Ensuring (Statistical) Privacy

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Code for this talk: https://github.com/alabid/pre_college_2019

See full course materials here: http://people.seas.harvard.edu/~salil/cs208/ [some slides taken from here]

My website: http://alabidan.me

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The Problem

We have a dataset with sensitive information, such as:

1. Health records (e.g. reveals which disease a patient has)
2. Census data (e.g. reveals income range)
3. Social network activity (e.g. which pages you like)

How can we allow:

1. Allow the use of the data?
2. Protect the privacy of the data subjects?
3. Achieve both (1) and (2)?

Some Approaches to Solve the Problem

Encrypt the Data:

Name	Sex	Blood	…	HIV?
James	O	B	…	N
Peter	M	O	…	Y
…	…	…	…	…
Paul	M	A	…	N
Eve	F	B	…	Y

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10101	01010	01000	…	00001
11010	01101	10111	…	10111
…	…	…	…	…
10100	10000	11101	…	01111
11000	10001	11110	…	10001

Some Approaches to Solve the Problem

Encrypt the Data: Are we happy with this solution? Why or why not?

Name	Sex	Blood	…	HIV?
James	O	B	…	N
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Some Approaches to Solve the Problem

"Anonymize the Data": Are we happy with this solution? Why or why not?

Name	Sex	Blood	…	HIV?
James	O	B	…	N
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…	…	…	…	…
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Name	Sex	Blood	…	HIV?
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XXXXX	M	O	…	Y
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XXXXX	M	A	…	N
XXXXX	F	B	…	Y

Some Approaches to Solve the Problem

“Anonymize the Data”: Not sufficient because of linkage attacks!

87% of US population have unique date of birth, gender, and postal code!

[Golle and Partridge 09]

Some Approaches to Solve the Problem

"Anonymize the Data": Reidentification via Linkage

Can uniquely identify > 60% of the U.S. population [Sweeny '00, Golle '06, Sweeney '97]

Name	Sex	Blood	…	HIV?
XXXXX	O	B	…	N
XXXXX	M	O	…	Y
…	…	…	…	…
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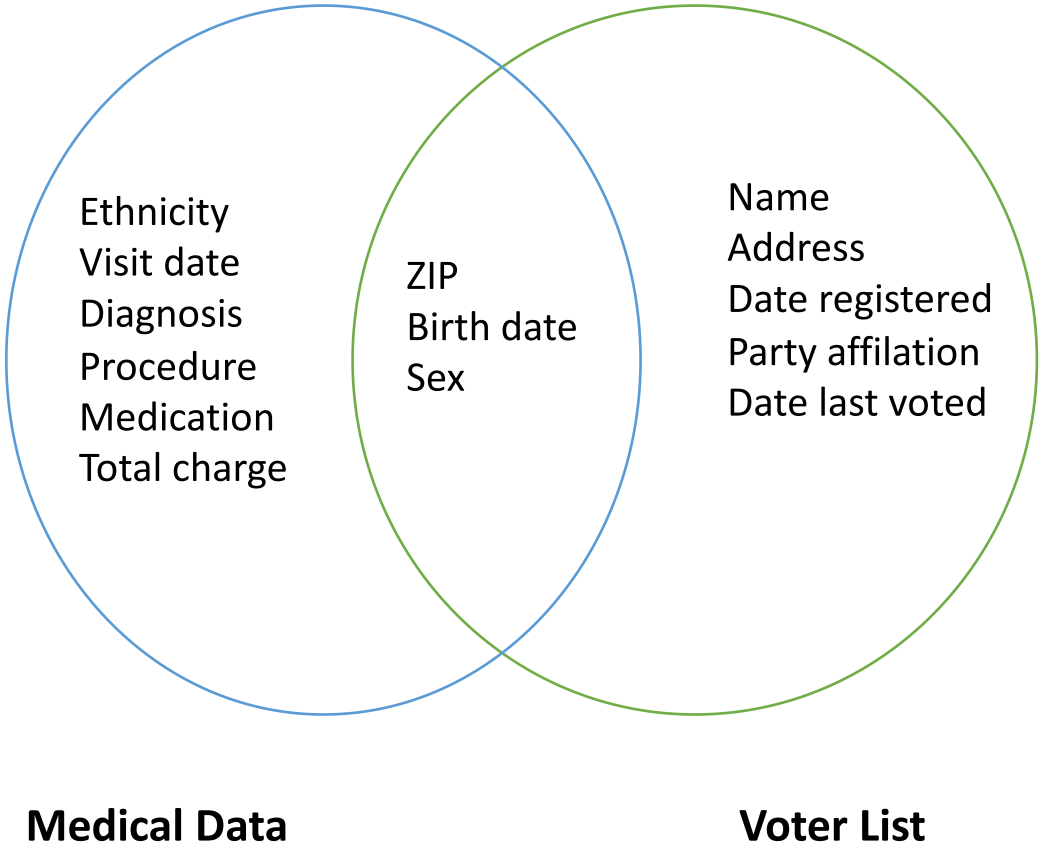

The story so far

- Motivations
  - Reidentification via Linkage Attacks
  - Reconstruction and Inference Attacks

<u>Reconstruction attack</u>: If we have dataset $x \in \{0,1\}^n$ and person i has sensitive bit x_i and attacker/adversary gets $q_S(x) = \sum_{i \in S} x_i$ for any $S \subseteq [n]$.

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<u>Inference attack</u>: Attacker gets n^2 answers and needs to know if someone is in dataset or not.

The story so far

Message

Releasing too many statistics with too much accuracy can lead to a reconstruction of the entire dataset or inference attacks

Some Approaches to Solve the Problem

So now what?

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Possible Responses:

- Privacy is an illusion!
- In the long run, it’s better to use data for research! Ignore privacy!
- Never release statistics about any dataset!
- Is there a way to add enough noise to queries and still allow for usefulness?

Main Message of this Talk

Yes, there is a way to add enough noise to queries and still allow for usefulness?

An approach: K-anonymity

[Sweeney '02]: A mechanism satisfies k-anonymity if for every dataset, the output of the mechanism has the property that every distinct row occurs at least k times.

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Intuition: Privacy ensured if I can’t isolate you!

An approach: K-anonymity

[Sweeney '02]: A mechanism satisfies k-anonymity if for every dataset, the output of the mechanism has the property that every distinct row occurs at least k times.

3-anonymous dataset:

Zip code	Age	Nationality
021**	< 30	*
021**	< 30	*
021**	< 30	*
021**	> 40	*
021**	> 40	*
021**	> 40	*
021**	3*	*
021**	3*	*
021**	3*	*

An approach: K-anonymity

It's a nice approach but doesn't:

- Compose well (e.g. if you have two k-anonymous datasets)
- Utility not as quantifiable as other approaches

Zip code	Age	Nationality
021**	< 30	*
021**	< 30	*
021**	< 30	*
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Differential Privacy

- Utility
- Privacy
- Definition

Differential Privacy

- Utility: enable "statistical analysis" on datasets
  - Can release (noisy) statistics such as means, sums, medians, etc.
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- Definition: pure and approximate

Differential Privacy

<u>Definition</u>: pure and approximate

[Dwork-McSherry-Nissim-Smith ‘06]

Other references:

Motivated from and based off of work in

[Dinur-Nissim ‘03, Dwork-Nissim ‘04, Blum-Dwork-McSherry-Nissim ‘05]

Differential Privacy

Definition: pure and approximate

[Dwork-McSherry-Nissim-Smith ‘06]

Intuition: for a statistic, the effect of each individual (whether in the dataset or not) should be close to nothing.

Differential Privacy

<u>Definition</u>: pure and approximate

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Intuition: for a statistic, the effect of each individual (whether in the dataset or not) should be close to nothing.

Worst-case notion: protects against all possible adversaries and any kind of individual.

Differential Privacy

Definition: pure and approximate

[Dwork-McSherry-Nissim-Smith '06]

For any algorithm $\mathcal{A}$, it satisfies ϵ differential privacy if

For all datasets D, D' differing in exactly one row all queries q

Distribution of $\mathcal{A}(D, q)$ is at most ϵ away from $\mathcal{A}(D', q)$

The smaller ϵ is, the more privacy is ensured!

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For all sets T,

$\Pr[\mathcal{A}(D, q) \in T] \leq (1 + \epsilon) \Pr[\mathcal{A}(D', q) \in T]$

Differential Privacy

Definition: pure and approximate

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For any algorithm $\mathcal{A}$, it satisfies ϵ differential privacy if

For all datasets D, D' differing in exactly one row all queries q

Distribution of $\mathcal{A}(D, q)$ is at most ϵ away from $\mathcal{A}(D', q)$

The probability is only over the randomness of the algorithm $\mathcal{A}$

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Mechanisms for Differential Privacy

Examples:

1. Laplace Mechanism [we’ll discuss and implement this one!]
2. Gaussian Mechanism
3. Exponential Mechanism
4. Geometric Mechanism

….

Laplace Mechanism

$\mathrm{Lap}(s)$ is the Laplace Distribution with scale s.

Some properties:

- Has mean 0
- Has standard deviation $\sqrt{2} \cdot s$
- It’s a “double-exponential” distribution

Laplace Mechanism for Sum and Average

1. $\mathcal{A}(x) = \sum_{i=1} x_i + \text{Lap}(\frac{1}{\epsilon})$

where $x_i \in [0, 1]$ for all $i \in [n]$.

Laplace Mechanism for Sum and Average

1. $\mathcal{A}(x) = \sum_{i=1} x_i + \text{Lap}(\frac{1}{\epsilon})$

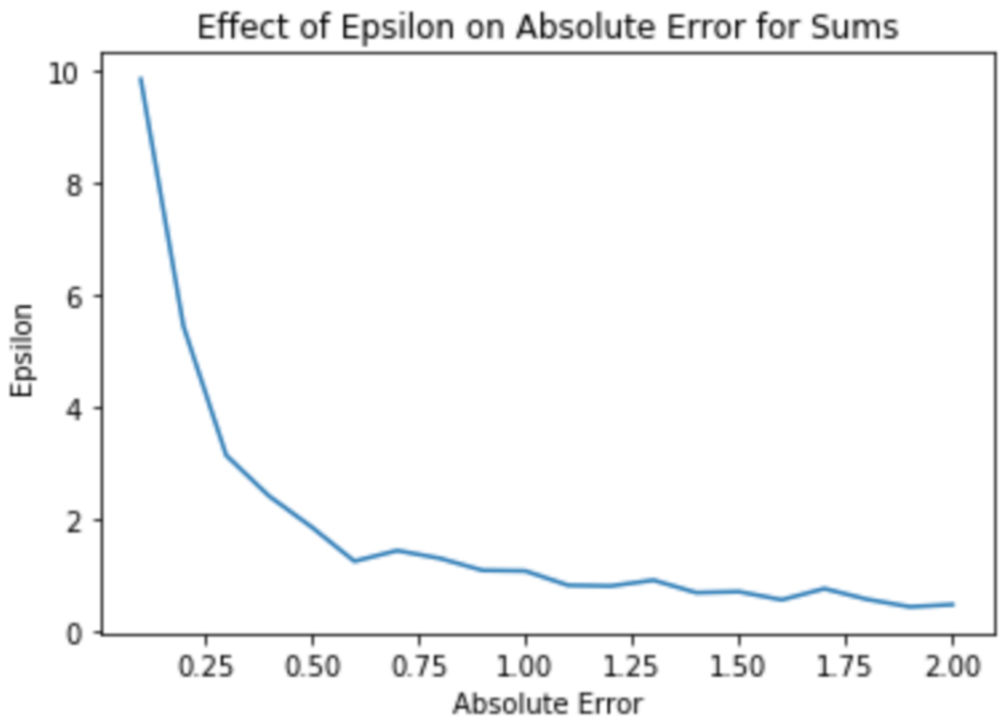
where $x_i \in [0, 1]$ for all $i \in [n]$.

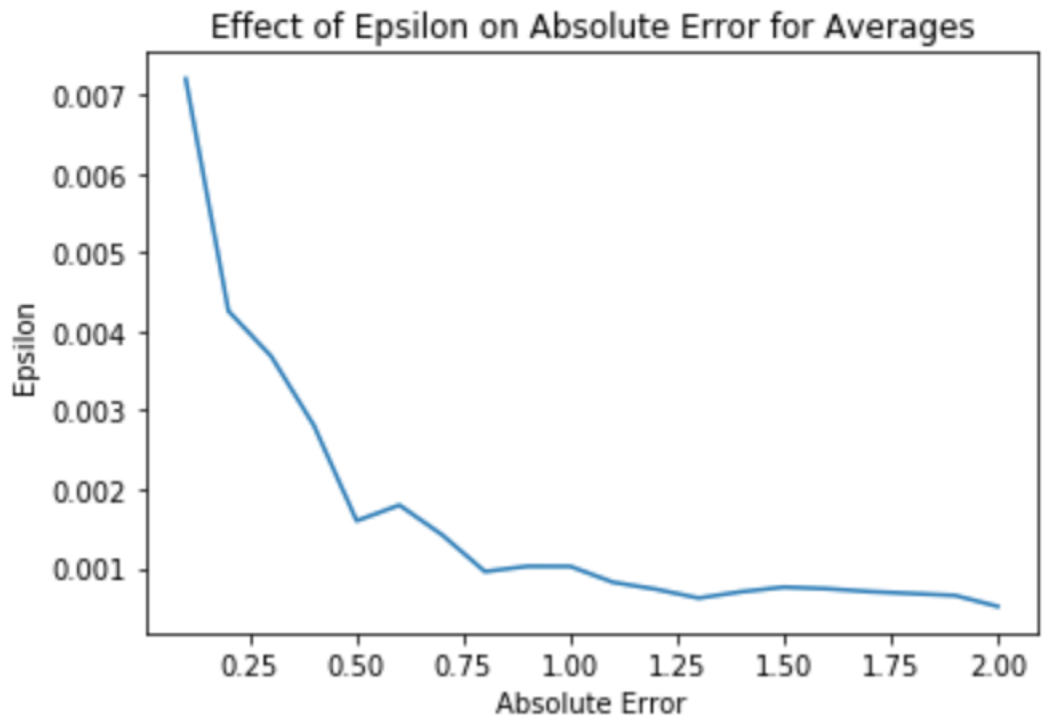
2. $\mathcal{A}(x) = \frac{1}{n} \cdot \sum_{i=1} x_i + \text{Lap}(\frac{1}{n \cdot \epsilon})$

where $x_i \in [0, 1]$ for all $i \in [n]$.

Code Demonstration

- https://github.com/alabid/pre_college_2019





Conclusion

- Differential Privacy is a mathematically rigorous definition of individual data privacy.
- YOU can code it up. See GitHub page – clone it and play with the code there!

https://github.com/alabid/pre_college_2019

- It's being used by the U.S. Census Bureau (for the 2020 Decennial Census), Google, Apple.