

# **DIFFERENTIAL PRIVACY APPROACHES IN A CLINICAL TRIAL**

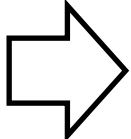
**MARTIN LEUCKERT**

**OTTO-VON-GUERICKE UNIVERSITY MAGDEBURG**

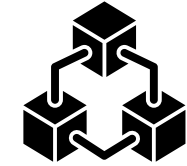
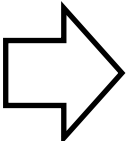
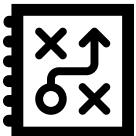
# INTRODUCTION



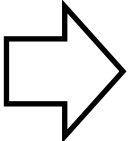
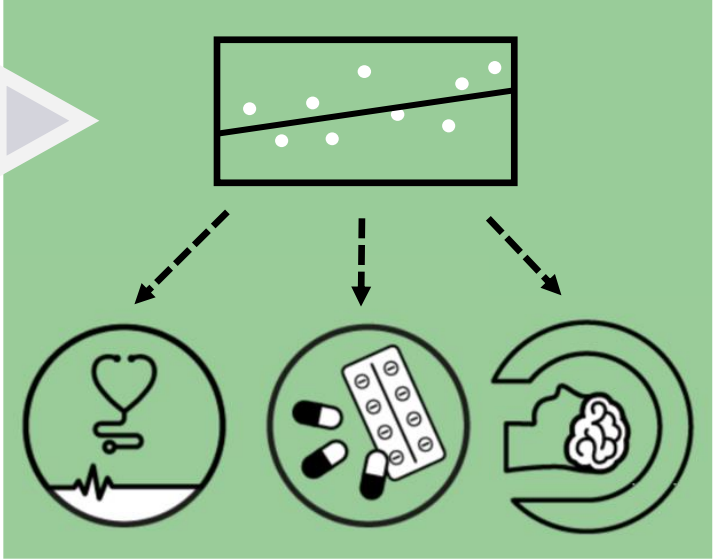
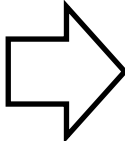
- Specialists
- Scientists



**Task**



**Model**

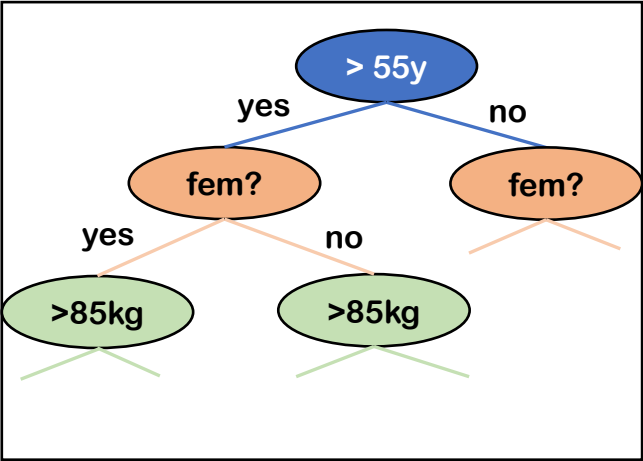


**Data**

# INTRODUCTION



- Specialists
- Scientists



Age: 68  
Weight: 78kg  
Sex: Female  
Diabetes Type: II

**Private data**

**Sensitive data**

# PROBLEM STATEMENT

## EUROPEAN REGULATIONS:

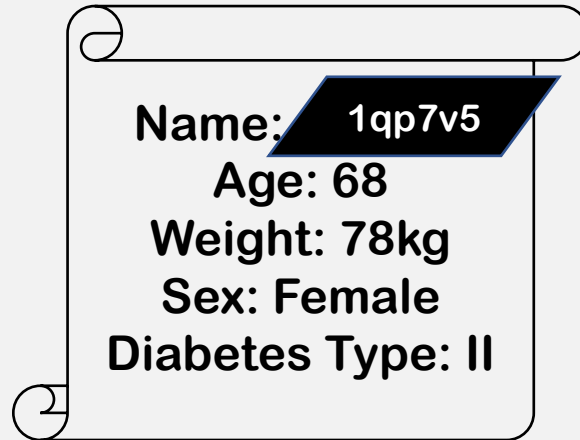
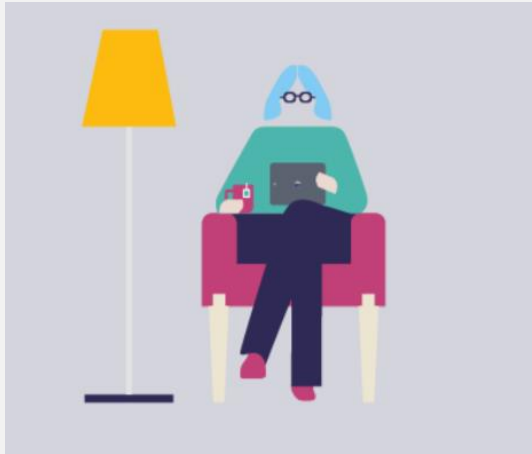
- **GENERAL PROTECTION REGULATION (GDPR)**
- **RL 93/42/EWG (MEDDEV)**
- **GCP DIRECTIVE (DIRECTIVE 2005/28/EC)**
- **CLINICAL TRIAL DIRECTIVE' (DIRECTIVE 2001/20/EC)**

## NATIONAL REGULATIONS

- **MEDIZINPRODUKTEGESETZ (MPG)**
  - **90/385/EWG**
  - **90/42/EWG**
  - **98/79/EG**

# PROBLEM STATEMENT

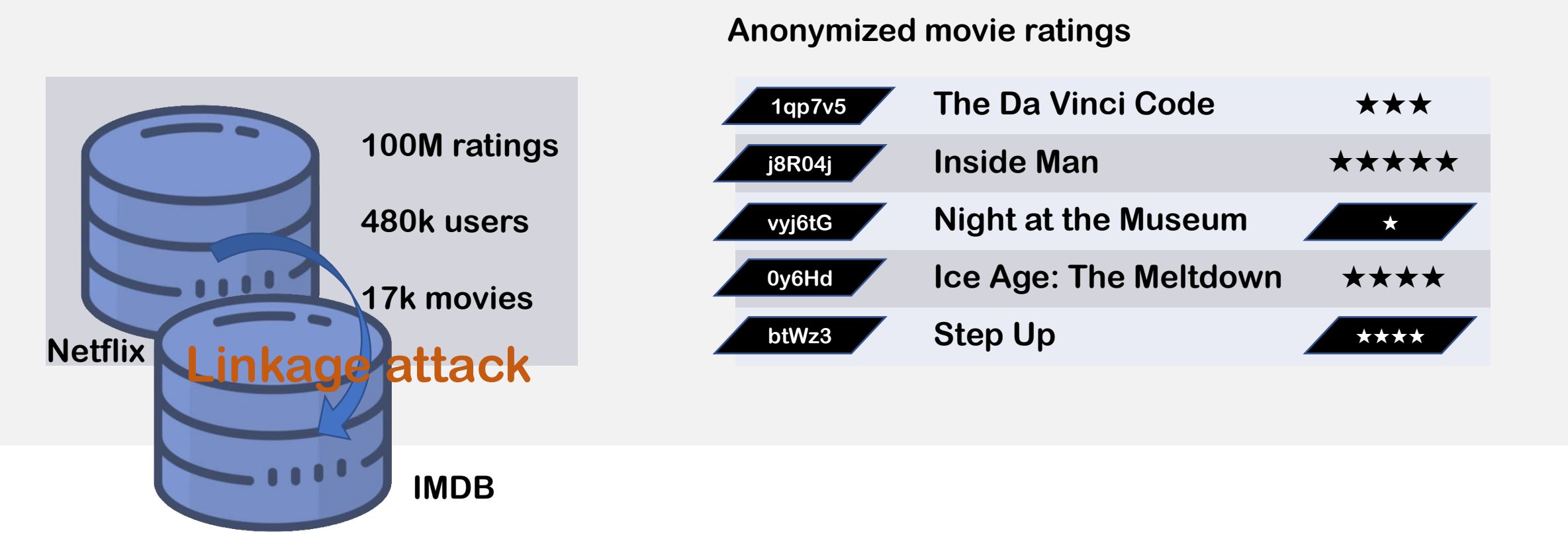
## SO WHAT EXACTLY IS THE PROBLEM?



**HOSPITALS ANONYMIZE OR RATHER PSEUDONYMIZE THE DATA  
BUT IS SUBJECT STILL AT RISK? YES.**

# INTRODUCTION & PROBLEM STATEMENT

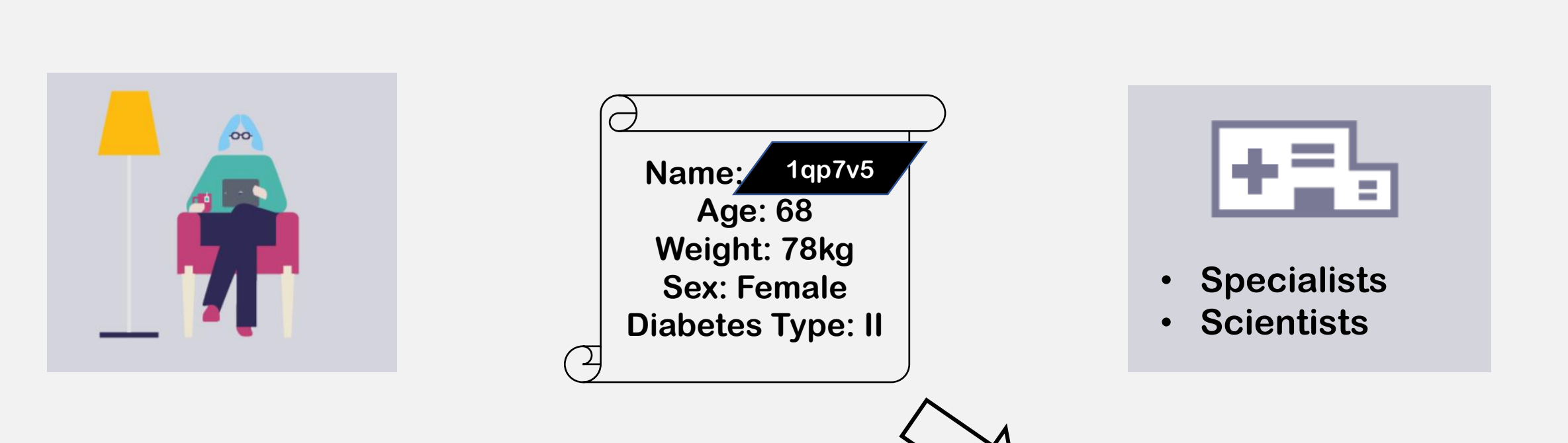
## NETFLIX PRIZE 2006



Many Netflix users rated the same movies similarly at IMDB.  
„Robust De-anonymization of Large Sparse Datasets“ by Arvind Narayanan and Vitaly Shmatikov, University of Texas at Austin, 2008

# PROBLEM STATEMENT

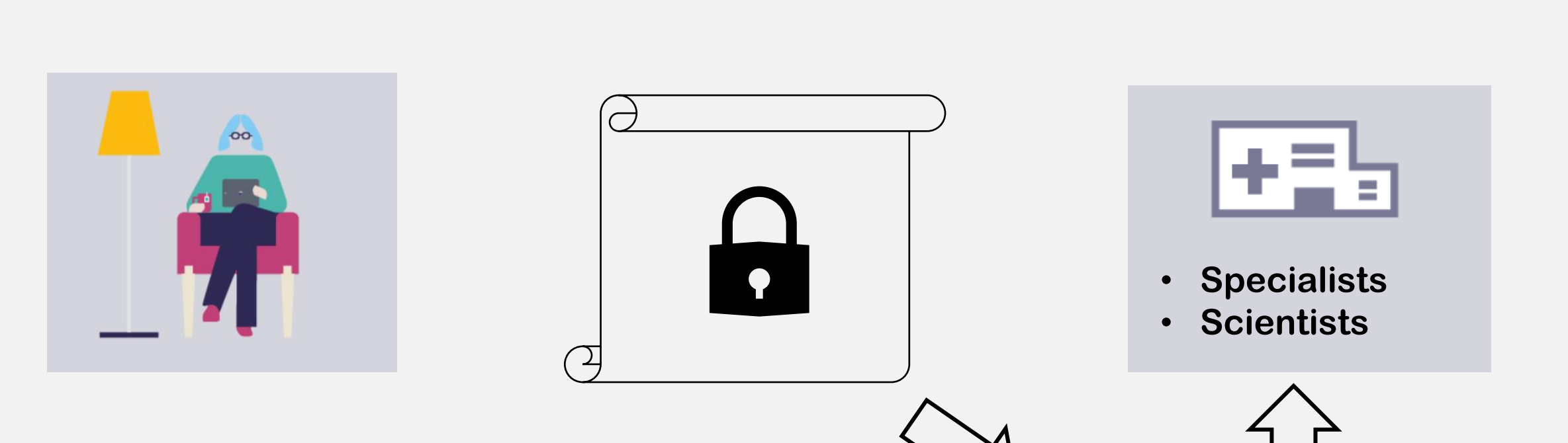
## SO WHAT EXACTLY IS THE PROBLEM?



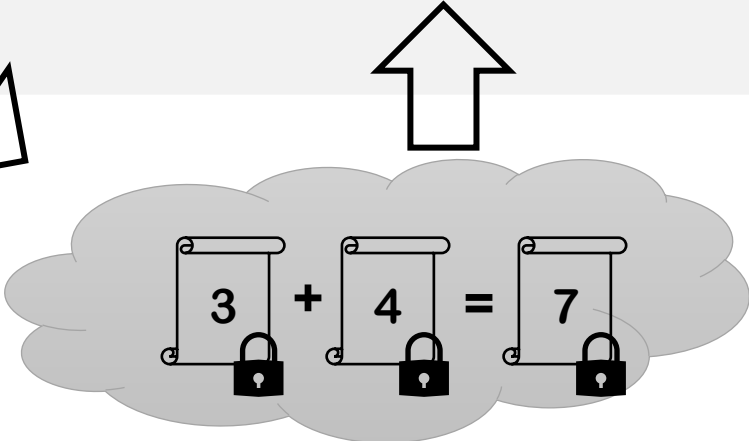
**INVOLVED THIRD PARTIES FOR DATA ANALYSIS  
MUST BE CONSIDERED MALICIOUS**

# INTRODUCTION & PROBLEM STATEMENT

## PURE CRYPTO SOLUTIONS EXIST



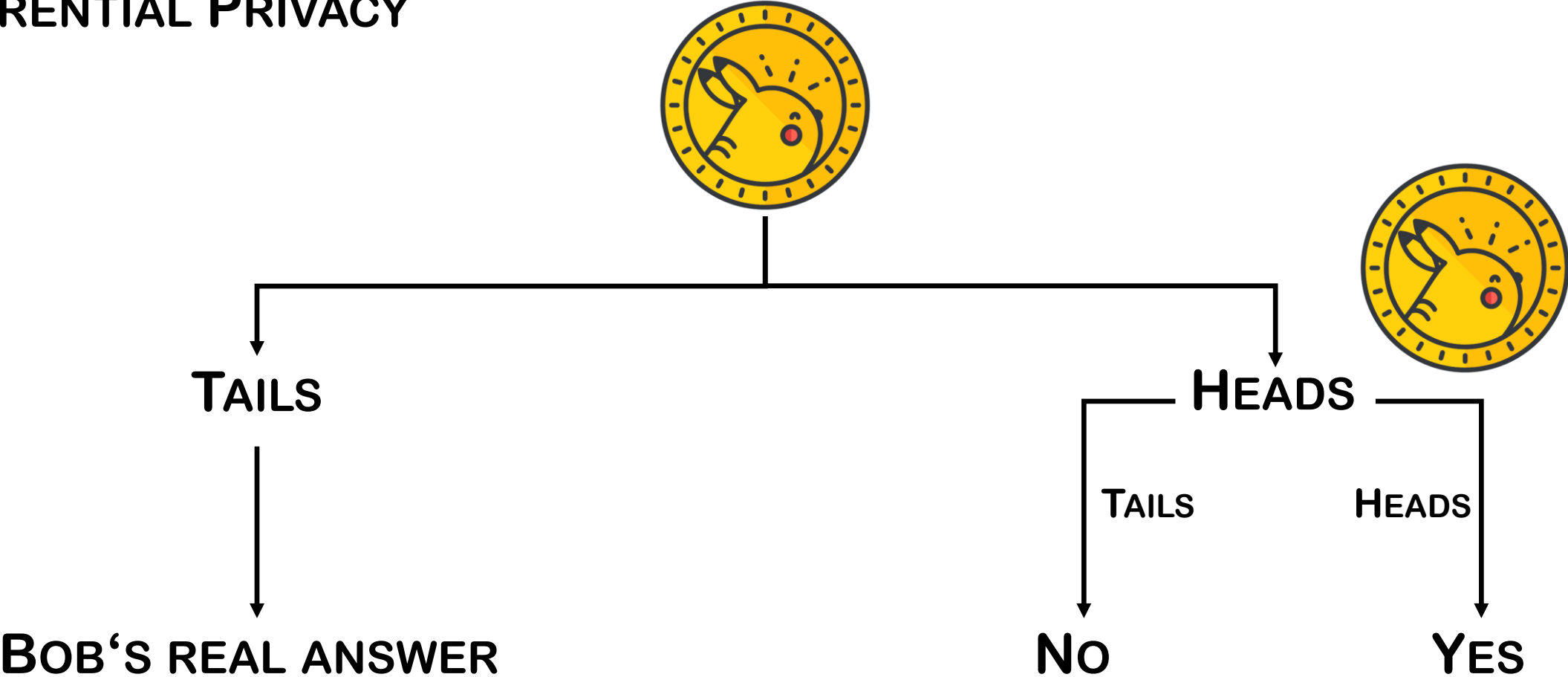
**FULLY HOMOMORPHIC ENCRYPTION  
GARBLED CIRCUITS, SECRET SHARING  
CAN BE EFFICIENT FOR SOME SPECIFIC CASES**





# INTRODUCTION & PROBLEM STATEMENT

## DIFFERENTIAL PRIVACY



# INTRODUCTION & PROBLEM STATEMENT

## DIFFERENTIAL PRIVACY

„The Algorithmic Foundations of Differential Privacy“ by Cynthia Dwork, Microsoft Research & Aaron Roth, University of Pennsylvania, 2014.

“Differential privacy” describes a promise, made by a data holder, or curator, to a data subject: “You will not be affected, adversely or otherwise, by allowing your data to be used in any study or analysis, no matter what other studies, data sets, or information sources, are available.”

*“Data cannot be Fully Anonymized and Remain Useful.”*

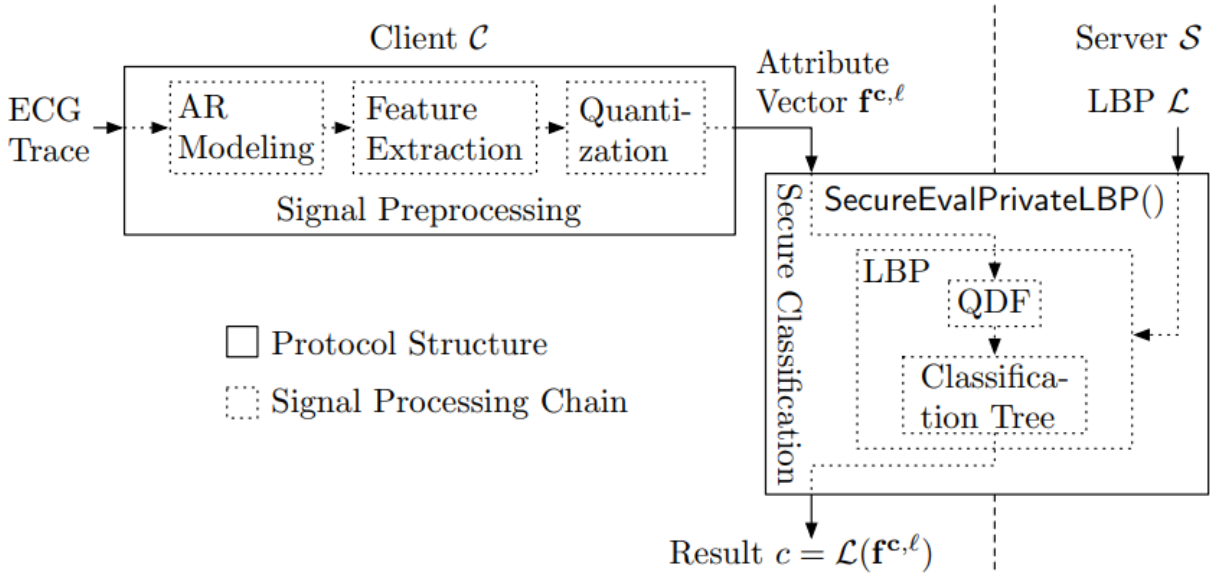
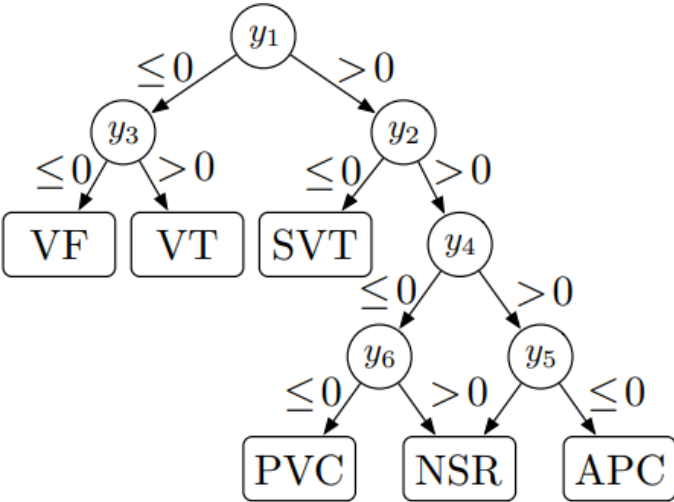
Can I call my algorithm  $\mathcal{M}$   $\varepsilon$ -DP?

$$L^\xi = \ln \left( \frac{\Pr[\mathcal{M}(x) = \xi]}{\Pr[\mathcal{M}(y) = \xi]} \right)$$

$\mathcal{M}$  is called  $\varepsilon$ -DP, if and only if  $|L^\xi| \leq \varepsilon$

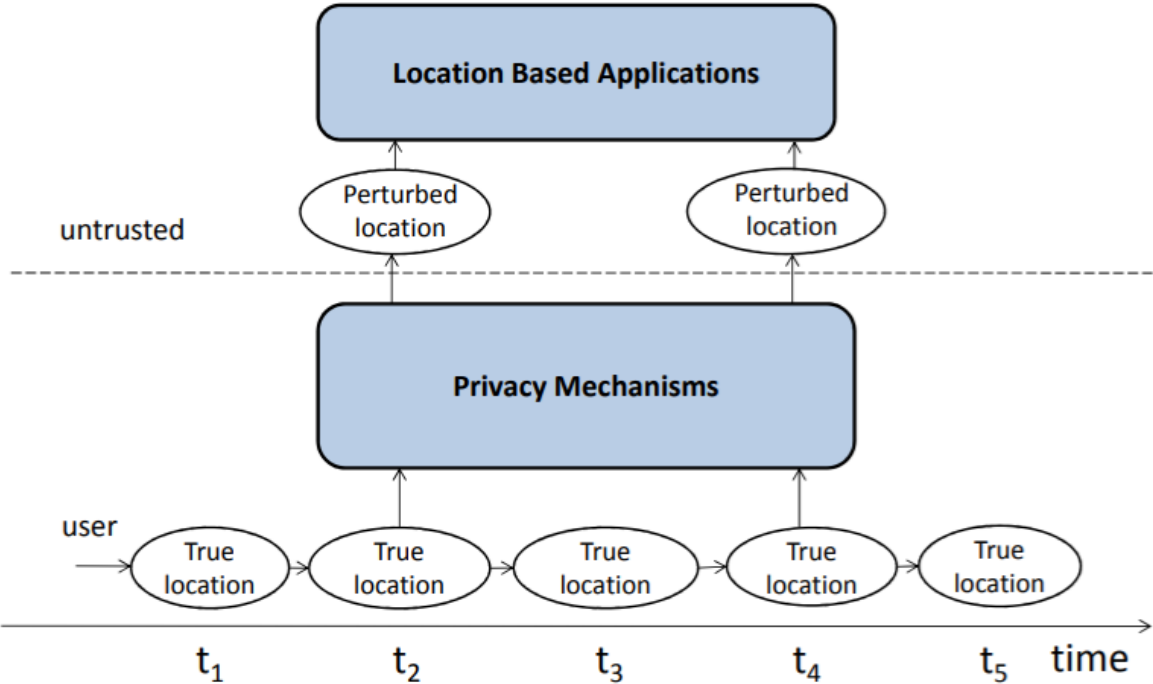
# BACKGROUND & SIGNIFICANCE

## EXAMPLE 1: “EFFICIENT PRIVACY-PRESERVING CLASSIFICATION OF ECG SIGNALS”, BARNI ET AL., 2009



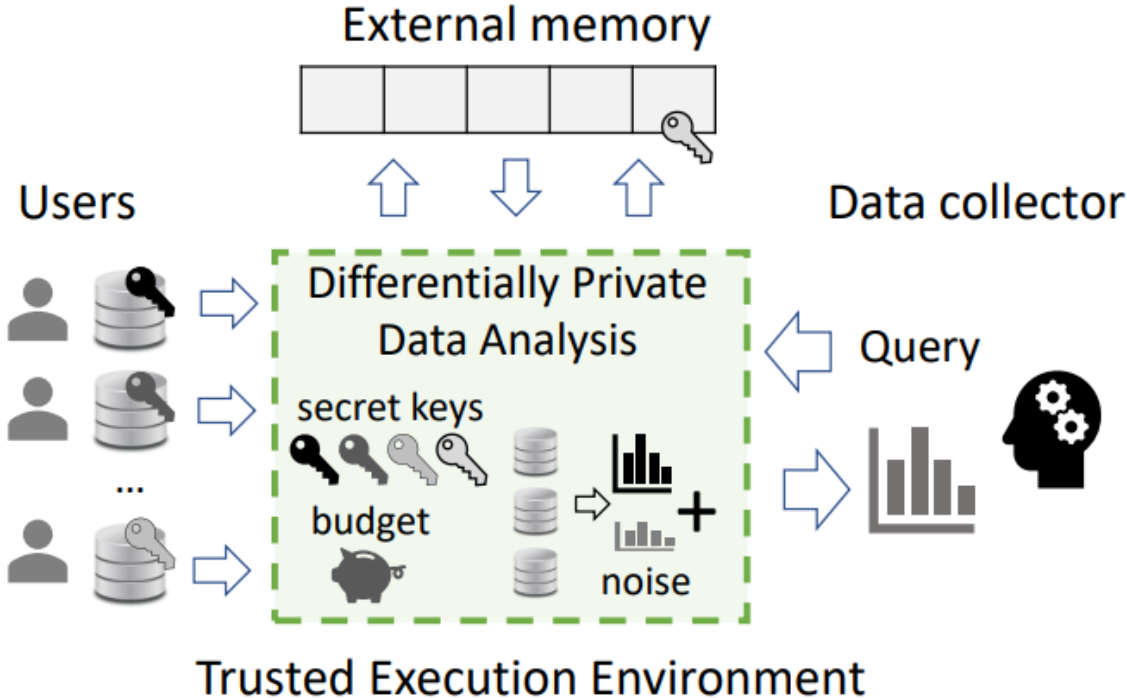
# BACKGROUND & SIGNIFICANCE

## EXAMPLE 2 - DIFFERENTIAL PRIVACY: “PROTECTING LOCATIONS WITH DIFFERENTIAL PRIVACY UNDER TEMPORAL CORRELATIONS”, YONGHUI, LI, EMORY UNIVERSITY AT ATLANTA, 2015.



# BACKGROUND & SIGNIFICANCE

## EXAMPLE 3 - HARDWARE SOLUTION: “AN ALGORITHMIC FRAMEWORK FOR DIFFERENTIALLY PRIVATE DATA ANALYSIS ON TRUSTED PROCESSORS”, ALLEN, OHRIMENKO ET AL.



# RESEARCH DESIGN & METHODS

## SMART PREVENT DIABETIC FEET: 300 SUBJECTS (150 USING DEVICE)

### ALL



Classic onsite screening every six months

### STUDY GROUP

Ambulant

An illustration showing a smartphone, a floor lamp with a yellow shade, and a person sitting in a red chair using a laptop.

Data inspection

An illustration showing a stylized hospital building with a cross and a doctor in a white lab coat with a stethoscope.

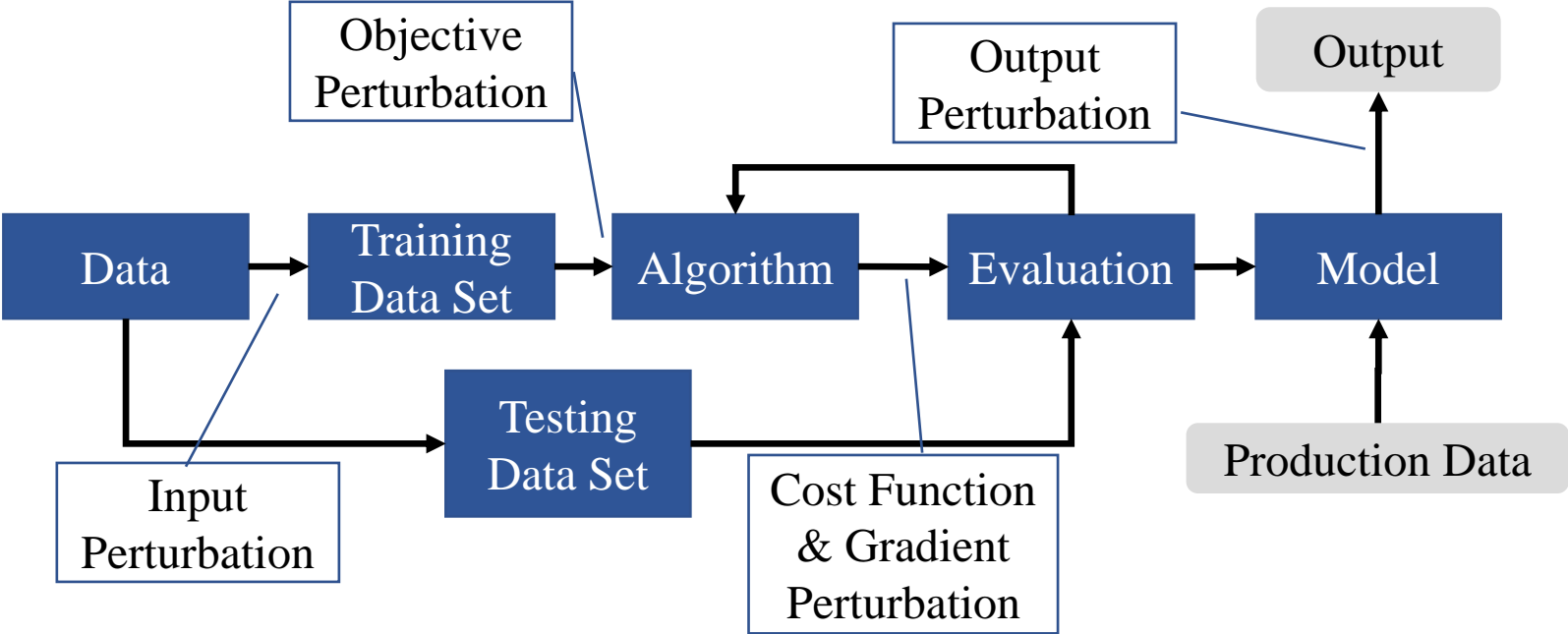
Combining results for a more sophisticated treatment of the subjects

An illustration showing a network diagram with nodes and lines, and a pen writing on it.

# RESEARCH DESIGN & METHODS

## COMPARE TWO BASIC MECHANISMS FOR NUMERIC INPUT PERTURBATION

- LAPLACIAN MECHANISM
- FUNCTIONAL MECHANISM



# RESEARCH DESIGN & METHODS

## EXPERIMENTAL SETUP

### HARDWARE & ENVIRONMENT

- INTEL CORE I7-8665U
- 48GB RAM
- MS ML.NET

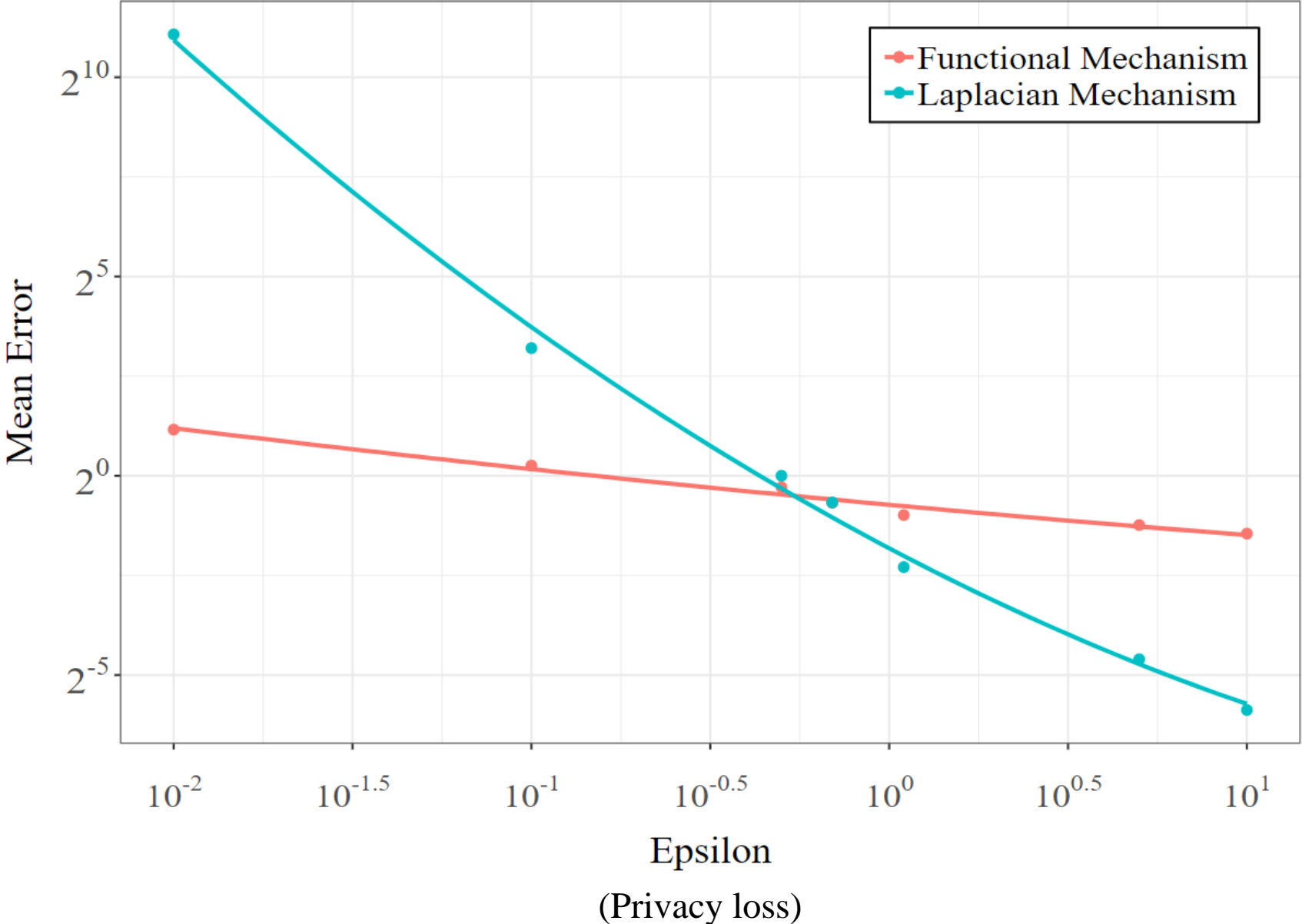
### DATA

- 10-FOLD CROSS-VALIDATION
- 200K DATA RECORDS

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - y_i^*)^2$$



# OVERVIEW



# CONCLUSION

## WE EXPLORED DIFFERENTIAL PRIVATE MACHINE LEARNING

### PERFORMANCE

**SIGNIFICANTLY FASTER  
THAN PURELY  
CRYPTOGRAPHIC  
SOLUTIONS**

### USABILITY

**INCREASES WITH HIGHER  
 $\epsilon$**

**STRONGLY INFLUENCED  
BY CHOSEN MECHANISM**

### SECURITY GUARANTEES

**DECREASE WITH  
HIGHER  $\epsilon$**

**STRONGLY INFLUENCED  
BY CHOSEN MECHANISM**

## CONCLUSION

**DIFFERENTIAL PRIVACY CAN BE APPLIED TO CLINICAL TRIALS**

**BUT SOPHISTICATED DECISIONS REQUIRED ABOUT MECHANISM, PERTURBATION,  $\epsilon$ ,  
USABILITY**

**Differential Privacy can provide security and privacy, if applied correctly.**

**Out-of-the-box solutions required for smaller scale clinical trials.**

**Thank you.**