Introduction to Digital Trace Data: Quality, ethics, and analysis

Lecture 1: Introduction

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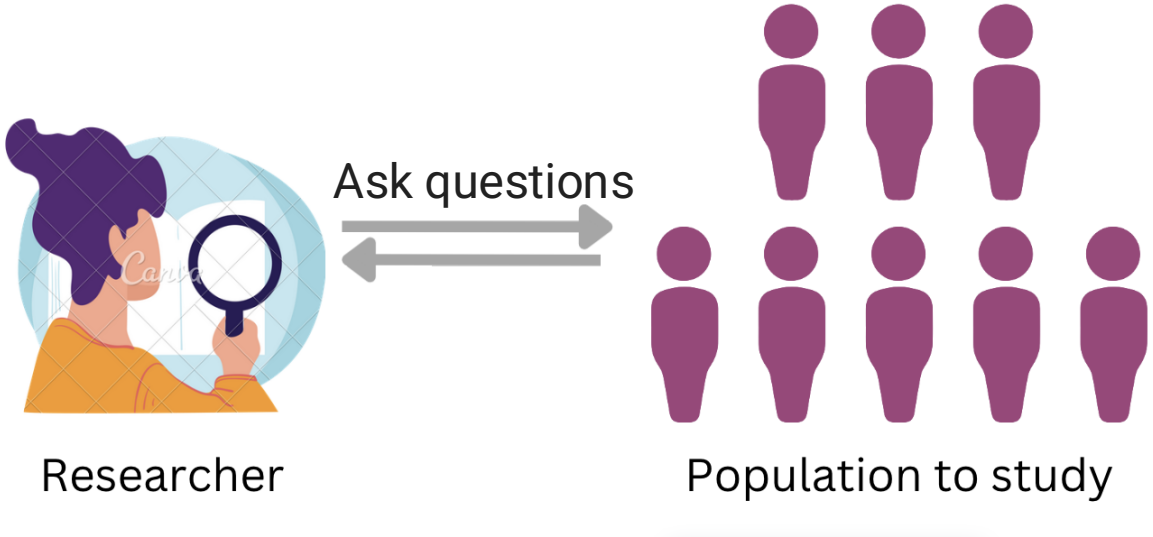
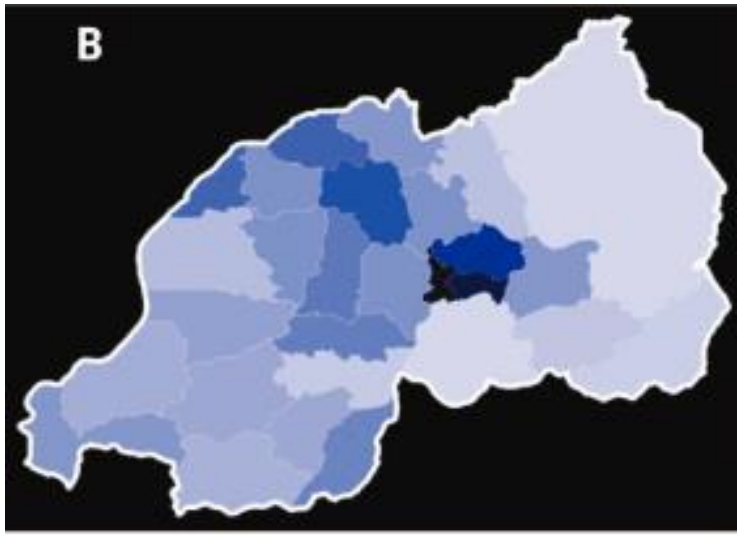
How do we understand human behavior/societies?

e.g. determining poverty in Rwanda

Our traditional approach:



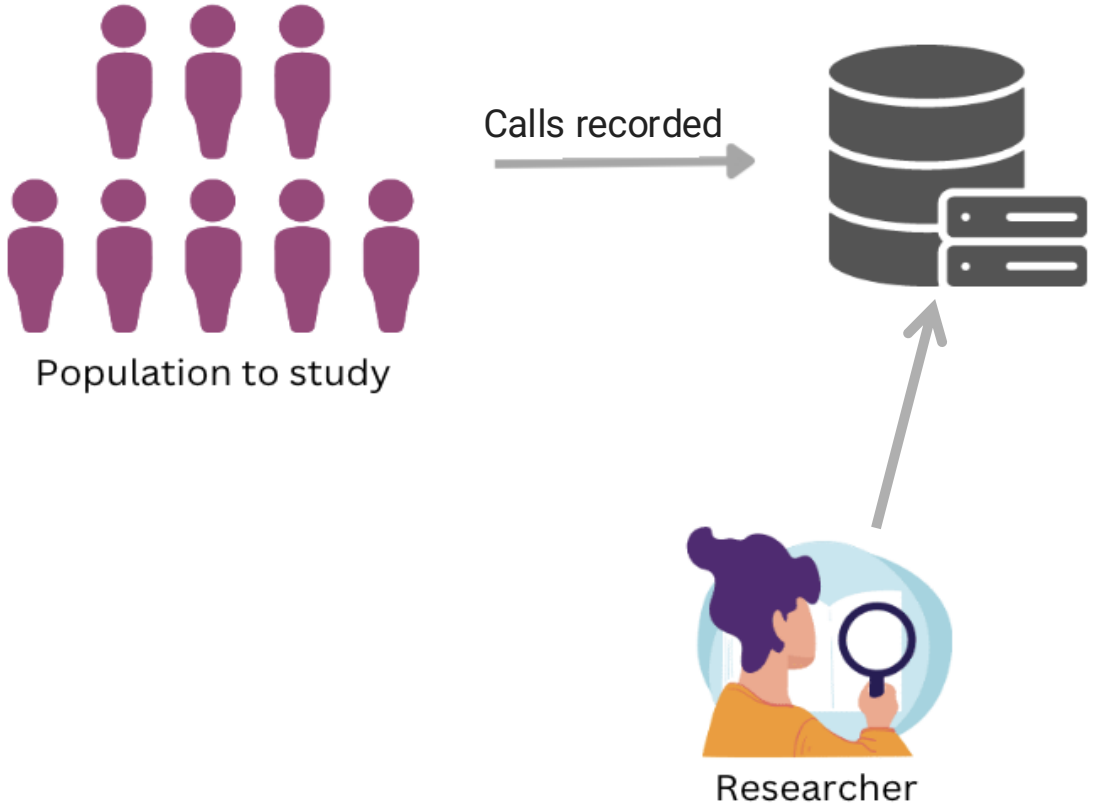


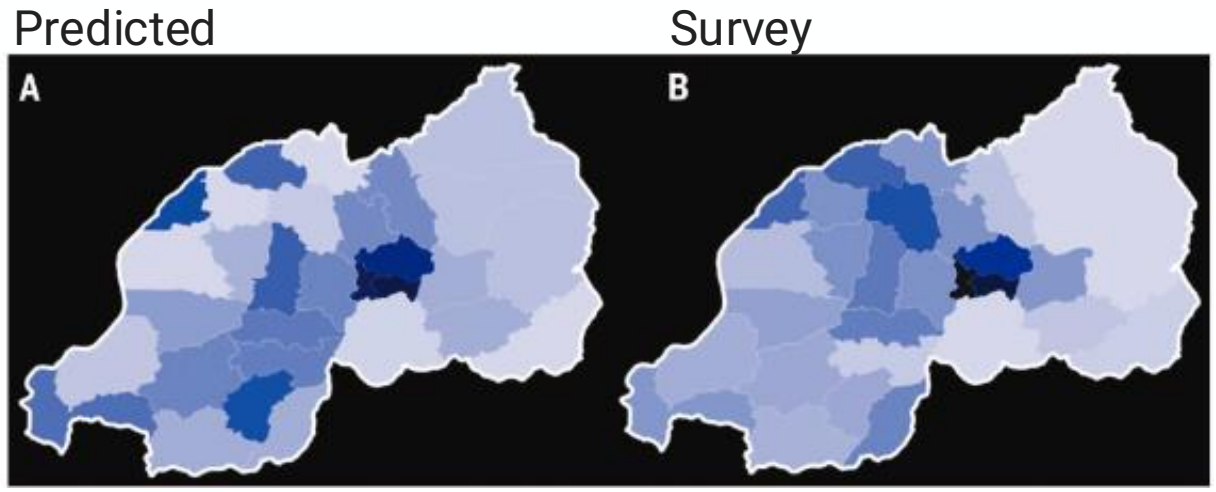
(Blumenstock et al., 2015)

How do we understand human behavior/societies?

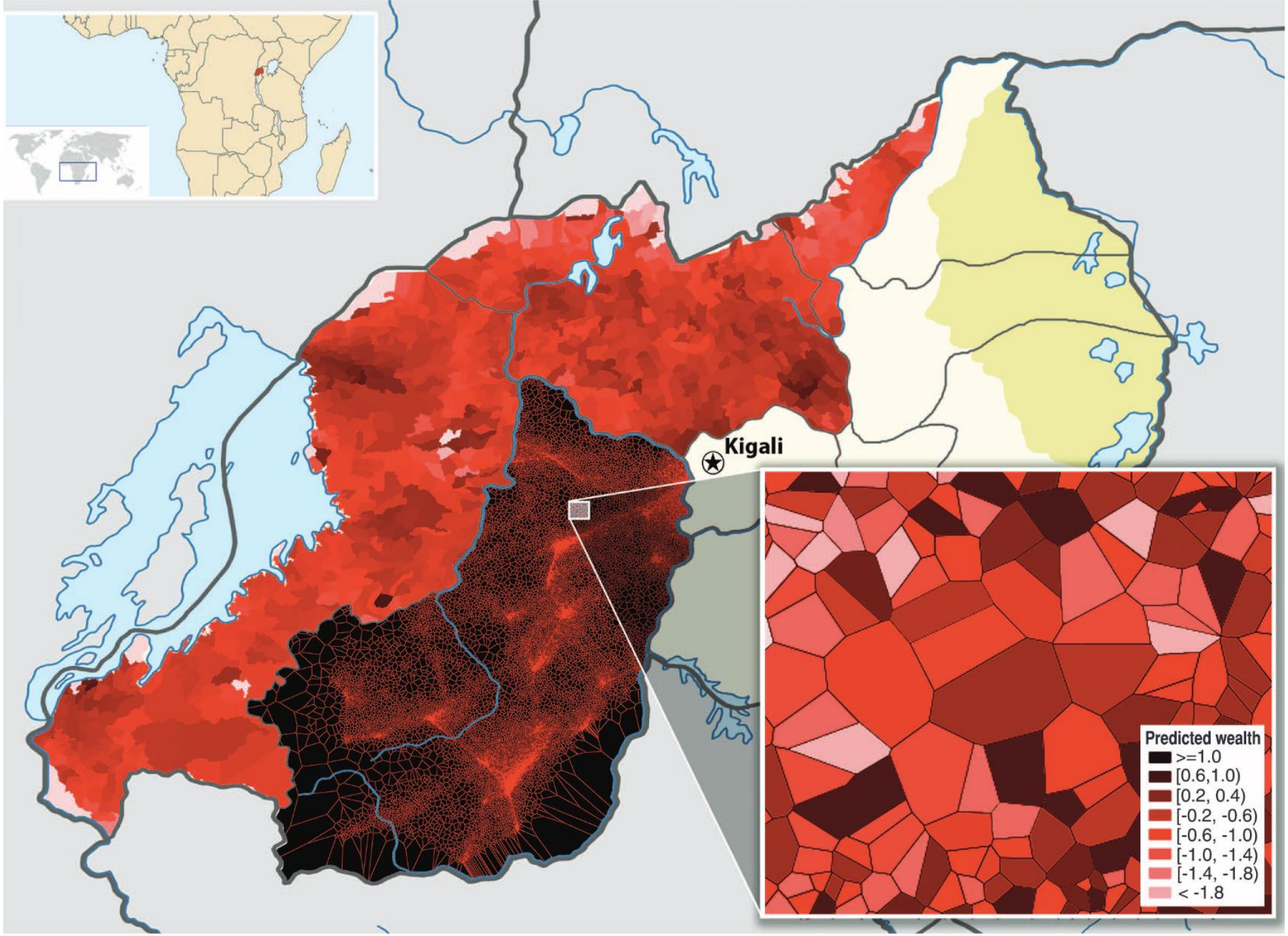
But we could also use the records of individuals' digital activities, such as phone call records.

Using Digital Trace Data:

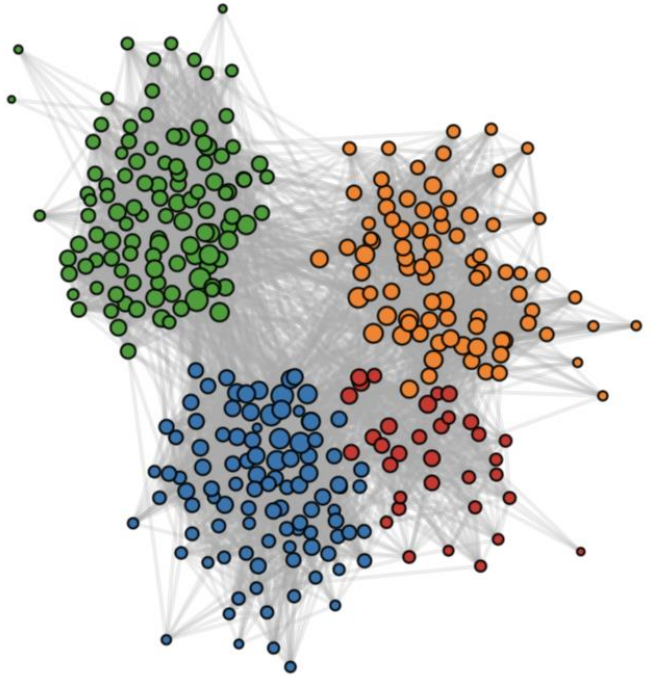




(Blumenstock et al., 2015)


Kigali
Predicted wealth
>=1.0
[0.6,1.0)
[0.2, 0.4)
[-0.2, -0.6)
[-0.6, -1.0)
[-1.0, -1.4)
[-1.4, -1.8)
< -1.8

Great power



Unprecedented level of granularity: study small groups

Cheaper than surveys

Longitudinal data (dynamics!)

New research possible: e.g. social interactions (we have bad memory)

It is non-reactive: it allows to study people “in-the-wild” (self-reported and real behaviour differ, sometimes widely).

More examples (by Chris Bail): https://www.youtube.com/watch?v=uuSWQN7uYhk

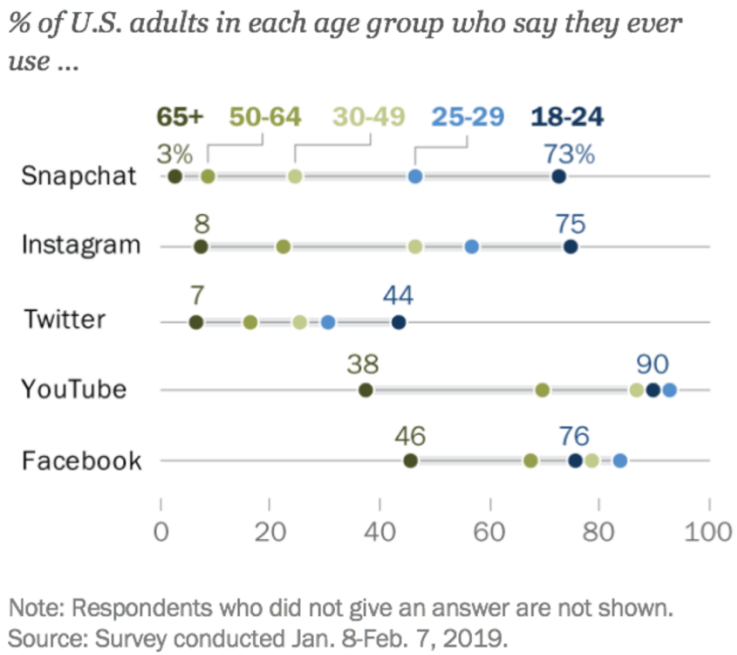
Great responsibility

Can we keep the data safe?

Is the data representative for different groups?

Are we measuring what we want to measure? How can we validate our results?

Can our analyses harm people?



Why is this important for you?

The age of surveillance capitalism

1. Data collection: Digital traces are thoroughly collected
2. Prediction products: Software uses that data to anticipate what a person likes and will do.
3. Behavioral markets: The software is used to target ads and products

Shoashana Zuboff

Understanding digital trace data will help you:

- Secure a job
- Be aware of the challenges associated with these data
- Prevent biases and reduce harm

Course set-up (digitaltracedata.github.io)

Fridays:

- Lecture: 11:00 – 12:45 (except last lecture)
- Practical: 13:15 – 15:00

Group project: deadlines:

- Oct 2nd: Written report (30% of the grade)
- Oct 25th : Final presentation (30% of the grade)

Feedback sessions: Wednesdays (Sep. 18th and 25th, Oct 16th and 23th)

Exam (Nov 1st) :

- 40% of the grade: mix of multiple choice and open questions

Instructors

Laura
Boeschoten

Javier
Garcia-Bernardo

Thijs
Carrière

What would you expect/like to learn in this course?

app.wooclap.com/DTD24

Course overview

Week	Date	Content
1	**Sep 9 (Fr)**	**Lecture/lab: Introduction to digital trace data**
1	**Sep 9 (Fr)**	**Group project starts**
2	Sep 13 (Fr)	Lecture/lab: User-centric approaches to DTD
3	Sep 18 (We)	*Group project feedback I*
3	Sep 20 (Fr)	Lecture/lab: Platform-centric approaches to DTD
4	Sep 25 (We)	*Group project feedback II*
4	Sep 27 (Fr)	Lecture/lab: Errors in DTD collection
5	*Oct 2 (We)*	*Deadline group project*
5	Oct 4 (Fr)	Lecture/lab: The role of AI in DTD
6	Oct 11 (Fr)	Lecture/lab: Ethics and Legislation
7	Oct 16 (We)	*Group project feedback III*
7	Oct 18 (Fr)	Lecture/lab: Designed big data
8	Oct 23 (We)	*Group project feedback IV*
8	Oct 25 (Fr)	*Deadline: Group presentation*
9	Oct 30 (We)	Final recap and Q&A
9	Nov 1 (Fr)	Final exam

TODAY

Lecture

Explain what is Digital Trace Data (DTD)

Understand the main advantages and disadvantages of DTD

Distinguish user and platform-centric approaches to study DTD

Lab

Learn the difference between different types of data formats

Hands-on experience with unstructured data from Twitter

Explore a data analysis workflow

What is Digital Trace Data?

Digital Trace Data (DTD)

"Records of activity (trace data) undertaken through an online information system (thus, digital)." — Howison et al., 2011

Very diverse, but key characteristics:

- Digital traces: Interactions with technology (online information system).
- Contains events – i.e., interactions with the information system is recorded.
- Ready-made data: The data is a byproduct of people's everyday actions, rather than produced for research. However, they are "designed" by someone for some other goal (often, profit-driven).

What are examples of DTD?

Social media posts

Web browsing history

GPS location data

Online purchase records

Email metadata

Mobile app usage logs

Mobile calls

Digital payment transactions

Cryptocurrency transactions

Fitness tracker data

Wi-Fi connection history

…

app.wooclap.com/DTD24

What do we need to study DTD?

1. Understand the potential and the challenges associated with DTD

- The focus of this course

2. Data Science skills

- Not the focus of this course
- Strong programming skills help: the Applied Data Science minor

Characteristics of Digital Trace Data

Based on Bit by Bit book (Salganik)

1. DTD is readymade data

David (Michelangelo)
Data generated to answer a RQ

Bull's Head (Pablo Picasso)
Data repurposed to answer a RQ

- Custom-made
  - Experiment — Answer RQ by changing the environment
  - Asking/observing — Answer RQ by asking questions or observing behavior
- Ready-made
  - Administrative — Collected by governments to keep the country running.
  - Other (including DTD) — Collected for a variety or reasons, mostly operational or profit-driven.

Readymade data is particularly affected by errors

Two main errors in DTD (more on this on week 4):

a. Measurement: i.e., does the data measure what you want it to measure?

DTD allows us to study phenomena that is very difficult to study otherwise:

- Concepts that are very difficult to study in other ways (e.g. social networks)
- Subpopulations that are difficult to track otherwise (e.g., conspiracies)

Example: we are interested in social networks.

- Are phone calls a good way to measure social networks?
- How to test this? → Validation, does our data match (aggregated) estimates?

b. Representation: i.e., is it biased towards specific subpopulations?

(later)

Exercise (in pairs)

Think about what type of DTD you could use to answer the following questions:

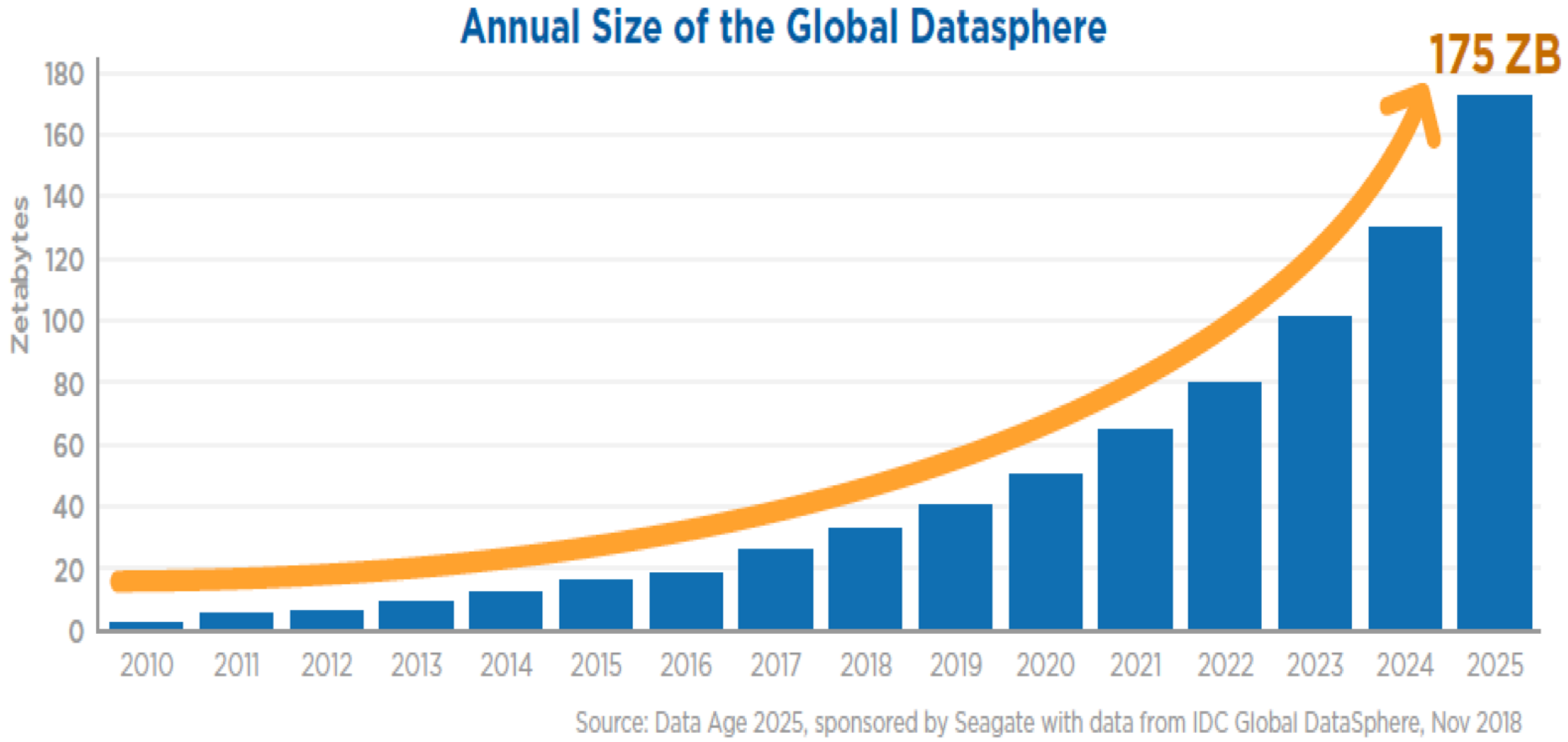
- How do social media influencers affect consumption of fake news?
- How did COVID-19 affect mobility patterns? (i.e., whether people travelled more/less to work, parks, do groceries, see friends)
- How do your friends and acquaintances affect job opportunities?
- Is exercise contagious? (if your friends exercise, do you start exercising?)

For one of the dataset, answer these questions:

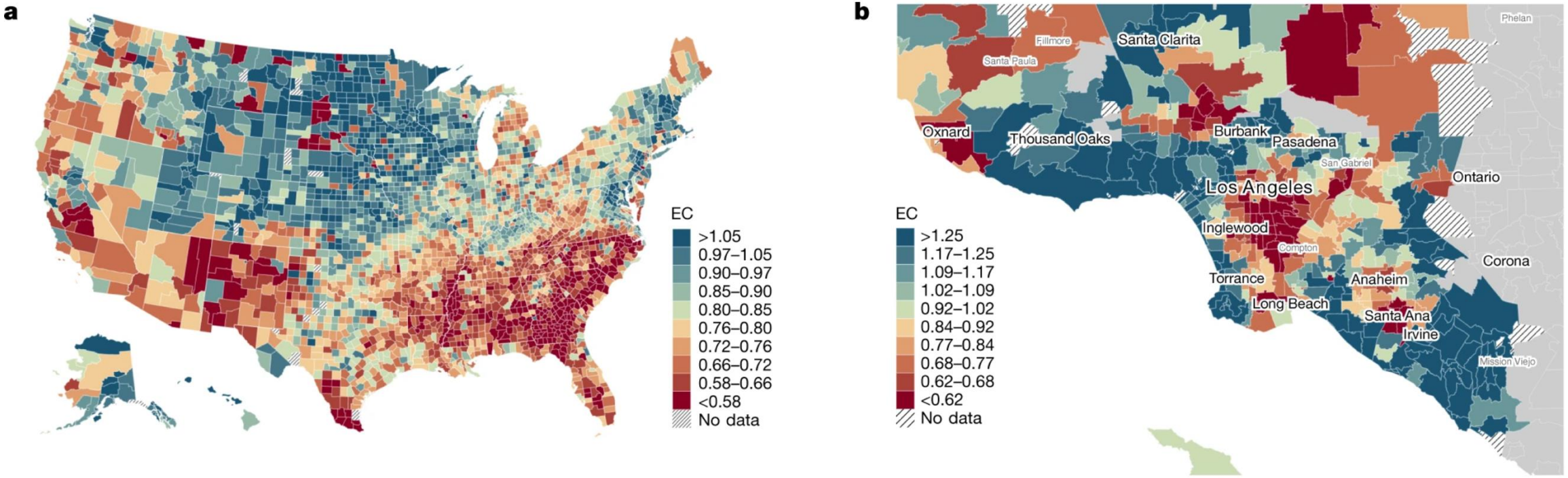
- What was the original purpose of that data?
- How would you measure your dependent/independent variables?
- Do you expect measurement error?

2. DTD is often large

2024: Equivalent of ~30 laptops full of data per person in the planet!

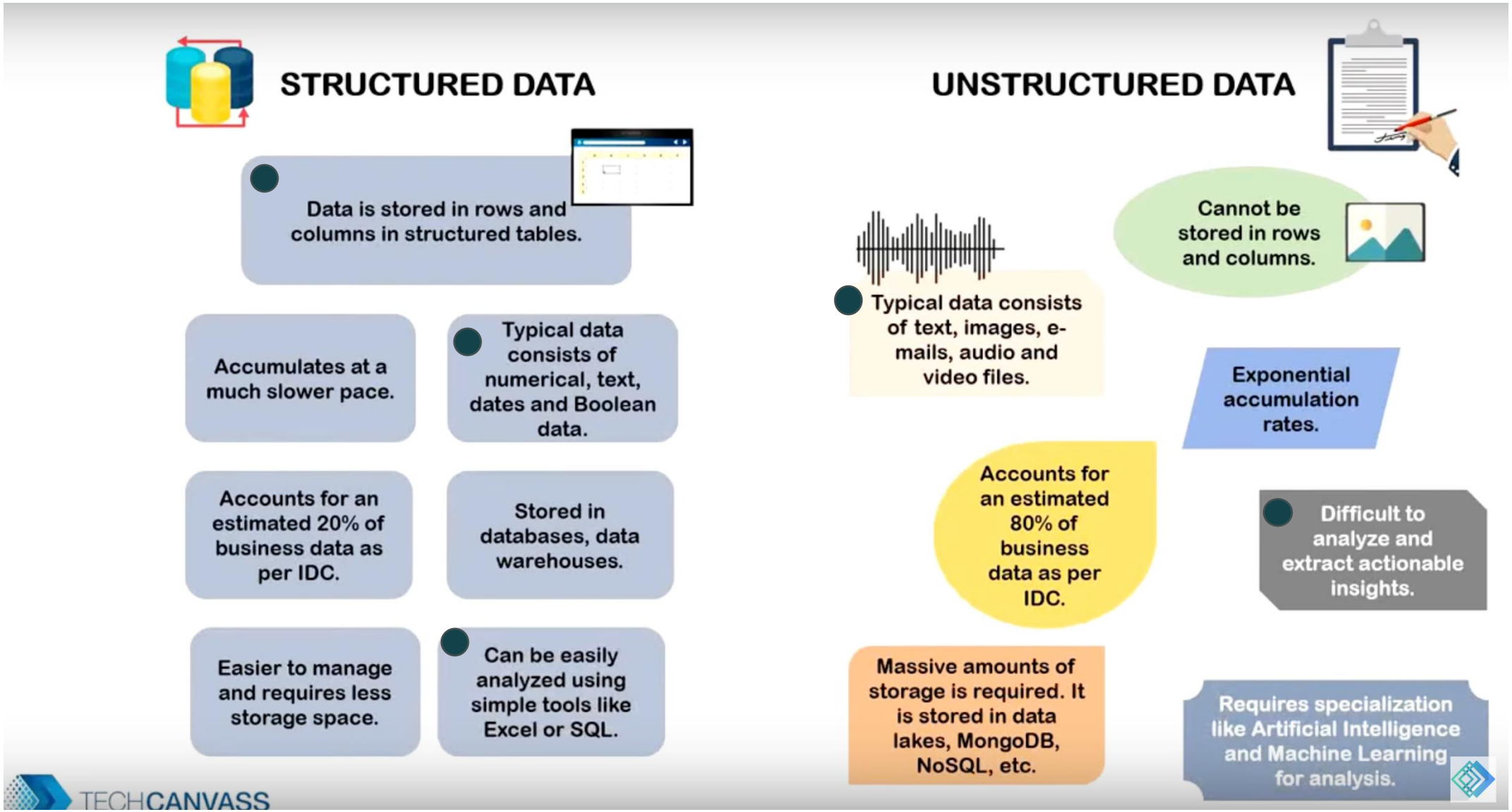


Big data allow us to study small subpopulations



Social capital I: measurement and associations with economic mobility
Chetty et al, 2022

Large/big data is often unstructured



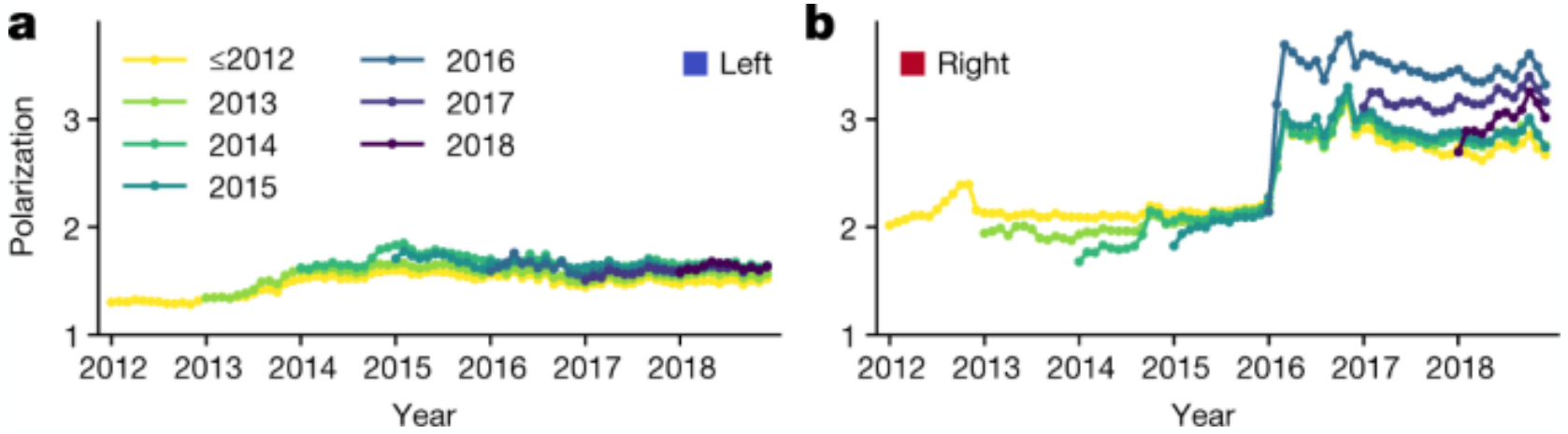
3. DTD is always-on

Systems are constantly collecting data (they are always-on)

Advantages:

- Provide real-time estimates
- Allows to travel back in time (historical data)

Google COVID-19 Community Mobility Reports



Quantifying social organization and political polarization in online platforms
Waller and Anderson, 2021, Nature

4. Incomplete and non-representative

Two main errors in DTD (more on this on week 4):

a. Measurement: i.e., does it measure what you want it to measure?

b. Representation: i.e., is it biased towards specific subpopulations?

You are studying political polarization around the 2016 US election studying political tweets. You find large polarization. Why could this be the case?

How to deal with this issue?

→ Combining DTD with (aggregated) sources to understand/correct the biases

→ Studying within-person phenomena (e.g. do individuals polarize? vs. does society polarize?). This works if those phenomena are expected to be ~universal

5. DTD data is drifting

i.e., the measurement and representation can change over time.

Example: you find out that mobile calls are a great measurement of wealth (Blumenstock et al., 2015)

Measurement drift:

But as mobile internet becomes cheaper, people increasingly rely on Internet calls (e.g. via WhatsApp). Our measurement of wealth may have changed!

Representation drift:

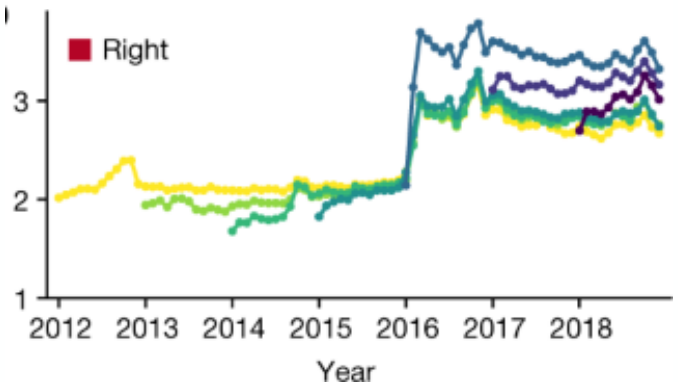
And our data may not be representative anymore, as younger people may not call

Another example: polarization changed in Reddit because the new user inflow

How to deal with this issue?

→ Keep validating the results

Waller and Anderson, 2021, Nature



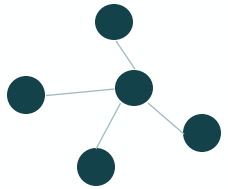
15 min break

6. Algorithmically confounded

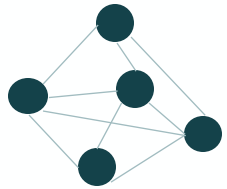
We may be interested in understanding how being part of a tight-knit community (social closure) affects wellbeing.

You cannot study this easily with surveys, so you decide to use Facebook data.

You decide to study social closure using the “clustering coefficient”. This coefficient is the probability that two of your friends are also friends themselves.



Low clustering



High clustering

What may have happened?

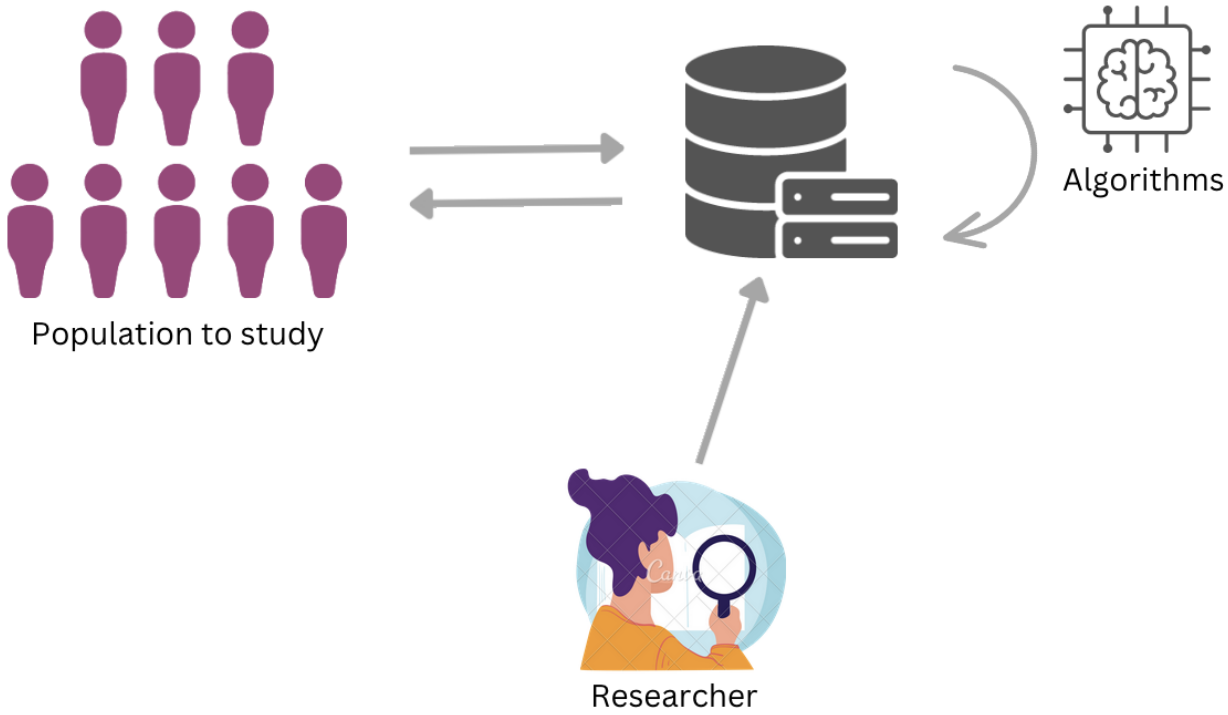
What type of error is this? (measurement/representation)

You find that the clustering coefficient is 14%, which is five times greater than expected (Ugander et al, 2011)

Algorithms can cause measurement error

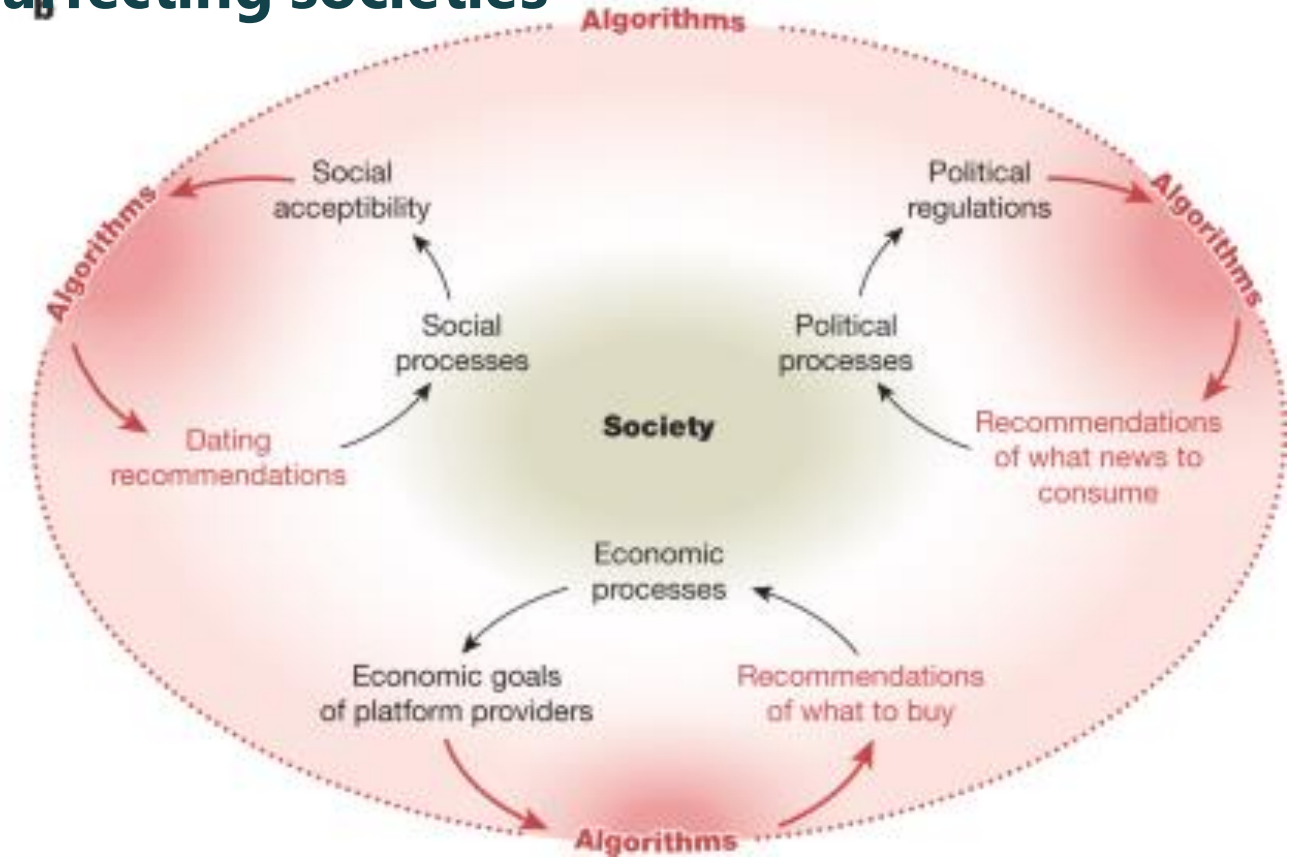
Facebook uses the “clustering coefficient” to recommend friends: e.g., if you have two friends, Sanne and Joep, that are not Facebook friends, Facebook will suggest Sanne and Joep to add each other as friends.

Your measurement of social closure (clustering coefficient) is measuring *both* social closure and the effect of the algorithm.



Algorithms create feedback effects, affecting societies

Sanne and Joep may become friends in real life.
Algorithms affect the world!



Measuring algorithmically infused societies
Wagner et al, 2021, Nature

Also:

- Who to hire – CV screening
- Who to promote – performance reviews
- Who to jail – predictive policing
- Who to kill – “we kill people based on metadata”

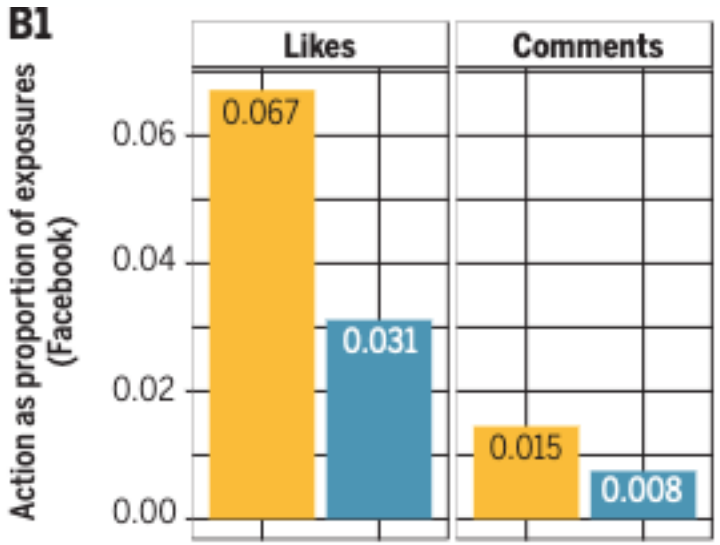
But what are the algorithms trying to optimize? Who profits?
e.g. Facebook knew its products damage teenagers’mental health, foment ethnic violence are allow misinformation to spread. But accepted those consequences as part of its business model (Frances Haugen scandal, 2021).

Exercise (in pairs)

You want to study how people consume news (i.e., given a set of news articles, which one do they choose to read).

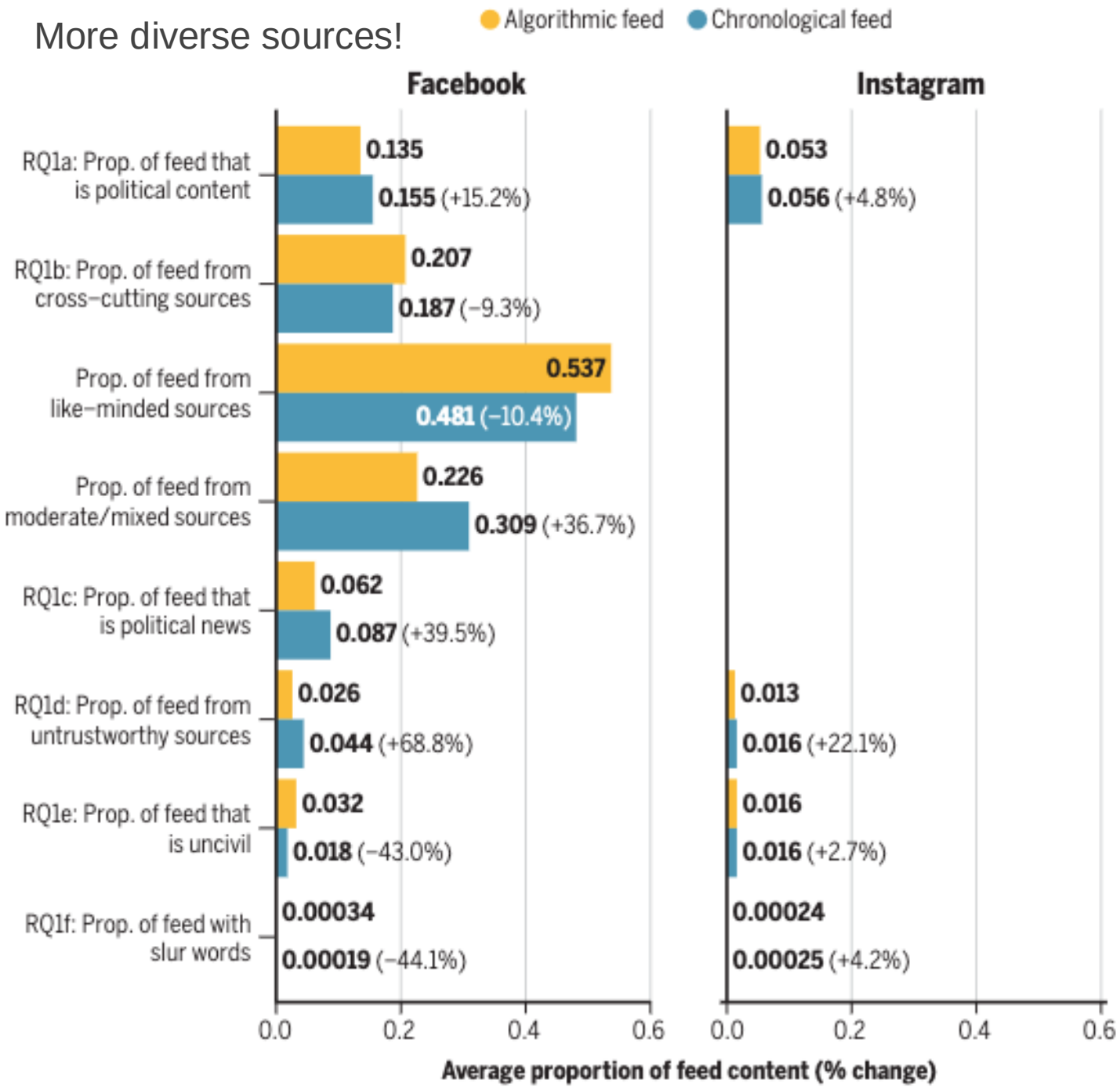
You have a friend at Facebook, and they give you access to Facebook data.

- How do you think Facebook's algorithm, which decides what people see in their feeds, affect news consumption? e.g., does it show users mostly posts from like-minded newspapers?
- What is the incentive for Facebook to show you certain news articles?
- What would happen if we saw posts in chronological order (instead of the order chosen by the algorithm)?



People less engaged!

More diverse sources!



How do social media feed algorithms affect attitudes and behavior in an election campaign?
Guess et al., 2023, Science

7. Dirty

DTD comes in a wide variety of formats

It contains many artifacts:

- Algorithmic effects
- Bots
- Organized groups (e.g. hackers)

8. Sensitive

What do your digital traces reflects about you?

- Age, gender, income, political and sexual preferences, beliefs, taste, addictions, traumas, location

Two risks:

- **Individual privacy:** Protecting personal data
  - DTD reveal intimate details about a person's preferences/behavior/location
  - Main risk: Personal identity leaked
- **Group privacy:** Protecting the interests of a collective
  - DTD reveal information on groups
  - Example: mobile call data show that refugees tend to call each other and foreign countries
  - Main risk: Unfair treatment of individuals for (allegedly) being part of a group – e.g., identification as a refugee

(more on this on weeks 5—7)

Exercise (in pairs)

Before you thought about which type of DTD you could use to answer the following questions:

- How do social media influencers affect misinformation consumption?
- How did COVID-19 affect mobility patterns (where people traveled to, such as work, parks, groceries, friends)?
- How do your friends affect job opportunities?
- Is exercise contagious? (if your friends exercise, do you also exercise)

Now discuss:

- Is the data you choose readily available?
- Is the data representative of the population you would like to study?
- Is the data sensitive? (i.e., what harm could be expected if the data is leaked, or if you identify specific groups)
- How could you guarantee individual privacy?

9. Inaccessible

DTD data is crucial to understand 21st century societies, especially the role of algorithms.

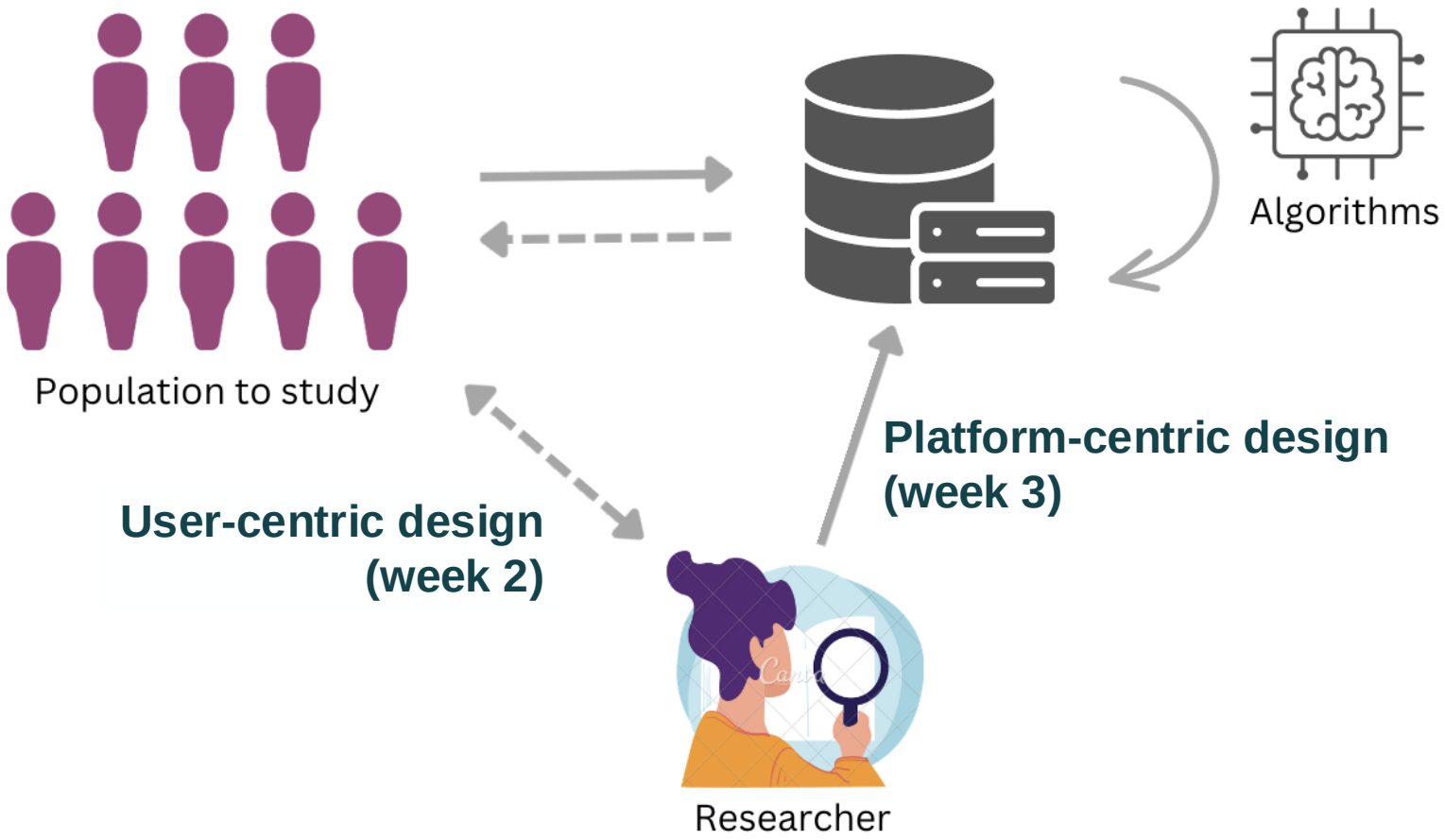
DTD is held (mostly) by companies and governments.

Sharing that data is difficult: legal, ethical and business barriers

How to access the data:

- **User-centric approaches:** Rely on the users to collect the data
- **Platform-centric approaches:** Use the information that platforms provide

Digital Trace Data Collection


Algorithms
Population to study
Platform-centric design
(week 3)
User-centric design
(week 2)
Researcher

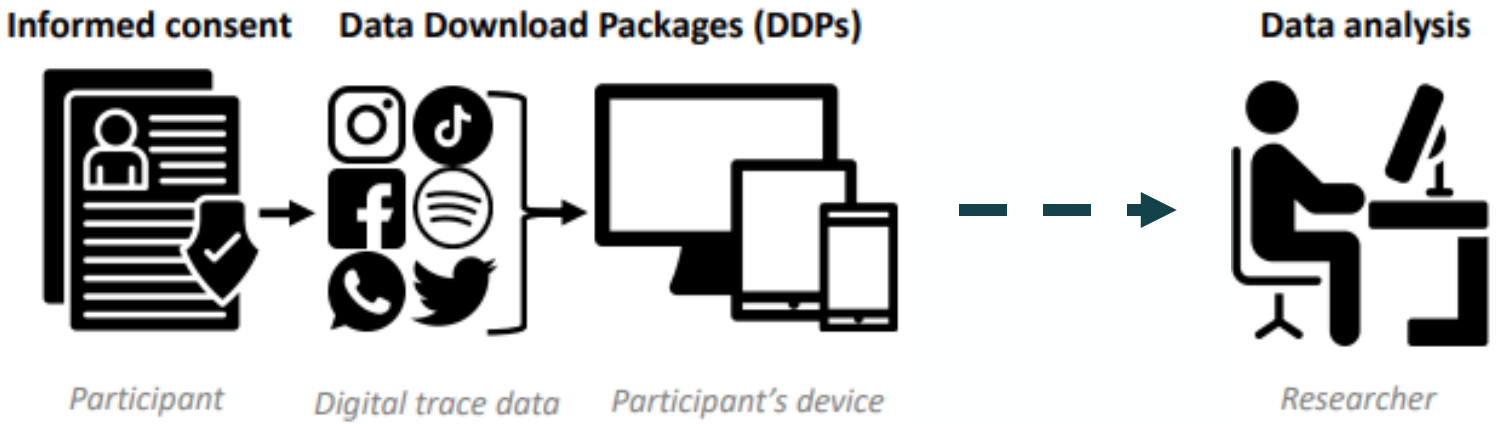
User-centric design

Tracking with wearables, apps and sensors

- E.g. data from browsers plugins, collecting data on how people interact with social media

Data donation:

- Ask people to donate their DTD. It takes advantage of the *right of access* by the data subject and *right to data portability (*General Data Protection Regulation (GDPR)).
- Researchers receive the data the platform has collected on people in (semi)structured, commonly used, and machine-readable format ("Data Download Package"; DDP).



Boeschoten et al. (2023)

Platform-centric design

Collaboration with the organization holding the data

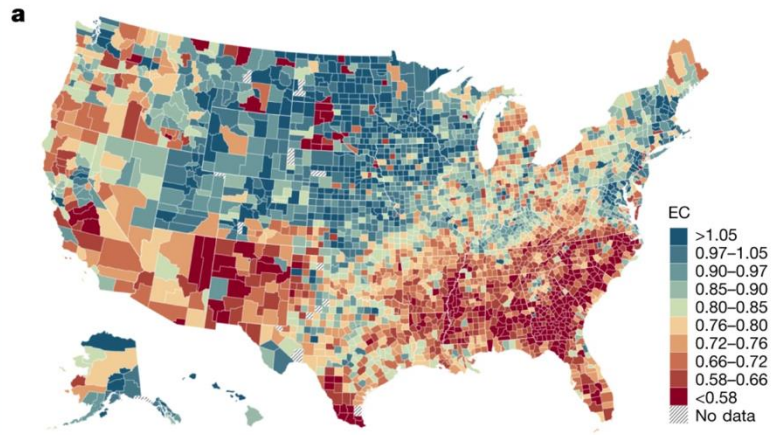
- The organization provides the data

APIs (Application Programming Interfaces)

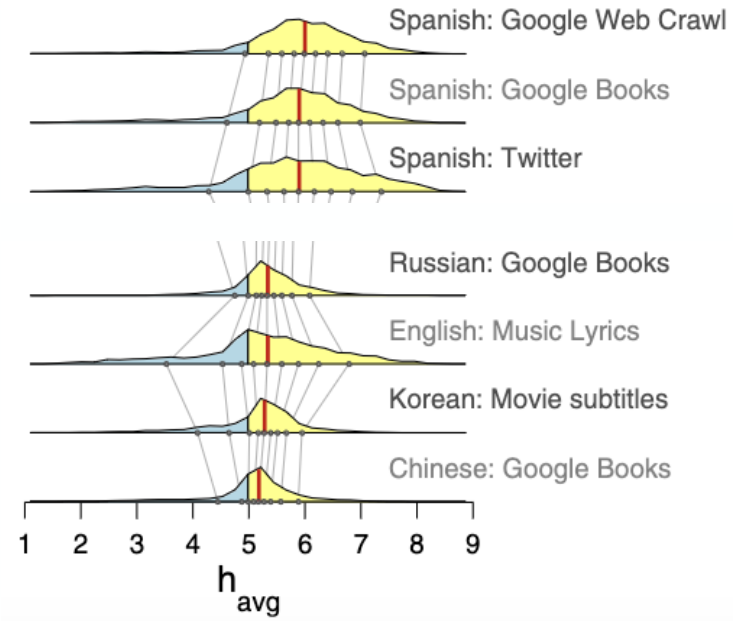
- The organization provide direct access to (parts) of the data.

Web-Scraping

- Downloads the information shown in website



Chetty et al, 2022, Nature



Dodds et al., 2015, PNAS

	API Data	Data Donations	Tracking
User- vs. platform centrality	Platform	User	User
Definition	Official data pipelines that offer different data types depending on the platform	Donation of existing digital traces with informed consent	Client-side tracking software that is installed with informed consent
Time frame of collected data	Retrospective	Retrospective (collects existing digital trace data)	Prospective (tracks digital traces as they are produced)
Consent of participants	No	Yes	Yes
Type of user involvement	None	Donate existing data to science	Generate data for science
Potential for reactivity/ social desirability biases	Low	Low	Medium to high
Reliance on third-party platform	High	Medium	Low to Medium (No, if researcher-developed)
Transparency to review DTD by user	Low	High	Medium
Level of gathered content	(Mostly) Aggregate-level data	Individual-level data	Individual-level data
Types of data	Includes published and public data from digital platforms	Includes non- or semi-public user data and data not visible to user (e.g., profiling, etc.)	Includes (mostly nonpublic) behavioral sequence data (e.g., click streams, screenshots, etc.)
Measurement unit	User Content	Account	Device
Predictability of content included in collected data	High	Medium	Low
Privacy risks in the collection of personally identifiable information	Medium to high	High	Very high
Examples	Twitter Academic API, Crowdtangle (for Facebook and Instagram)	OSD2F, PORT, Webhistorian, PIEGraph	Screenomics-App, ScreenLife-App Commercial companies such as Netquest and Comscore

Ohme et al, 2024, Communication Methods and Measures

Exercise (in pairs)

You want to study how people consume news (i.e., given a series of news articles, which one they choose to read).

You do not have a friend working at Facebook and are *not* able to access Facebook data directly to study news consumption.

How would you study this using:

- A user-centric approach?
- A platform-centric approach?

Think also about:

- Can the analysis be (easily) replicated by other researchers?
- Is your approach easy?
- Is your approach compliant with regulations?

Summary

Main take away message

Advantages of DTD

Disadvantages of DTD

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TODAY

Lecture

Explain what is Digital Trace Data (DTD)

Understand the main advantages and disadvantages of DTD

Distinguish user and platform-centric approaches to study DTD

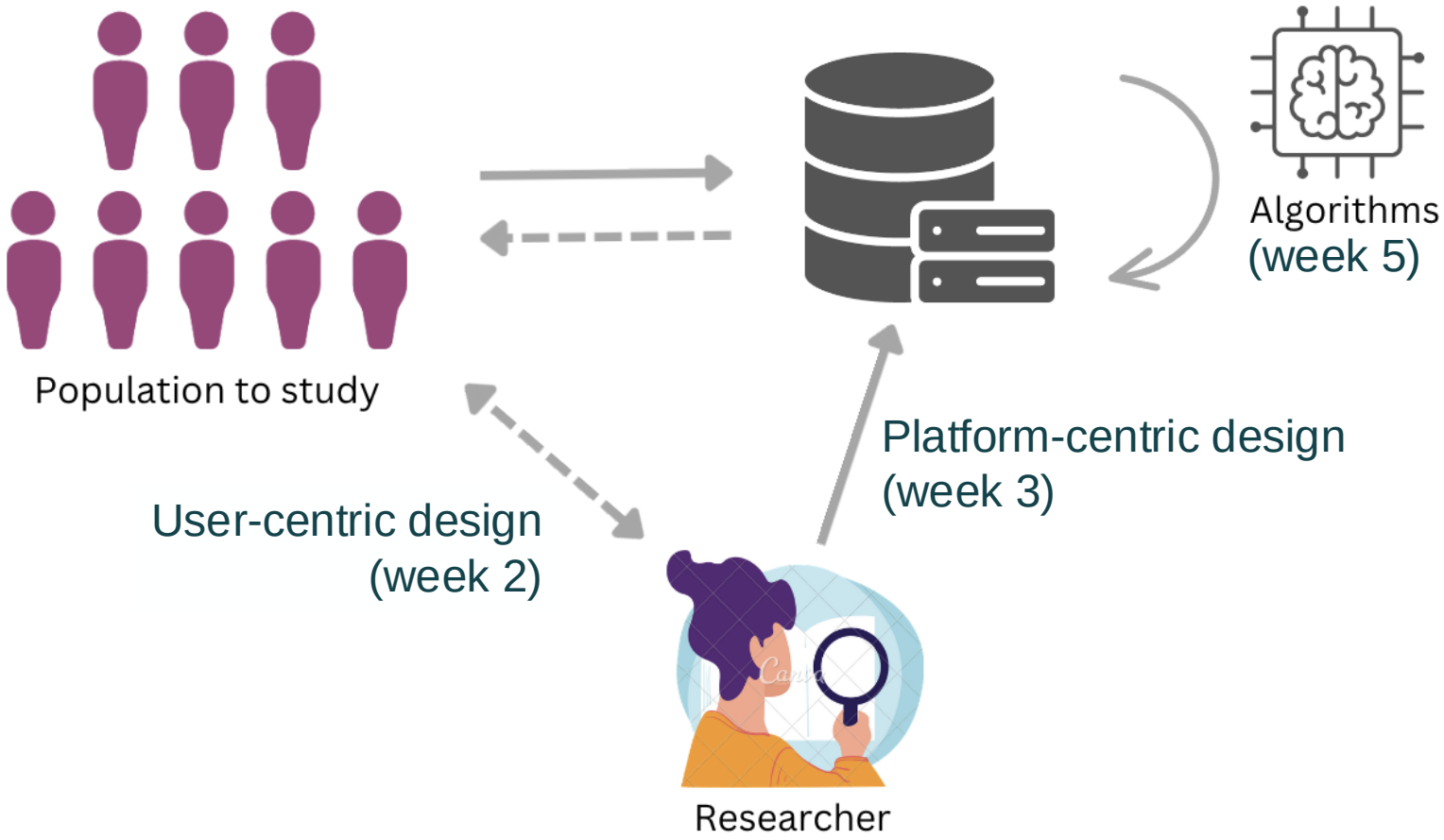
Lab

Learn the difference between different types of data formats

Hands-on experience with unstructured data from Twitter

Explore a data analysis workflow

Summary of the course



Week 4: Errors in DTD
Week 6: Ethics and Legislation
Week 7: Designed big data
Week 8: Beyond DTD and Q&A

See you after lunch!