_f = \max_{x, x' \text{ neighbors}} \|f(x) - f(x')\|_1$$

ell-one norm

$\|\cdot\|_1$

$$\|v\|_1 = \sum_{j=1}^d |v_j|$$



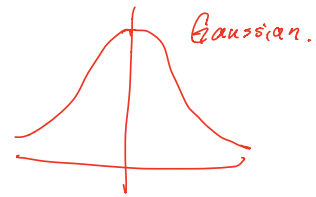
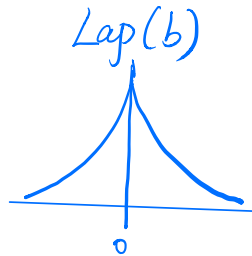
Laplace Mechanism.

$$A_L(x) = f(x) + (Z_1, \dots, Z_d)$$

where each Z_i drawn i.i.d. from $\text{Lap}\left(\frac{GS_f}{\epsilon}\right)$

Global
Sensitivity of
 f
↓

Laplace
Distribution :



Facts: $Z \sim \text{Lap}(b), \mathbb{E}[|Z|] = b$

Prob. density function \rightarrow PDF(z) = $\frac{1}{2b} \exp(-|z|)$.

$\exp(a) = e^a$

Theorem. A_L is ϵ -differentially private.

Examples.

- Proportion.

$$GS_f = \max_{x, x'} \|f(x) - f(x')\|_1$$

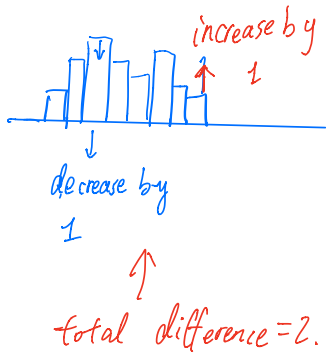
$$f(x) = \frac{1}{n} \sum_{i=1}^n x_i$$

"fraction of people wearing socks"

$$GS_f = \frac{1}{n}.$$

$$= \max_{x, x'} \left| \frac{1}{n} x_i - \frac{1}{n} x'_i \right| \leq \frac{1}{n}$$

- Histogram.



Data domain $\mathcal{X} = B_1 \cup B_2 \cup \dots \cup B_d$

$$f(x) = (n_1, \dots, n_d), \quad n_j = \#\{i : x_i \in B_j\}$$

↑
count

$$x \rightarrow x'$$

$$f(x) - f(x')$$