Privacy models: Summary

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Outline

• Privacy models

Privacy models



Privacy models. A computational definition for privacy. Examples.

- **Reidentification privacy.** Avoid finding a record in a database.
- k-Anonymity. A record indistinguishable with k-1 other records.
- Secure multiparty computation. Several parties want to compute a function of their databases, but only sharing the result.
- **Differential privacy.** The output of a query to a database should not depend (much) on whether a record is in the database or not.
- **Result privacy.** We want to avoid some results when an algorithm is applied to a database.
- Integral privacy. Inference on the databases. E.g., changes have been applied to a database.
- Homomorphic encryption. We want to avoid access to raw data and partial computations.

Privacy models. A computational definition for privacy. Publish a DB

- Reidentification privacy. Avoid finding a record in a database.
- **k-Anonymity.** A record indistinguishable with k 1 other records.
- k-Anonymity, I-diversity. *l* possible categories
- Interval disclosure. The value for an attribute is outside an interval computed from the protected value: values different enough.
- **Result privacy.** We want to avoid some results when an algorithm is applied to a database.



Privacy models. A computational definition for privacy. Publish a DB

• Modify DB X to obtain a DB X' compliant with the privacy model.

| Original DB X: | Respondent | c City | Ag | e III | ness | |
|------------------|------------|-----------------|------|---------|--------|--|
| | DRR | RR Barcelona 30 | | Heart | attack | |
| | ABD | Barcelona | a 32 | Ca | ncer | |
| | COL | Barcelona 33 | | Cancer | | |
| | GHE | Tarragona | a 62 | A | AIDS | |
| | CIO | Tarragona | a 65 | A | IDS | |
| | HYU | Tarragona | a 60 | Heart | attack | |
| Published DB X': | | - | | | | |
| | | City | Age | Illness | | |
| | _ | Barcelona | 30 | Cancer | | |
| | — | Barcelona | 30 | Cancer | | |
| | — | Barcelona | 30 | Cancer | | |
| | _ | Tarragona | 60 | AIDS | | |
| | — | Tarragona | 60 | AIDS | | |
| | | | — | | | |

• Difficulties

Naive anonymization does not work, highly identifiable data, high dimensional data

Examples of successful reidentification attacks
Sweeney analysis of USA population, data from mobile data, shopping cards, film ratings

Privacy models. A computational definition for privacy. Share a result

• Secure multiparty computation. Several parties want to compute a function of their databases, but only sharing the result.



Privacy models. A computational definition for privacy. Share a result

• Compute

 $f(DB_1, DB_2, DB_3, DB_4)$

without sharing DB_1, DB_2, DB_3, DB_4

• Example: national age mean of hospital-acquired infection patients (hospitals do not want to share the age of their infected patients!)

• Difficulties

Distributed approach (no trusted-third party) – computational cost of solutions

Privacy models. A computational definition for privacy. Compute result

- **Differential privacy.** The output of a query to a database should not depend (much) on whether a record is in the database or not.
- Integral privacy. Inference on the databases. E.g., changes have been applied to a database.
- Homomorphic encryption. We want to avoid access to raw data and partial computations.



- Difficulties. A simple function can give information on who is in the database
 - E.g., mean salary