Sampling: Privacy

```
$ echo "Data Sciences Institute"
```

Key Texts

- Salganik, M. (2019). Understanding and managing informational risk. In *Bit by bit: Social research in the Digital age* (pp. 307–314). Chapter, Princeton University Press.
- Wood, A., Altman, M., Bembenek, A., Bun, M., Gaboardi, M., Honaker, J., Nissim, K., OBrien, D.R., Steinke, T., & Vadhan, S. (2018). *Differential privacy: A primer for a non-technical audience* . *Vanderbilt Journal of Entertainment & Technology Law, * 21(1) 209-275.

Privacy and Confidentiality

Key Terminology

- **Data privacy** = the ability to control when and where your personal data are shared
- **Informational Risk** = potential for harm resulting from the disclosure and sharing of data
- **Personally identifying information (PII)** = includes name, address, telephone number, age, gender, personal opinions or views

Key Terminology

- **Anonymization** = process of removing PII from a dataset
- **Confidentiality** = granted to respondents; only the researcher knows the identities of respondents
    - E.g. I interview Sam, I know Sam is Sam, but in my paper, I refer to Sam only as ‘Participant A’ or by a pseudonym
- **Anonymity** = granted to respondents; identities of individual respondents not known to researcher
    - E.g. I create a survey, Sam fills out the survey anonymously online, I never know that Sam is the one who filled out the survey

Confidentiality Considerations

- Data collection medium
    - In person – who might see the participants walking into the lab or interview location?
    - Digital – Is third party software safe?
- Data storage
    - Password protected computer? Double-locked office and filing cabinet? Portable hard drive?
    - Cloud – Institutional OneDrive?
- Who has access to the data?
    - Think about: shared offices, IT or other colleagues
    - Have to balance need for backups with reduced risk

Confidentiality Considerations

- Retention and disposal schedule
  - How long will you keep data for? Why? Balance storage resources vs data needs
  - How will you dispose of data when retention period is done? (Shredding hard copies? Deleting digital files?)
- Clarify limits on confidentiality
  - What if someone discloses something illegal?
  - Statements like ‘confidentiality is not absolute, a disclosure of personal information may occur if required by law’
- If no confidentiality - why?
  - E.g. Respondents are key informants in their fields (world leaders, expert academics in niche areas)

Explore 'Real World' Resources

Academic

- U of T offers research support to ensure data security and confidentiality
- https://research.utoronto.ca/data-security-standards-personally-identifiable-other-confidential-data-research

Public Sector

- A privacy checklist!
- https://www.ipc.on.ca/wp-content/uploads/2015/04/best-practices-for-protecting-individual-privacy-in-conducting-survey-research.pdf

Differential Privacy

Introduction to Differential Privacy by Simply Explained

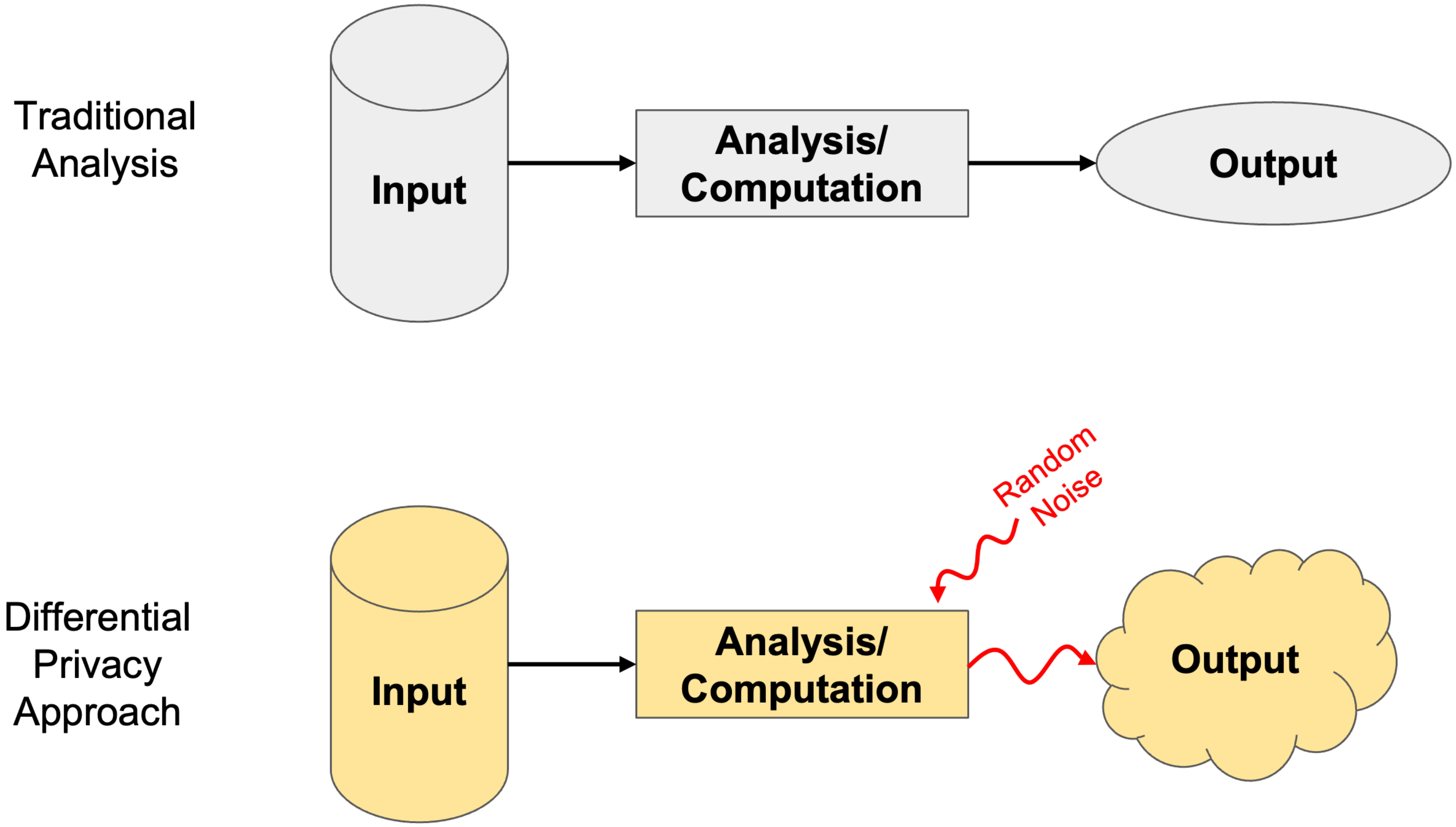
📼 the video

Differential Privacy

> ⚠️ The goal of **differential privacy** is to analyze and share information about a data set without revealing information about any given individual within the data set ⚠️

- Differential privacy techniques add random noise to computations on the data set
- Randomness obscures any one individual's contribution to the data set
- Randomness means that all output is approximate
- Generally used for aggregate statistics and modelling – counts, proportions, averages, linear regression, machine learning algorithms

Based on Nissim et al., Figure 2



“Opt-out” Scenarios

- Suppose John is invited to participate in a study about the relationship between socioeconomic factors and medical outcomes in the US. Participants are asked to complete a questionnaire covering topics related to their finances and medical history. John is concerned that information he provides, such as his HIV status, may be used against him if de-identified data is released and accessed by his insurance company. However, he recognizes that participating in the study would benefit the researchers and perhaps generate important results.

“Opt-out” Scenarios

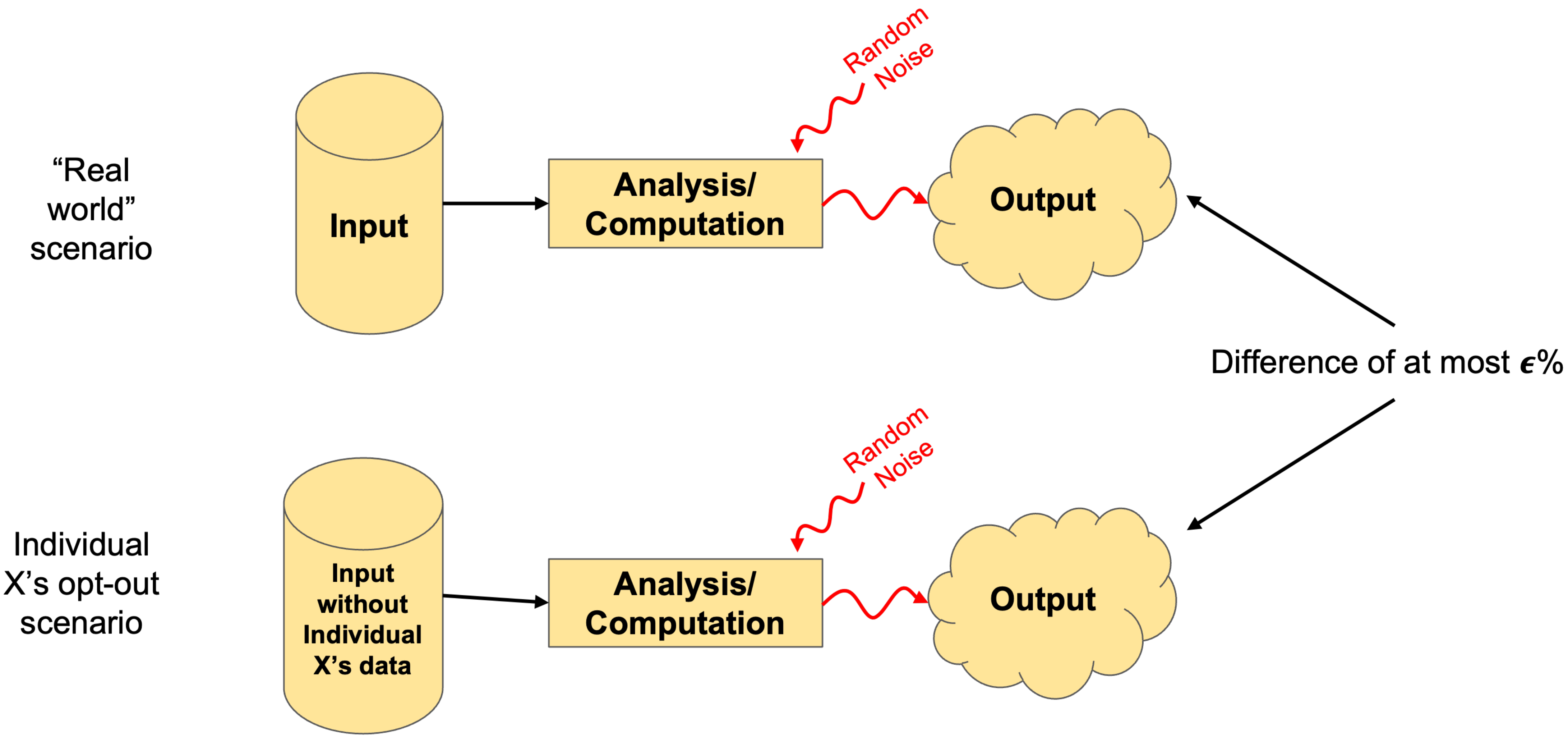
- John’s **opt-out scenario** refers to the case where John decides not to participate and the analysis is conducted without his health or financial data
- Differential privacy ensures that:
    - Results of the study will stay approximately the same regardless of whether or not John participates
    - Output of the analysis will not disclose any information that is specific to John
- Thus, John faces minimal additional informational risk by participating in the study

Privacy Loss Parameter

- Estimates from a data set should remain approximately the same regardless of any one individuals' data being included or excluded
- Differential privacy allows a slight difference between actual analysis and any individual opt-out scenario
- Privacy loss parameter, ϵ , represents the **additional informational risk** that any individual would face **beyond the risk incurred in the opt-out scenario**

> $0 \leq \epsilon \leq 1$
>
> Low ϵ = Low accuracy, stronger privacy protection
>
> High ϵ = High accuracy, weaker privacy protection

Based on Nissim et al., Figure 3



From Nissim et al., pp. 12

- John is concerned that a potential health insurance provider will deny him coverage in the future, if it learns certain information about his health, such as his HIV positive status, from a medical research database that health insurance providers can access via a differentially private mechanism.
- If John believes his probability of being denied insurance coverage is at most 5% (due to various outside factors) if his information is not included in the medical research database, then adding his information to the database can increase this probability to, at most,

> $$5\% \cdot (1 + \epsilon) = 5\% \cdot 1.01 = 5.05\%.$$

- Hence, the privacy loss parameter ($\epsilon = 0.01$, in this example) ensures that the probability that John is denied insurance coverage is almost the same, whether or not information about him appears in this medical research database.

How do we implement differential privacy?

Differential privacy adds uncertainty to data in the form of **random noise**

> - Suppose you are looking to measure the fraction p of some trait in a population. You have a sample of size n , and within this sample there are m individuals with the trait.
> - Without differential privacy, $p = m/n$.
> - *With* differential privacy, random noise Y is added to the computation to hide the contribution of a single individual.
> - Instead of m , we have $m' = m + Y$.
> - Instead of $p = m/n$, we have $p' = m'/n = (m + Y)/n$.

Random Noise

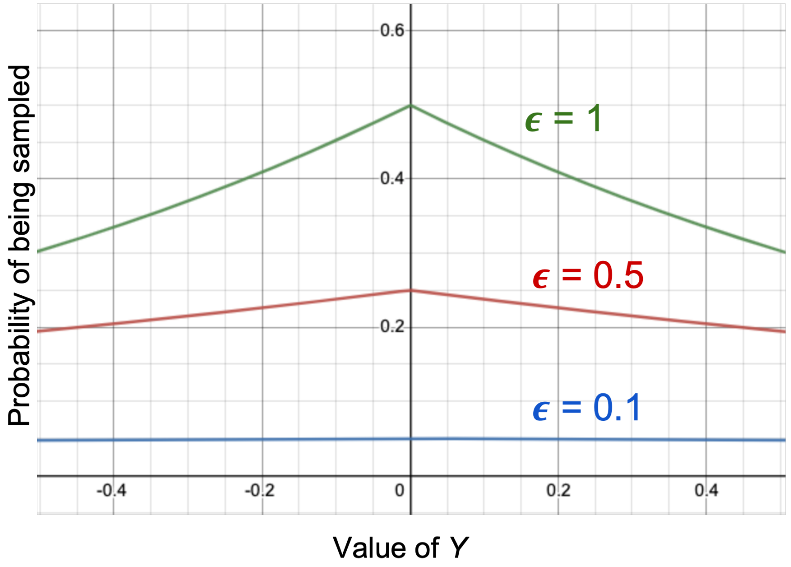
- Magnitude of the random noise Y depends on ϵ
- ϵ and Y are **inversely proportional** – smaller ϵ = larger Y = more noise
- The relationship between the true and measured values of m can be described as,

> $$|m' - m| \approx \frac{1}{\epsilon}$$

- Y is often sampled from the **Laplace distribution** with mean 0 and standard deviation $\sqrt{2}/\epsilon$
  - Denoted Laplace (0, 1/ϵ)

Laplace Distribution

- Distribution is **symmetric** – differential privacy estimates are equally likely to be higher or lower than the true value
- When $\epsilon = 1$, there is a ~63% chance that $-1 \leq Y \leq 1$
  - *m′* will likely be very close to *m*
  - High accuracy, low privacy
- When $\epsilon = 0.1$, there is a ~10% chance that $-1 \leq Y \leq 1$
  - *m′* will likely **not** be very close to *m*
  - Low accuracy, high privacy



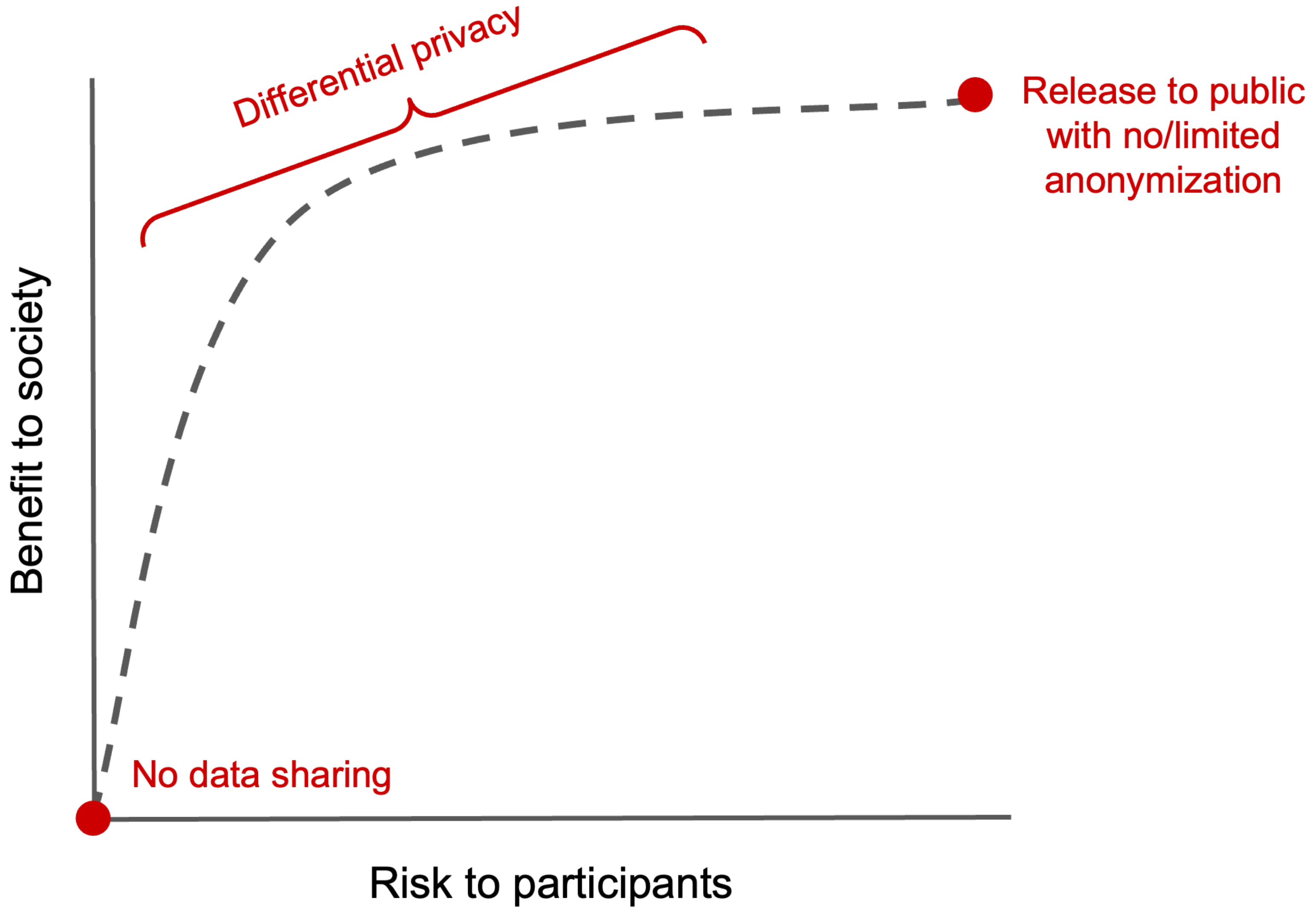
Practical Considerations of Differential Privacy

- Accuracy
  - Large sample sizes/data sets are required for accurate estimates
- Informational risk
  - Combining differentially private data sets or conducting multiple queries on the same differentially private data set increases informational risk
  - Total informational risk is bounded by the sum of the informational risk of any individual data set
    - For a combination of *n* differentially private data sets, $\epsilon_T = \epsilon_1 + \epsilon_2 + \ldots + \epsilon_n$
  - Different types of analyses will require different balances of informational risk and accuracy

Ethical Considerations of Differential Privacy

- Data sensitivity
  - Sensitivity is subjective
  - Assume that all data is *potentially* identifiable and *potentially* sensitive
  - Privacy concerns apply to all data sets to some degree
- Data sharing
  - Data sharing increases informational risk
  - Access to data provides great benefit to other researchers and the general public
  - Do not ignore the potential benefits of data sharing

Based on Salganik (2018), Figure 6.6



Differential Privacy: Resources

Check out https://privacytools.seas.harvard.edu/courses-educational-materials

- Lots of lecture-length videos with technical insights
- Deep-dives into differential privacy from a dedicated lab group!