0x3B Privacy Exercise Session

hexhive

EPFL

Introduction to Data Privacy

The challenge: Utility vs. Privacy

Goal: release datasets for research and improvements
Problem: protect privacy of individuals in those datasets
Reality: removing direct identifiers is rarely enough.

Agenda:

1. Attack: Breaking “anonymity” via Linkage
2. Defense: Guaranteed protection via Differential Privacy

Real world Context: The Netflix Prize

History repeats itself

The Event: 2006, released 100 million *anonymized* rating from 480,000 users
The Method: They stripped user IDs and replaced them with random numbers
The Attack: (Narayanan & Shmatikov, 2008):

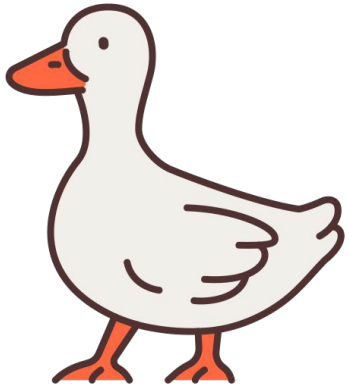
- They used public IMDb ratings as *side information*.
- Result: They successfully identified specific users in the anonymous Netflix dataset.
- Consequence: Netflix was sued and canceled the second prize competition.

Our Exercise: We are recreating this exact scenario.

Data de-anonymization

- **Netflix Prize**
  - An open competition for the best algorithm to predict user ratings for films
  - Netflix Prize Dataset: Netflix released anonymous ratings of 500,000 Netflix users
- **Netflix data de-anonymization**
  - “How to Break Anonymity of the Netflix Prize Dataset” Narayanan and Shmatikov
  - correlated rankings with IMDB records to de-anonymize users

Ex1. What are Donald’s favorite movies



Theory: Pseudonymization vs. Anonymization

Why Hashing Fails

- **Pseudonymization**:
  - Replacing `donald.trump@whitehouse.gov` with **SHA256(salt|email)**.
  - Vulnerability: The structure of the data remains unique. The history of ratings acts as a fingerprint.
- **Quasi-Identifiers:**
  - Data points that are not unique individually, but unique in combination.
  - Example: Gender + Zip Code + Birthdate = 87% of the US population.
  - In our case: (Date, Rating)or (Movie, Rating).
- **Linkage Attack**: connecting these Quasi-Identifiers between two datasets.

Exercise 1.1 - The Attack (Exact Match)

Scenario: Dates are giving it away

Data:

- Public (IMDb): email, movie, date, rating.
- Private (COM-402): email_hash, movie_hash, date, rating.

Vulnerability: date and rating are identical in both files.

Algorithm:

1. Profile: Extract Donald's set of (date, rating) from IMDb.
2. Match: Find the email_hash in COM-402 that has the exact same set of (date, rating).
3. Deanonymize: Use the matched rows to look up the movie names using the shared dates.

Setting

- Goal: de-anonymize “anonymized” datasets
- Download zip file from Moodle
- “anonymized” COM-402 databases - similar to Netflix DB
  - com402-1.csv
  - com402-2.csv
  - com402-3.csv

```
sha256(salt | email), sha256(salt | movie), date, rating
```

- Public IMDB databases
  - imdb-1.csv
  - imdb-2.csv
  - imdb-3.csv

```
email,movie,date, rating
```

- Task: find out what movies a user with email `donald.trump@whitehouse.gov` has rated.
- The answer for true movies are given in files:
  - user-1.csv
  - user-2.csv
  - user-3.csv

3 parts

Ex1-1: Dates are giving it away

- Each user rated the movie at the same date in both datasets Ex1-2:

  More realistic

- Dates are randomized, reflecting the fact that you might not rate a movie on Netflix and on IMDb on the same day.

Ex1-3: Even more realistic (optional)

- Dates are within 14 days, and are following a triangular distribution using Python's `random.choices` and weights: `[1, 2, …, 14, 13, …, 1]`.

Ex. 1.1)

$$\text{IMDB}_1 \subset \text{COM-402}_1$$

```
email,
movie,
date, rating
```

```
sha256(salt | email),
sha256(salt | movie),
date, rating
```

- You can test with the user-*.csv file if the guesses are true
  - `assert movie_guesses == true_movies`
  - `print(movie_guesses)`

Ex. 1.1) - solution idea

- If the date and stars match in public and anonymized dataset, then record the candidate plaintext email and movie
  - `hash2movie[anon_entry.movie].append(pub_entry.movie)`
  - `user2hash[pub_entry.user].append(anon_entry.user)`
- Guess the victim's email hash as the most common candidate.
  - `Get_most_common helper method`
- Filter the ratings made by this victim’s email hash

Ex. 1.2)

$$\boxed{\text{IMDB}_2 \subset \text{COM-402}_2}$$

`email,`	`sha256(salt | email),`
`movie,`	`sha256(salt | movie),`
`date,`	`randomize(date),`
`rating`	`rating`

Where $\text{randomize} : \mathcal{D} \to \mathcal{D}$ maps each date (uniquely) to some random date

Ex. 1.2) - solution idea

- Match movie hashes to plaintexts by frequency.
  - `Sort_by_freq method in helpers.py`
  - `movie2hash[movie_name] = movie_hash`
  - `hash2movie[movie_hash] = movie_name`
- Get the victim's movie hashes from the public data.
  - `filter_ratings_by_user(public, victim_email)`
- Identify the victim's email hash:
  - Map the email hashes to the corresponding movie hashes from the anonymized data.
  - find the hash that has all the movie hashes from above.
    - If multiple possibilities, then the generated datasets are not good.

Ex. 1.3) [OPTIONAL]

$$\boxed{\text{IMDB}_3 \subset \text{COM-402}_3}$$

```
email,                          sha256(salt | email),
movie,                          sha256(salt | movie),
date,                           real_randomize(date),
rating                          rating
```

$$\text{real\_randomize} : \mathcal{D} \to \mathcal{D}$$

Where *real_randomize* maps randomly maps each date according to a triangular distribution within 14 days of the initial date

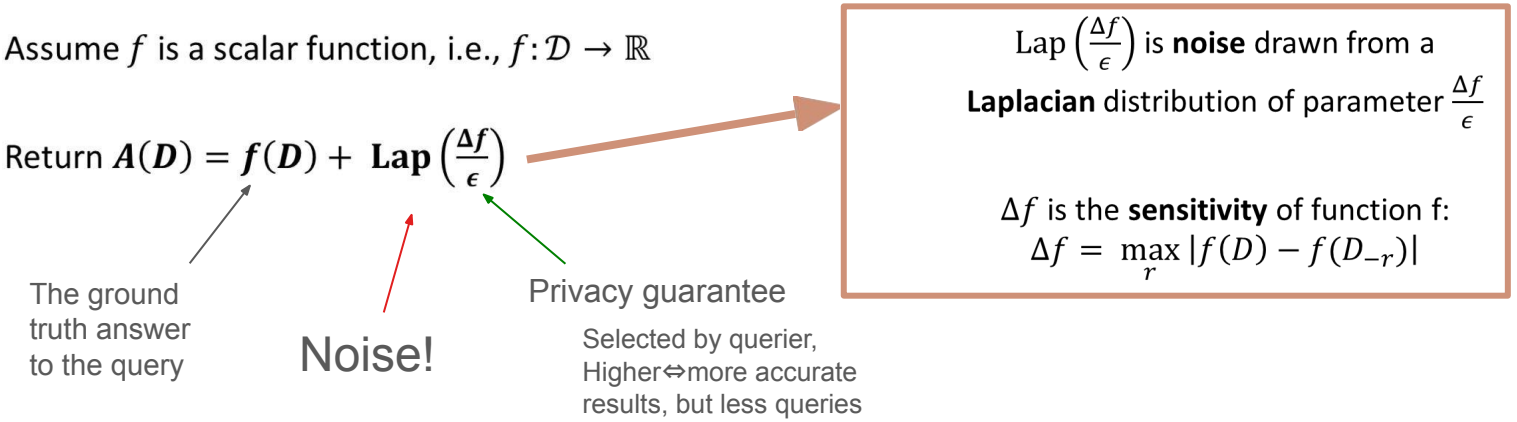
Ex2. Differentially Private Queries

[optional]

Ex2

- Playing the role of the company: IMDB
- Researchers send you queries, you respond in a differentially private way
- Query : “For a given movie, how many reviews are above a threshold?”
  - `get_count(movie_name, rating_threshold, epsilon)`
- Each researcher gets their own **privacy budget** $\varepsilon_{\text{total}}$: the total epsilon a researcher can use across queries.
- for each query, an epsilon value can be specified
  - the higher epsilon is, the higher the accuracy of the response will be, but will allow for less queries. and vice versa, a lower epsilon will allow for more queries.

Laplace mechanism for adding noise



- In your database, a user can only rate one movie once. This means sensitivity $\Delta f = 1$
- `np.random.laplace(loc=0, scale=1. / epsilon)`

Sequential composition

- Sequential composition property: **If algorithms $\mathbf{A_1}$, $\mathbf{A_2}$, …, $\mathbf{A_k}$** use independent randomness and each $\mathbf{A_i}$ satisfies ε_i-differential privacy, respectively. Then (A_1, A_2, …, A_k) is **$(\varepsilon_1 + \varepsilon_2 + ... + \varepsilon_k)$**-differentially private
  - can keep account of spent privacy budget and ensure that the queries do not exceed it.

Testing with verify.py

```
(base) ➜  solution git:(main) ✗ /usr/local/anaconda3/bin/python

Running tests...

> Basic privacy budget accounting
PASSED 👌

> Privacy budget depletion control
PASSED 👌

> DP noise distribution
PASSED 👌

> Multiple query behavior (I)
PASSED 👌

> Multiple query behavior (II)
PASSED 👌
```