ORIE 5355: People, Data, & Systems

Lecture 16: Introduction to differential privacy

Nikhil Garg

Course webpage: https://orie5355.github.io/Fall_2021/

Announcements

- Online-only guest lecture on Wednesday; link to be posted on Edstem
- Project details released; Part 1 due 11/23
- OHs
  - Zhi today (regular time; Zoom)
  - Nikhil Wednesday office hours this week – Zoom only
  - Friday
    - Nikhil 12:30 – 1:30 (regular time; Zoom)
    - Zhi 1:30 – 2:30 (regular time; Zoom)

Plan for today

- Differential privacy
- [Time-permitting] Final project questions
- [Time-permitting] Experimentation module miscellaneous topics

Introduction to (Differential) Privacy

(Special thanks for Juba Ziani, Georgia Tech, for slides)

Introduction: fundamental trade-off

Want to share and release information to do aggregate analyses

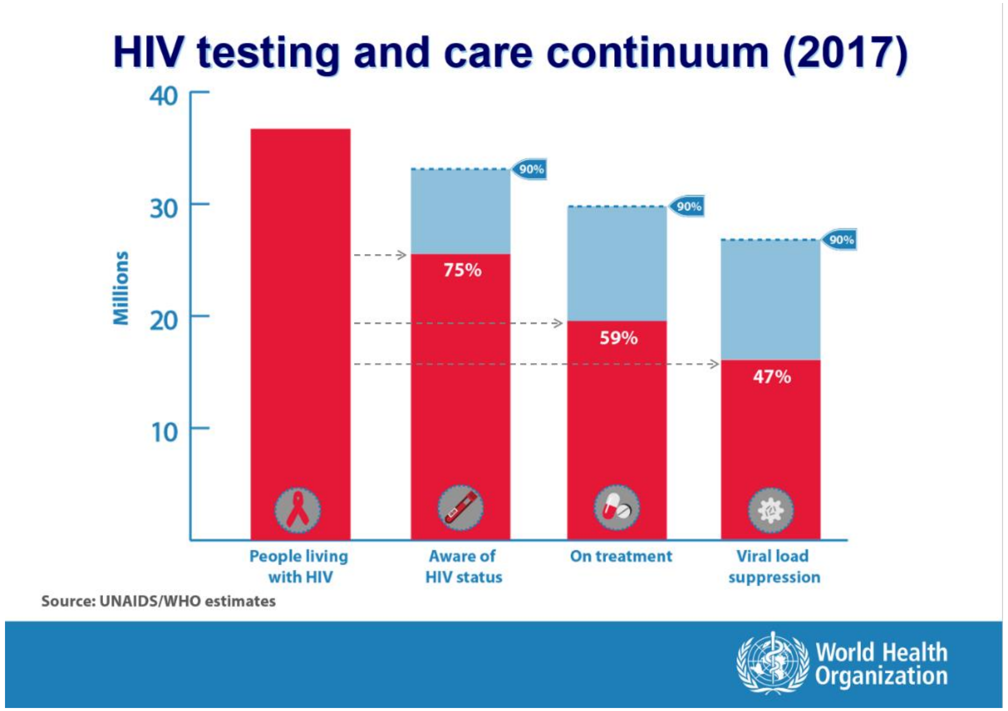
- Public audits (transparency)
- Want to help others do useful analyses (e.g., research reproducibility)
- Potentially legally mandated to share information (e.g., census)

Don’t want to leak sensitive information about individuals

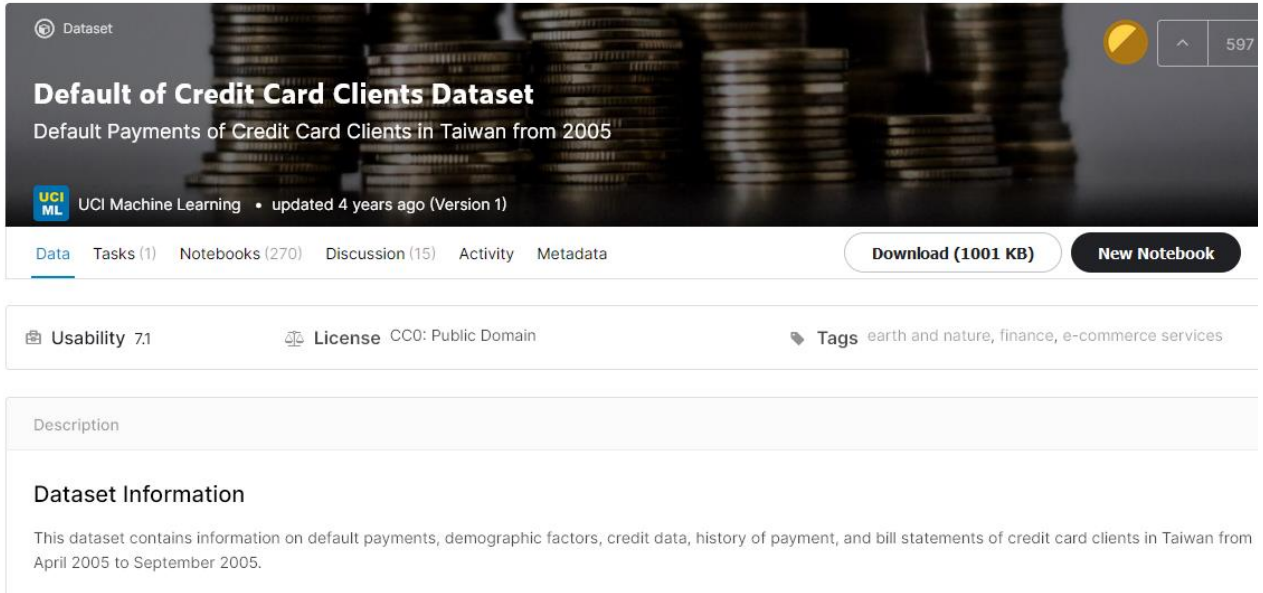
Problem: These two desiderata conflict, often in subtle ways!

Slide credit:
Juba Ziani,
Georgia Tech

Why is privacy important?



Source: UNAIDS/WHO estimates



Default of Credit Card Clients Dataset

Default Payments of Credit Card Clients in Taiwan from 2005

UCI Machine Learning • updated 4 years ago (Version 1)

Usability 7.1

License CC0: Public Domain

Tags earth and nature, finance, e-commerce services

Description

Dataset Information

This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005.

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Juba Ziani,
Georgia Tech

Failures of data privacy: anonymization

What is data anonymization?

Name	DOB	Gender	State/zip code	Has cancer?
Nikhil Garg	…	Male	NY 10044	No
Marge Simpson	04/19/1987	Female	SP 75234	No
Rick Sanchez	01/15/1943	Male	WA 98101	Yes
Misty	04/01/1983	Female	KT 16983	No

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Failures of data privacy: anonymization

So what’s the problem?

“Simple Demographics Often Identify People Uniquely”; Latanya Sweeney 2000

- A few attributes are enough to uniquely identify most of the US population
- (Zip, gender, date of birth) → identifies **87%** of US population
- What if I had this information (Zip, gender, date of birth) for much of the US?

Name	DOB	Gender	State/zip code	
1das4fg5d5as2	…	Male	GA 30309	
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Failures of data privacy: anonymization

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- In Mass, some anonymized health care data was publicly available to researchers
- Sweeney spent only $20 for public DOB/gender/zip codes info in Cambridge. Bought voter rolls.
- Same birthday as the governor of Mass: 6 people in Cambridge
- Only 3 were male
- Only 1 had the right zip code

➔ Sweeney was able to ***uniquely identify the governor’s medical records***! Sent them to his office.

This year: “NYC Board of Elections glitch reveals how Mayor de Blasio’s son voted in city’s primary election”

> “Researchers with the Princeton lab were able to track down the results — which are supposed to be confidential — by cross-referencing state voter files against precinct-level results from election districts where only one voter is registered.”

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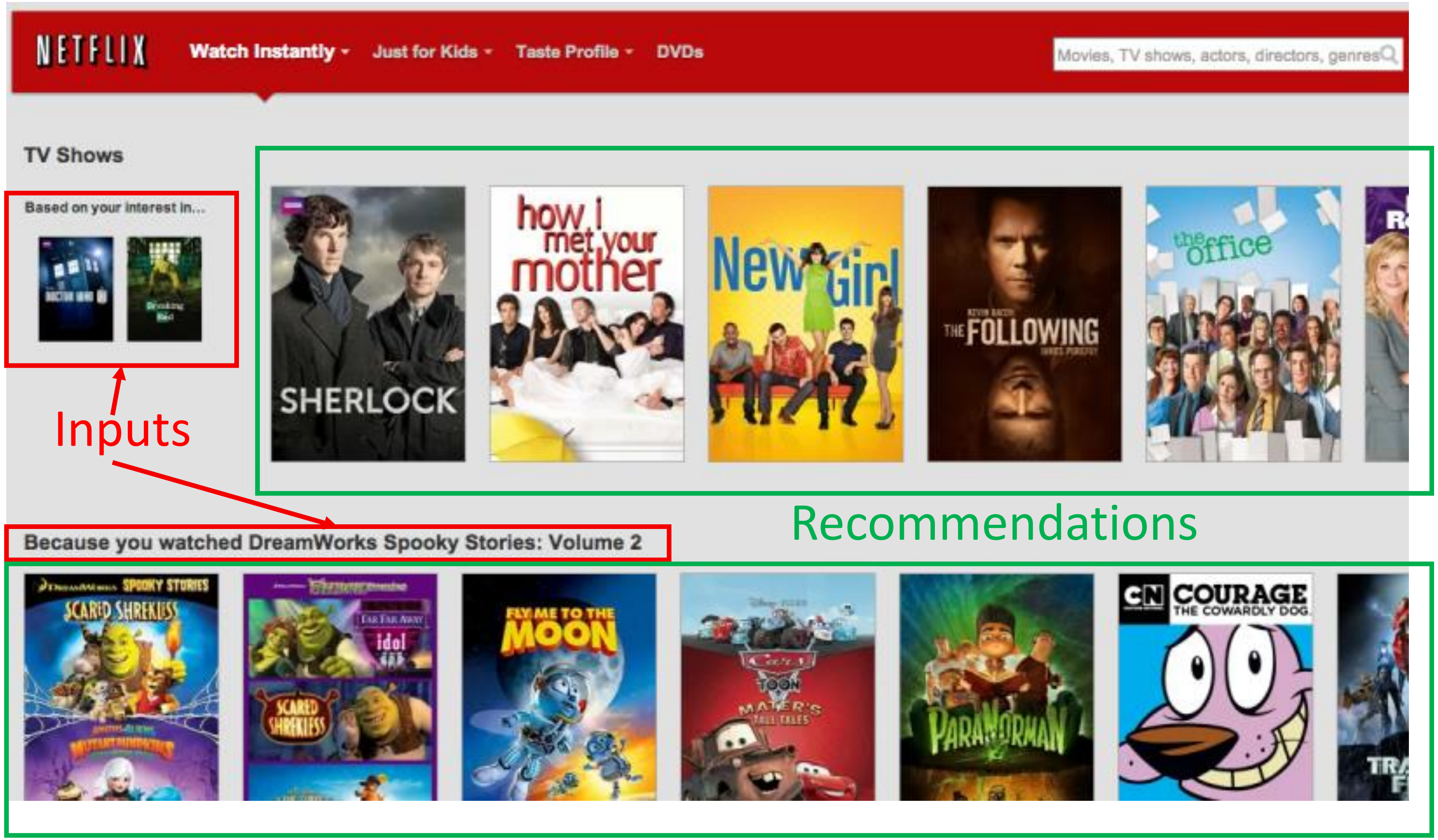
The Netflix Competition



TV Shows

Based on your interest in...

Because you watched DreamWorks Spooky Stories: Volume 2

Inputs

Recommendations

Slide credit:
Juba Ziani,
Georgia Tech

The Netflix Competition

How to improve recommendation system?

- Machine learning competition
- Try to predict user ratings from historical data as well as possible
- Provide “*anonymized*” data to participating teams

Netflix did more than just anonymization of data:

- Only small subsets of the full data; reduced the number of attributes
- Deleted some of the ratings
- Modified dates/temporal data

Slide credit:
Juba Ziani,
Georgia Tech

The Netflix Competition

“How To Break Anonymity of the Netflix Prize Dataset”, Arvind Narayanan and Vitaly Shmatikov, 2006

Only 2 weeks after the Netflix competition

What they show:

Only need imperfect info:

1. approx. dates of rating ($\pm$2 weeks) for 6 movies
2. 2 ratings and dates (with a 3-day error)

Can uniquely identify the person:

1. 99% of the time
2. 68% of the time

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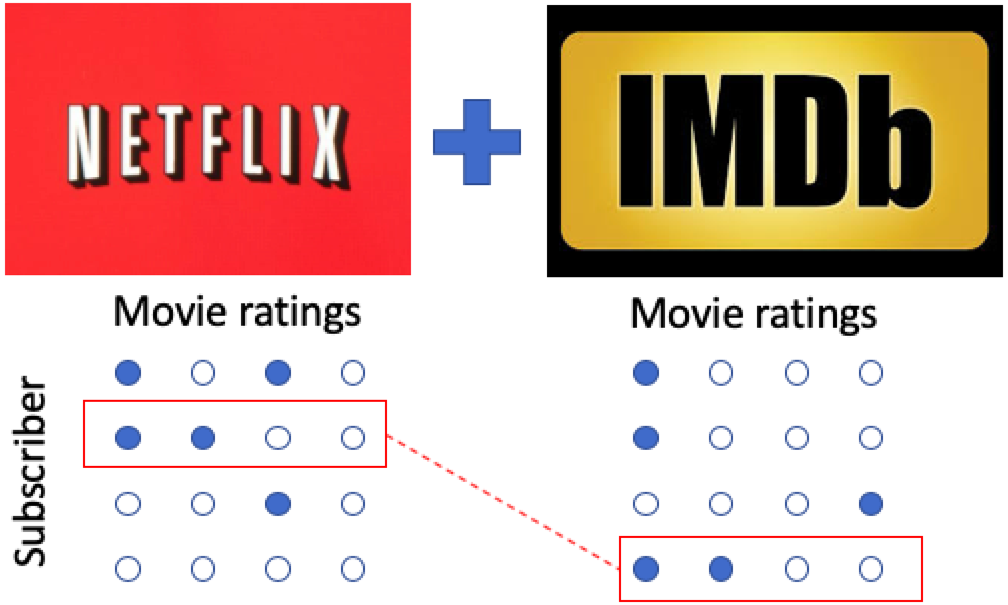
The Netflix Competition

How did they do it?



Why is it bad?

- Netflix watch history: more expansive and private than IMDb public rating
- Link IMDb and Netflix profile ➔ learn private watch history on Netflix
- Gay mother sued Netflix: watch history could reveal her sexual orientation to others

Privacy summary so far

Privacy is important, but trades off with other values

Idea: Do things to the data to preserve privacy before release

- Anonymization: remove personal identification
- Edit some of the entries a little bit
- Delete some entries

Even with above techniques, many privacy failures!

Common attack: Use *external* data (IMBb, voter file, etc) to extract more information from the anonymized data

Slide credit:
Juba Ziani,
Georgia Tech

Next idea: *Aggregate data before release*

Idea: Only release aggregated statistics/model.

Examples

- Population-level statistics such as averages, etc.
- Neural net (only see the final model, not the training data)

Why should it naively work?

- No individual-level details or features!
- Cannot identify a single row in a database: no access to such row-by-row data

Issue: If you release enough statistics, that's statistically identally to releasing the actual dataset

Slide inspiration:
Juba Ziani,
Georgia Tech

Data Aggregation fails! Example 1

How? For each “column” of the data, we have a summary statistic (mean). One column doesn’t tell us if any particular row is there. But if we have hundreds of thousands of columns in the dataset…

Example: genomic data

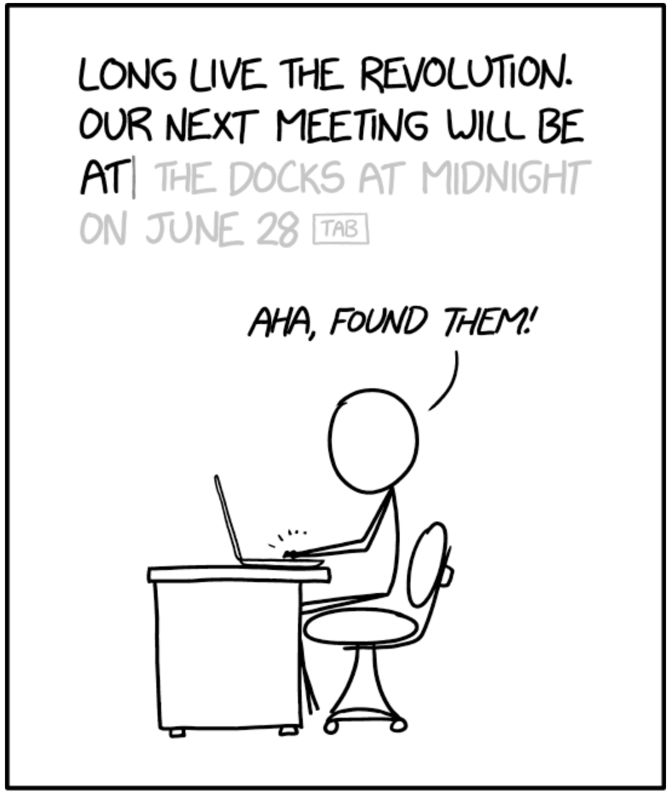
- Can you tell that someone’s data was in a DNA database, if all you have is allele frequency data from the database?
- Yes: “Resolving Individuals Contributing Trace Amounts of DNA to Highly Complex Mixtures Using High-Density SNP Genotyping Microarrays”, Homer et al., 2008

This is a problem

- Genomic data is more and more commonplace (ancestry tests, etc.)
- What if study only contains cancer patients/tries to link alleles to some rare disease? Can learn that you have a rare disease!

Slide credit: Juba Ziani, Georgia Tech

Data Aggregation fails! Example 2


LONG LIVE THE REVOLUTION. OUR NEXT MEETING WILL BE AT| THE DOCKS AT MIDNIGHT ON JUNE 28 TAB
AHA, FOUND THEM!

WHEN YOU TRAIN PREDICTIVE MODELS ON INPUT FROM YOUR USERS, IT CAN LEAK INFORMATION IN UNEXPECTED WAYS.

xkcd: Predictive Models

"The Secret Sharer: Evaluating and Testing Unintended Memorization in Neural Networks", Carlini et al., 2019

Predictive models tend to memorize:

- Imperfect generalization/overfitting to dataset
- More obvious in language models:
  - Work by memorizing characters/word associations
  - Can repeat word associations from training data

Potential attack:

- Predict next word: "My SSN is…"
- Recovers some SSN used in training data

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Beyond aggregating: adding noise

Answering queries exactly is not enough for privacy, even if queries aggregate a lot of data (e.g., if release many columns in the dataset)

Natural next step:

- Do not answer queries exactly!
- Anonymize/aggregate, AND add noise/randomness to data or to queries

Q: Is this enough?

A: Yes!, but you have to be careful ***how and how much noise*** you add

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Fundamental tradeoff: privacy vs accuracy

“Giving overly accurate answers to too many questions will inevitably destroy privacy.” -- Cynthia Dwork, Aaron Roth

- If you want to release a dataset that answers many questions about individuals, then you need to add more noise to each answer
- How much noise?

“Revealing information while preserving privacy”, Irit Dinur & Kobbi Nissim

Theorem: There exists a reconstruction attack that issues $O(n)$ (random) queries, obtains answers with error αn, and reconstruct the secret bits of all but $O(\alpha^2 n^2)$ users. → To protect privacy on most of the database against computationally efficient attacks, need noise of the order of at least $n^{1/2}$.

Idea: [More] noise leads to [more] privacy

What happens if I probabilistically change the data?

Original Database D

ID	Other Cols…	Has Cancer?
Nikhil	…	No
Rick	…	Yes
Homer	…	No

Flip each datapoint with probability ϵ →

Released database D’

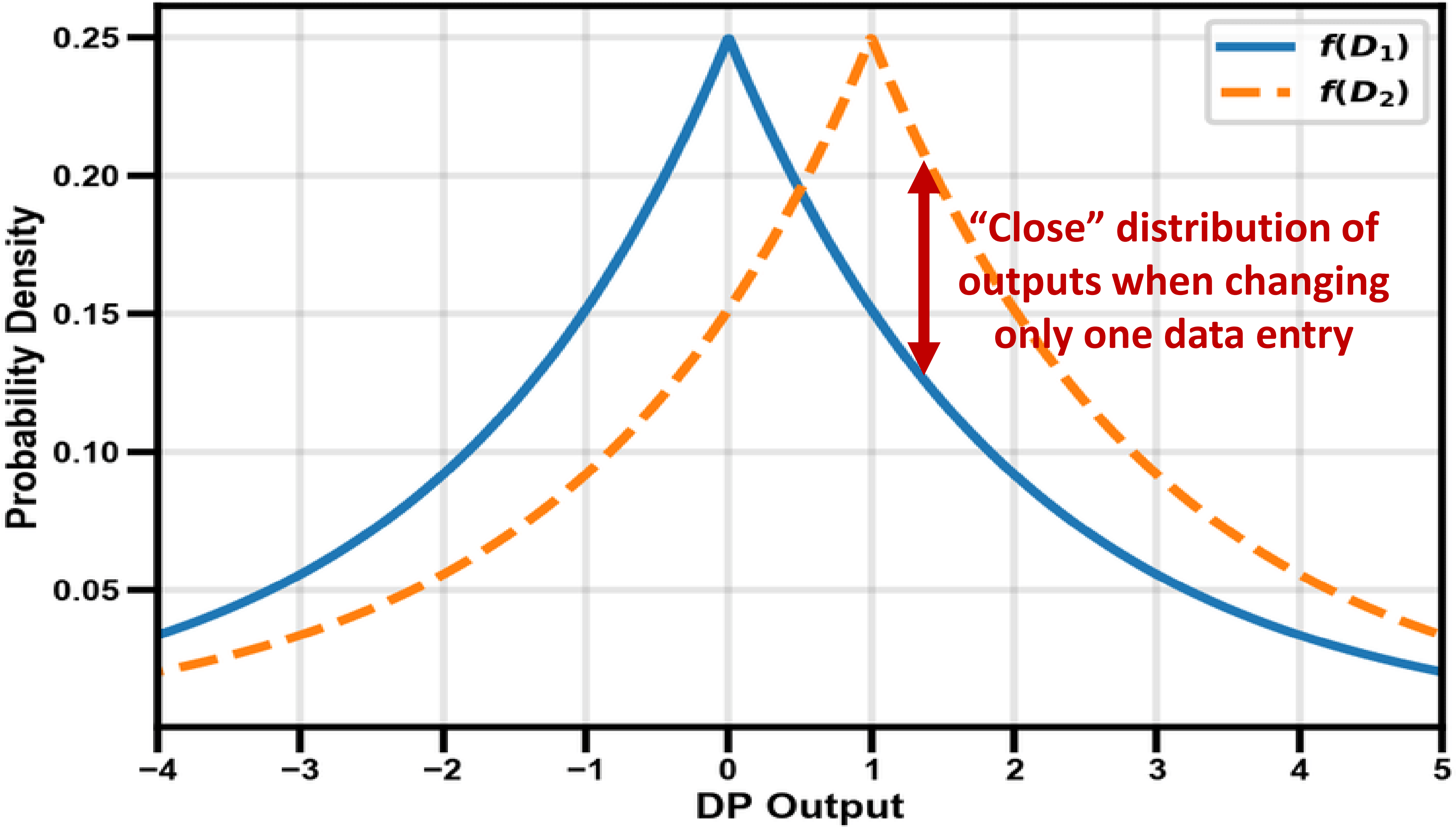
ID	Other Cols…	Has Cancer?
Nikhil	…	No
Rick	…	No
Homer	…	Yes

Distribution of outputs of computation ***almost unchanged*** *(with small ϵ)*

- If $\epsilon = 0$, then *no privacy – we are releasing exact dataset*
- If $\epsilon = \frac{1}{2}$, then *no accuracy – learn nothing from the dataset*

ϵ is a **policy choice**, not a technical one.

Can do the same thing with numeric columns



"Close" distribution of outputs when changing only one data entry

Image credit: Juba Ziani, Georgia Tech

Differential privacy

Differential privacy

- Fundamental limit: How much noise is needed
- Algorithm: What type (distribution) of noise to add

“Differential privacy is the only known framework to rigorously prevent such reconstruction attacks and privacy violations”

Now used in many places

- [Controversially] In the 2020 U.S. Census
- Google, Apple, Microsoft, LinkedIn…

Questions on course project?

Miscellaneous topics in experimentation

Universal holdout

Downsides of standard approaches:

- Test one product at a time
- Usually enroll as few users as possible (don’t want to waste sample size)
- Experiments are usually short → Don’t observe long-term metrics

What if you want to know, “What is the total effect on everything I launched last quarter on customer retention?”

Solution: Universal holdout

- Each quarter (or month or year…), hold out same set of users from *every product* you launch that quarter
- End of quarter, compare metrics for that group to all other users; re-enroll a new set of universal holdout for next quarter

Universal Holdout Groups at Disney Streaming | by Tian Yang | disney-streaming | Oct, 2021 | Medium

Ethics and Communication

When is an experiment unethical to run?

What if your strong intuition is that the new product is bad?

- Challenge trials in medicine: very controversial, especially during Covid
- Can you purposely degrade your product to evaluate how it usually performs?

What if Uber purposely broke surge during New Years?

What if your strong intuition is that the old product is bad?

Should you launch the replacement product immediately, or can you experiment first?

"Objecting to experiments that compare two unobjectionable policies or treatments” PNAS, Michelle Meyer et al. 2019

Various treatment effects

- So far we've discussed the "Global Average Treatment Effect" (GATE)

  How does the world where *everyone* receives the treatment, compare to the world where *everyone* receives the control?

- If there is no interference (and 1 more condition; SUTVA), this is equal to the "Average Treatment Effect" (ATE)

  On average, if *I* receive the treatment, how does that compare to if *I* received the control?

- "Local Average Treatment Effect" (LATE) or "Complier ATE" (CATE)

  Example: if treatment is *access to vaccine*, CATE only counts as treated those who *take* the vaccine; ATE would count everyone given *access*

- *Heterogeneous treatment effect:*
  - *What if the treatment effect differs for different sub-populations?*
  - Example: Giving students coupons to Broadway shows vs giving professors coupons

Experimentation summary

- Classic A/B Test
- In social networks and marketplaces, *interference* ruins tests
  - Social networks: Social effect; Me getting treatment effects you
  - Marketplaces: Competition and scarcity introduces interference
- Experiments in the face of interference:
  - (Spatial or Graph-based) Cluster randomized assignment
  - Time-based experimentation: Switchbacks
- Causal inference without experiment: Synthetic control
- Naïve peeking in experimentation is bad, but can be done smartly

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