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ISMB 2022 - Theory Session

Privacy-Enhancing Techniques

Overview

1. Why use privacy enhancing techniques ?
2. Outdated approaches (k-anonymity)
3. Differential Privacy (DP)
4. Secure Multi Party Computation (SMPC)
5. Homomorphic Encryption
6. Summary

Why use privacy enhancing techniques?

https://emerging-europe.com/voices/gdpr-looking-back-and-looking-forward/

https://www.hxnwrk.com/verschiedene-typen-von-hackern/

Outdated Approaches

De-identification
→ bad bad
K-anonymity (https://opendp.github.io/cs208/spring2022/presentations/overview-reidentification.pdf)
- Quasi-identifier fallacy (Netflix challenge)
- Other Attacks (composition, downcoding)
- Problems with summary statistics
- Membership attacks
  - Classical
  - Inference of sensitive attributes

→ also bad

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Outdated Approaches

Basic Idea: De-Identification via Suppression

Name	Age	Height	Sex	Disease
Peter	46	1.70	M	N
Jane	27	1.72	F	N
Joe	30	1.85	M	Y
Liza	24	1.65	F	Y

Basic Idea: De-Identification via Suppression

Name	Age	Height	Sex	Disease
Peter	46	1.70	M	N
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Basic Idea: De-Identification via Generalization

Name	Age	Height	Sex	Disease
-	46	1.70	M	N
-	27	1.72	F	N
-	30	1.85	M	Y
-	24	1.65	F	Y

Name	Age	Height	Sex	Disease
-	41–50	1.70	M	N
-	21-30	1.72	F	N
-	21-20	1.85	M	Y
-	21-30	1.65	F	Y

Basic Idea: De-Identification via Generalization

Name	Age	Height	Sex	Disease
-	46	1.70	M	N
-	27	1.72	F	N
-	30	1.85	M	Y
-	24	1.65	F	Y

Name	Age	Height	Sex	Disease
-	41–50	1.7*	M	N
-	21-30	1.7*	F	N
-	21-20	1.8*	M	Y
-	21-30	1.6*	F	Y

K-Anonymity

Formally, we say that a dataset D satisfies k-Anonymity for a value of k if:

- For each row $r_1 \in D$, there exists at least $k-1$ other rows $r_2 \ldots r_k \in D$ such that

$$\prod_{qi(D)} r_1 = \prod_{qi(D)} r_2, \ldots, \prod_{qi(D)} r_1 = \prod_{qi(D)} r_k$$

where $qi(D)$ is the quasi-identifiers of D, and $\prod_{qi(D)} r$ represents the columns of r containing quasi-identifiers ($i.$ e. the projection of the quasi-identifiers).

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Quasi-identifiers – ‘important’ features

- 2006 Netflix 1 Mio $ movie-recommendation challenge.
- **100,480,507 movie ratings** of **480,189 Netflix subscribers** from 1999 to 2005
- FAQ: “Is there any customer information in the dataset that should be kept private?”

  Answer: “**No**, all customer **identifying information** has been removed; all that remains are ratings and dates. This follows our privacy policy. […] **Even** if, for example, you knew all **your own ratings** and their dates you probably **couldn’t identify** them reliably in the data because only a small sample was included […] and that data was subject to perturbation.”

Quasi-identifiers – ‘important’ features

Narayanan-Shmatikov Set-Up (Narayanan & Shmatikov, 2008)

Dataset: x = set of records r (e.g. Netflix ratings)

Adversary’s inputs:
x’ = subset of x, possibly distorted
aux = auxiliary information about record r (e.g. public IMDB ratings)

Adversary’s goals:
Output either r’ that is close to r or output ‘no match’

Quasi-identifiers – ‘important’ features

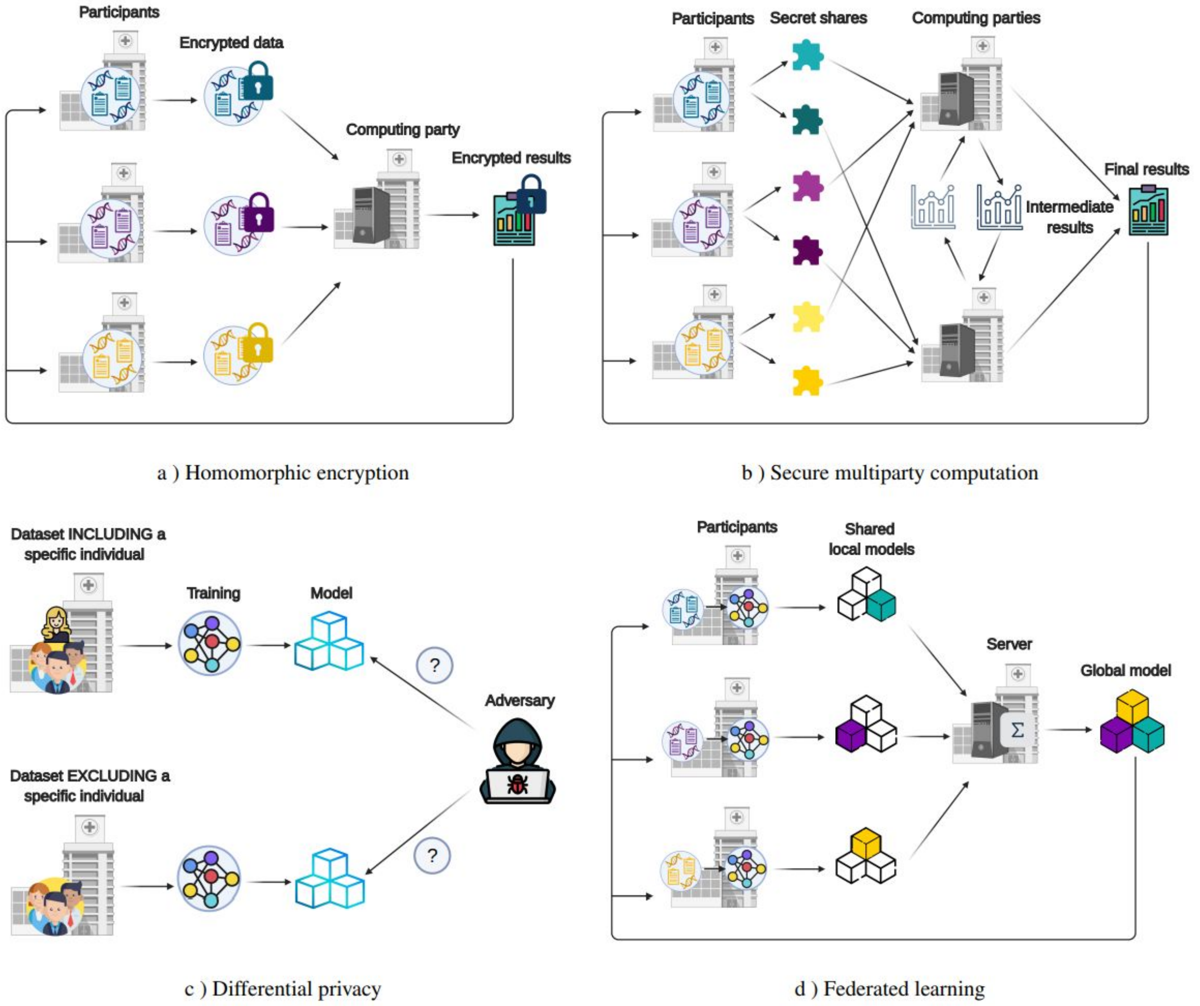
$$\text{score}(aux, r') = \underbrace{\sum_{a \in \text{supp}(aux)}}_{\text{IMDB rating}} \underbrace{sim(aux_a, r'_a)}_{\text{Similarity of rating and date}} * \underbrace{\frac{1}{\log |\{r' \in \hat{x} : a \in \text{supp}(r')\}|}}_{\text{Downweight popular movies}}$$

Sampled 50 IMDB users → identified 2 in Netflix dataset

(→Class action lawsuit, no Netflix Challenge II)

→ **every feature can be a quasi identifier!**

Better working approaches



https://arxiv.org/pdf/2007.11621v2.pdf

Differential privacy (http://people.seas.harvard.edu/~salil/cs208/spring19/)

- introduce concepts (http://people.seas.harvard.edu/~salil/cs208/spring19/DP-foundations1-lecture.pdf)
- And application examples (http://people.seas.harvard.edu/~salil/cs208/spring19/DP-foundations2-lecture.pdf)
- Programming example (?) (https://gist.github.com/julianspaeth/5f410cd706fdf2d9bec73c8b794cd357)
- Attack vectors (Privacy budget attack) (https://css.csail.mit.edu/6.858/2013/readings/dp-under-fire.pdf) (?)
- Pro/Con

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Differential Privacy

Differential Privacy

Age	Height	Sex	…	Disease
46	1.70	M	…	N
27	1.72	F	…	N
30	1.85	M	…	Y
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57	1.69	M	…	N
32	1.79	F	…	Y
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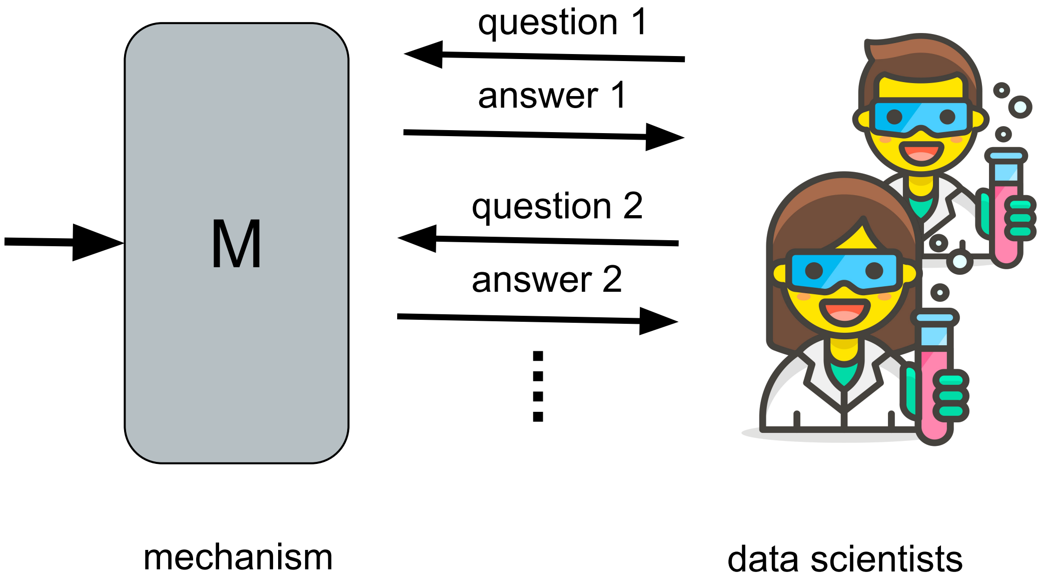

Differential Privacy

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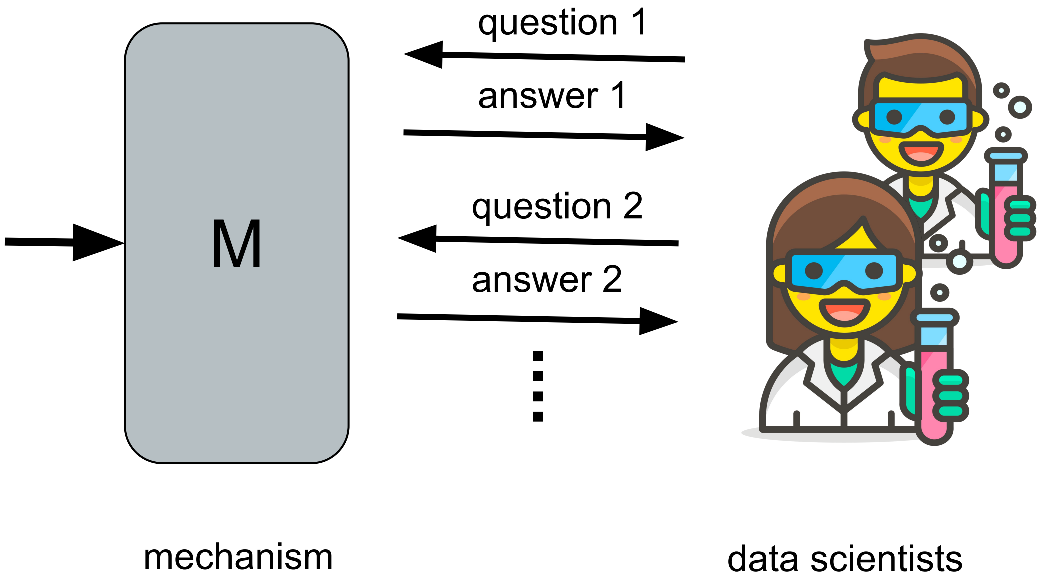

→ effect of each individual should be ‘hidden’

Differential Privacy

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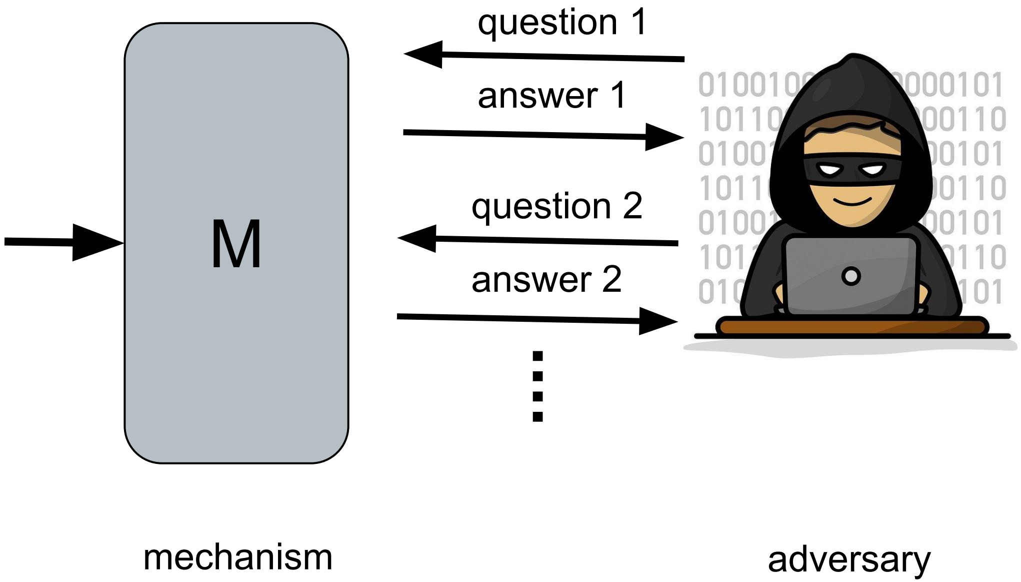

→ adversary shouldn't be able to tell if any one person's data were to change arbitrarily

Differential Privacy

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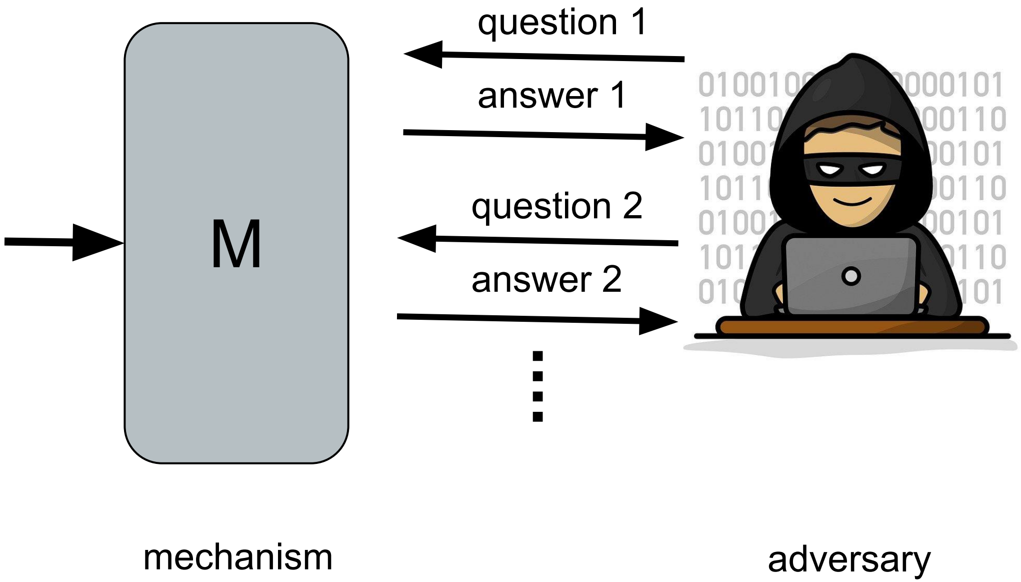

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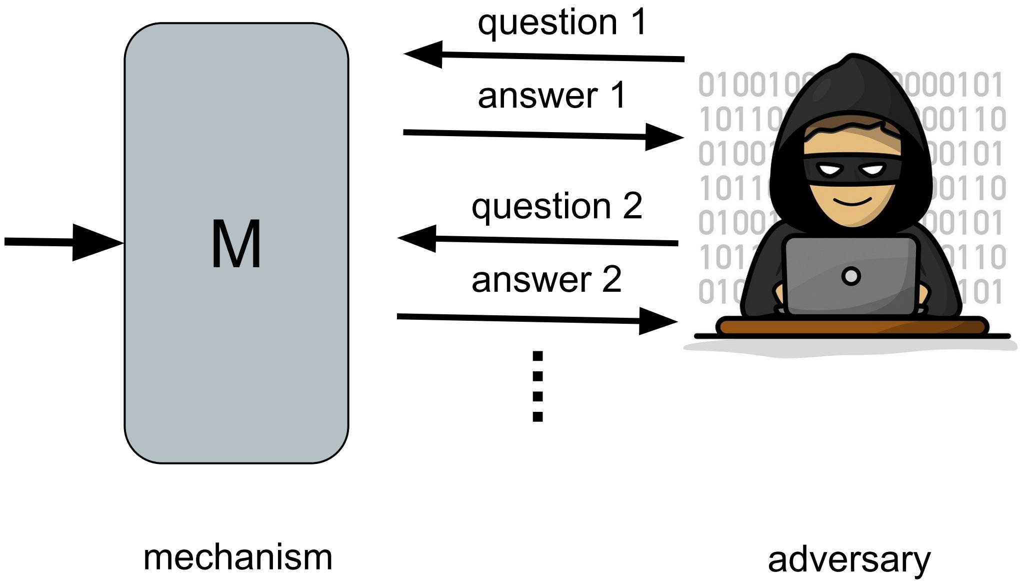

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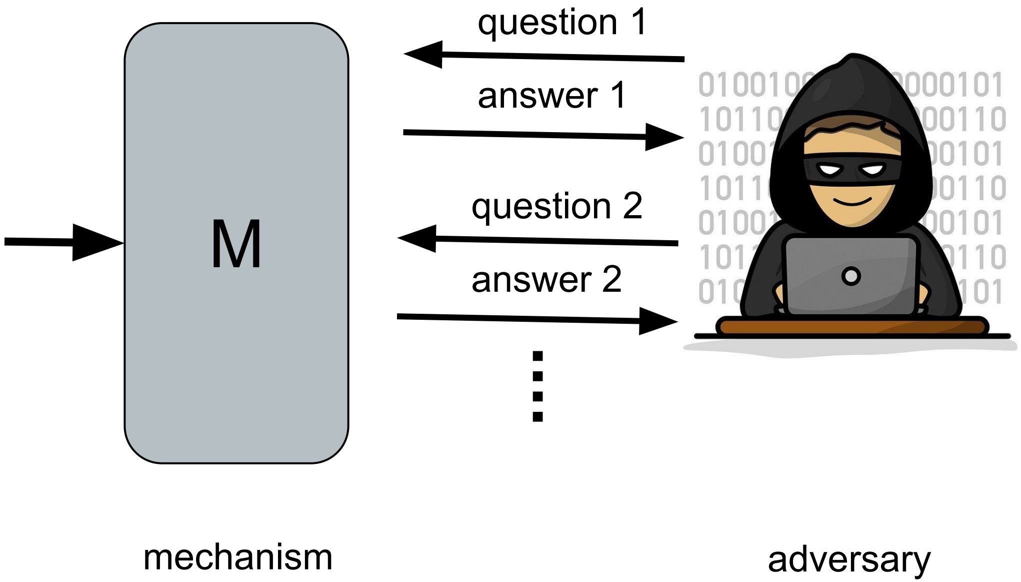
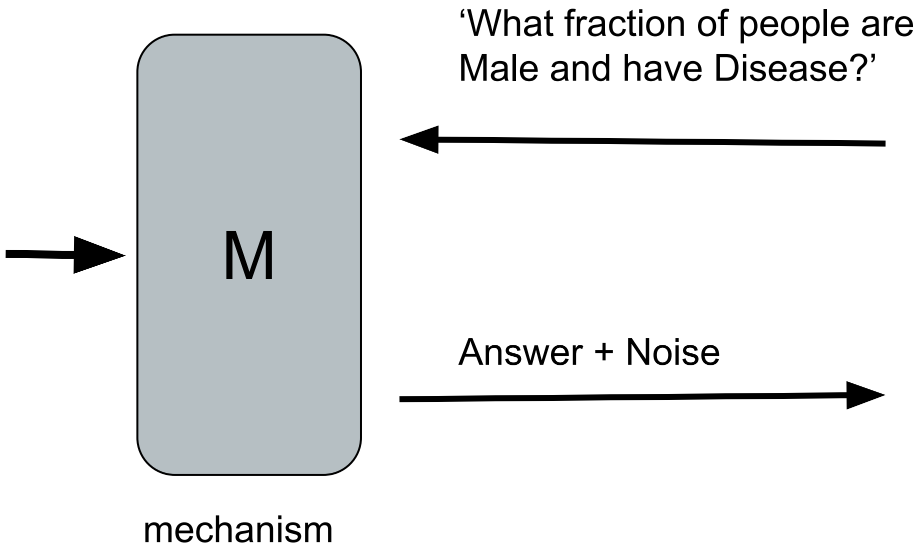


→ adversary shouldn’t be able to tell if any one person’s data were to change arbitrarily

Differential Privacy – output perturbation

Age	Height	Sex	…	Disease
46	1.70	M	…	N
27	1.72	F	…	N
66	1.55	F	…	N
24	1.65	F	…	Y
57	1.69	M	…	N



- Very little noise needed as number of entries n → ∞.
- This is just for **one** query

Differential Privacy – Laplace Mechanism

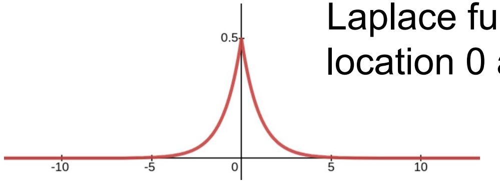
For a function f(x) that returns a number, this definition of F(x) satisfies ϵ-differential privacy:

$$F(x) = f(x) + \mathrm{Lap}\left(\frac{s}{\epsilon}\right)$$

where Lap(S) samples from the Laplace distribution and s is the sensitivity of f. The sensitivity s of f denotes the amount f's output changes when its input changes by 1.

The Laplace function with location 0 and scale b has the density:

$$p(x) = \frac{1}{2b}\exp\left(-\frac{|x|}{b}\right)$$



Laplace function with location 0 and scale b=1

Differential Privacy – output perturbation

n

Age	Height	Sex	…	Disease
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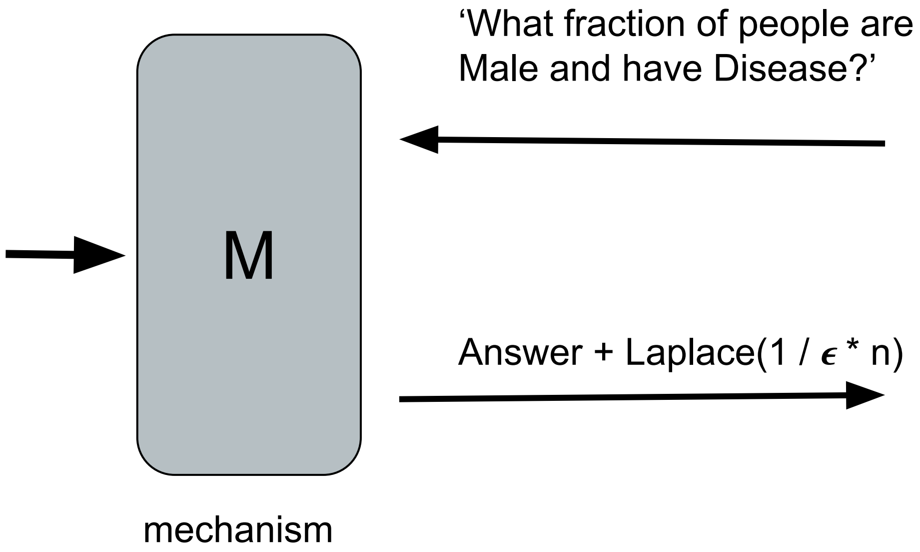

- Very little noise needed as number of entries n → ∞.

Differential Privacy – Privacy Budget

- If M is ϵ-DP for one query, it is k*ϵ-DP for k queries.
- To maintain global privacy loss at most ϵ_{global}, can set $\epsilon = \epsilon_{global}$ /k and stop answering after k queries.
- More queries → smaller ϵ → less accuracy
  Some tradeoff is necessary

  Typicall recommendation for ‘good’ privacy guarantee:

  $0.01 \leq \varepsilon \leq 1$

Differential Privacy – Summary

- Whatever an adversary learns **about me**, it could have been learned **from everyone** else’s data
- No leakage of data **specific to individuals**
- This holds regardless of **computational power** or **auxiliary information**

But:

- **No guarantee** that adversary won’t **infer sensitive attributes**.
- **No guarantee** that subjects won’t be ‘**harmed**’ by results of analysis
- **No protection** for information that is not localized to a few rows

SMPC

- Concept
- Programming example (?) (https://github.com/OpenMined/SyMPC, https://github.com/iamaldi/smpc)
- attack vectors (https://eprint.iacr.org/2020/300.pdf, https://arxiv.org/pdf/1005.5020.pdf) (?)
- Pro/Con

Secure Multi Party Computation (SMPC)

Secure Multiparty Computation – Example

→ Average salary

	Salary k€/year
Niklas	50
Mohammad	60
Jan	100
	210 / 3 = 70

Secure Multiparty Computation – Example

	Salary k€/year
Niklas	5[illegible]
Mohammad	60
Jan	10[illegible]
	210 / 3 = 70

→ Average salary **without sharing**

Secure Multiparty Computation

	Salary k€/year	Shard 1	Shard 2	Shard3
Niklas	50			
Mohammad	60			
Jan	100			

Secure Multiparty Computation

	Salary k€/year	Shard 1	Shard 2	Shard3
Niklas	50	-20	0	70
Mohammad	60	40	70	-50
Jan	100	60	30	10

Secure Multiparty Computation

Niklas	Mohammad	Jan
-20	0	70
40	70	-50
60	30	10

Secure Multiparty Computation

Niklas	Mohammad	Jan
-20	0	70
40	70	-50
60	30	10
80	100	30

Secure Multiparty Computation

Niklas	Mohammad	Jan
-20	0	70
40	70	-50
60	30	10
80	100	30

210 / 3 = 70

Homomorphic encryption (?)

- Concept (https://www.ibm.com/security/digital-assets/fhe/unlock-value-of-sensitive-data-without-decryption/)
- Application (in FL) (https://developer.nvidia.com/blog/federated-learning-with-homomorphic-encryption/)
- Pro/Con

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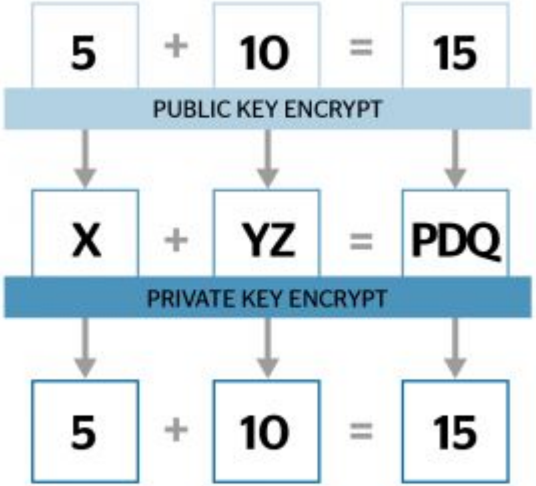
Homomorphic Encryption

Homomorphic encryption



https://atos.net/en/lp/cybersecurity-magazine-enter-a-new-cybersecurity-era/the-challenges-of-homomorphic-encryption

Pre FHE timeline

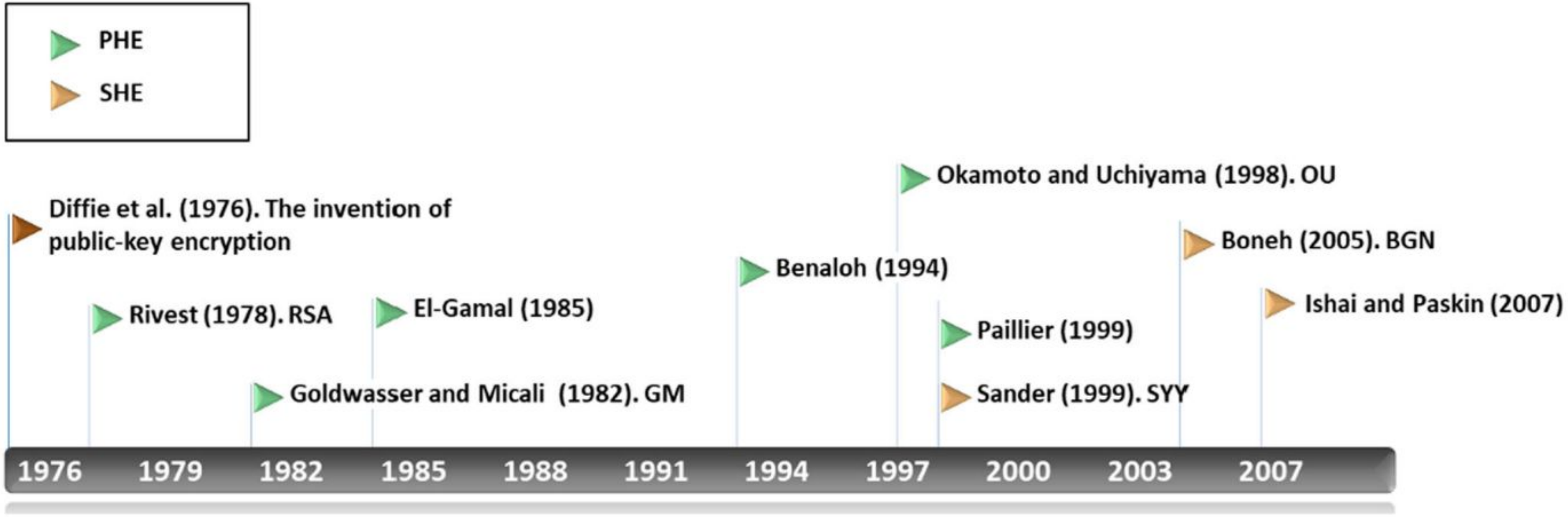


Fig. 1 Homomorphic encryption timeline

FHE timeline

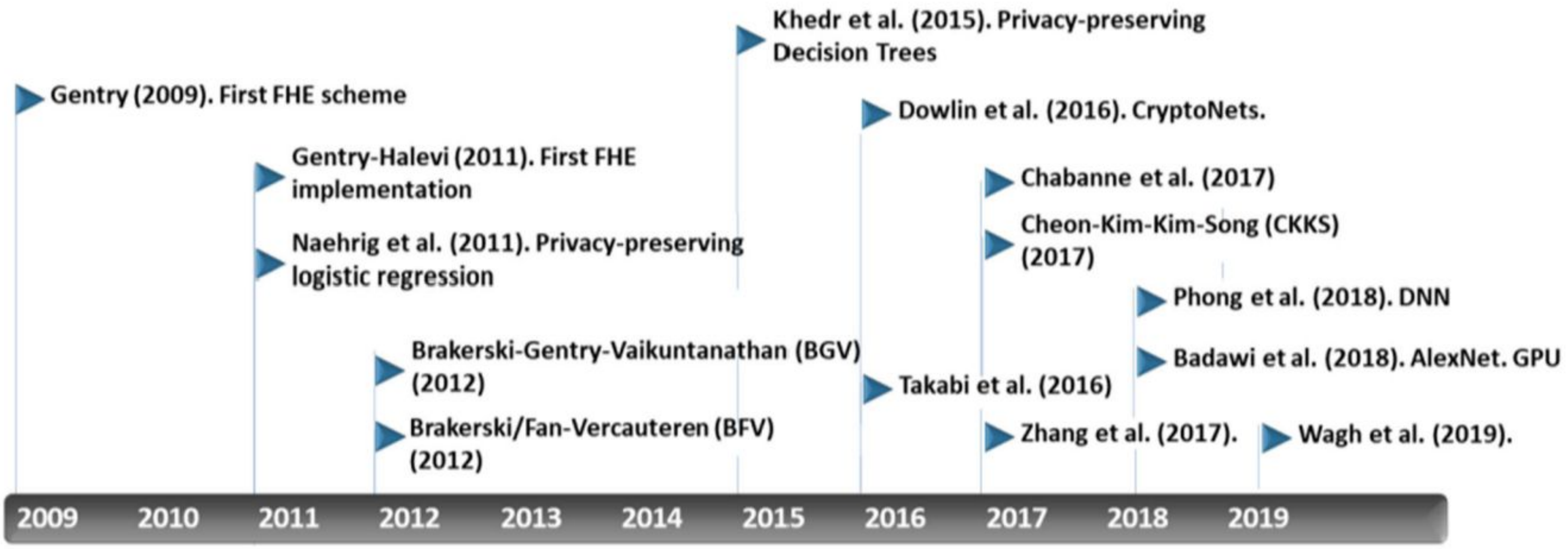


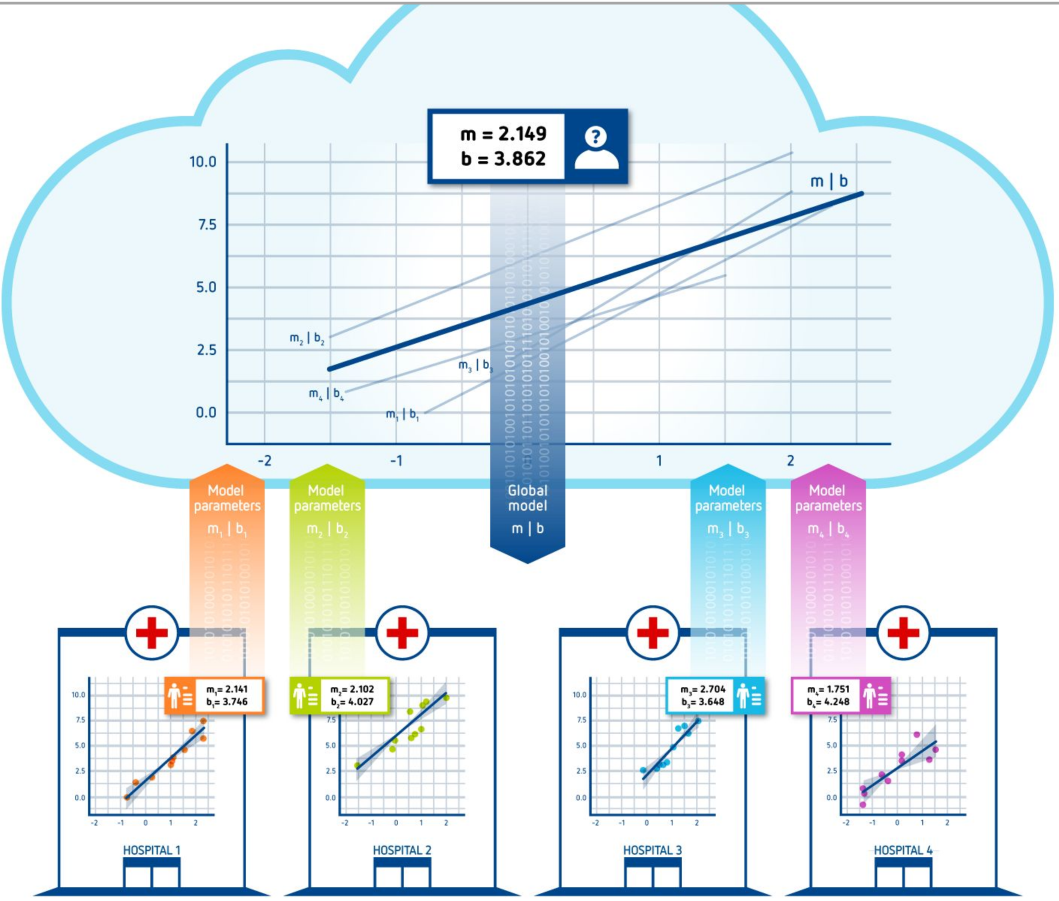
Fig. 2 Fully Homomorphic Encryption timeline

So why aren’t we using it?

- Speed.
- Fastest FHE algorithm still factor 1 Mio slower than normal operation
- Normal calculation of 1 sec -> ~11 ½ days of FHE calculation

Summary

Federated Machine Learning

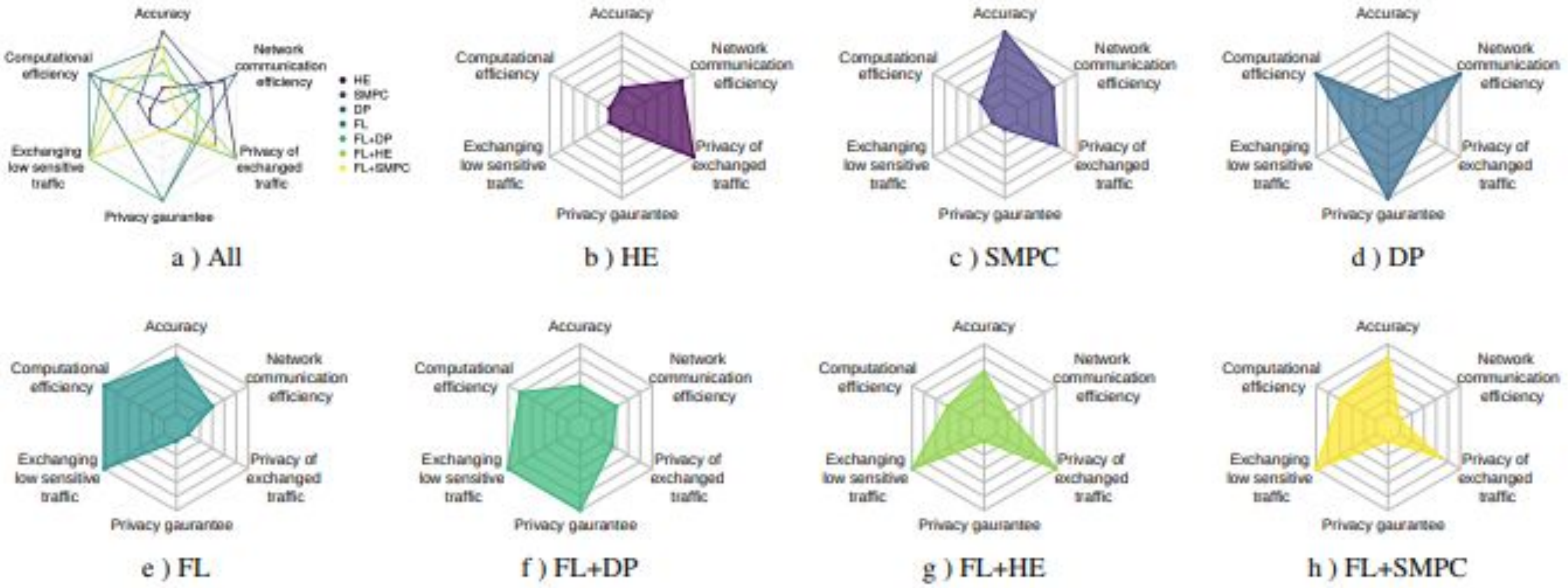


FeatureCloud concept: Hospital's cloud communication with FeatureCloud

Summary

	HE	SMPC	DP	FL	FL+DP	FL+HE	FL+SMPC
Accuracy	2	6	1	5	3	4	5
Computational efficiency	1	2	NA	6	5	3	4
Network communication efficiency	5	4	NA	3	3	2	1
Privacy of exchanged traffic	4	3	NA	1	2	4	3
Exchanging low sensitive traffic	✗	✗	NA	✓	✓	✓	✓
Privacy guarantee	✗	✗	✓	✗	✓	✗	✗

Comparison of Privacy Enhancing Techniques



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Synthetic Data (?)

- General concepts (https://research.aimultiple.com/synthetic-data/)
- Example Methods:
    - VAE (https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73)
    - GAN (https://wiki.pathmind.com/generative-adversarial-network-gan)

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Sources:

https://arxiv.org/abs/2105.05734
https://arxiv.org/abs/2007.11621

Inspired by CS208: Applied Privacy for Data Science
School of Engineering & Applied Sciences, Harvard University

ISMB 2022 - Tutorial - Federated Learning in Biomedicine

Thank you!