Privacy

Introduction

Guillaume Raschia — Nantes Université

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original slides from J. Near (Univ. of Vermont, CS211: Data Privacy)
and A. Machanavajjhala, M. Hay, X. He; Differential Privacy in the Wild, VLDB'16 & SIGMOD'17 Tutorial

Outline

Next Topic

Course Information

- Course website on Madoc: ipolytech_info5_donneesperso (Données personnelles)
- Instructor: Guillaume Raschia, `mailto:guillaume.raschia@univ-nantes.fr`
- Lectures: three 1h15 sessions
- Practice: one 1h30 lab session
- Grading: 1 Homework Assignment (40%) ● 1 Final Exam (60%)

Questions ?

Next Topic

Administrative

What is data privacy, and how is it violated?

How do data privacy breaches affect us?

A Non-Definition

Information privacy

24 languages

Article Talk Read Edit View history

From Wikipedia, the free encyclopedia

Information privacy is the relationship between the collection and dissemination of data, technology, the public expectation of privacy, contextual information norms, and the legal and political issues surrounding them.[1] It is also known as **data privacy**[2][3] or **data protection**.

A First Attempt Towards a Definition

Analysis of data preserves data privacy if:

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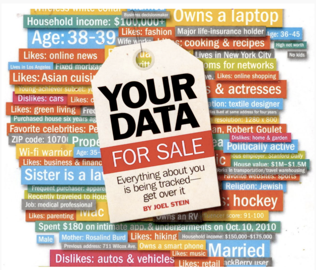
Danger
This is a very strong statement

Unleash Personal Data!



Source: TIME

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  - Advertising, advertising, advertising
  - Genome wide association studies
  - Human mobility analysis

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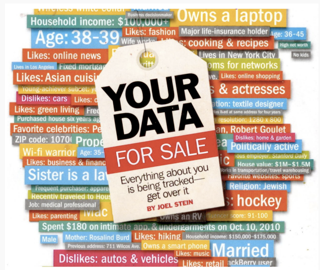

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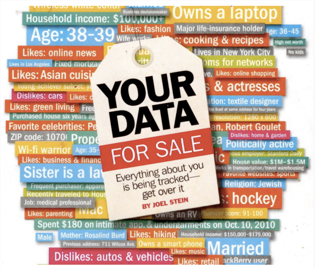

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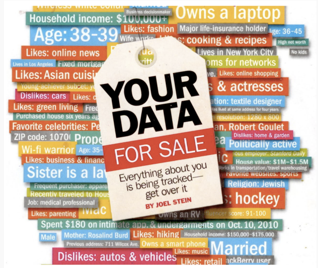

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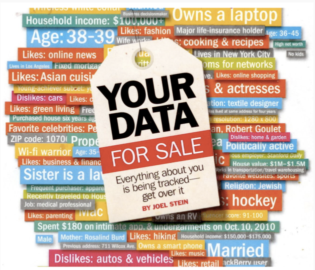

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  - Foreign interference in democratic processes
  - Physical, mental or financial harm

Personal data is protected

GDPR in Europe (2018), Privacy Act (1974) and HIPAA (1996) in the USA (as well as State laws like CCPA in California, 2020), PIPL in China (2021)

Aside: Privacy is not Security

Data privacy is distinct from data security

Data security is concerned with who can touch the data:

- **Confidentiality**: ensuring that only the appropriate people can view the data
- **Integrity**: ensuring that only the appropriate people can modify the data

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Data privacy is concerned with what can be learned from the data (i.e. its information content)

Example: Census Data

Census protect data privacy via **aggregation**

Label	United States					
	Total	Percent	Male	Percent Male	Female	Percent Female
	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Total population	334,914,896	(X)	165,729,373	(X)	169,185,523	(X)
AGE						
Under 5 years	18,333,697	5.5%	9,373,156	5.7%	8,960,541	5.3%
5 to 9 years	19,799,430	5.9%	10,136,158	6.1%	9,663,272	5.7%
10 to 14 years	21,203,879	6.3%	10,877,744	6.6%	10,326,135	6.1%
15 to 19 years	22,168,390	6.6%	11,364,472	6.9%	10,803,918	6.4%
20 to 24 years	21,618,383	6.5%	11,073,959	6.7%	10,544,424	6.2%

S0101 Age and Sex (2023: ACS 1-Year Estimates Subject Tables)

Grouping participants makes it difficult to learn something specific to any individual

Example: Violating Privacy under Aggregation

A company releases the average salary of its employees each year:

Year	Average salary
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$$\frac{\sum e_i}{58} = 73\,568 \qquad \frac{\sum e_i + B}{59} = 74\,872$$

Bob's salary: $150\,504$€ Differencing Attack!

2020 Census uses Differential Privacy!

2017: Announcement [Dajani et al., 2017]

2018: The Disclosure Avoidance System TopDown Algorithm (TDA) [Abowd, 2018].

2021–: Impact and Technical, Social, Ethical Analyses [Dwork, 2019, United States. Bureau of the Census, 2021, Gong et al., 2022, Garfinkel, 2022]

Privacy Violations that Aren't

[Reminder] An individual's privacy is violated if:

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- A study states that coffee drinkers have 100% chance of being mean to pets
- **Auxiliary information**: Joe drinks coffee
- **Conclusion**: Joe is probably mean to his pets

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Consider:
The breach happens **whether or not Joe participates in the study!**

A Revised Definition

A data analysis violates an individual's privacy if:

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In other words:

- A privacy-preserving analysis should have the same outcome, **regardless of the participation** of any particular individual

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A Series of Disclosures

Identity disclosure or attribute disclosure of individuals

- AOL Web Search Logs
- Netflix Prize
- NYC Taxi Data
- James Comey's X Account
- The Governor of Massachussetts
- GSM Mobility Trace
- Strava's Heatmap

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Auxiliary data:
biographical information (dog ownership, location)

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Auxiliary data:
Internet Movie Database (IMDb) ratings

NYC Taxi Data

- 20GB, 179M individual trips
- pickup and drop-off location and time, income, anonymized hack license number and medallion number

```
6B111958A39B24140C973B262EA9FEA5,D3B035A03C8A34DA17488129DA581EE7,
VTS,5,,2013-12-03 15:46:00,2013-12-03 16:47:00,1,3660,22.71,
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- Side concern: where was XXX dropped-off that day? Where does YYY live? Who are those that frequent place ZZZ?

NYC Taxi Data (cont'd)

Tracking Bradley Cooper and Jessica Alba

Riding with the Stars: Passenger Privacy in the NYC Taxicab Dataset, September 15, 2014 by ATOCKAR.

NYC Taxi Data (cont'd)

Bradley Cooper's Query

```
SELECT D.dropoff_latitude,
       D.dropoff_longitude,
       F.total_amount,
       F.tip_amount
FROM tripData AS D JOIN tripFare AS F
    ON D.hack_license = F.hack_license AND
       D.pickup_datetime = F.pickup_datetime
WHERE D.pickup_datetime BETWEEN "2013-07-08 19:33:00" AND
                                "2013-07-08 19:37:00"
  AND D.pickup_latitude BETWEEN 40.719 AND 40.7204
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Auxiliary data:
geo-tagged celebrity gossip photos

James Comey's X (formerly Twitter) Account

Former FBI director James Comey was behind the account of Reinhold Niebuhr

> *Goodbye Iowa. On the road home. Gotta get back to writing.*
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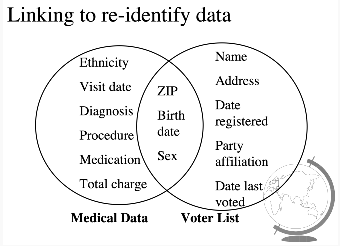
Auxiliary data:

social network (Comey's son)

Latanya Sweeney & Medical Records



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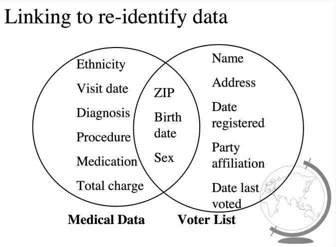

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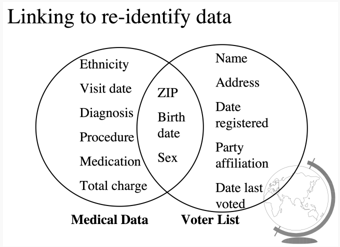

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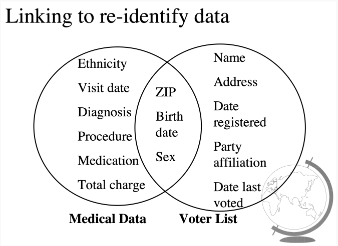

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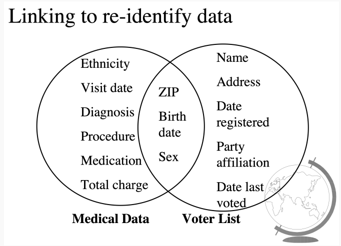

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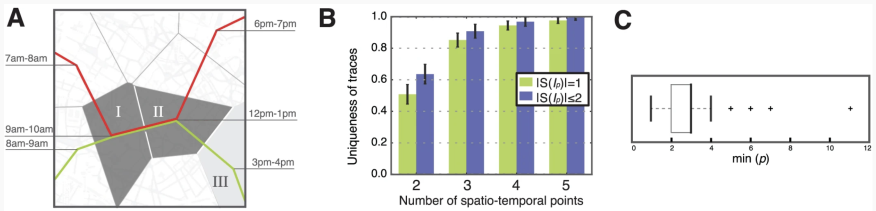
Same technique, used more than a decade later, against the Personal Genome Project [Sweeney et al., 2013] and Health Data as well [Sweeney, 2015].

GSM Mobility Trace

Back in time, 12 points uniquely identify a fingerprint [Locard, 1931]



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- 114 interactions per user per month for nearly 6 500 antennas

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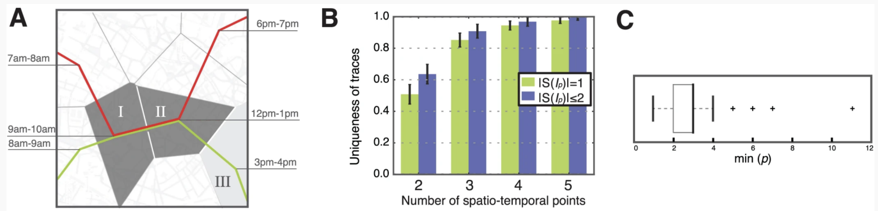

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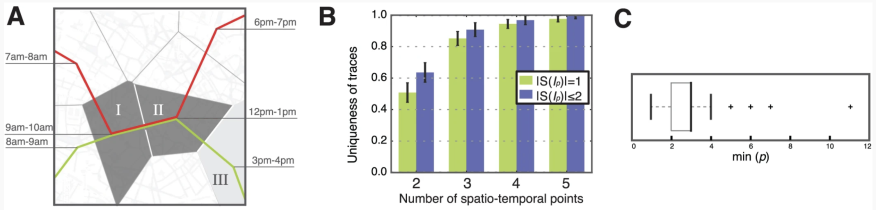

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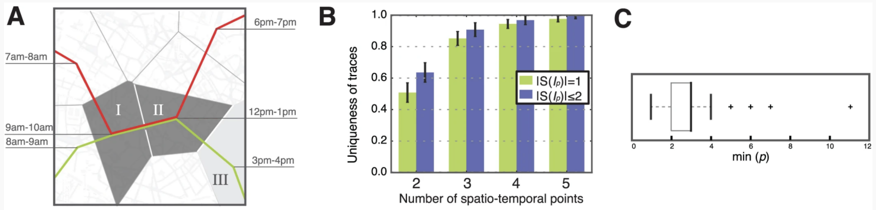

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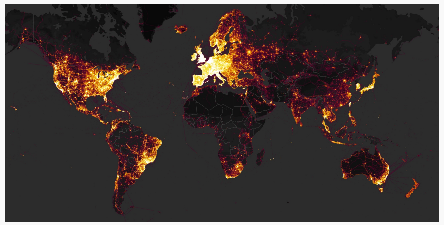
(C) At most 11 points to re-identify all users

Strava's Heatmap

13 trillion GPS points from Strava users released in 2017 as a global heatmap with local leaderboards



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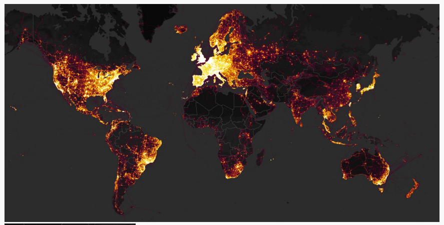

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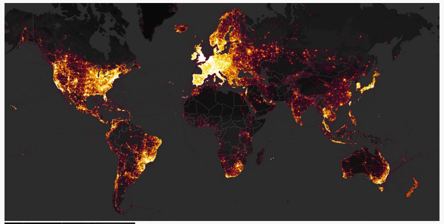

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Is this a privacy violation at all?

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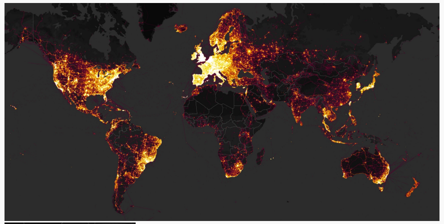

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StravaLeaks (Le Monde, 2024)

Auxiliary data:

social media posts, public profiles

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- ML models are elaborate kinds of aggregate statistics!
- As such, they are susceptible to membership inference attacks, i.e. inferring the presence of a known individual in the training set [Shokri et al., 2017][Carlini et al., 2022]

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Also, **machine learning** doesn't necessarily protect individual privacy

- ML models are elaborate kinds of aggregate statistics!
- As such, they are susceptible to membership inference attacks, i.e. inferring the presence of a known individual in the training set [Shokri et al., 2017][Carlini et al., 2022]

As a rule of thumb, **defining privacy is hard**

Principles for Protecting Privacy

- Privacy threats are counter-intuitive
- We must do something "extra" to ensure privacy
- We should define privacy carefully and precisely
- Challenge: tension between **accuracy and privacy**

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