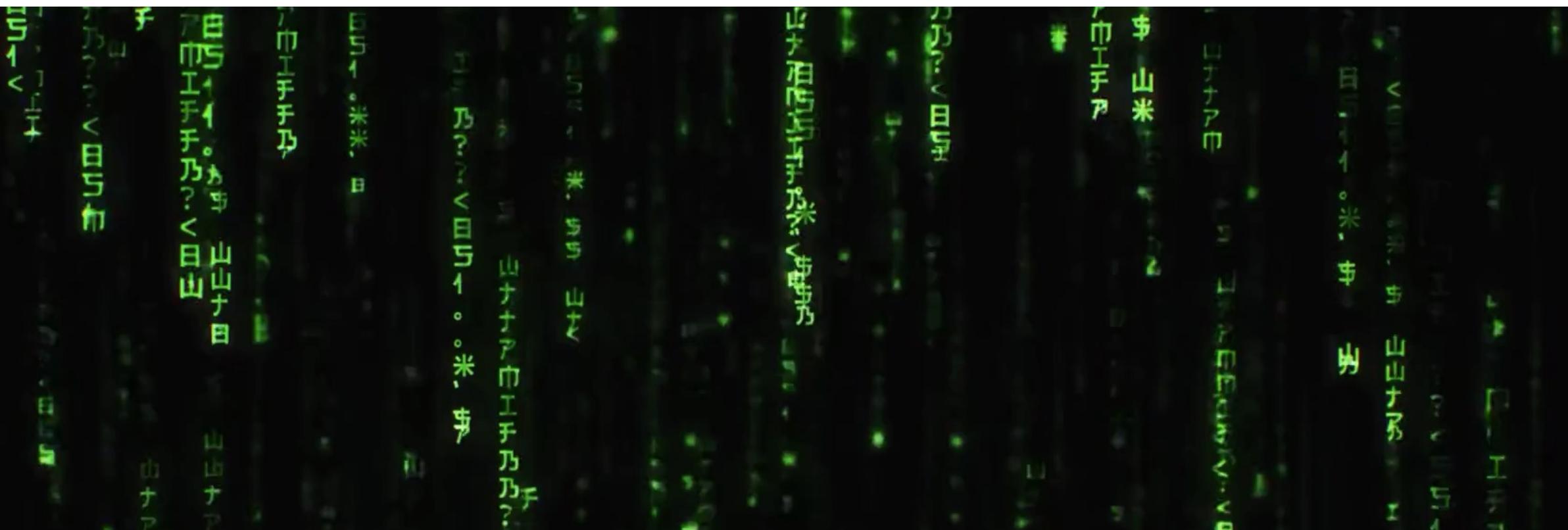


Data, Politics and Society

W2 – Data II: The Bad



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:

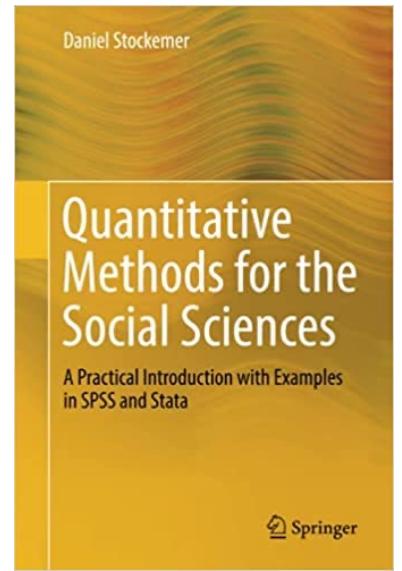
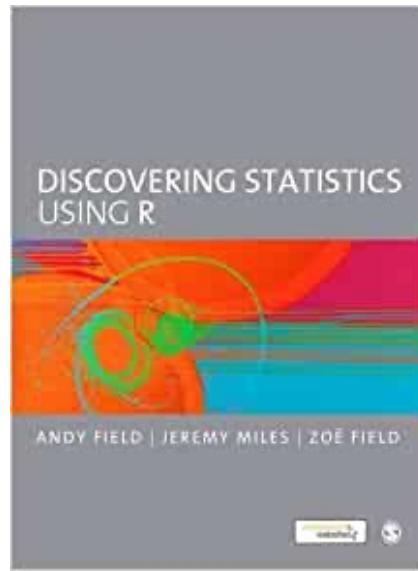
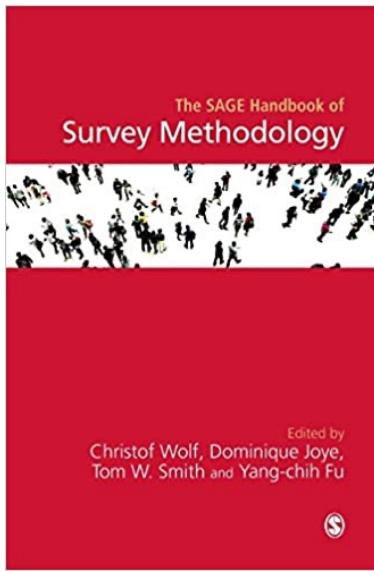
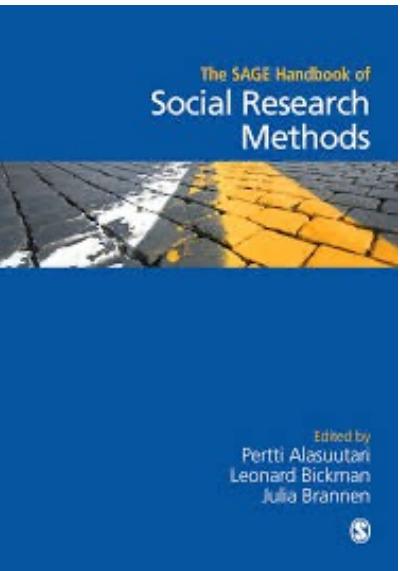
"Data then are a key resource in the modern world. Yet, given their utility and value, and the amount of effort and resources devoted to producing and analysing them, it is remarkable how little conceptual attention has been paid to data in and of themselves." (p.2)

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



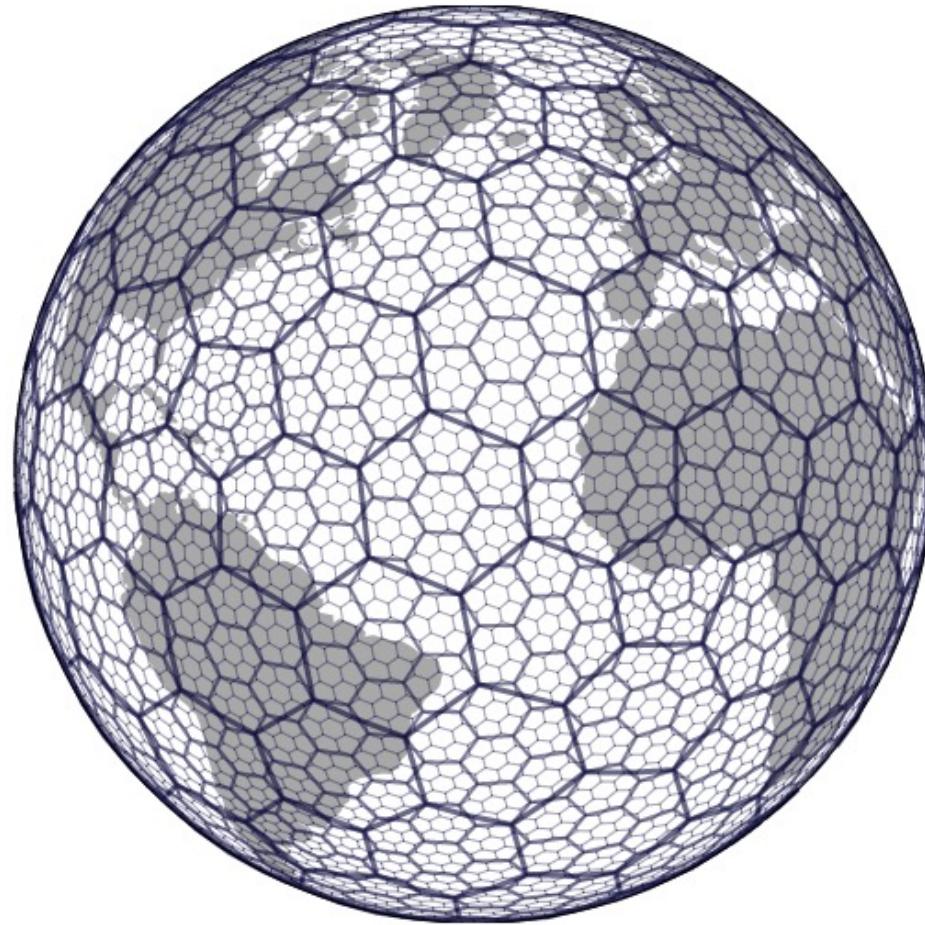
GIS data models

Traditionally, geographic information is represented in two ways:

vector a finite set of geometric objects

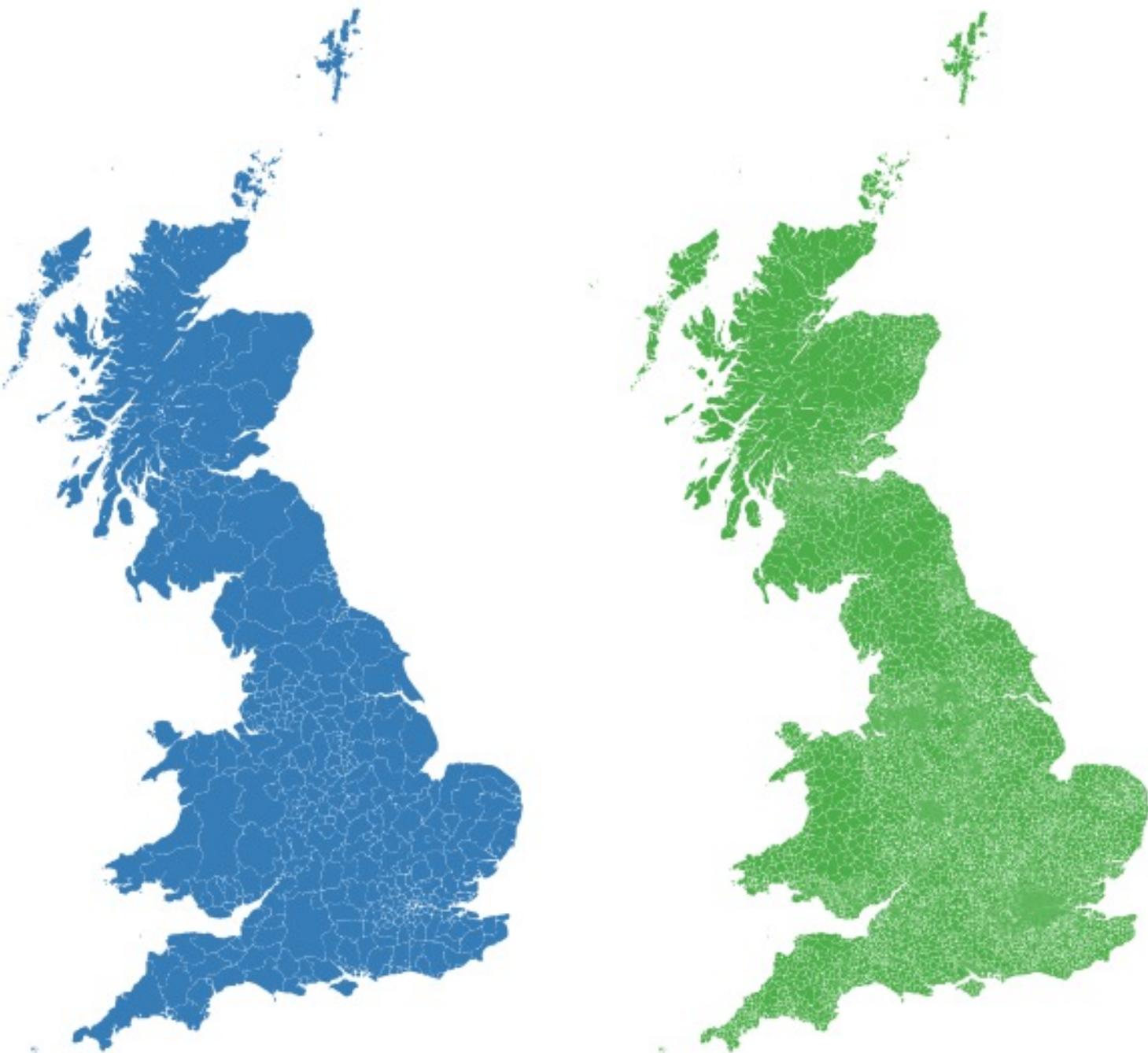
raster images representing a surface (values, colours)

Vector



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

Vector



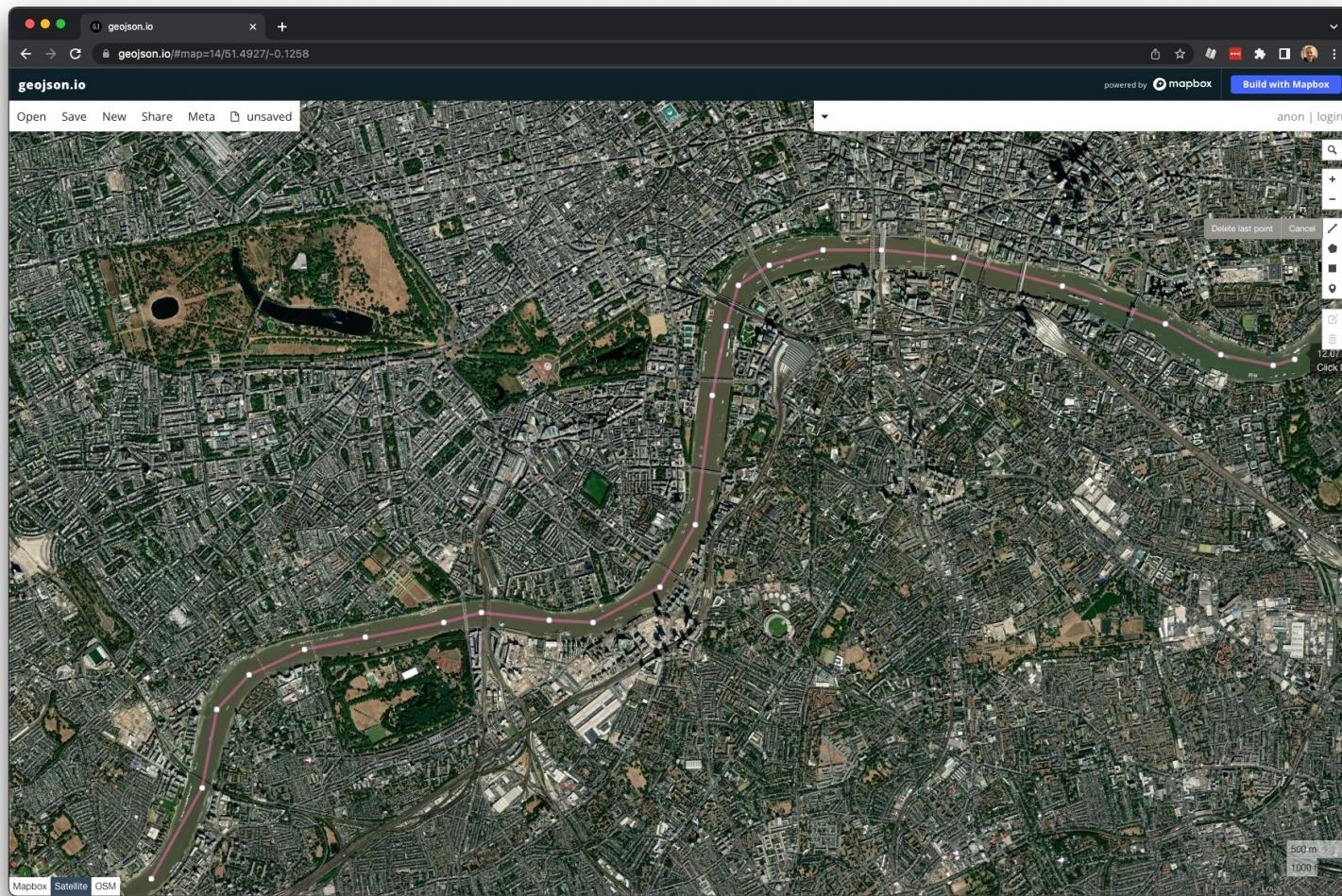
Raster



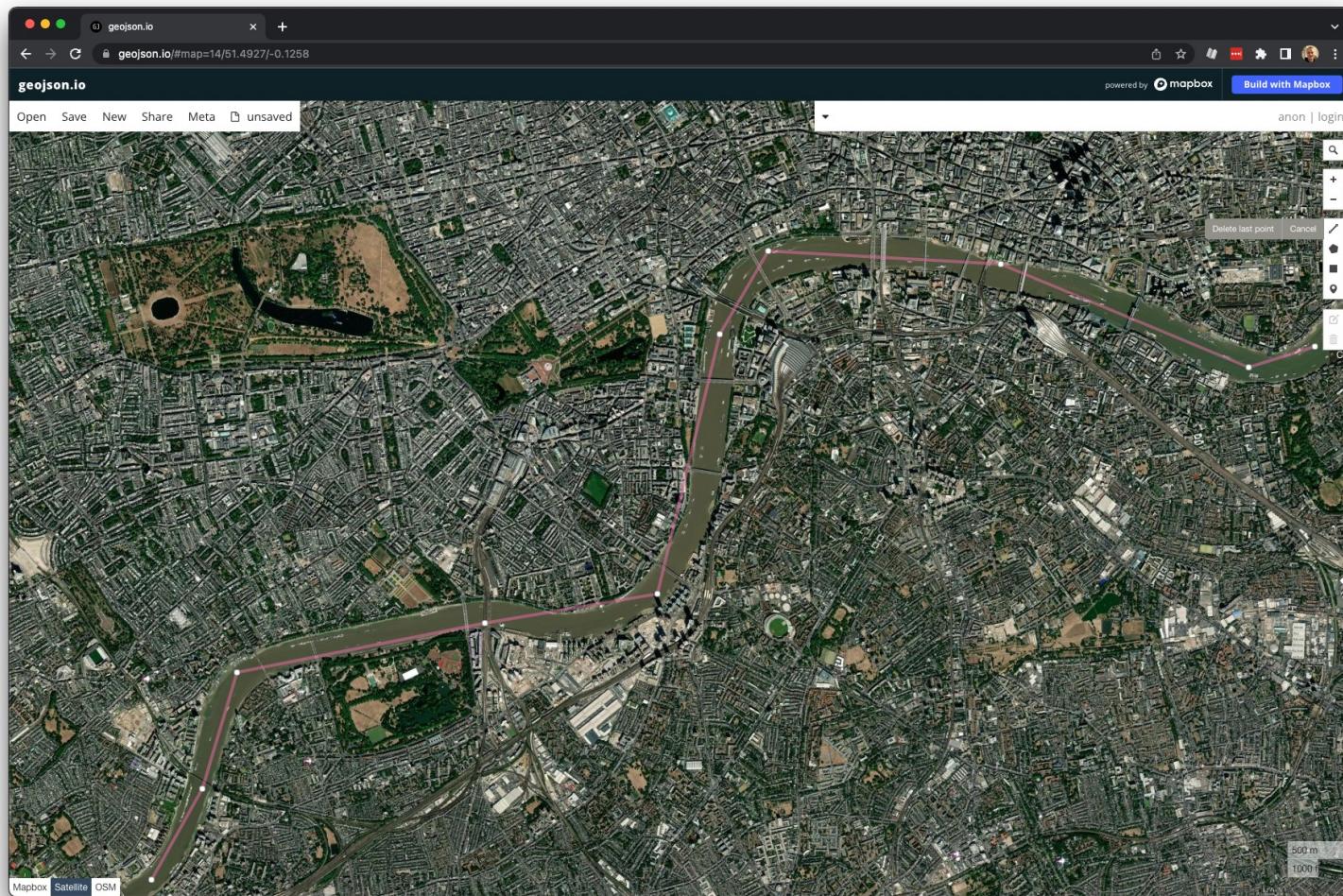
Sampling scheme

- 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

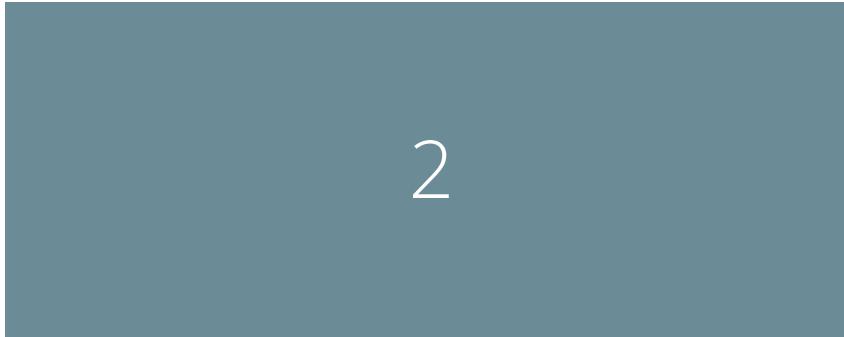
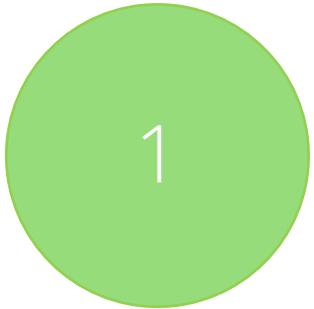


Sampling scheme



Sampling scheme

Representing Anatomy Building



Sampling scheme

Well defined but does depend on purpose / context.

COVID-19 Infection Survey

The screenshot shows a web browser displaying the 'Coronavirus (COVID-19) Infection Survey: methods and further information' page from the Office for National Statistics (ONS) website. The URL in the address bar is [ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/methodologies/covid19infectionssurveypilotmethodsandfurtherinformation](https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/methodologies/covid19infectionssurveypilotmethodsandfurtherinformation).

The page features a dark header with the ONS logo and navigation links for Home, Business, Industry and trade, Economy, Employment and labour market, People, population and community, and Taking part in a survey?.

A search bar is located above a purple banner that reads 'census 2021 Data and analysis from Census 2021'. Below the banner, the breadcrumb navigation shows: Home > People, population and community > Health and social care > Coronavirus (COVID-19) > Coronavirus (COVID-19) Infection Survey: methods and further information.

Coronavirus (COVID-19) Infection Survey: methods and further information

This methodology guide is intended to provide information on the methods used to collect the data, process it, and calculate the statistics produced from the Coronavirus (COVID-19) Infection Survey.

Contact: Kara Steel and Dr. Rhiannon Yapp | Last revised: 5 August 2022

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1. Coronavirus (COVID-19) Infection Survey	9. Antibody and vaccination estimates
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3. Study design: data we collect	11. Confidence intervals and credible intervals
4. Processing the data	12. Statistical testing
5. Test sensitivity and specificity	13. Geographic coverage
6. Analysing the data	14. Analysis feeding into the reproduction number
7. Positivity rates	15. Uncertainty in the data
8. Incidence	

Print this methodology

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COVID-19 Infection Survey

The screenshot shows a web browser window with the title "Coronavirus (COVID-19) Infection Survey" and the URL "ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/methodologies/covid19infectionssurveypilotmethodsandfurtherinformation#study-design-sampling". The main content is titled "2. Study design: sampling".

The text describes the sampling strategy for the survey in England, Wales, and Scotland, mentioning AddressBase and the Northern Ireland Statistics and Research Agency (NISRA). It also details the inclusion of children aged 2 years and over, adolescents, and adults, and the collection of blood and swab samples.

Most of the sample (greater than 70%, but it varies by country) have been invited to give blood, and we collect up to 120,000 blood samples every month. To ensure we maintain this target, we send a small number of additional invites to give blood samples at regular intervals. Up until December 2021, we also asked all individuals from any household, where anyone had tested positive on a nose and throat swab, to give blood samples.

COVID-19 Infection Survey

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

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

A screenshot of a web browser displaying the Office for National Statistics (ONS) website. The page is titled 'Annual cost of the COVID-19 Infection Survey'. The URL in the address bar is [ons.gov.uk/aboutus/transparencyandgovernance/freedomofinformationfoi/annualcostofthecovid19infectionsurvey](https://www.ons.gov.uk/aboutus/transparencyandgovernance/freedomofinformationfoi/annualcostofthecovid19infectionsurvey). The page header includes the ONS logo, language links (English (EN) | Cymraeg (CY)), and navigation links for Release calendar, Methodology, Media, About, and Blog. A search bar is present at the top. Below the header, a purple banner reads 'census 2021 Data and analysis from Census 2021'. The main content area shows the title 'Annual cost of the COVID-19 Infection Survey' and a release date of '8 July 2021'. To the left, a 'You asked' section contains the question 'Please provide the annual cost to the tax payer for the Covid-19 Infection study.' To the right, a 'Making an FOI request' section provides information about Freedom of Information requests. At the bottom, there are links for Help (Accessibility, Cookies, Privacy, Terms and conditions), About ONS (What we do, Careers, Contact us, News, Freedom of Information), and Connect with us (Twitter, Facebook, LinkedIn, Consultations, Discussion forums, Email alerts).

£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*; terabytes 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 extensibility and scalability

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.

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.

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.

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.

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 simply unknown.

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?

Temporal coverage

- 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).

Spatial coverage

- 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’.

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

Construct validity

Type II research goals: understand/influence phenomena beyond social platforms

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
Filtering

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

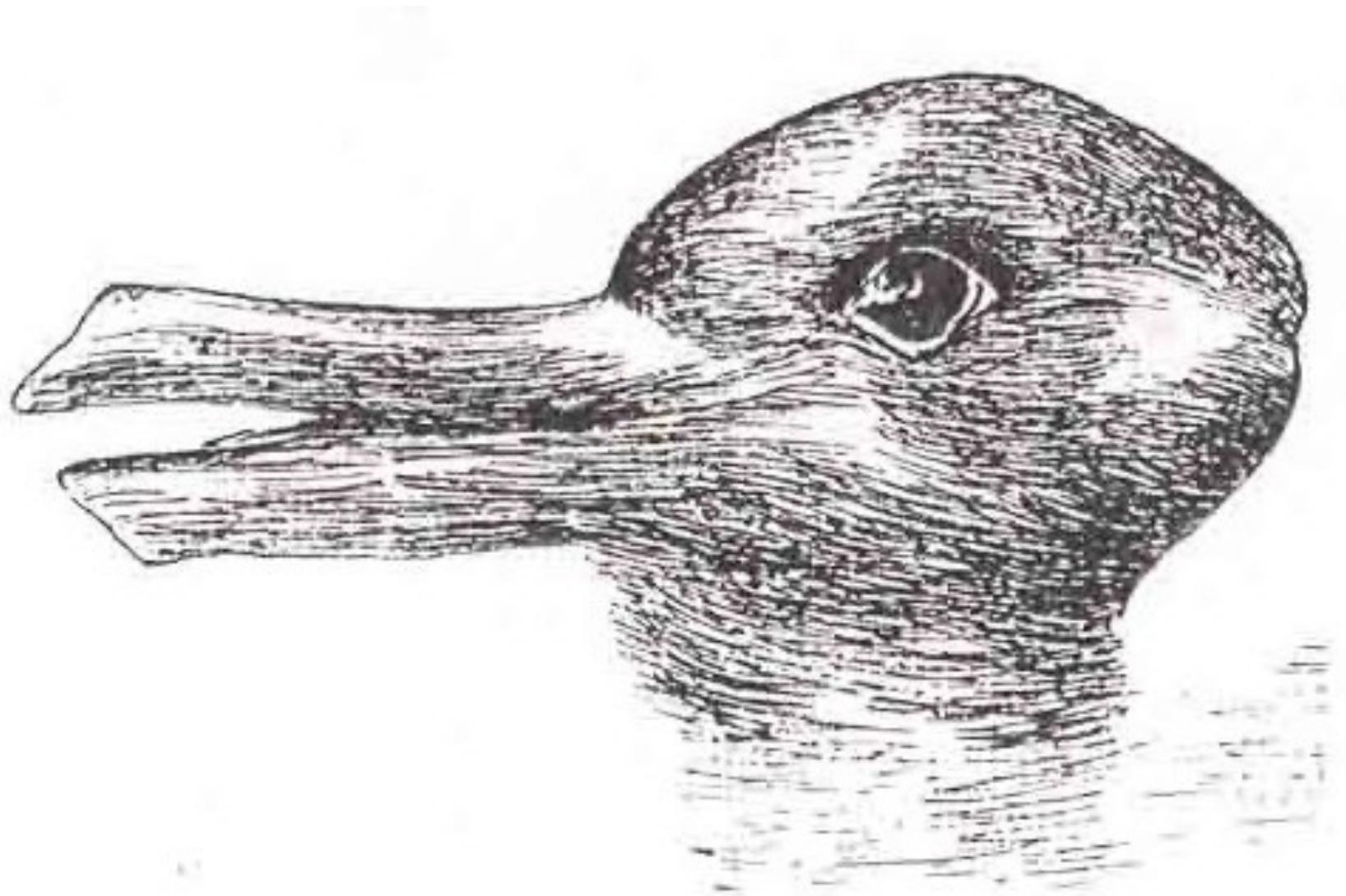
- What is knowledge in the first place?
- What is **a good basis** for judgements about 'truth'?

... 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



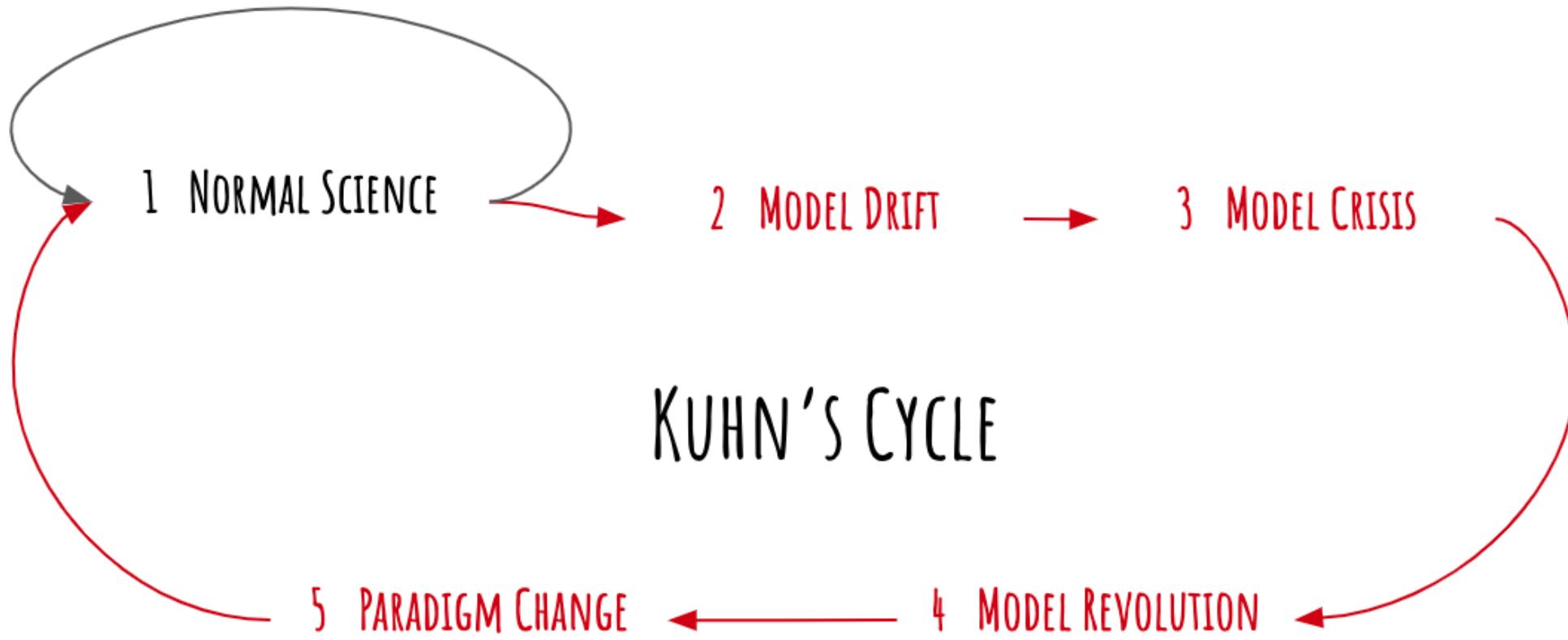
Verification and falsification

- 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



Kitchen

Table I. 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

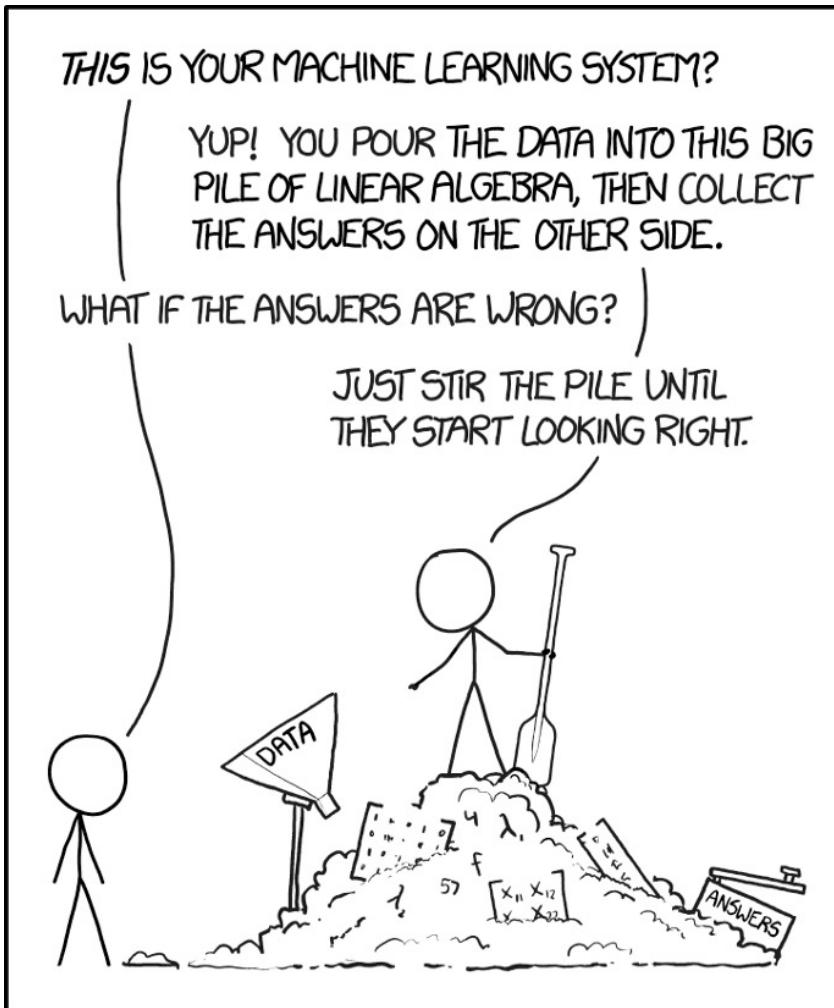
Kitchen 2014 discusses:

- 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?

Illustration by PM Images/Getty Images.

Sun 9 Jan 2022 09.00 GMT

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Humans turn out to be deeply uncomfortable with theory-free science

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.

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!

Continuous Module Dialogue

Go to www.menti.com and use the code 7170 7756

Questions

Justin van Dijk

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