Designing Access with Differential Privacy

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Background for this Talk

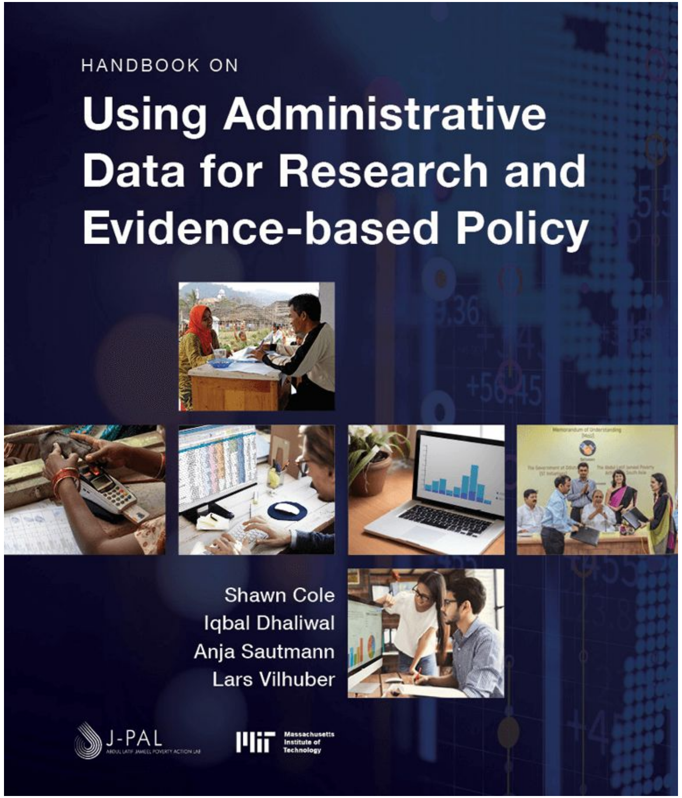
Excerpts from
"Designing Access with Differential Privacy"

a chapter in
Using Administrative Data for Research and Evidence-based Policy

(Full text of Handbook is online.)

This talk focuses on a conceptual overview…

For design, deployment, case studies and resources: Q&A and full online chapter



Why DP? Attacks on Privacy

- **Re-identification**: identifying whose record it is even after "PII" removed
  - Applied to medical data, Netflix challenge, …
- **Database Reconstruction**: reconstructing almost the entire underlying dataset
  - Applied to Census releases and Diffix
- **Membership Inference**: determining whether a target individual is in the dataset
  - Applied to genomic data and ML as a service

Attacks on "Aggregate" Statistics

Takeaways from Privacy Failures

- **Specific findings:**
  - Redaction of identifiers is insufficient for protecting privacy
  - Similarly: aggregation, noise addition, …
  - Auxiliary information needs to be taken into account
  - Regulation and technology only considered a limited scope of privacy failures
    - New failure modes: whether an individual participated in study, inferences
  - Any useful analysis of personal data must leak some information about individuals
  - Leakages accumulate with multiple analyses/releases

Mathematical facts, not matters of policy

Hope is not lost.

Rather, we need a rigorous approach to privacy to guarantee privacy in a dynamically changing data ecosystem

Introduction of Differential privacy (2006):

- Rich theory and new privacy concepts
- Mathematically provable privacy guarantees
- In first stages of implementation and real-world use
    - US Census, Google, Apple, Uber, …

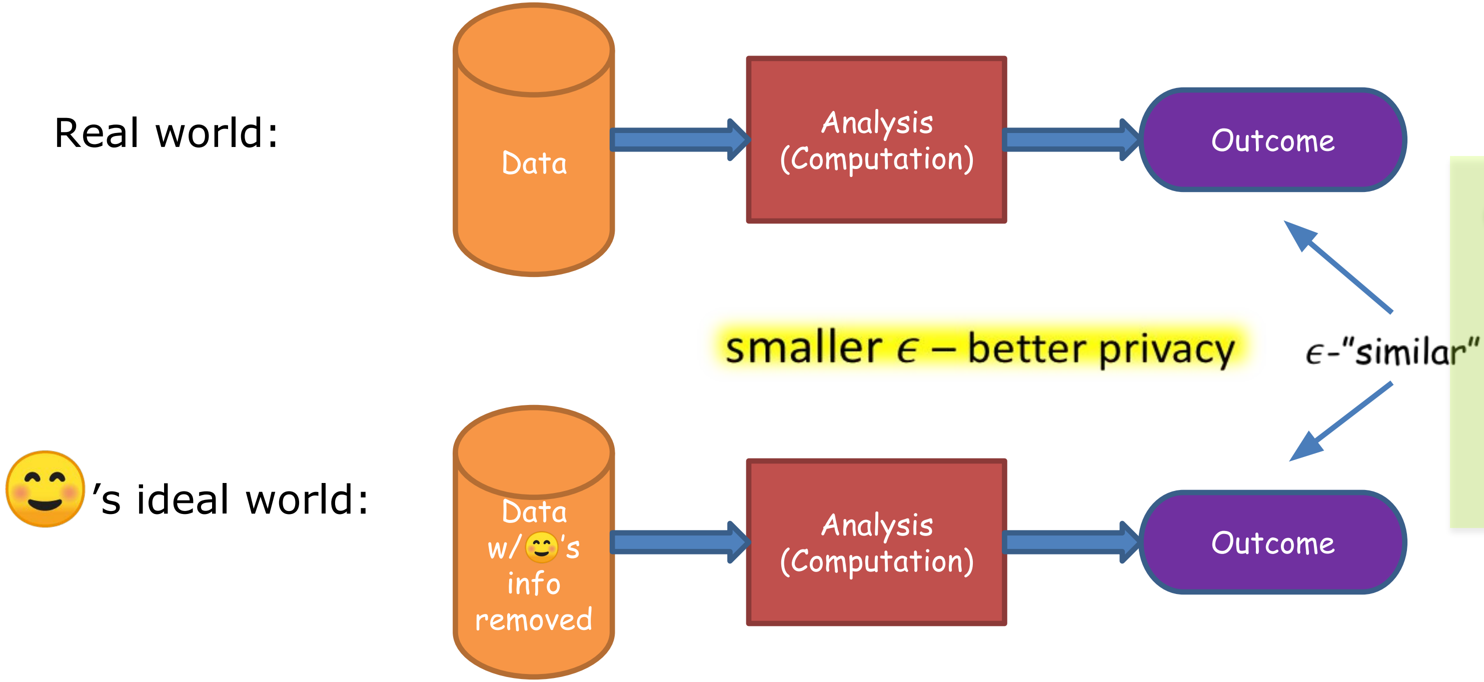
Differential Privacy is …

… a definition (i.e., a standard) of privacy for “statistical releases”

It expresses a specific desiderata of an analysis:

Any information-related risk to a person should not change significantly as a result of that person’s information being included, or not, in the analysis

Differential Privacy [Dwork McSherry Nissim Smith '06]



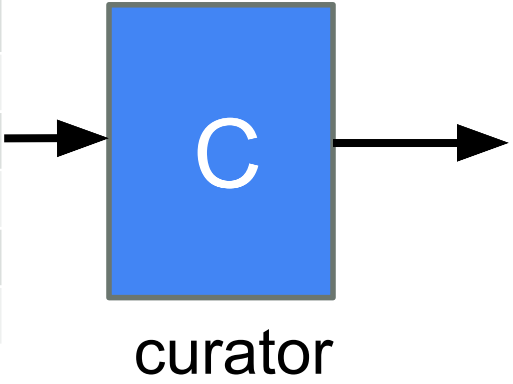
Chance of bad event almost the same in everybody's ideal and real worlds

Features of Differential Privacy

- Designed for analysis of populations, not individuals
- Requires the introduction of statistical noise
- Robust to auxiliary information, composition, and post-processing

Differential Privacy in Statistical Releases

Name	Sex	Blood		HIV?
Chen	F	B		Y
Jones	M	A		N
Smith	M	O		N
Ross	M	O		Y
Lu	F	A		N
Shah	M	B		Y



statistical tables,
trained ML model,
synthetic data etc.

Statistical Query Systems

Name	Sex	Blood		HIV?
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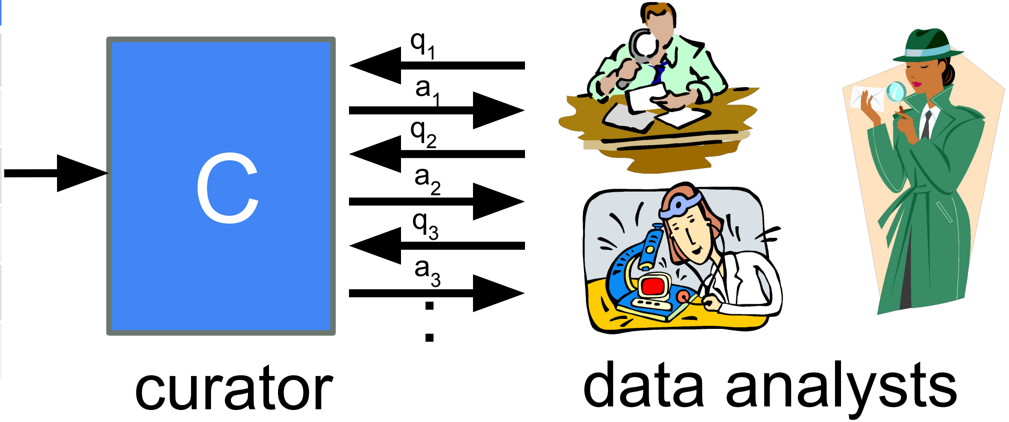
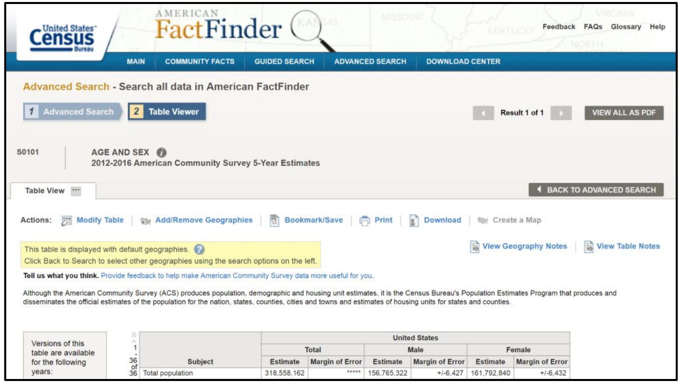
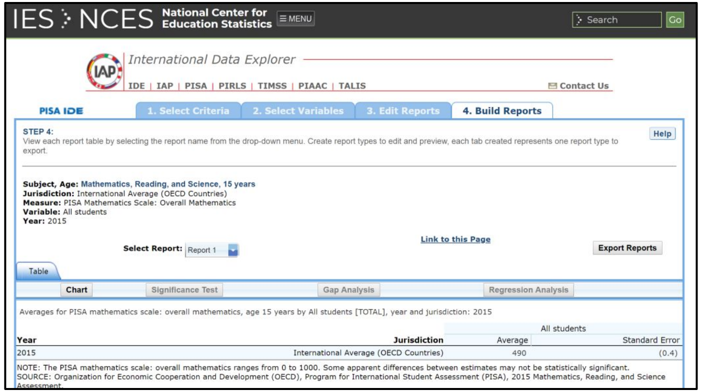
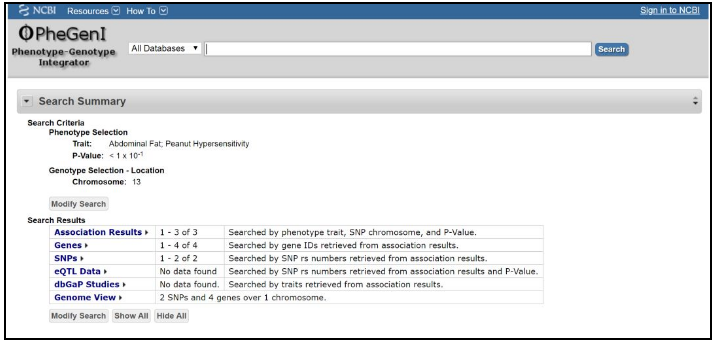
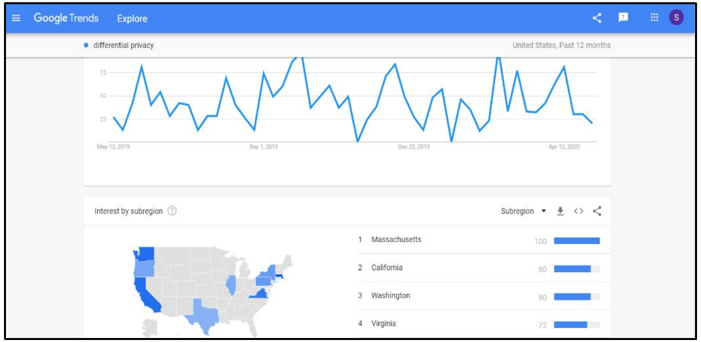


Existing Query Interfaces









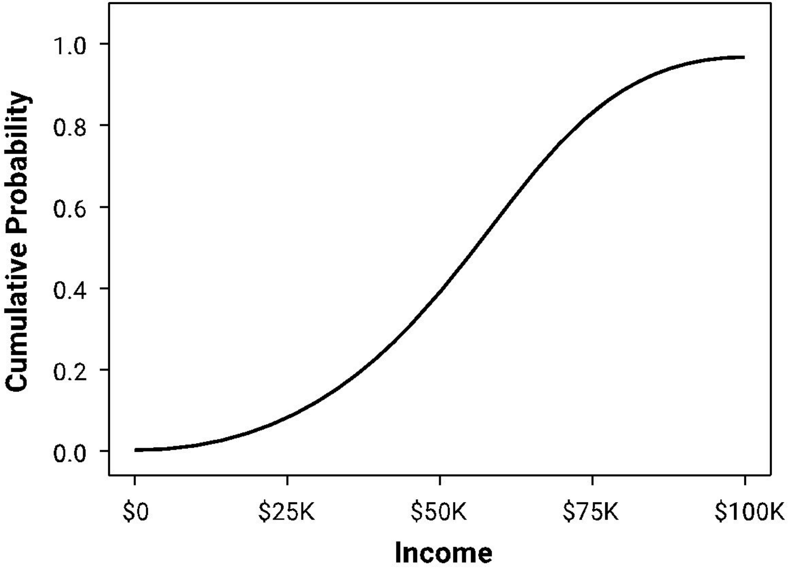
What Can Be Computed with Differential Privacy?

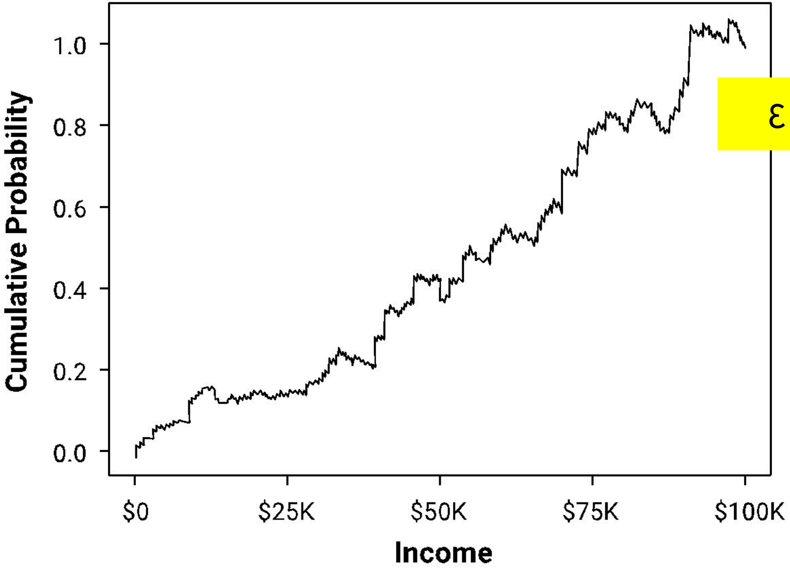
- **Descriptive statistics**: counts, mean, median, histograms, contingency tables, boxplots, CDFs, etc.
- **Supervised and unsupervised ML tasks**: classification, regression, clustering, distribution learning, etc.
- **Generation of synthetic data**

Because of noise addition, differentially private algorithms work best when the number of data records is large.

Differentially Private Computations

Algorithms maintain differential privacy via the introduction of *carefully crafted* random noise into the computation





ε = 0.005

(These CDFs are stylized examples.)

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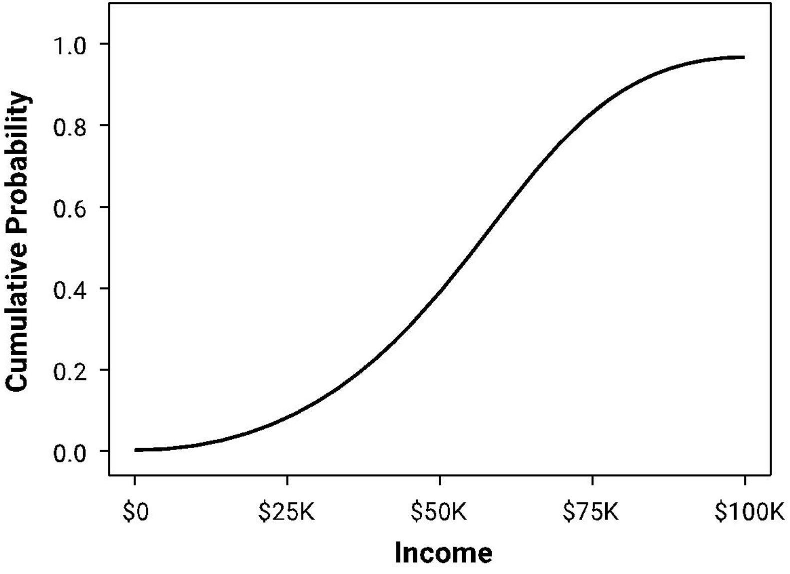

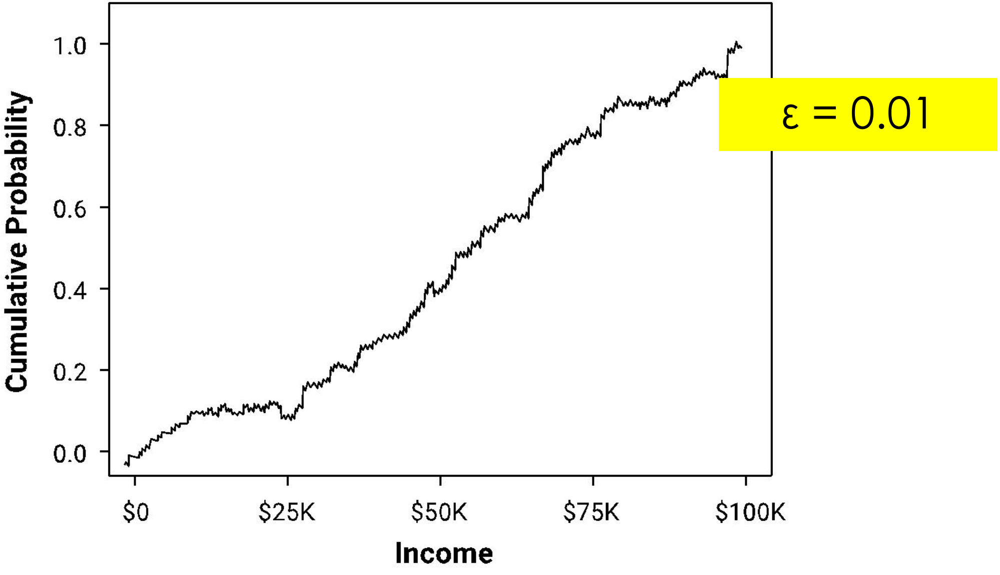

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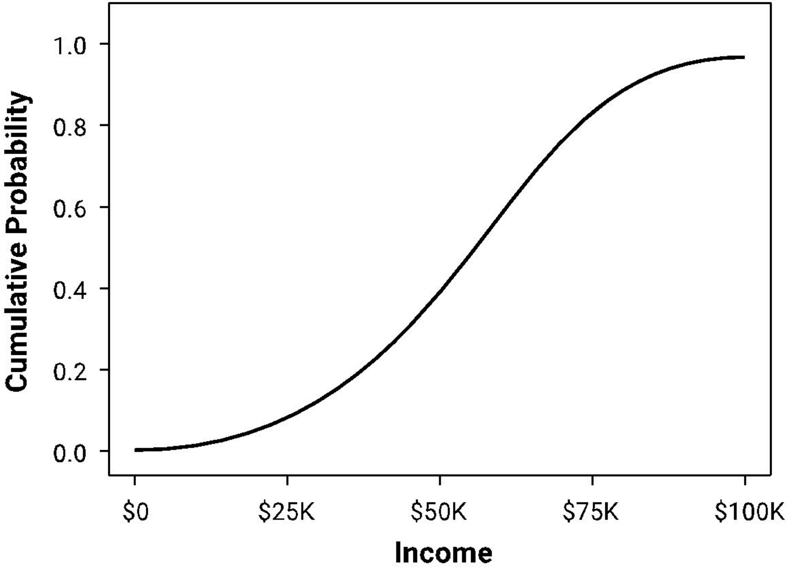
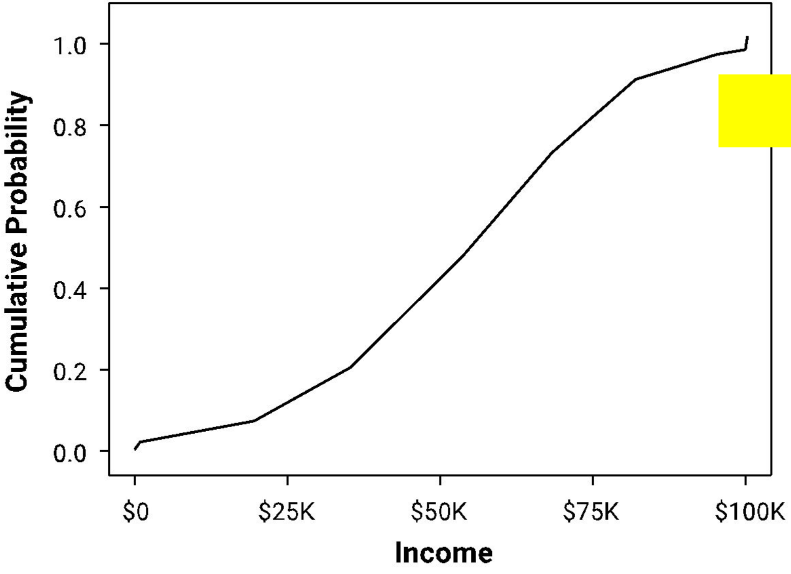




ε = 0.1

(These CDFs are stylized examples.)

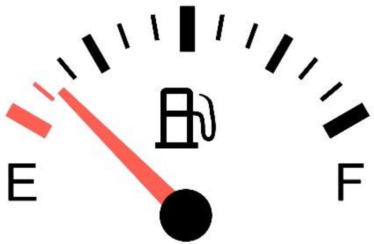
Managing the (Inherent) Privacy-Utility Tradeoff with a Privacy "Budget"

DP provides provable privacy guarantees with respect to the cumulative risk from successive data releases

- Every statistical release incurs some privacy loss ε
- More noise $\rightarrow$ more privacy (smaller ε), less accuracy (and vice versa)
- Tradeoff is less stark on larger populations ($n \rightarrow \infty$)
- Combination of ε-differentially private computations results in differential privacy (with larger ε)

This is a key feature, not a bug!

- Consider: ignoring the gauge does not prevent a car from using fuel



Understanding Differential Privacy

- **"Automatic" opt-out**: I am protected (almost) as if my info was not used at all
- **I incur limited risk**: Contributing my real info can increase the probability I will be denied insurance by at most 1%
    - When compared with not participating, or contributing fake info
- These privacy guarantees are provided independent of the methods used by a potential attacker and in the presence of arbitrary auxiliary information
- **Future proof**: Avoids the "penetrate and patch" cycle

DP Has the Benefit of Transparency

It is not necessary to maintain secrecy around a differentially private computation or its parameters

- Benefits of transparency include:
    - **Possibility of accounting for DP in statistical inference**
    - Knowledge accumulation
    - Scrutiny by the scientific community

Application for Public Access to Data

DP can be used to provide broad, public access to data or data summaries in a privacy-preserving way

- Can consider data publications that were otherwise impossible
  - Whereas traditional techniques would (more often) require applying controls in addition to de-identification

Example: Reasoning About Risk
Gertrude’s Life Insurance

- Gertrude:
  - Age: 65
  - She has a $100,000 life insurance policy
  - She is considering participating in a medical study but is concerned it may affect her insurance premium

Example: Reasoning About Risk
Gertrude’s Life Insurance

- Based on her age and sex, she has a 1% chance of dying next year. Her life insurance premium is set at 0.01 x $100,000 = $1,000

- Gertrude is a coffee drinker. If the medical study finds that 65-year-old female coffee drinkers have a 2% chance of dying next year, her premium would be set at $2,000.
    - This would be her **baseline risk**: Her premium would increase to $2,000 even if she didn’t participate in the study.

- **Can Gertrude’s premium increase beyond her baseline risk?**
    - She is worried that the study may reveal more about her, such as that she *specifically* has a 50% chance of dying next year. This can increase her premium from $2,000 to $50,000!

Example: Reasoning About Risk Gertrude's Life Insurance

- **Reasoning about Gertrude's risk**
  - Imagine instead the study is performed using differential privacy with $\varepsilon = 0.01$.
  - The insurance company's estimate of Gertrude's risk of dying in the next year can increase to at most

$$\approx (1 + 2\varepsilon) \cdot 2\% = 2.04\%$$

  - Her premium would increase to at most \$2,040. Therefore, Gertrude's risk would be $\leq$ \$2040 - \$2000 = \$40

Example: Reasoning About Risk
Gertrude's Life Insurance

- **Generally, calculating one's baseline is very complex (if possible).**
  - In particular, in our example the 2% baseline depends on the potential outcome of the study
  - The baseline may also depend on many other factors Gertrude does not know
- **However, differential privacy provides simultaneous guarantees for every possible baseline value.**
  - The guarantee covers not only changes in Gertrude's life insurance premiums, but also her health insurance and more

Transitioning to Practice: Challenges

- DP changes how data is accessed
  - Noise added, attention on privacy-utility tradeoff
  - May require shift from static to interactive modes of access
- DP has implications for the data lifecycle
  - The privacy-loss budget is an unavoidable mathematical fact
  - Setting the budget is a policy question
- Potential implications for collection, storage, transformation, retention
- Implicates legal requirements as well as technical ones

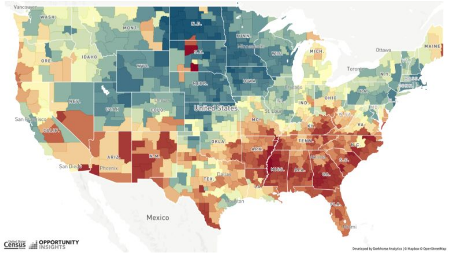
Transitioning to Practice: Design

In the chapter (print and online version):

- Aligning risks, controls, and uses
  - Where is the use of differential privacy appropriate?
  - Selecting privacy controls based on harm and informational risk
  - Combining DP with other tools
    (especially as part of a tiered access system)
  - Regulatory and policy compliance implications
- Detailed case studies
  - 2020 Decennial Census, Opportunity Atlas, Dataverse Repositories

Case Studies - Overview

United States® Census 2020



The Opportunity Atlas

The Dataverse® Project

Transitioning to Practice: Deployment

In the **online** version:

- Key differential privacy design choices

  Review of trust models, privacy-loss settings, privacy granularity, static vs. interactive publication, estimating and communicating uncertainty.

- Data life cycle management

  Technical and legal implications of differential privacy design choices for data collection, transformation, access, and retention.

- Additional resources

  Open software for differentially private analysis. Enterprise software and consulting. Further readings.

Conclusions

- **Accumulating failures**
  - Anonymization & traditional SDL techniques are not enough
- **Differential privacy**
  - A standard providing a rigorous framework for developing privacy technologies with provable quantifiable guarantees
- **Moving to practice**
  - Best when combined with other technical and policy tools
  - Chapter provides guidance for design & deployment