Data, Politics and Society

W2 – Data II: The Bad

UCL

Where we at?

W1
W2
W3

Data: The Good, The Bad, The Ugly

W4
W5

Societal and environmental impacts of data and technology

The Bad

Today

- New sources of data
- Different sources of bias
- Some notes on epistemology

Data

Kitchen 2014:

“Data are commonly understood to be the raw material produced by abstracting the world into categories, measures and other representational forms – numbers, characters, symbols, images, sounds, electromagnetic waves, bits – that constitute the building blocks from which information and knowledge are created.” (p.2)

Data

Kitchen 2014:

”Data then are a key resource in the modern world. Yet, given their utility and value, and the amount of effort and resources devoted to producing and analysing them, it is remarkable how little conceptual attention has been paid to data in and of themselves.” (p.2)

Data

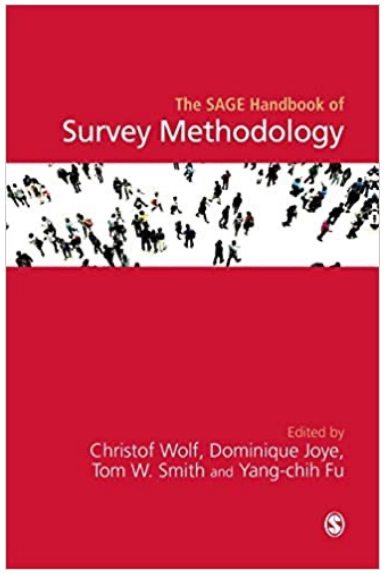
Traditionally, data sets in geography and the social sciences:

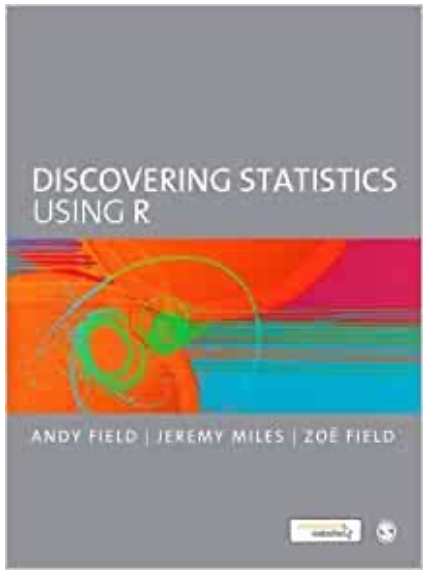
- … are collected for a specific purpose, following a careful study and design
- … contain very detailed information on a particular topic
- … are of high quality and of known provenance

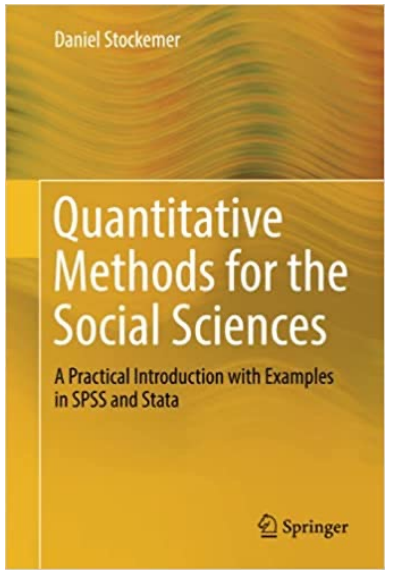
Data


Lior Gideon Editor
Handbook of Survey Methodology for the Social Sciences
Springer


The SAGE Handbook of
Social Research Methods
Edited by
Pertti Alasuutari
Leonard Bickman
Julia Brannen


The SAGE Handbook of
Survey Methodology
Edited by
Christof Wolf, Dominique Joye,
Tom W. Smith and Yang-chih Fu


DISCOVERING STATISTICS
USING R
ANDY FIELD | JEREMY MILES | ZOË FIELD


Daniel Stockemer
Quantitative Methods for the Social Sciences
A Practical Introduction with Examples in SPSS and Stata
Springer

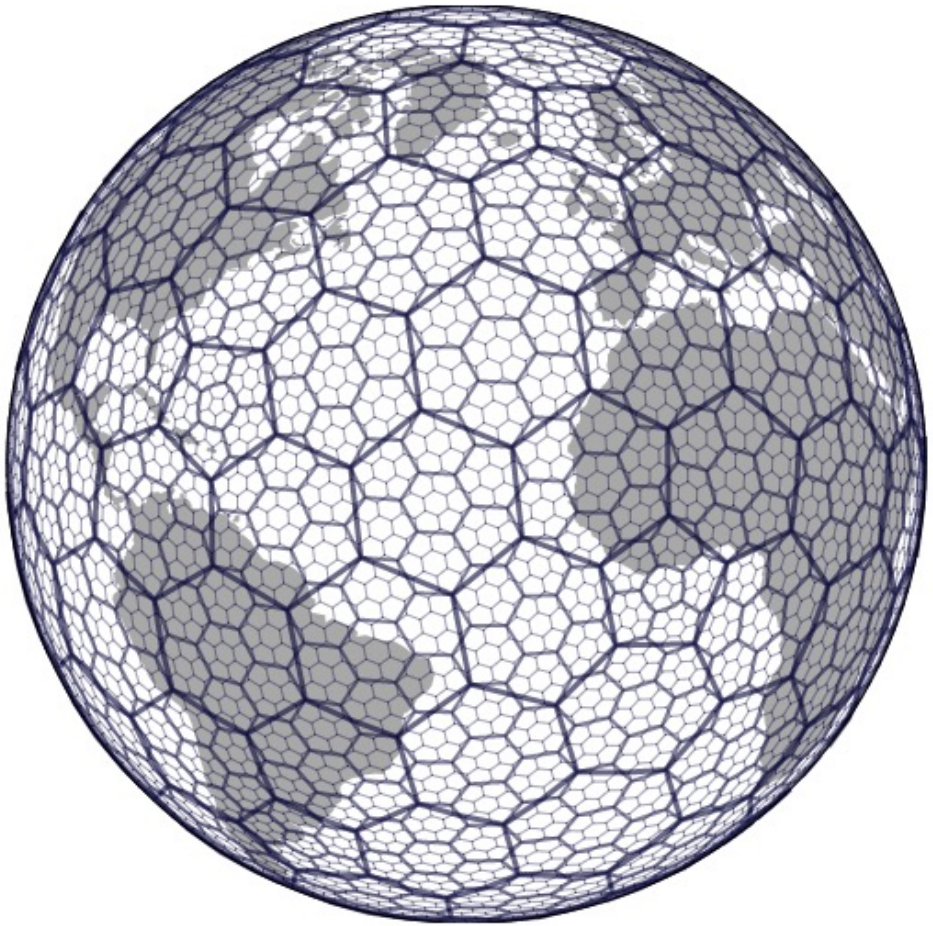
GIS data models

Traditionally, geographic information is represented in two ways:

vector a finite set of geometric objects

raster images representing a surface (values, colours)

Vector



Uber. 2018. *H3: Uber's Hexagonal Hierarchical Spatial Index*. [online] https://eng.uber.com/h3/

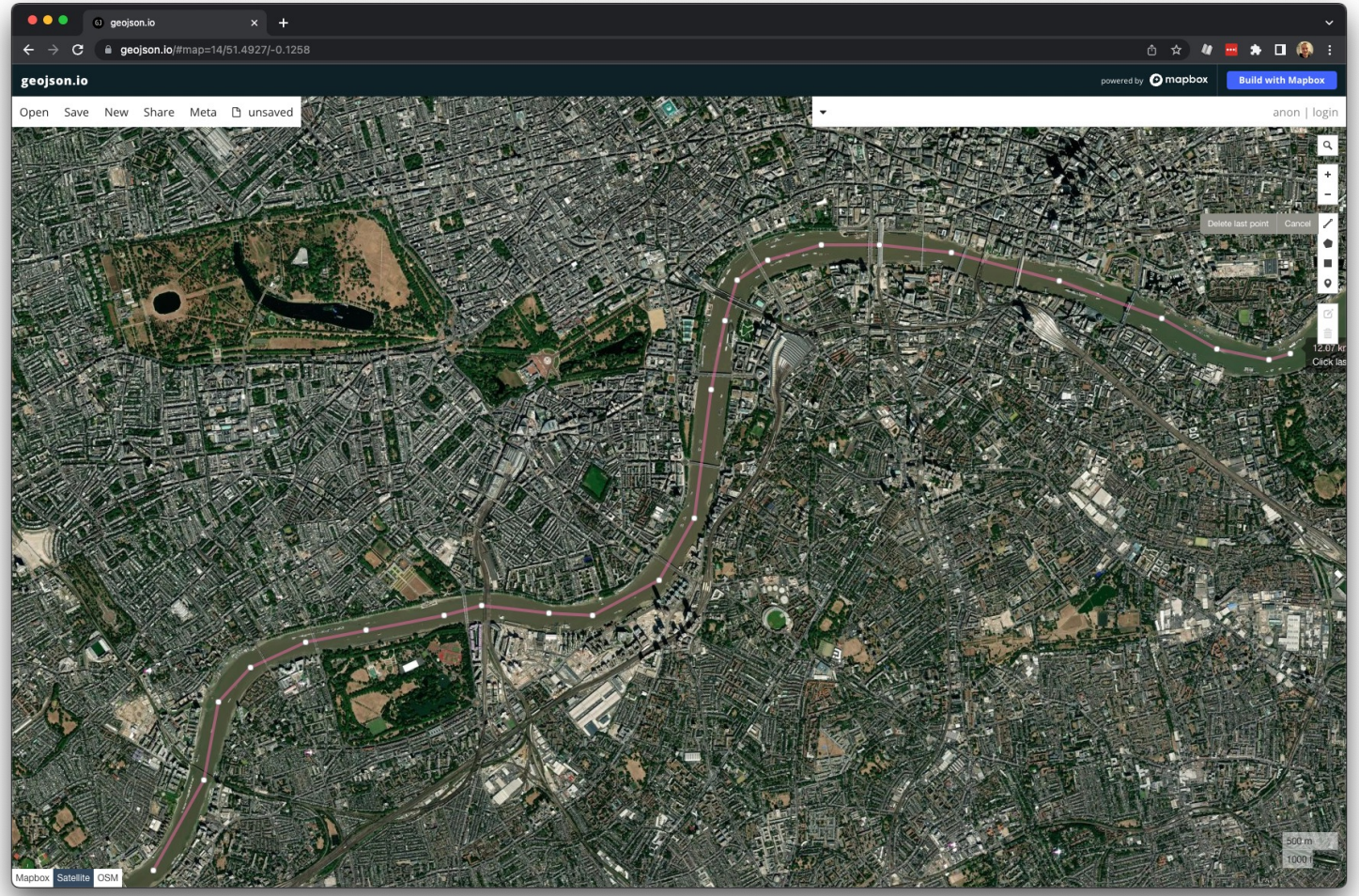
Vector

Raster

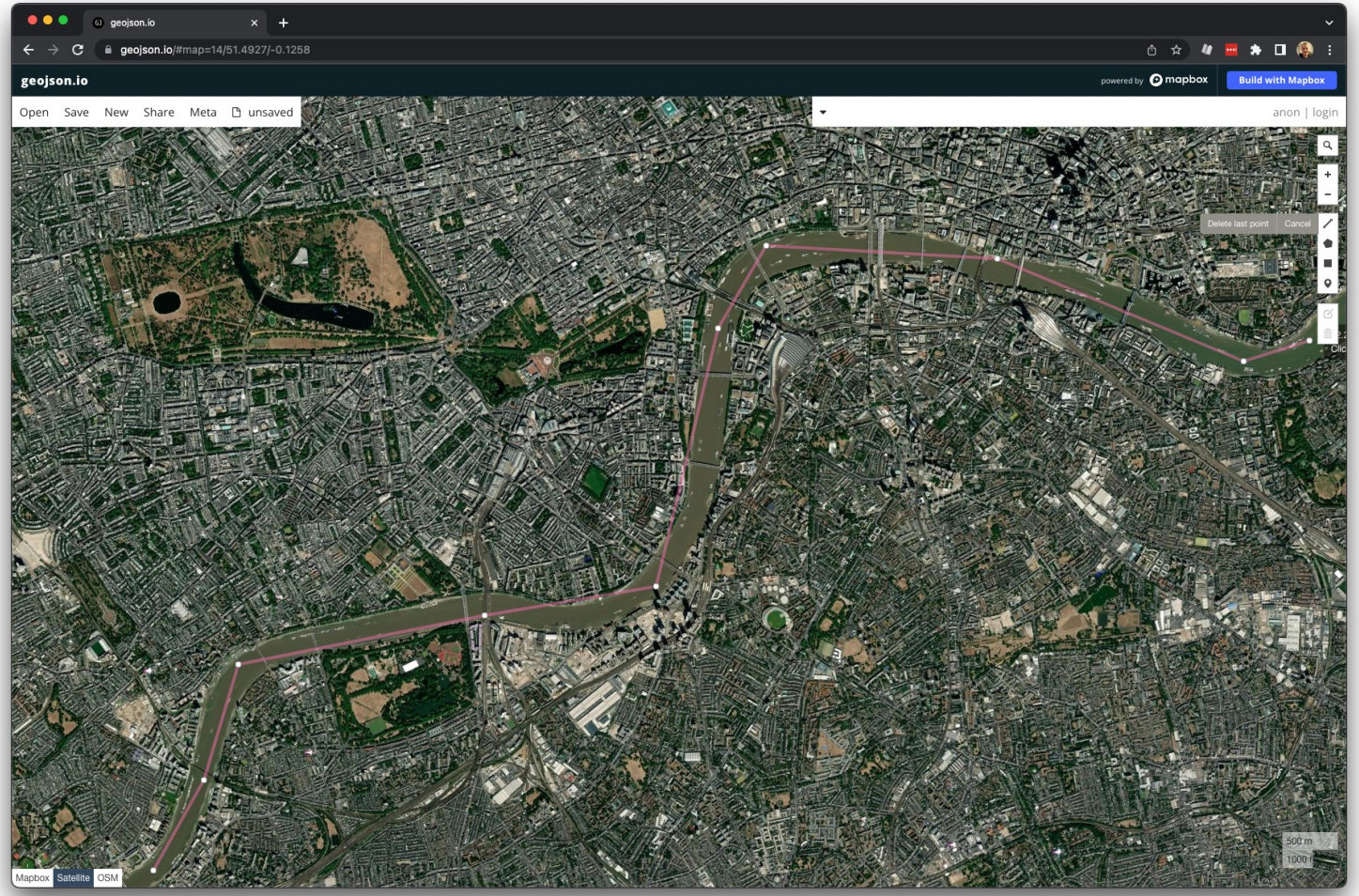
Sampling scheme

- Both for the vector and raster data model real life features are ‘sampled’ or represented in a certain way. How to represent the spatial information? With which level of detail?
- It must be fine enough to provide general consistency in our feature or field as well as accurately represent its distribution.
- It must be fine enough also to capture the important changes in our feature, e.g. a turn in a road, or a certain measurement change in a variable, such as temperature or rainfall.
- But we must also not over sample – we need to consider efficiency and efficacy of our sampling as we collect the data and store it digitally.

Sampling scheme

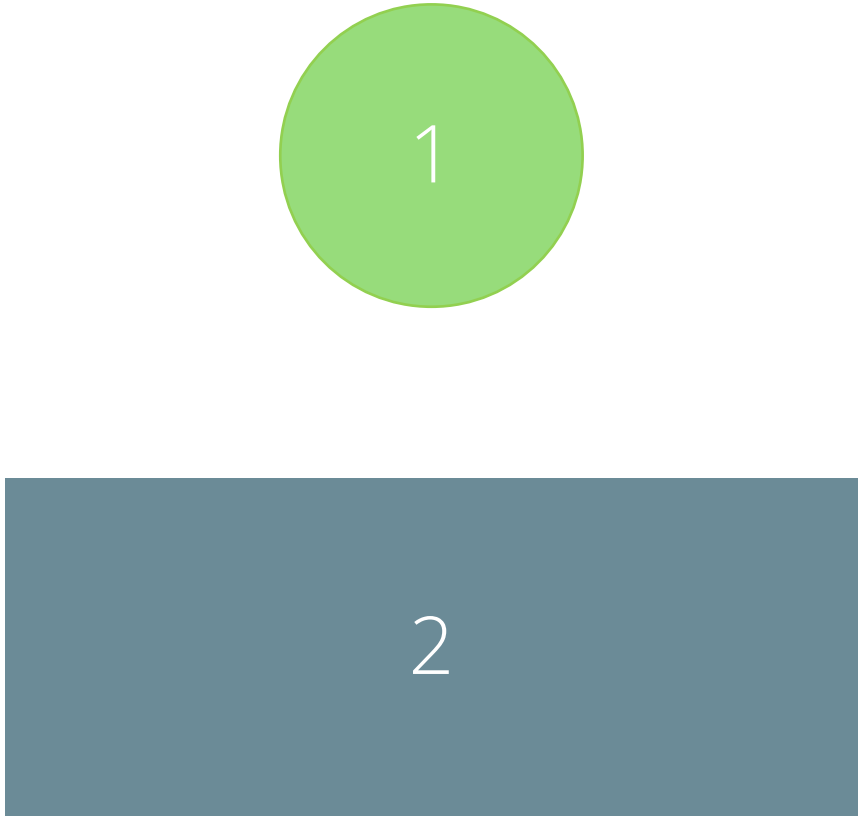


Sampling scheme



Sampling scheme

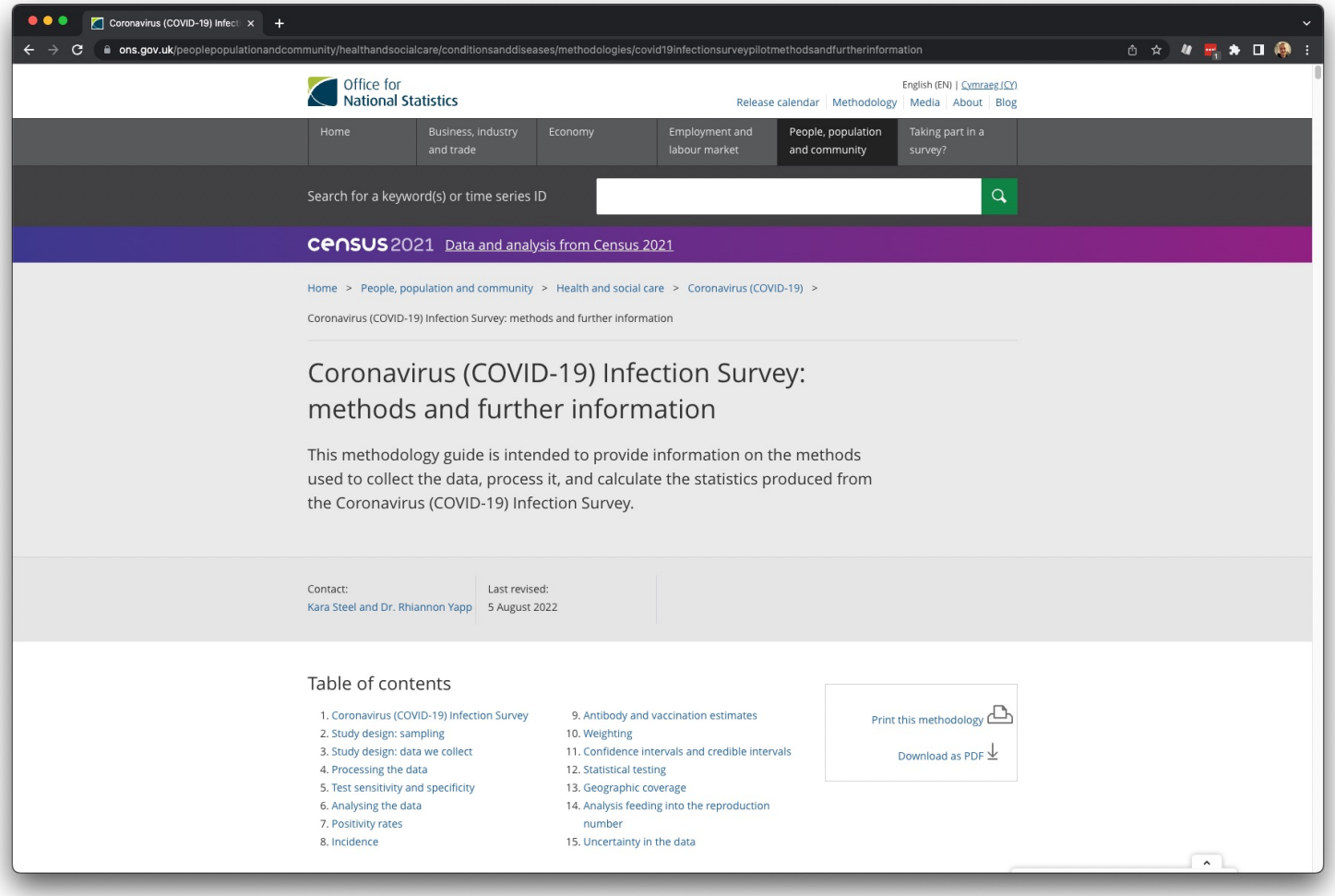
Representing Anatomy Building



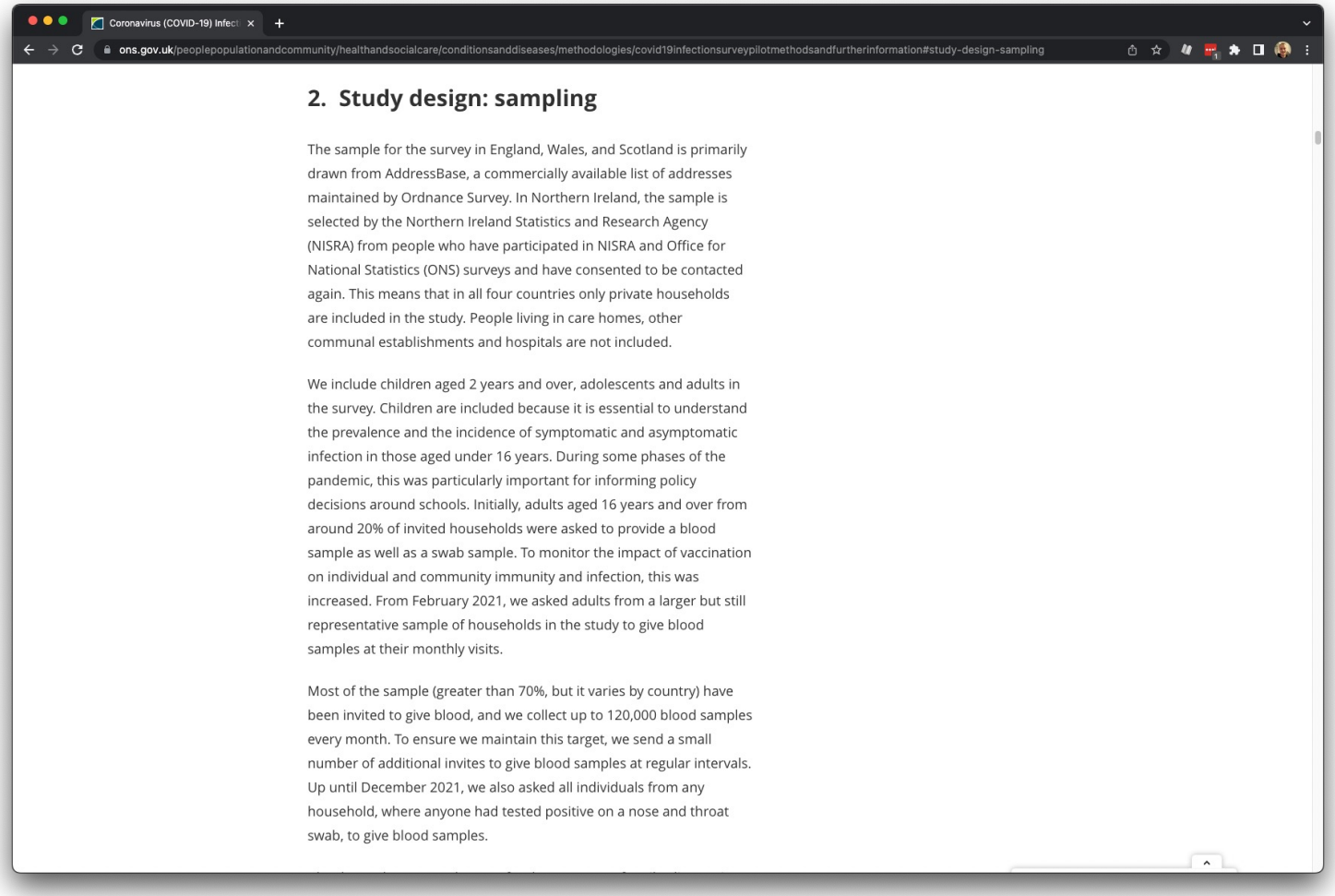
Sampling scheme

Well defined but does depend on purpose / context.

COVID-19 Infection Survey



COVID-19 Infection Survey



COVID-19 Infection Survey

Current sample sizes (per 28 days):

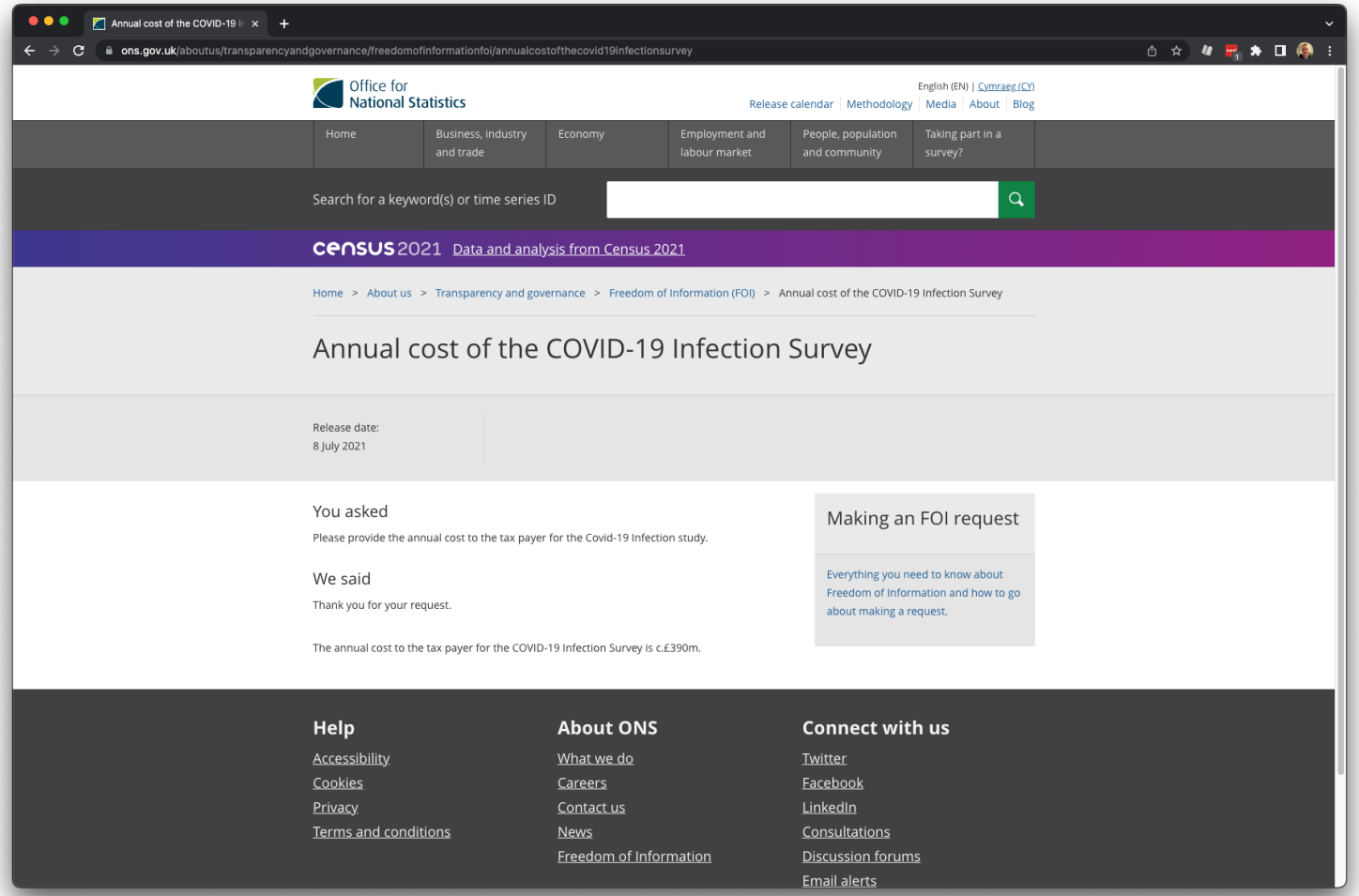
- 227,300 swab tests in England
- 15,650 swab tests in Wales
- 10,050 swab tests in Northern Ireland
- 23,200 swab tests in Scotland

COVID-19 Infection Survey

Current sample sizes (per 28 days):

- 227,300 swab tests in England / population 56,489,800
- 15,650 swab tests in Wales / population 3,107,500
- 10,050 swab tests in Northern Ireland / population 1,903,100
- 23,200 swab tests in Scotland / 5,479,900

COVID-19 Infection Survey



£390m

Data

Traditionally, captured data sets in geography and the social sciences:

- ...very costly (e.g. census, longitudinal surveys)
- ...of relatively poor spatial granularity (privacy preserving)
- ...of relatively poor temporal granularity (slow update cycles)

New sources of data

New sources of data like the one we discussed last week tend to be:

- accidental: ‘the digital exhaust’
- diverse in quality and resolution
- arguably: higher spatial granularity?
- arguably: higher temporal granularity?

New sources of data

Lazer and Radford 2017:

digital life	social media (e.g. Instagram, Facebook, Twitter)
digital traces	records of digital actions (e.g. CDR)
digitised life	digitised records (e.g. public version of the electoral roll)

New sources of data

Kitchen 2014:

- huge in *volume*; terrabytes of data
- high in *velocity*; being created in near real-time
- diverse in *variety*; both structured and unstructured
- *exhaustive* in scope; striving for *n = all*
- finegrained in *resolution*
- *relational* in nature; allows for conjoining different data sets
- *flexible* in terms of extensionality and scaleability

New sources of data

Kitchen 2014:

“Traditionally, data analysis techniques have been designed to extract insights from scarce, static, clean and poorly relational data sets, scientifically sampled and adhering to strict assumptions (such as independence, stationarity, and normality), and generated and analysed with a specific question in mind. The challenge of analysing Big Data is coping with abundance, exhaustivity and variety, timeliness and dynamism, messiness and uncertainty, high relationality, and the fact that much of what is generated has no specific question in mind or is a by-product of another activity.” (p.2)

Data bias

Different sources of bias are contained within these ‘new’ data sources.

Data bias

A common definition of data bias is that the available data does not accurately represent the population or phenomenon of study. Bias can get introduced in a variety of ways.

Bias through data representation

- All data is a partial and selective representation of real-world phenomena, but normally we devise a sample scheme to collected data.
- Sampling frames are meticulously designed to reduce sample errors and sample biases.
- However, within these ‘new’ data sets: not everyone is equally represented. The primary objectives of most big datasets are not to acquire complete coverage of the population at large, thus data are prone to representing particular subsets of the population that engage with the various activities that generate data.

Bias through data representation

- Systematic distortions in demographics or other user characteristics between a population of users represented in a data set or on a platform and some target population.
- Social media data are a good example; think Twitter, Instagram, Facebook.

Bias through data quality

- Data quality can be a source of measurement bias.
- What do we want from our data? Coverage? Completeness? Accurate? Reliable? Valid? Timely? Relevant? We want high quality.
- Data quality is a multifaceted concept with an open-ended list of desirable attributes such as completeness, correctness, and timeliness and undesirable attributes such as sparsity (lack or low amount of data) and noise (incomplete, corrupt, errors).
- Data quality is difficult to account for with ‘new’ data.

Bias through data quality

- Errors can arise in all parts of data generation and amalgamation process, from measurement to adjustment errors – which can then further contaminate other data when linked.
- Volume and velocity of ‘new’ big data prevents any efficient means of validation records.
- Simply adding more data may also increase the level of noise and reduce the quality and reliability of results.
- Sometimes quality is actually unknown.

Bias through data availability

- Using whatever data is available because it is available, rather than because you believe it will truly answer your research question.
- Easier to use passive, large-scale data sets as a proxy than to set up an extensive study?

Bias through temporal factors

- Data set being limited to the time in which it is created due to systematic distortions across user populations or behaviours over time.
- Data collected at different points in time may differ along diverse criteria, including who is using the system, how the system is used.
- Some human phenomena vary seasonally – or change completely, e.g. altered movement patterns due to COVID-19.
- Not per se exclusively related to ‘new’ data (e.g. Census).

Bias through spatial factors

- Modifiable Areal Unit Problem (MAUP) – the idea that outcomes change when data or processes are summarised in some way over different spatial units.
- Digital divide – which areas are the data coming from, data are collected ‘somewhere’.

Bias through measurement

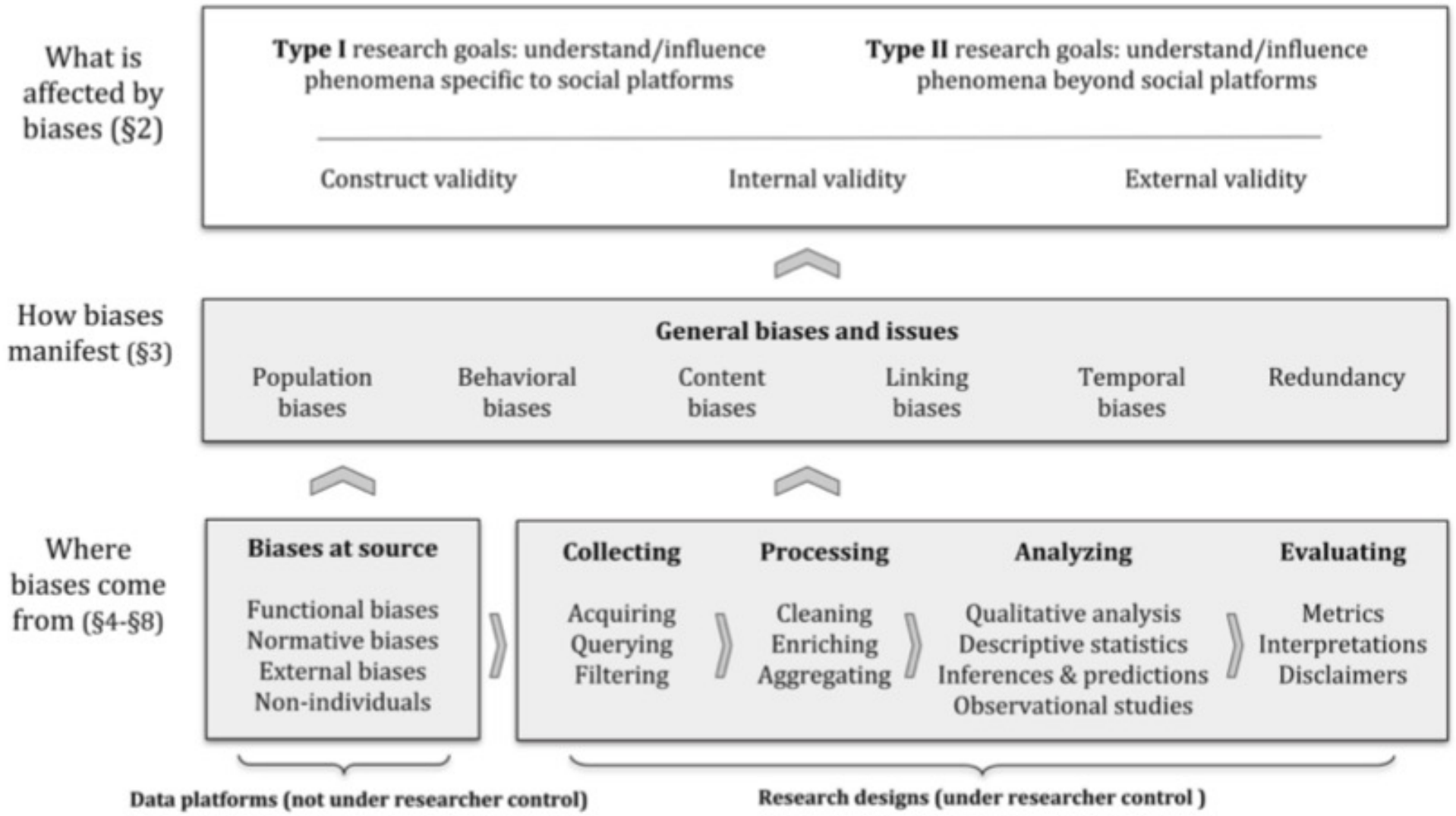
- Systematic or non-random error that occurs in the collection of data (also known as detection bias).
- For any measured variable, the difference between the true score and the observed score results from measurement error. This error is common, but it can be controlled through systematic measure development in small controlled studies.
- For ‘new’ data: users may be unaware of how study variables were measured and low reliability of some measures should be expected.

And some other possible sources of bias

Olteanu *et al*. 2019

- Linkage bias: behavioural biases that are expressed as differences in the attributes of networks obtained from user connections, interactions or activity.
- Redundancy bias: single data items that appear in the data in multiple copies, which can be identical (duplicates), or almost identical (near duplicates).
- Non-individual accounts: Interactions on social platforms that are produced by organisations or automated agents.
- But also: further biases introduced when data processing and analysing.

The problem


What is affected by biases (§2)
Type I research goals: understand/influence phenomena specific to social platforms
Type II research goals: understand/influence phenomena beyond social platforms
Construct validity
Internal validity
External validity
How biases manifest (§3)
General biases and issues
Population biases
Behavioral biases
Content biases
Linking biases
Temporal biases
Redundancy
Where biases come from (§4-§8)
Biases at source
Functional biases
Normative biases
External biases
Non-individuals
Collecting
Acquiring
Querying
Filtering
Processing
Cleaning
Enriching
Aggregating
Analyzing
Qualitative analysis
Descriptive statistics
Inferences & predictions
Observational studies
Evaluating
Metrics
Interpretations
Disclaimers
Data platforms (not under researcher control)
Research designs (under researcher control)

The problem

We want:

- True positives
- True negatives

Through biases we are more likely to get:

- False positives
- False negatives

The problem

- This raises new epistemological challenges.
- ‘what do we know and how can we know it’
- ‘what tools do we use to study the world’
- “Big Data analytics enables an entirely new epistemological approach for making sense of the world; rather than testing a theory by analysing relevant data, new data analytics seek to gain insights ‘born from the data’.” (Kitchen 2014, p.2)

Epistemology

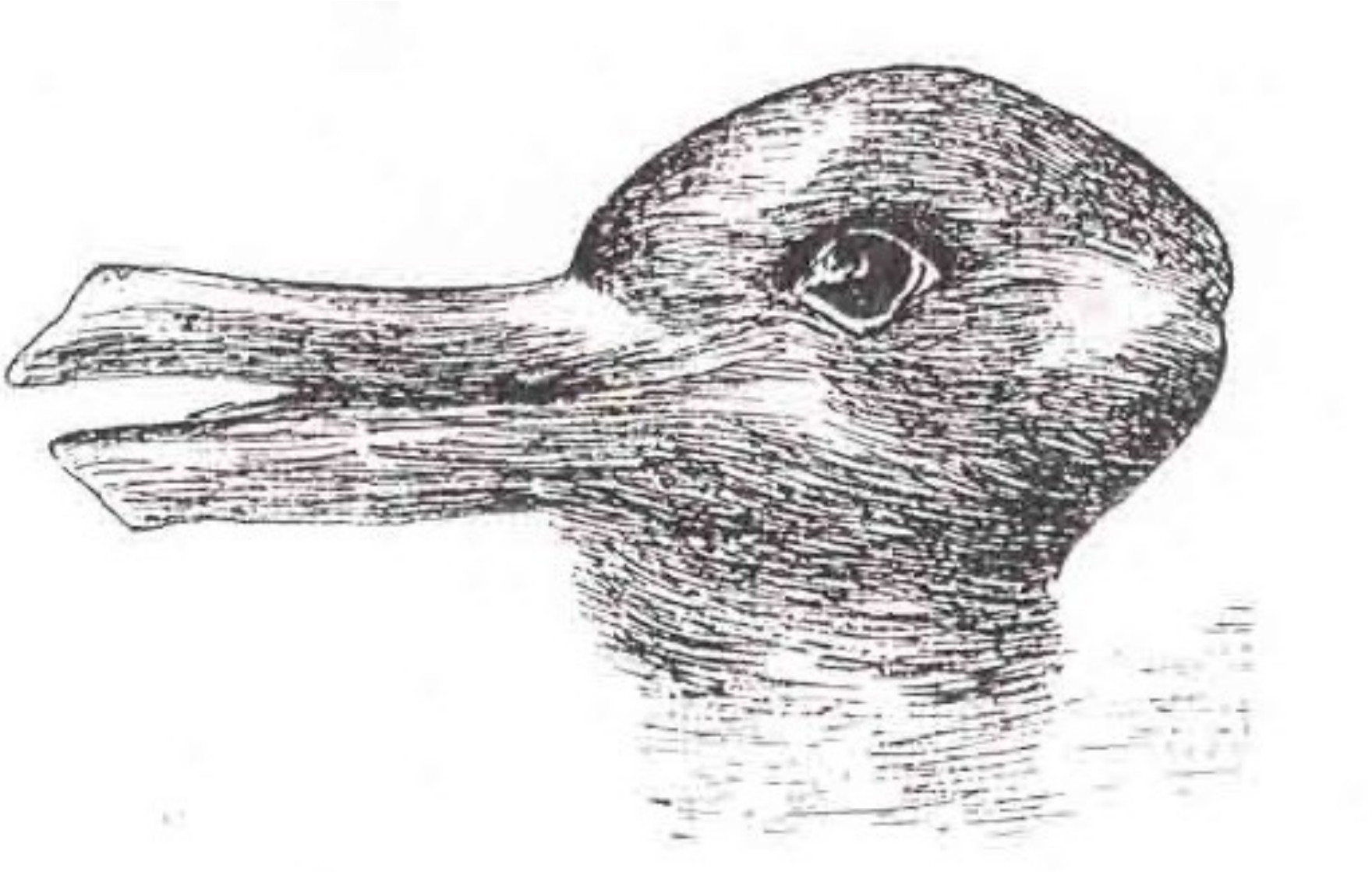
- What is knowledge in the first place?
- What is a good basis for judgements about ‘truth’?

… but this is a controversial and contested question!

Skepticism

- Academic skeptics would argue that sensory impressions, often taken to be the foundational knowledge of the world, don't enable you to know anything.
- Zhuang Zhou: butterfly or man?
- Modern day: The Matrix?
- How can present experience prove you are not dreaming or trapped in the Matrix?
- Extreme position of knowledge being impossible.

Skepticism



Hempel’s paradox

What does constitute as evidence for a statement?

Hempel’s paradox

I will prove the hypothesis that all ravens are black.

I will use my grey laptop as evidence.

Hempel’s paradox

(1) Hypothesis: *All ravens are black.*

(2) This can be expressed as: *If something is a raven, then it is black.*

(3) This is equivalent to: *If something is not black, then it is not a raven.*

(4) This means that for all situations where (2) is true, (1) is also true—and likewise, in all circumstances where (2) is false (1) is also false.

(5) If you own a black pet raven you could say: *My pet raven is black.*

This is then evidence supporting the hypothesis that all ravens are black. Agreed?

Hempel’s paradox

Now look at my grey computer. I can now say:

This grey computer is not black, and not a raven.

This supports the statement that:

If something is not black then this is not a raven.

However, remember that this statement was equivalent to:

All ravens are black.

Hempel’s paradox: what constitutes as evidence?

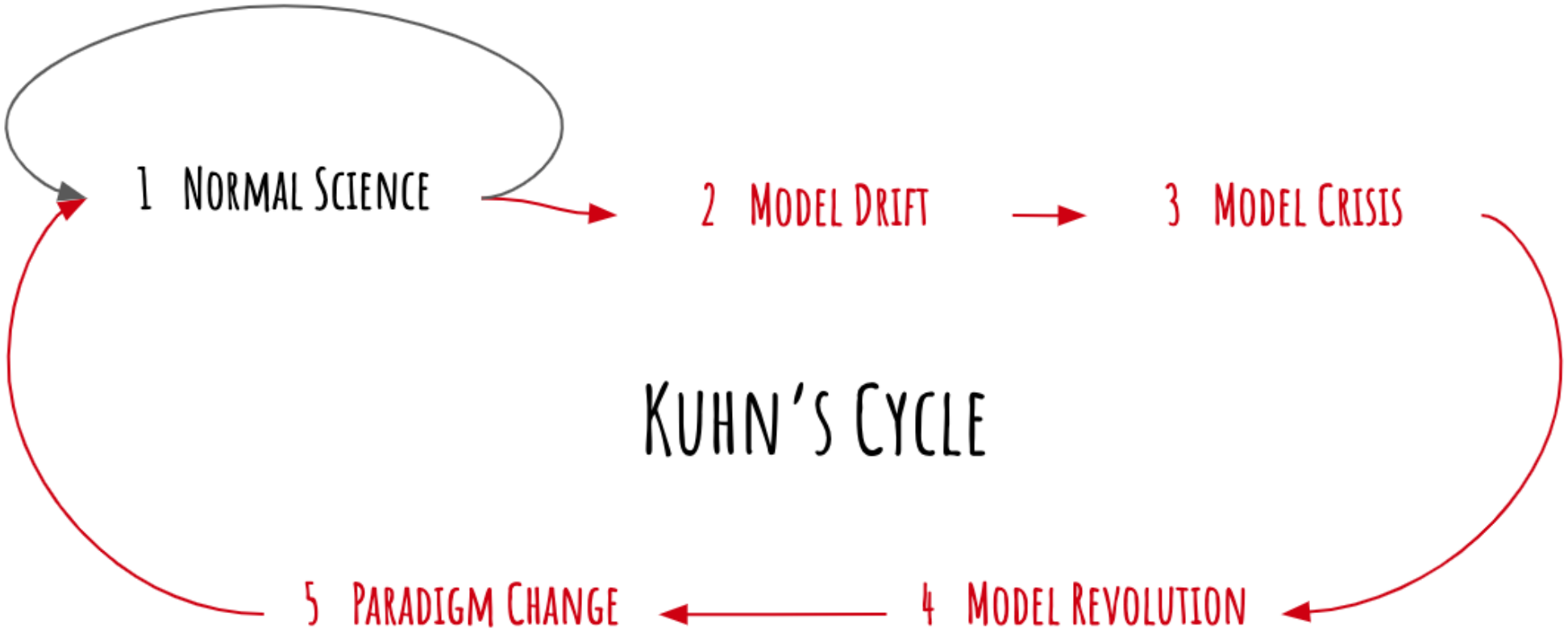
Verification and falsification

- Logical positivism / empirical positivism
- Only statements verifiable through direct observation or logical proof are meaningful in terms of conveying truth value. Basic principle: verification / induction
- Contested by Karl Popper ('theories are never fully verified'. Basic principle: falsification/deduction
- Further contested by Duhem-Quine thesis: hypothesis do not get tested in isolation, so if a hypothesis gets refuted an entire theory should get refuted.

Thomas Kuhn

- More concerned with the ‘workings’ of science.
- Periods of ‘normal science’ with incremental advantages with occasional paradigm shifts with a sudden shift to a new explanatory framework (e.g. heliocentrism, evolution).
- A paradigm constitutes an accepted way of interrogating the world and synthesising knowledge common to a substantial proportion of researchers in a discipline at any one moment in time.
- Big Data as new research paradigm?

Thomas Kuhn


1 Normal Science
2 Model Drift
3 Model Crisis
4 Model Revolution
5 Paradigm Change
Kuhn's Cycle

Kitchen

Table 1. Four paradigms of science.

Paradigm	Nature	Form	When
First	Experimental science	Empiricism; describing natural phenomena	pre-Renaissance
Second	Theoretical science	Modelling and generalization	pre-computers
Third	Computational science	Simulation of complex phenomena	pre-Big Data
Fourth	Exploratory science	Data-intensive; statistical exploration and data mining	Now

Kitchen 2014, p.3

Kitchen

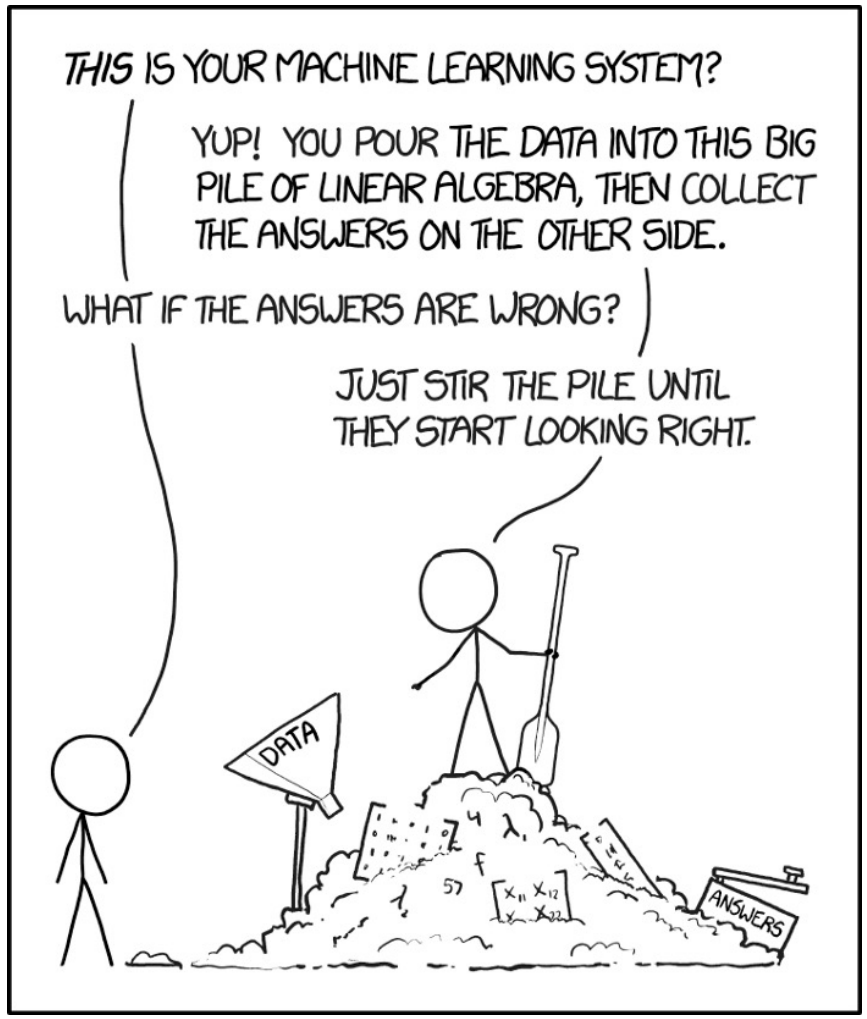
Kitchen 2014 discusses:

- Anderson: ‘the death of theory’
- ‘Return’ of empiricism and induction? But what about interpretation, how data are generated?

Kitchen

- Can data-driven science be a model?
- “Whilst Big Data analytics might provide some insights, it needs to be recognized that they are limited in scope, produce particular kinds of knowledge, and still need contextualization with respect to other information, whether that be existing theory, policy documents, small data studies, or historical records, that can help to make sense of the patterns evident.” (Kitchen 2014, p.9)

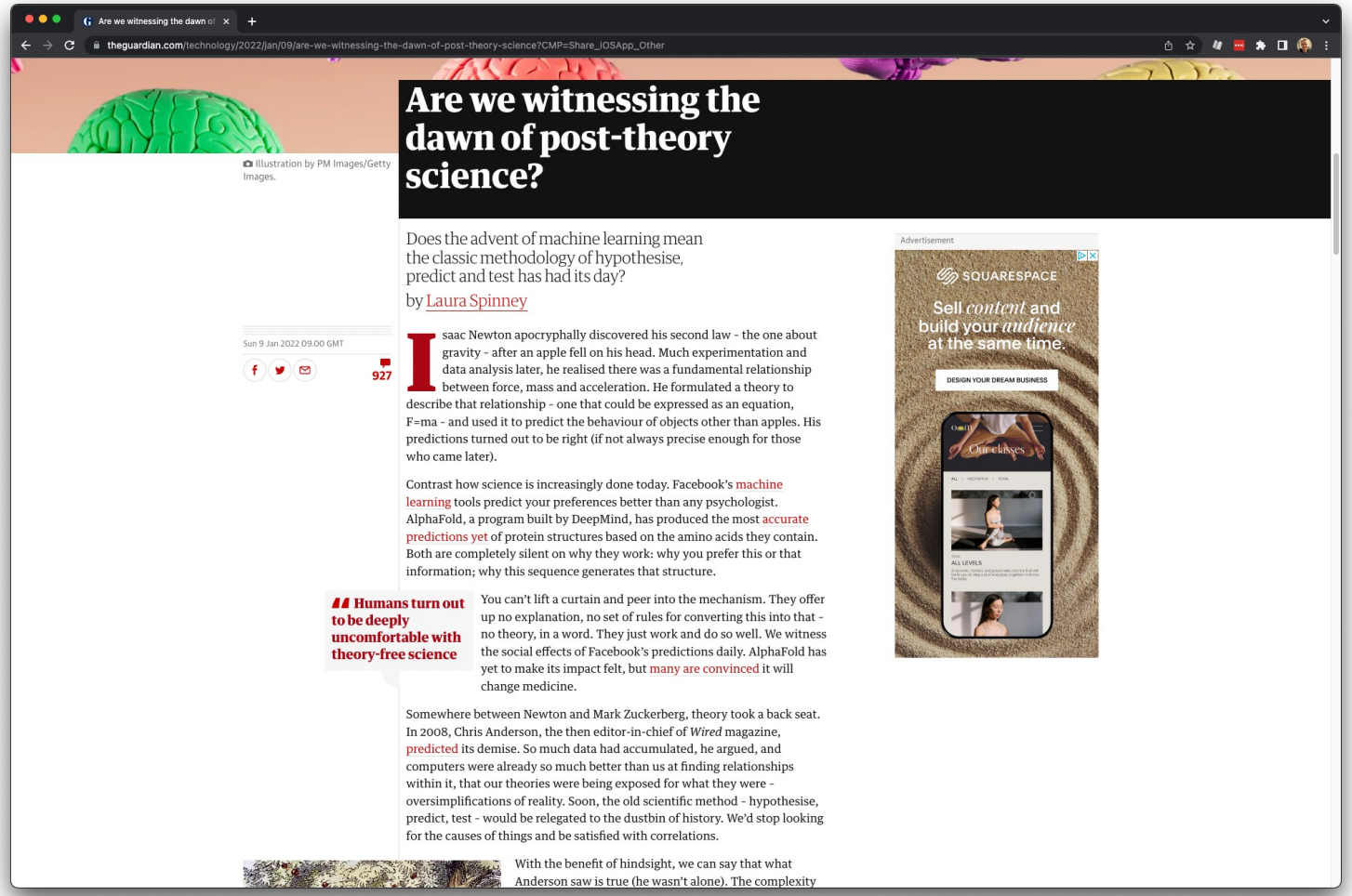
Machine learning and AI?



Conclusion

- We explored some of the ‘bad’ side of human-generated data sets.
- Lots of different sources of representation and bias. Bad!
- Bias can get introduced at many different stages; think collecting, processing, analysing, evaluating.
- Clearly problematic to think of ‘new’ data as resulting in the ‘death of theory’.
- A need for a new data-driven epistemology: an approach that, grounded in scientific theories, extends their traditional approaches, adopting data and computation as an additional tool not only to test existing theories but also to develop new ones.

Conclusion


Are we witnessing the dawn of post-theory science?
theguardian.com/technology/2022/jan/09/are-we-witnessing-the-dawn-of-post-theory-science?CMP=Share_iOSApp_Other
Are we witnessing the dawn of post-theory science?
Illustration by PM Images/Getty Images.
Does the advent of machine learning mean the classic methodology of hypothesise, predict and test has had its day?
by Laura Spinney
Sun 9 Jan 2022 09.00 GMT
927
Isaac Newton apocryphally discovered his second law - the one about gravity - after an apple fell on his head. Much experimentation and data analysis later, he realised there was a fundamental relationship between force, mass and acceleration. He formulated a theory to describe that relationship - one that could be expressed as an equation, F=ma - and used it to predict the behaviour of objects other than apples. His predictions turned out to be right (if not always precise enough for those who came later).
Contrast how science is increasingly done today. Facebook's machine learning tools predict your preferences better than any psychologist. AlphaFold, a program built by DeepMind, has produced the most accurate predictions yet of protein structures based on the amino acids they contain. Both are completely silent on why they work: why you prefer this or that information; why this sequence generates that structure.
Humans turn out to be deeply uncomfortable with theory-free science
You can't lift a curtain and peer into the mechanism. They offer up no explanation, no set of rules for converting this into that - no theory, in a word. They just work and do so well. We witness the social effects of Facebook's predictions daily. AlphaFold has yet to make its impact felt, but many are convinced it will change medicine.
Somewhere between Newton and Mark Zuckerberg, theory took a back seat. In 2008, Chris Anderson, the then editor-in-chief of Wired magazine, predicted its demise. So much data had accumulated, he argued, and computers were already so much better than us at finding relationships within it, that our theories were being exposed for what they were - oversimplifications of reality. Soon, the old scientific method - hypothesise, predict, test - would be relegated to the dustbin of history. We'd stop looking for the causes of things and be satisfied with correlations.
With the benefit of hindsight, we can say that what Anderson saw is true (he wasn't alone). The complexity
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Seminar preparation

In preparation for the next seminar, in groups of two, identify and carefully read a published article that makes use of 'new' geographic data. *This cannot be an article that is currently on the reading list!* For this article:

- Write a 100-words summary of what you think is the article's main contribution.
- Identify at which points the data set used may be biased, how the authors have tried to mitigate these biases, and what the authors could have done more to account for the biases you identified.
- Add it to the Google Spreadsheet linked on the module page!

Questions

Justin van Dijk

j.t.vandijk@ucl.ac.uk