AI Ethics:
Privacy & Machine Learning

CS229: Machine Learning
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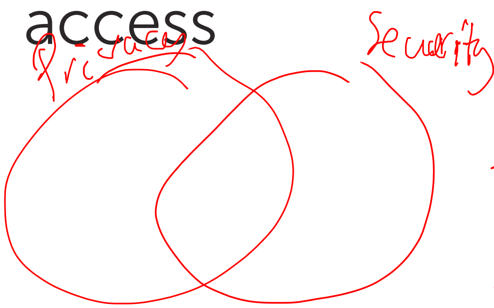
Privacy Definition *(dictionary.com)*

2. the state of being free from unwanted or undue intrusion or disturbance in one's private life or affairs; freedom to be let alone.

3. freedom from damaging publicity, public scrutiny, secret surveillance, or unauthorized disclosure of one's personal data or information, as by a government, corporation, or individual.

Privacy vs Security

- Privacy is about your control of your personal information (and how it's used)
- Security is about protection against unauthorized access



privacy + security	Bank protects your data & only uses to provide banking services
Security + no privacy	Bank protects your data & sells your data to advertizers
no security + no privacy	Data breach & your data is sold in dark web

Utility-Privacy Tradeoff

Can we preserve privacy, and provide utility?

train an ML model?

All privacy

All utility

Company A

"we collect no data"

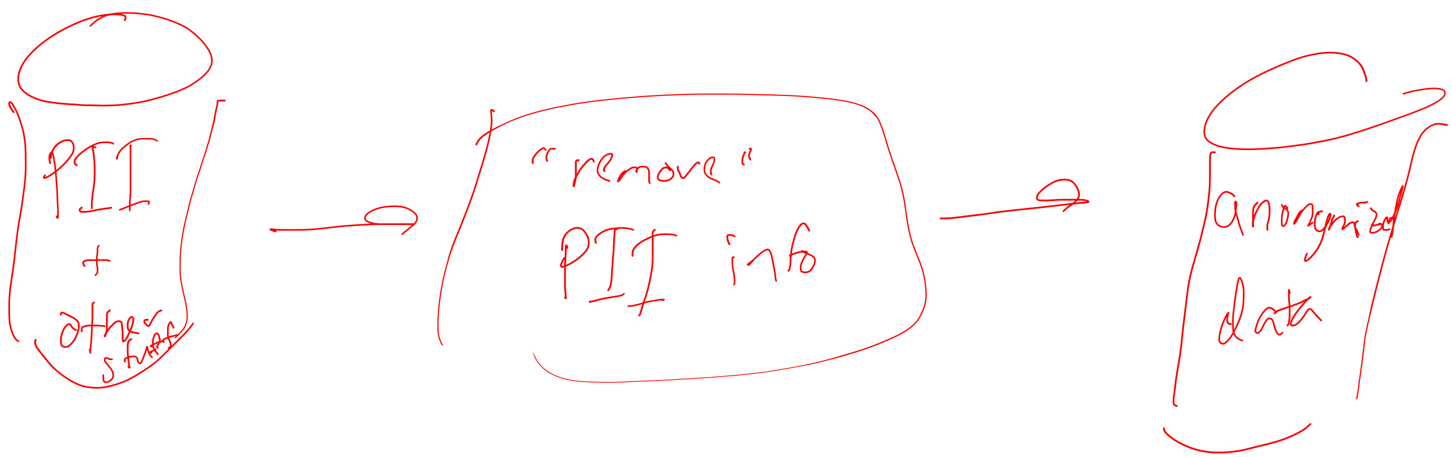
Company B

"Trust me, and give me all your data!"

Privacy by Anonymization

PII

- A trusted curator removes personally-identifying information (name, SSN,…)



Linkage Attack [Sweeney '00]

- Group Insurance Commission (GIC)
  - Anonymized data for ~135k patients for researchers and policy-makers
    - Including ZIP, birthdate and sex

~~name~~
~~address~~

ZIP
Birthdate
sex

Diagnosis
medications

ZIP
Birthdate
Sex

Name
Address

Linkage Attack [Sweeney '00]

- Group Insurance Commission (GIC)
  - Anonymized data for ~135k patients for researchers and policy-makers
    - Including ZIP, birthdate and sex
- Voter registration records
  - Name, ..., ZIP, birthdate, sex
- Uncovered health records, e.g., of William Weld (governor of Massachusetts at that time)

Netflix Prize Linkage Attack

Netflix Prize 2006
Predict user rating

100 million movie ratings

IMDB

Anonymous ID

Movies Ratings

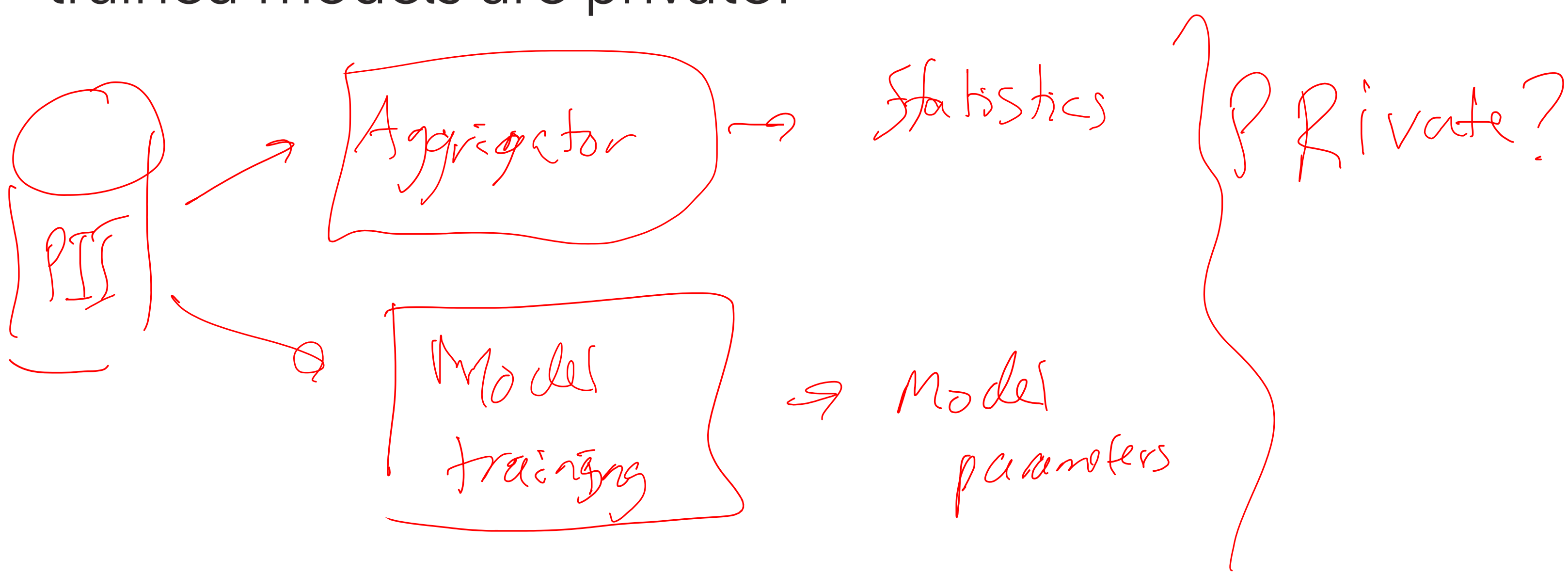
Username

Movie Rating

identified 99% of users who had at least 6 ratings

Privacy by Aggregation

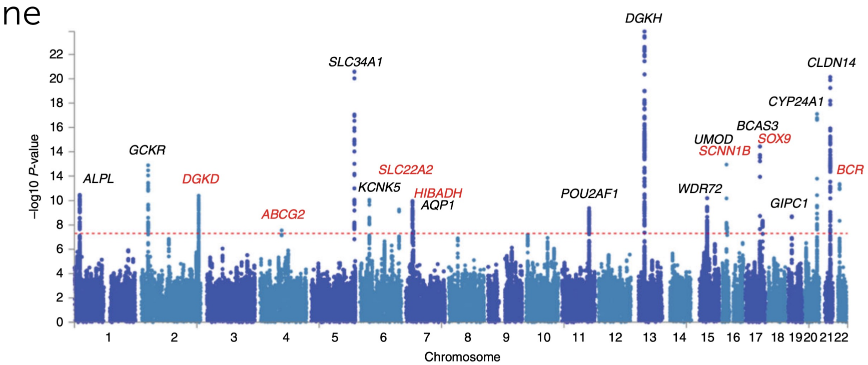
- Common approach: aggregate counts, averages, trained models are private?



Genome Wide Association Studies (GWAS) with single-nucleotide polymorphisms (SNPs): **Membership Attack**

[Dwork et al.]

Kidney stone disease

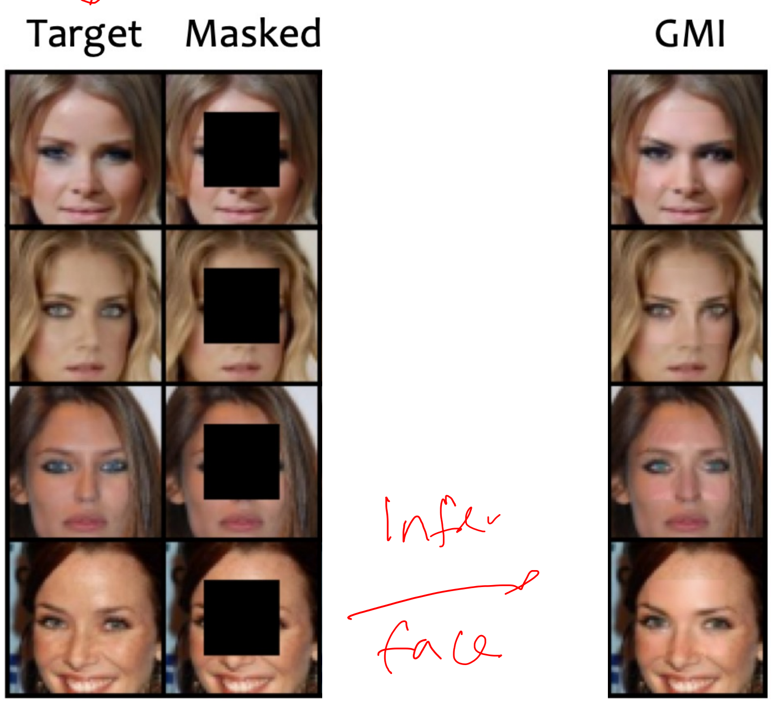


HIPAA Compliant
NIH Processes

- Able to infer if an individual's DNA is part of study

Generative Model Inversion Attack [Zhang et al 2020]

Train data



Infer

face

Randomized Response [Warner 1965]

Randomized Response: Intuition

$\tilde{\mu}$ has high variance if variance of w_i is large

- Add noise to each data point, e.g., estimate average salary

Salary

$x_1 = \$500k$

$\vdots$

$x_n = \$522k$

Add Noise

- zero mean
- Large variance

e.g., $w_i \sim N(0, 100{,}000^2)$

Report

$z_i \leftarrow x_i + w_i$

$\hat{\mu} = \frac{1}{N} \sum_i x_i$

$\tilde{\mu} = \frac{1}{N} \sum_i z_i$

$E_{\text{Noise}}[\tilde{\mu}] = E\left[\frac{1}{N} \sum_i x_i + w_i\right]$

$= \underbrace{\frac{1}{N} \sum_i x_i}_{\hat{\mu}} + \frac{1}{N} \sum_i \cancel{E[w_i]}$ 0

high noise: more privacy, less utility

low noise: less privacy, more utility

Differential Privacy [Dwork et al. 2006] (Dwork and Roth 2014 Book is great reference: https://www.cis.upenn.edu/~aaroth/Papers/privacybook.pdf)

Formal Framework for Privacy

- Provide provable privacy-preserving guarantees

- Develop efficient methods to add noise and learn from data

Global Differential Privacy Framework

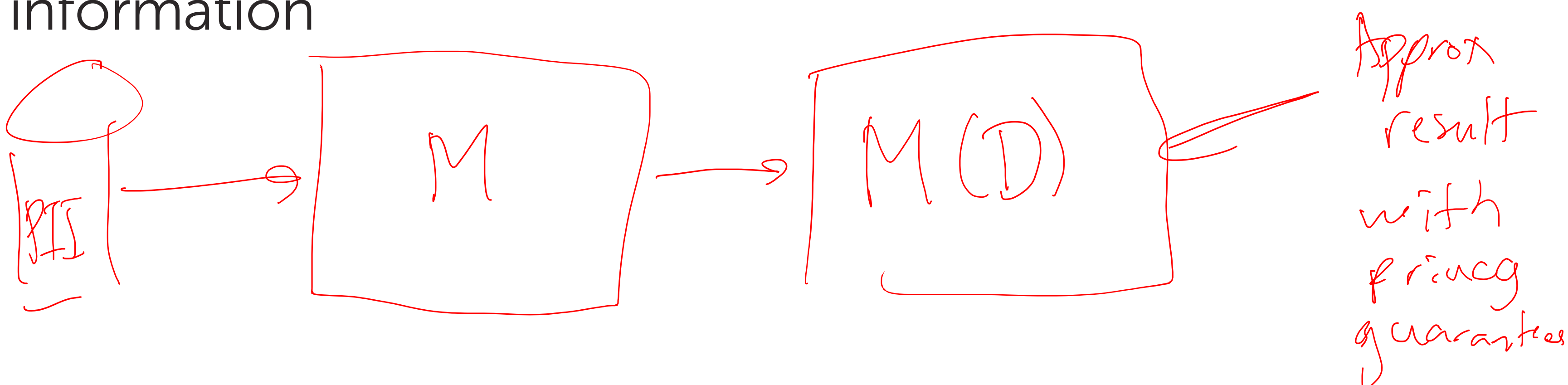
- You participate in "study"
  - i.e., provide data to trusted party
- Trusted party performs computations on data, but reveals answers that (attempt to) preserve privacy

Trusted DB P.I.I. → Compute query → Statistics → Add Noise → Privacy preserving statistics

- Goal: Provide provable privacy-preserving guarantees

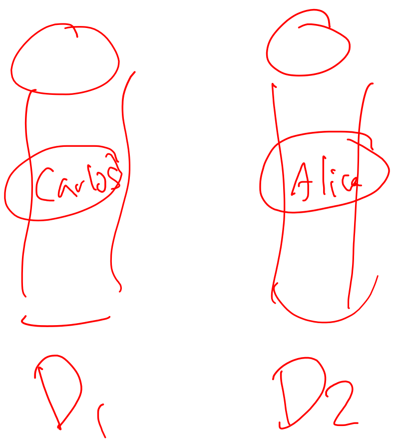
Differential Privacy Setup

- Database D includes sensitive information
- Data analyst asks queries on D
- (Randomized) Mechanism M attempts to get response R to query, while attempting to avoid leaking of individual information



Differential Privacy: Neighboring Databases

- **Neighboring databases:** two databases D_1 and D_2 only differ in a single entry



How many people grew up in Brazil

$Q(D_1) = 1221$ Carlos yes

$Q(D_2) = 1220$ Alice No

$M(D_1) = Q(D_1) + \underbrace{w_1}_{\text{Noise}}$

$M(D_2) = Q(D_2) + w_2$

Noise large enough to hide Carlos' Contribution

Differential Privacy Definition [Dwork et al. '06]

- **Neighboring databases:** two databases D_1 and D_2 only differ in a single entry
- A mechanism M is ε-differentially private if, for any two neighboring databases, and any set R of possible responses:

$$\frac{P(M(D_1) \in R)}{P(M(D_2) \in R)} \leq e^{\varepsilon}$$

prob. WRT noise you add, M adds

- Note: Differential Privacy is a definition, not algorithm to achieve it

Differential Privacy Intuition

- You can't tell if it's me or someone else in the database
  - You can't tell if I was part of the study

$$e^{-\varepsilon} \le \frac{P(M(D_1)\in R)}{P(M(D_2)\in R)} \le e^{\varepsilon}$$

for small ε, $e^{\varepsilon} \approx 1+\varepsilon$

$\Rightarrow M(D_1) \approx M(D_2)$ in probability

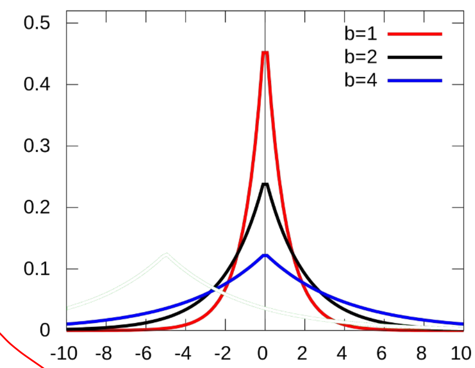
$$\frac{1}{1+\varepsilon} \le \frac{P(M(D_1)\in R)}{P(M(D_2)\in R)} \le 1+\varepsilon$$

Laplace Mechanism

Laplace Mechanism

$$p(w) = \frac{1}{b}\exp\left(-\frac{|w|}{b}\right)$$

noise



- Add Laplace noise to the response

Query: Count (A in CS229), return Count + w

- How much noise to add?
  - Depends on magnitude of results
  - Suppose want to compute function f on database D, *sensitivity* of f:

$\Delta f = \max_{D_1, D_2 \text{ neighboring}} \|f(D_1) - f(D_2)\|_1$ $\qquad \Delta f = 1$

- *To achieve* **ε-differential privacy**, noise level is:

$w \sim \text{Laplace}\left(0, \frac{\Delta f}{\varepsilon}\right) \rightarrow$ achieve ε differential privacy

Laplace Mechanism Example: Counts

- Suppose you want to count how many people have salary>$500~~k &~~ got an A in CS281 CS229
  - f is count function
- Sensitivity of f: $\Delta f = 1$

- *To achieve* **ε-differential privacy**, noise level is:

$$\text{Laplace}(0, 1/\varepsilon)$$

Proof for 1D Laplace Mechanism

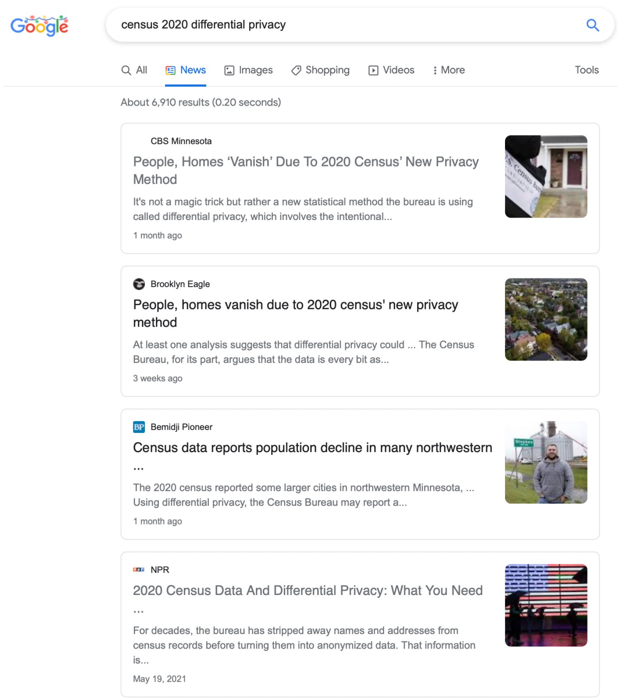
$$p(w) = \frac{1}{b} \exp\left(-\frac{|w|}{b}\right)$$

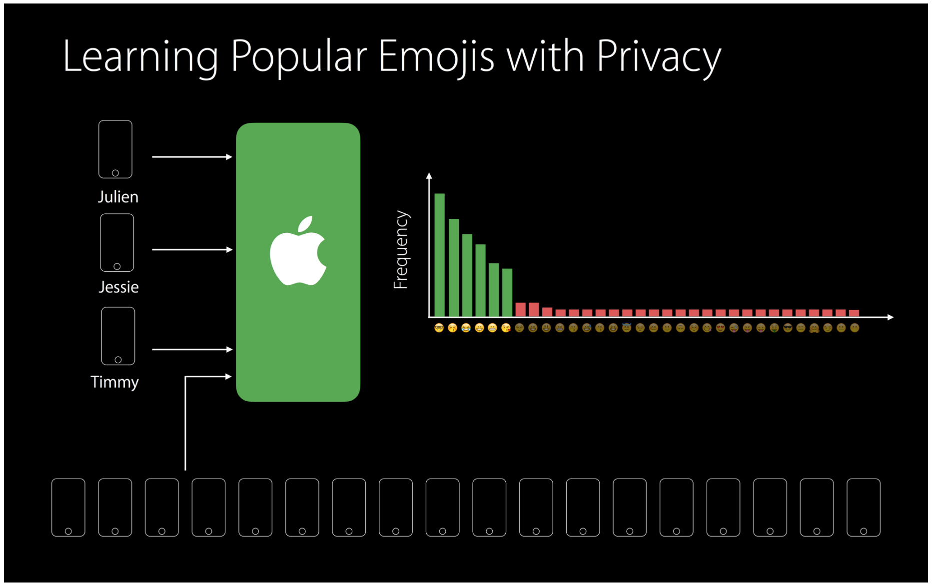
- Neighboring databases D_1 and D_2
- Mechanism M to compute f returns:

- Achieving ε-differential privacy:

Practical Examples of Differential Privacy

Practical Applications of Differential Privacy





Summary

- As we develop ML-based systems, it's important to consider privacy at every stage of the process
- Many methods and tools can help
- Ultimately, must manage the utility-privacy tradeoff

Closing a busy quarter… ☺

You did amazing things…

- Huge number of topics
- Remote learning
- Challenging homeworks and midterm
- Amazing project
- …

This is just the start…

- You now have the skills to have real-world impact with ML
- But, machines are not the only ones who keep learning… ☺
  - CS229 prepares you for many other classes at Stanford
  - And beyond
- We can't wait to see the amazing things you come up with!

Thank you to the amazing course staff!!!!!!!!

Course Manager

Swati Dube

Head Course Assistant

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Lantao Yu

Emmanuel Balogun

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Thank you!!!!!!!!! ☺