Introduction to Data Science

Session 1: What is data science?

Simon Munzert
Hertie School | GRAD-C11/E1339

Welcome!

Introductions

Course

https://github.com/intro-to-data-science-25

Much of this course lives on GitHub. You will find lecture materials, code, assignments, and other people's presentations there. We also have Moodle, which is is for everything else.

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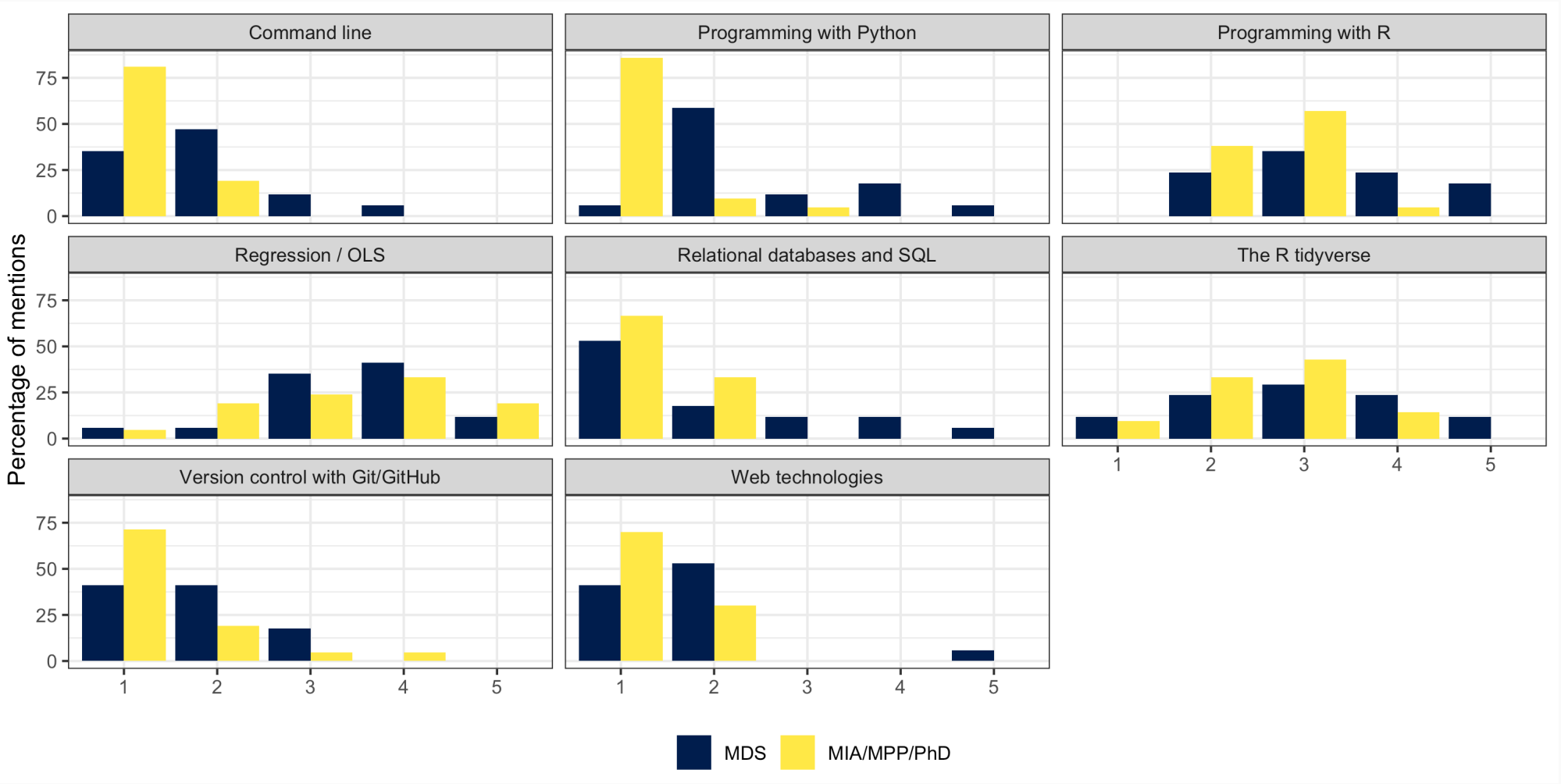
You

Let's find out!

More about you



The labs

Who & how

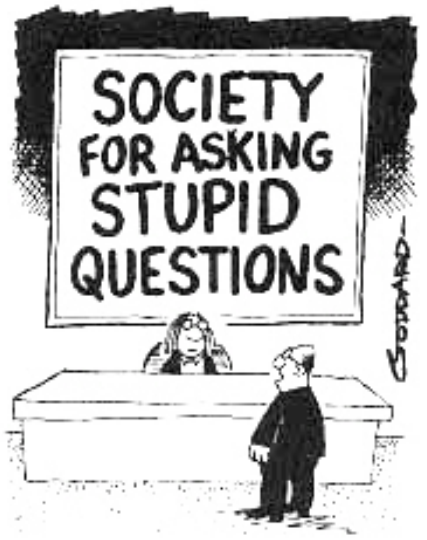
- This course is accompanied by labs administered by **Carol Sobral** and **Killian Conyngham**.
- The labs are mandatory (MDS) / optional (the rest). Please attend them in any case.
- As with the regular classes, please stick to the lab you are assigned to.

What for

- What these sessions are meant for:
  - Applying tools in practice
  - Discussion of issues related to the assignments
  - Boosting your R skills
- What these sessions are **not** meant for:
  - Solving the assignments for you
  - Taking care of developing your coding skills

Class etiquette

- Learning how to code can be challenging and might lead you out of your comfort zone. If you have problems with the pace of the course, let me and the TAs know. I expect your commitment to the class, but **I do not want anyone to fail.**
- You are all genuinely interested in data science. But there is also considerable variation in your backgrounds. This is how we like it! Some sessions will be more informative for you than others. If you feel bored, **look out for and help others**, or explore other corners of R you don't know yet.
- **Be respectful** to each other, all the time. This includes the TAs and me.
- **Ask questions** whenever you feel the need to do so!



"Excuse me, but is this The Society for Asking Stupid Questions?"

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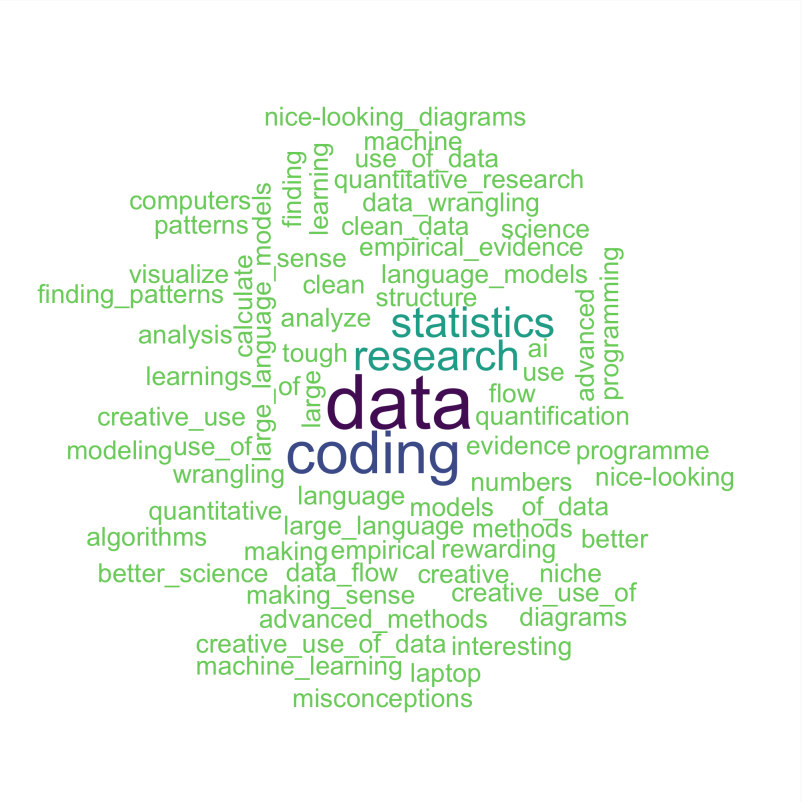
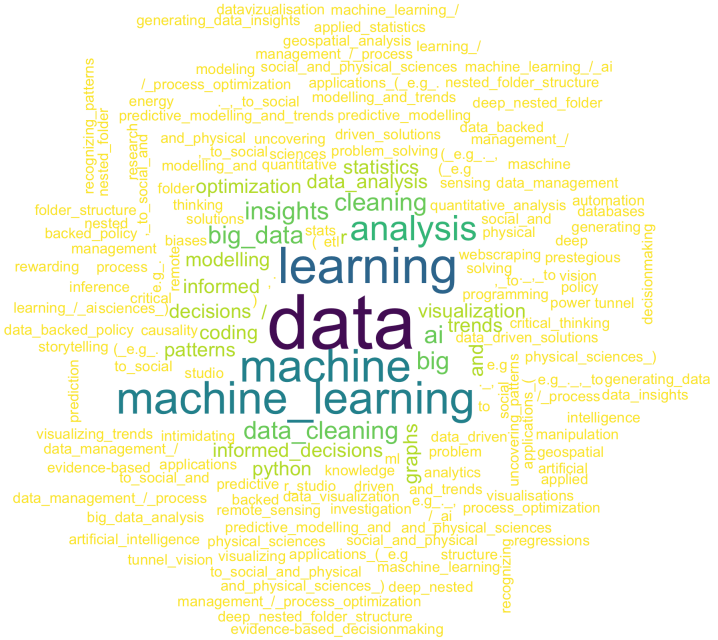
What is data science?

What you think data science entails

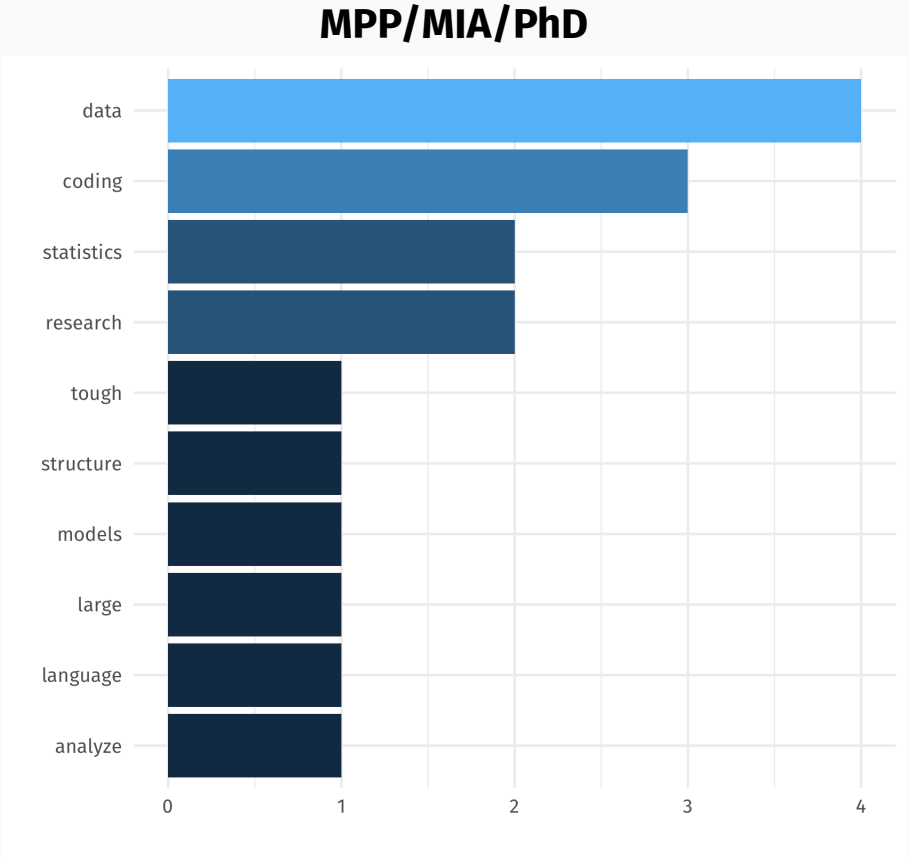
MPP/MIA/PhD

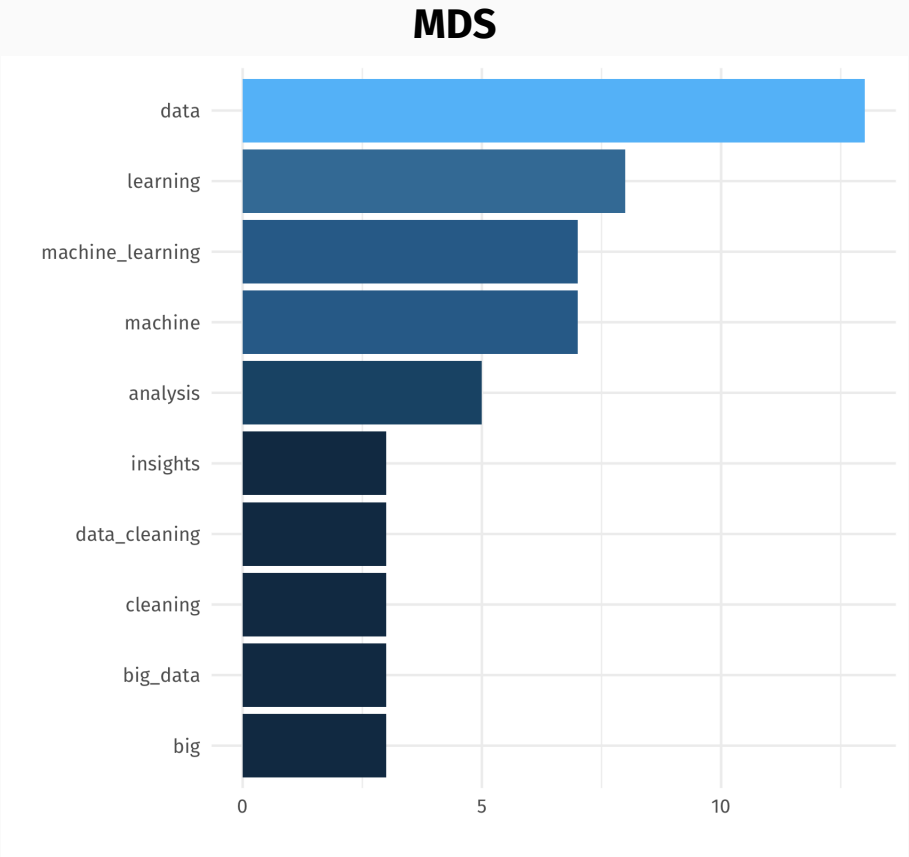


MDS



What you think data science entails





Definitions of data science

What is data science?

> "Data science is an **interdisciplinary academic field** that uses statistics, scientific computing, scientific methods, processes, algorithms and systems to extract or extrapolate knowledge and insights from potentially noisy, structured, or unstructured data." - Wikipedia
>
> "Data science is a concept to **unify statistics, data analysis, informatics**, and their related methods to understand and analyze actual phenomena with data." - Chikio Hayashi
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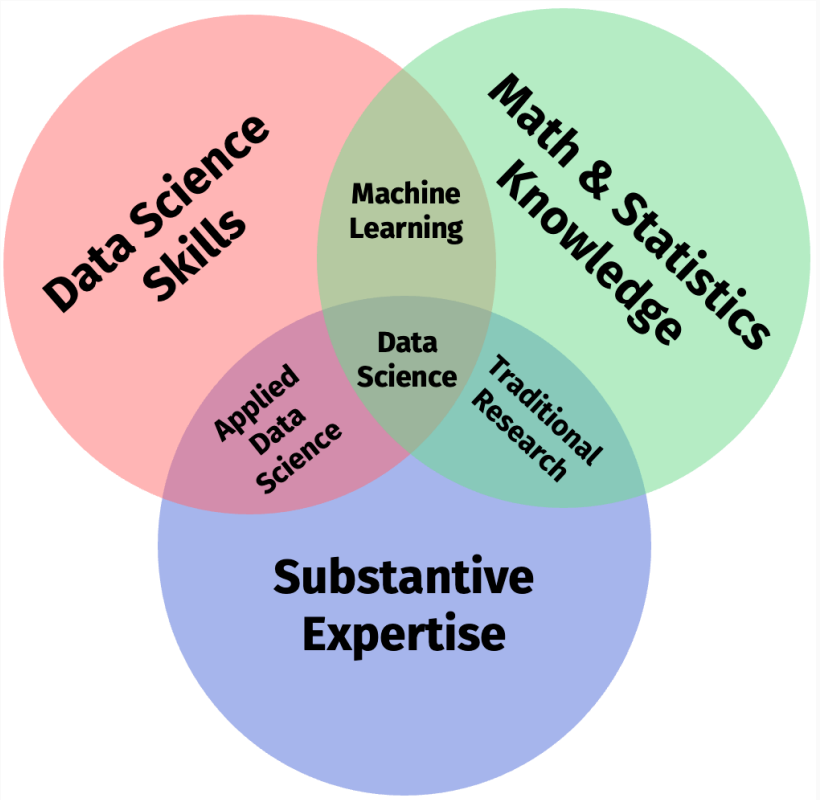
A working definition



`Source` Drew Conway, 2010 (adapted)

The data science pipeline

Preparatory work

- **Problem definition** predict, infer, describe
- **Design** conceptualize, build data collection device
- **Data collection** recruit, collect, monitor

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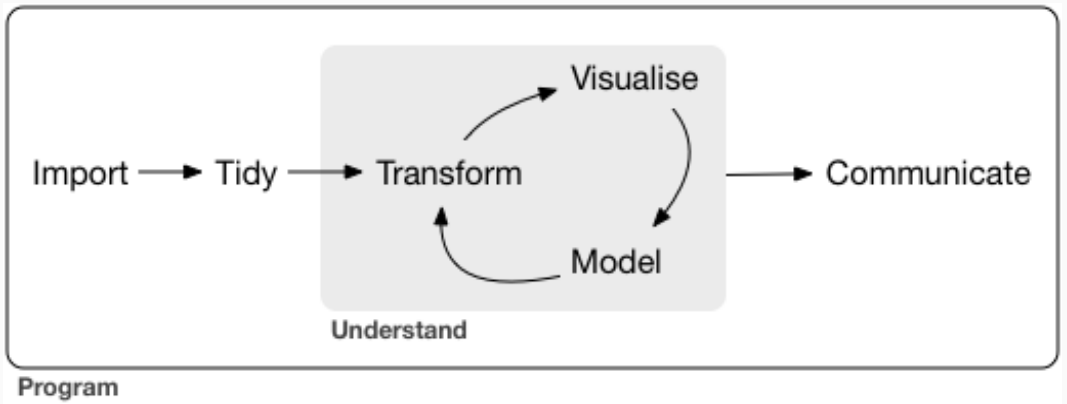

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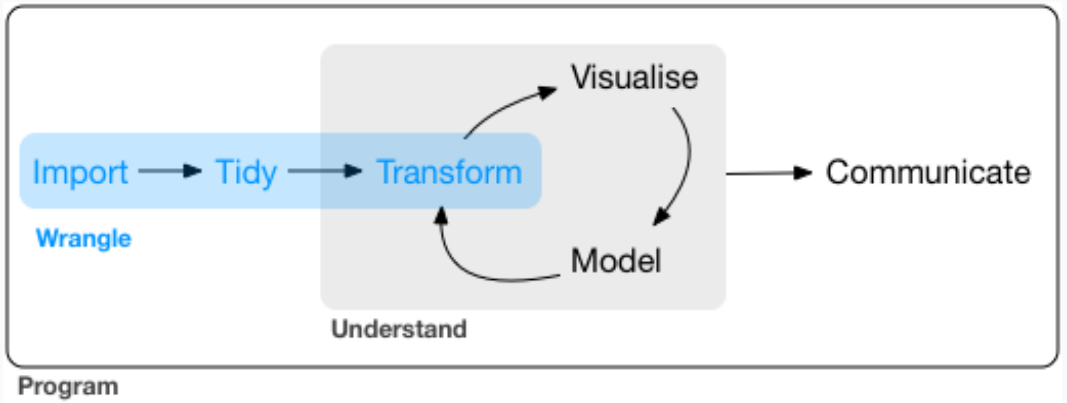

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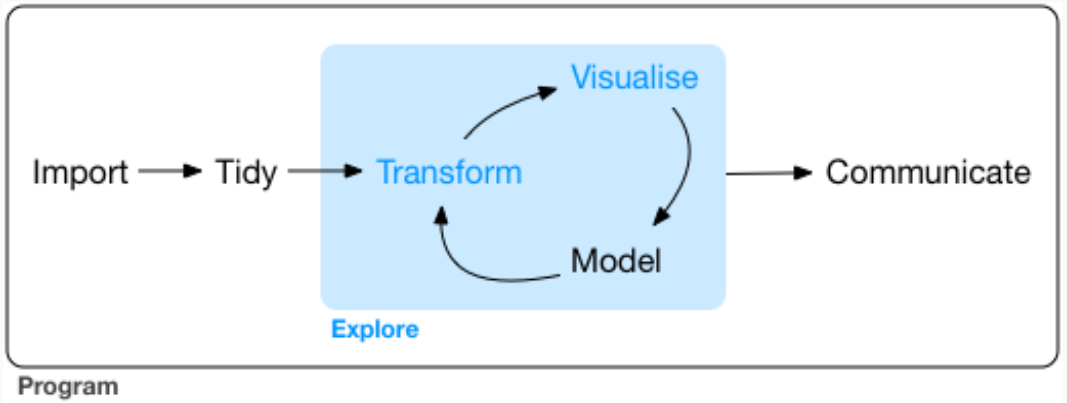

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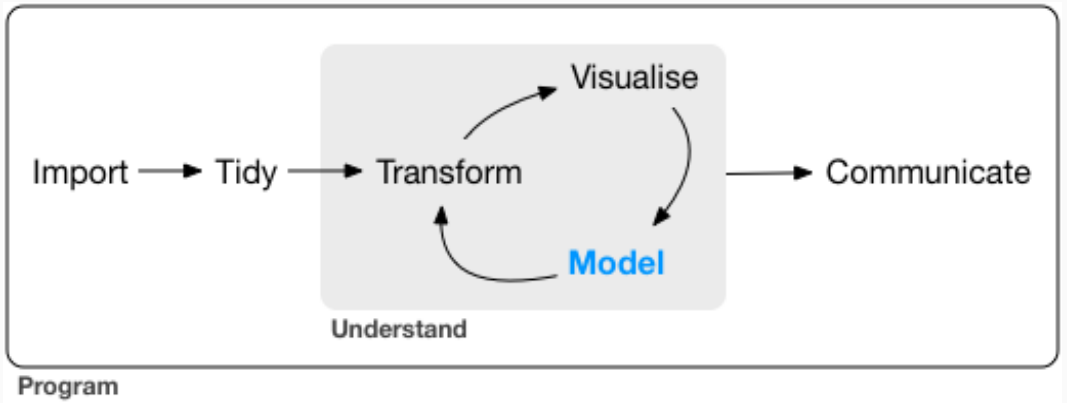
- **Model**: build, test, infer, predict



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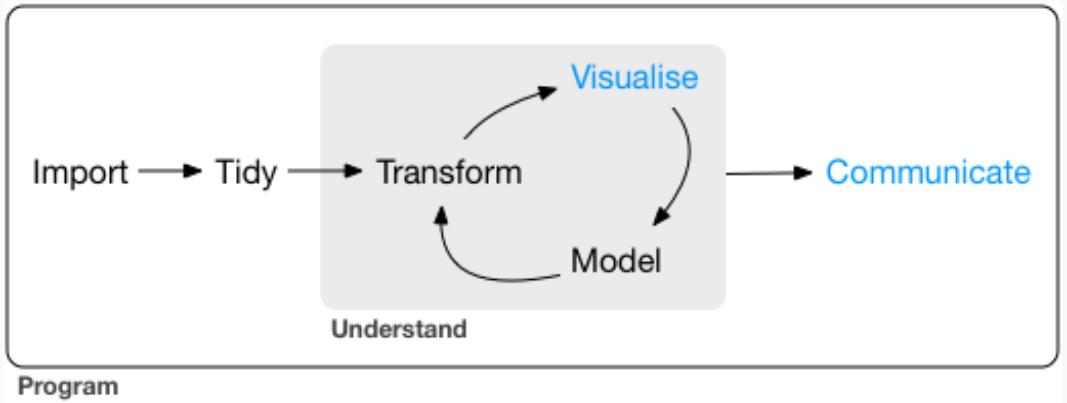
- **Publish**: journals/proceedings, blogs, software
- **Productize**: make usable, robust, scalable



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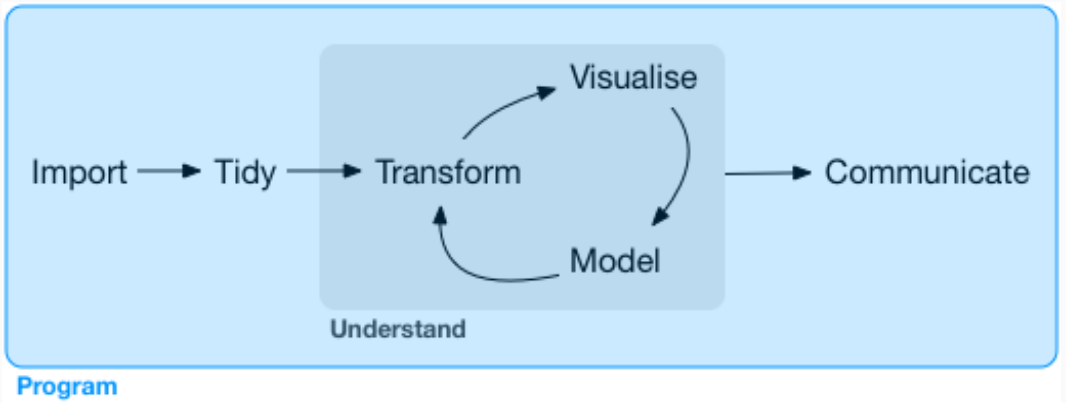
Meta skill: programming



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Meta skill: programming with R

(Data) science for public policy

Types of data-driven research and their role for policy

1. Description

- What is the state of the world?
- What are the trends over time?
- What are the differences between groups?

The value for policy-making

- At the center of **monitoring**
- "How many people consume misinformation online?"
- "How many people are unemployed in a certain district?"
- "How does the distribution of income vary across educational segments of the population?"

Types of data-driven research and their role for policy

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3. Prediction

- What is the path of an indicator?
- (When) will future events happen?
- What class does this observation most likely belong to?

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The value for policy-making

- At the center of **forecasting** but also **targeting** and **measurement**
- "Will there be conflict?"
- "How many people will be unemployed in a certain district next year?"
- "Which individuals are most likely to be affected by a policy?"

The MIT Billion Prices Project

Journal of Economic Perspectives—Volume 30, Number 2—Spring 2016—Pages 151–178

The Billion Prices Project: Using Online Prices for Measurement and Research

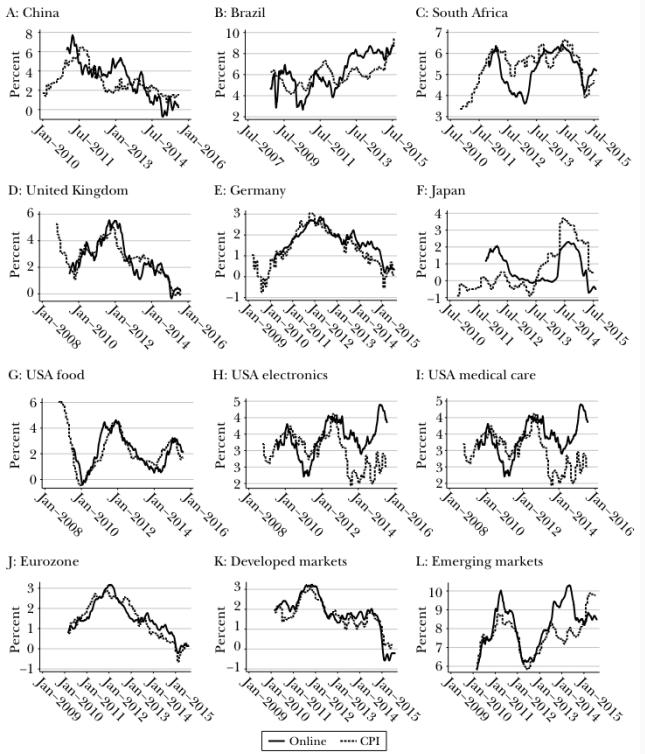
Alberto Cavallo and Roberto Rigobon

New data-gathering techniques, often referred to as "Big Data," have the potential to improve statistics and empirical research in economics. This paper presents one example of how this can be achieved by using the vast number of online prices displayed on the web. We describe our work with the Billion Prices Project at MIT, and emphasize key lessons that can be used for both inflation measurement and some fundamental research questions in macro and international economics. In particular, we show how online prices can be used to construct daily price indexes in multiple countries and to avoid measurement biases that distort evidence of price stickiness and international relative prices.

The basic procedure used in most countries to collect inflation data has remained roughly the same for decades. A large number of people working for national statistical offices visit hundreds of stores on a monthly or bimonthly basis to collect prices for a preselected basket of goods and services. The micro data are then processed and used to construct consumer price indexes and other related indicators. This process is expensive, complex, and often too slow for some users of the data. Infrequent sampling and slow updates to the baskets can complicate

Figure 4

Online versus Consumer Price Index (CPI) Annual Inflation Rates



Source: Authors using online price indexes computed by PriceStats and consumer price indexes sourced from the national statistical office in each country.

Notes: Figure 4 compares inflation as measured by online prices and by the offline prices in the official consumer price index for a selection of countries, sectors, and regions. Annual inflation rates for daily online price indexes are computed as the percentage change in the average of the previous 30 days compared to the same average 365 days before. The series are nonseasonally adjusted. Indexes are "all-items" with the exception of China, where an online supermarket index is shown next to the official food index. Global aggregates in the last row are computed using 2010 consumption weights in each country and CPIs from official sources.

See also: https://thebillionpricesproject.com/ and https://www.pricestats.com/

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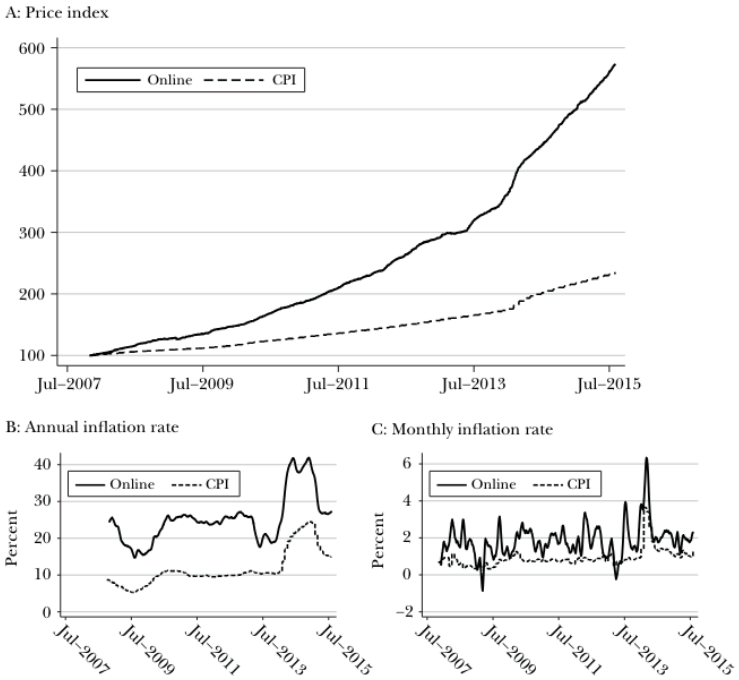
Figure 1
Argentina



Source: Authors using online price index computed by PriceStats and the consumer price index from the national statistical office in Argentina (INDEC).
Notes: The figure compares a price index produced with online data to a comparable official consumer price index (CPI) for the case of Argentina from 2007 to 2015. It also looks at annual and monthly inflation rates using each source of data. Monthly inflation rates for the online index are computed as the percentage change in the average of the previous 30 days compared to the same average a month before. Annual inflation rates for the online index are computed as the percentage change in the average of the previous 30 days compared to the same average 365 days before. All price indexes are nonseasonally adjusted.

See also: https://thebillionpricesproject.com/ and https://www.pricestats.com/

The COMPAS algorithm to predict criminals' recidivism

Background

- Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is a decision support tool developed by Northpointe (now Equivant) used by U.S. courts to **assess the likelihood of recidivism**
- Produced several scales (Pretrial release risk, General recidivism, Violent recidivism) based on factors such as age, criminal history, and substance abuse
- The algorithm is proprietary and its inner workings are not public

`Source` Practitioner's Guide to COMPAS Core

Practitioner's Guide to COMPAS Core

The Practitioner's Guide provides an overview of the COMPAS Core Module in the Northpointe Suite. The Northpointe Suite is an integrated web-based assessment and case management system for criminal justice practitioners. The Northpointe Suite has modules designed for pretrial, jail, probation, prison, parole and community corrections applications. COMPAS Core is designed for both male and female offenders recently removed from the community or currently in the community. The Practitioner's Guide to COMPAS Core covers case interpretation, validity and reliability, and treatment implications. Most of the information provided is specific to COMPAS Core. Throughout this text we use the term COMPAS Core to distinguish an element (scale, typology, decile type) specific to COMPAS Core from general elements in the Northpointe Suite, such as scales found in both COMPAS Core and COMPAS Reentry.

COMPAS is a fourth generation risk and needs assessment instrument. Criminal justice agencies across the nation use COMPAS to inform decisions regarding the placement, supervision and case management of offenders. COMPAS was developed empirically with a focus on predictors known to affect recidivism. It includes dynamic risk factors, and it provides information on a variety of well validated risk and needs factors designed to aid in correctional intervention to decrease the likelihood that offenders will reoffend.

COMPAS was first developed in 1998 and has been revised over the years as the knowledge base of criminology has grown and correctional practice has evolved. In many ways changes in the field have followed new developments in risk assessment. We continue to make improvements to COMPAS based on results from norm studies and recidivism studies conducted in jails, probation agencies, and prisons. COMPAS is periodically updated to keep pace with with emerging best practices and technological advances.

In overloaded and crowded criminal justice systems, brevity, efficiency, ease of administration and clear organization of key risk/needs data are critical. COMPAS was designed to optimize these practical factors. We acknowledge the trade-off between comprehensive coverage of key risk and criminogenic factors on the one hand, and brevity and practicality on the other. COMPAS deals with this trade-off in several was; it provides a comprehensive set of key risk factors that have emerged from the recent criminological literature, and it allows for customization inside the software. Therefore, ease of use, efficient and effective time management, and case management considerations that are critical to best practice in the criminal justice field can be achieved through COMPAS.

The COMPAS algorithm to predict criminals' recidivism

The ProPublica and other investigations

- In 2016, ProPublica published an investigation showing that COMPAS was **biased against African Americans**
- **Bias:** The algorithm was more likely for African Americans to wrongly predict that defendants would re-offend.
- **Accuracy:** only 20% of people predicted to commit violent crimes actually went on to do so (in a later study estimated with 65%, still worse than a group of humans with little expertise)

`Source` ProPublica 2016

Machine Bias*

Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner

There's software used across the country to predict future criminals. And it's biased against blacks.

ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid's blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.

Just as the 18-year-old girls were realizing they were too big for the tiny conveyances—which belonged to a 6-year-old boy—a woman came running after them saying, "That's my kid's stuff." Borden and her friend immediately dropped the bike and scooter and walked away.

But it was too late—a neighbor who witnessed the heist had already called the police. Borden and her friend were arrested and charged with burglary and petty theft for the items, which were valued at a total of $80.

Compare their crime with a similar one: The previous summer, 41-year-old Vernon Prater was picked up for shoplifting $86.35 worth of tools from a nearby Home Depot store (Figure 6.1.1).

Prater was the more seasoned criminal. He had already been convicted of armed robbery and attempted armed robbery, for which he served five years in prison, in addition to another armed robbery charge. Borden had a record, too, but it was for misdemeanors committed when she was a juvenile.

Yet something odd happened when Borden and Prater were booked into jail: A computer program spat out a score predicting the likelihood of each committing a future crime. Borden—who is black—was rated a high risk. Prater—who is white—was rated a low risk.

Two years later, we know the computer algorithm got it exactly backward. Borden has not been charged with any new crimes. Prater is serving an eight-year prison term for subsequently breaking into a warehouse and stealing thousands of dollars' worth of electronics.

Scores like this—known as risk assessments—are increasingly common in courtrooms across the nation. They are used to inform decisions about who can be set free at every stage of the criminal justice system, from assigning bond amounts—as is the case in Fort Lauderdale—to

* Julia Angwin, Jeff Larson, Surya Mattu, Lauren Kirchner, "Machine Bias," *ProPublica* (May 23, 2016). Reprinted with permission.

254 DOI: 10.1201/9781003278290-37

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SCIENCE ADVANCES | RESEARCH ARTICLE

RESEARCH METHODS

The accuracy, fairness, and limits of predicting recidivism

Julia Dressel and Hany Farid*

Algorithms for predicting recidivism are commonly used to assess a criminal defendant's likelihood of committing a crime. These predictions are used in pretrial, parole, and sentencing decisions. Proponents of these systems argue that big data and advanced machine learning make these analyses more accurate and less biased than humans. We show, however, that the widely used commercial risk assessment software COMPAS is no more accurate or fair than predictions made by people with little or no criminal justice expertise. In addition, despite COMPAS's collection of 137 features, the same accuracy can be achieved with a simple linear predictor with only two features.

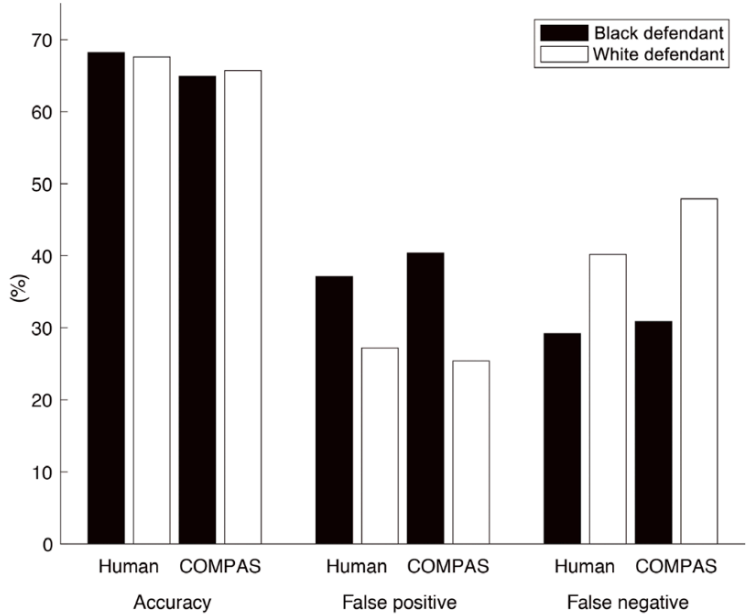

Fig. 1. Human (no-race condition) versus COMPAS algorithmic predictions (see also Table 1).

`Source` Dressel and Fair, 2018, Science Advances

The Meta US 2020 Election study

How do social media feed algorithms affect attitudes and behavior in an election campaign?

Andrew M. Guess[1]*, Neil Malhotra[2], Jennifer Pan[3], Pablo Barberá[4], Hunt Allcott[5], Taylor Brown[4], Adriana Crespo-Tenorio[4], Drew Dimmery[4,6], Deen Freelon[7], Matthew Gentzkow[8], Sandra González-Bailón[9], Edward Kennedy[10], Young Mie Kim[11], David Lazer[12], Devra Moehler[4], Brendan Nyhan[13], Carlos Velasco Rivera[4], Jaime Settle[14], Daniel Robert Thomas[4], Emily Thorson[15], Rebekah Tromble[16], Arjun Wilkins[4], Magdalena Wojcieszak[17,18], Beixian Xiong[4], Chad Kiewiet de Jonge[4], Annie Franco[4], Winter Mason[4], Natalie Jomini Stroud[19], Joshua A. Tucker[20]

We investigated the effects of Facebook's and Instagram's feed algorithms during the 2020 US election. We assigned a sample of consenting users to reverse-chronologically-ordered feeds instead of the default algorithms. Moving users out of algorithmic feeds substantially decreased the time they spent on the platforms and their activity. The chronological feed also affected exposure to content: The amount of political and untrustworthy content they saw increased on both platforms, the amount of content classified as uncivil or containing slur words they saw decreased on Facebook, and the amount of content from moderate friends and sources with ideologically mixed audiences they saw increased on Facebook. Despite these substantial changes in users' on-platform experience, the chronological feed did not significantly alter levels of issue polarization, affective polarization, political knowledge, or other key attitudes during the 3-month study period.

Reshares on social media amplify political news but do not detectably affect beliefs or opinions

Andrew M. Guess[1]*, Neil Malhotra[2], Jennifer Pan[3], Pablo Barberá[4], Hunt Allcott[5], Taylor Brown[4], Adriana Crespo-Tenorio[4], Drew Dimmery[4,6], Deen Freelon[7], Matthew Gentzkow[8], Sandra González-Bailón[9], Edward Kennedy[10], Young Mie Kim[11], David Lazer[12], Devra Moehler[4], Brendan Nyhan[13], Carlos Velasco Rivera[4], Jaime Settle[14], Daniel Robert Thomas[4], Emily Thorson[15], Rebekah Tromble[16], Arjun Wilkins[4], Magdalena Wojcieszak[17,18], Beixian Xiong[4], Chad Kiewiet de Jonge[4], Annie Franco[4], Winter Mason[4], Natalie Jomini Stroud[19], Joshua A. Tucker[20]

We studied the effects of exposure to reshared content on Facebook during the 2020 US election by assigning a random set of consenting, US-based users to feeds that did not contain any reshares over a 3-month period. We find that removing reshared content substantially decreases the amount of political news, including content from untrustworthy sources, to which users are exposed; decreases overall clicks and reactions; and reduces partisan news clicks. Further, we observe that removing reshared content produces clear decreases in news knowledge within the sample, although there is some uncertainty about how this would generalize to all users. Contrary to expectations, the treatment does not significantly affect political polarization or any measure of individual-level political attitudes.

The Meta US 2020 Election study

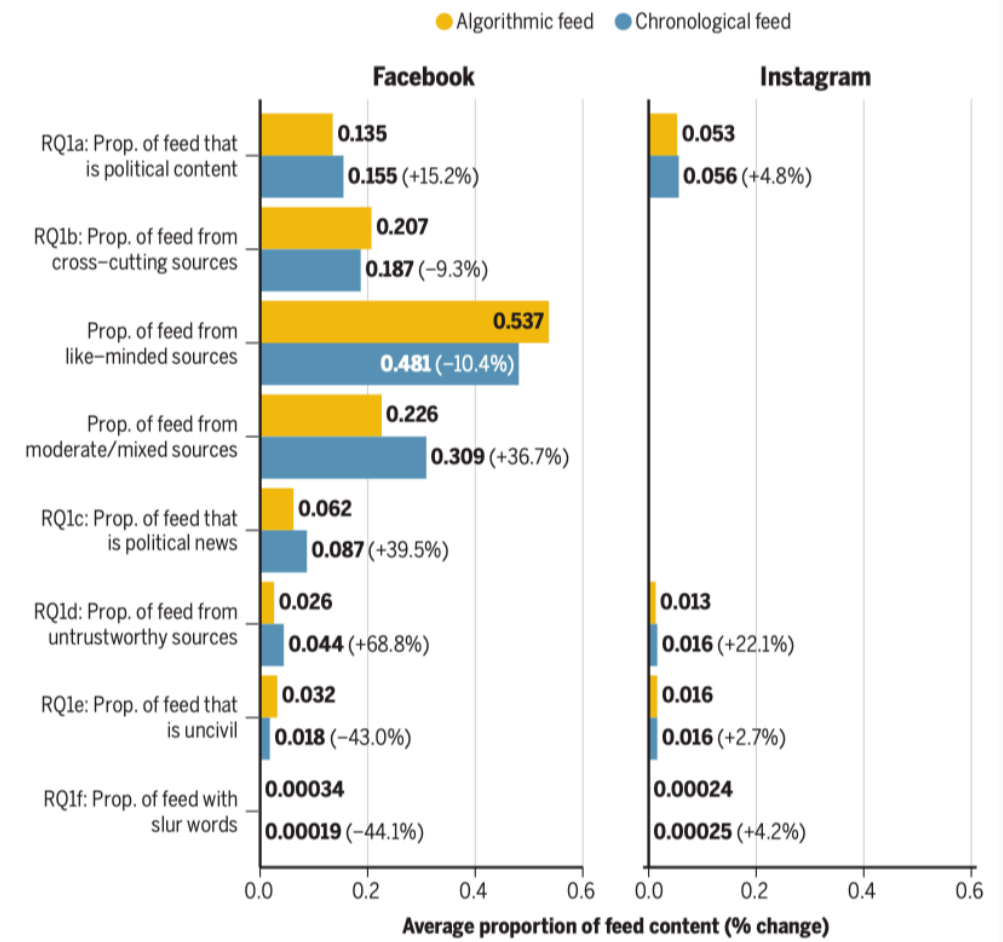

Fig. 2. Estimated changes in prevalence of feed content on both Facebook and Instagram. (**Left**) Facebook. (**Right**) Instagram. Values are average unweighted proportions within each group, with percent changes relative to the Algorithmic Feed control group in parentheses. All differences are significant at the $p < 0.005$ level, except RQ1f for Instagram ($p < 0.05$); confidence intervals are thus not shown. RQ1b and RQ1c were not tested for Instagram because political and ideology classifications are not available on that platform. Fully specified regression models with survey weights are reported in the SM, section S2.2.

`Source` Guess et al. 2023, Science

The Meta US 2020 Election study

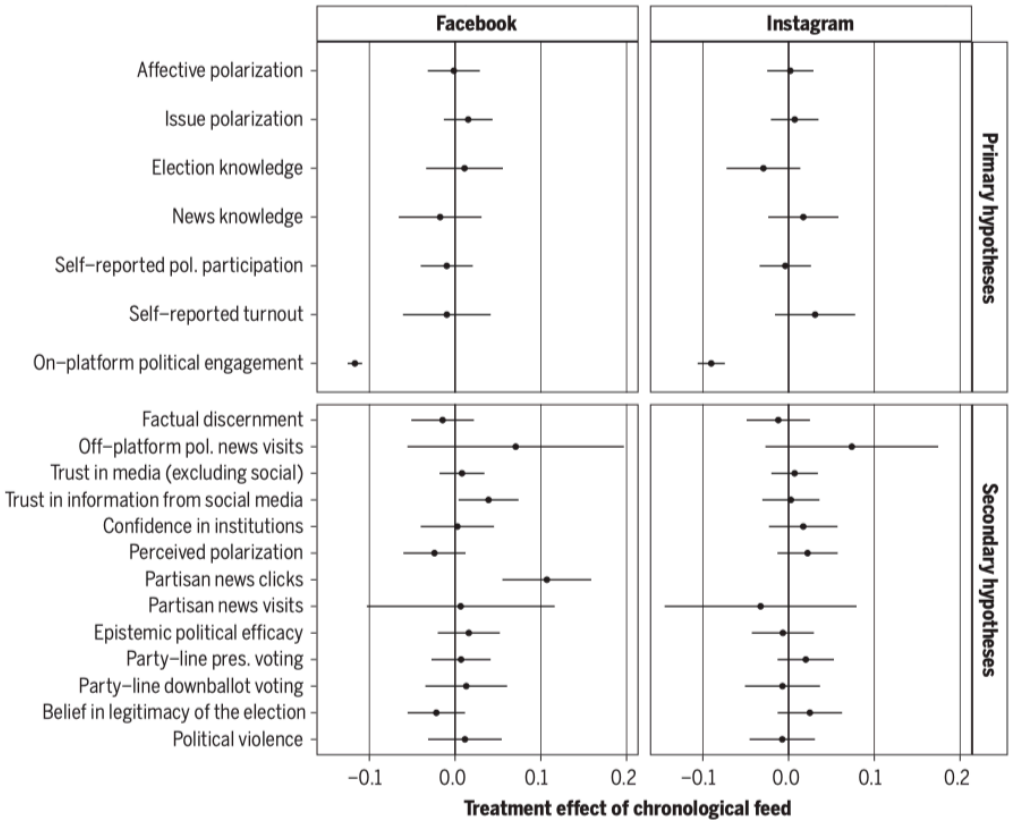

Fig. 3. Population average treatment effects of the Chronological Feed, relative to the Algorithmic Feed control group, on both Facebook and Instagram. (**Left**) Facebook. (**Right**) Instagram. Estimates are presented in standard deviations with 95% confidence intervals (not adjusted for multiple comparisons). Partisan news clicks are estimated only for Facebook because source-level estimates of political ideology are not available for Instagram. pol., political; pres., presidential.

`Source` Guess et al. 2023, Science

Class logistics

You at the beginning of the course

You at the end of the course

Introduction to Data Science in a nutshell

Session	Session Title	A	Date
	Fundamentals		
1	What is data science?	-	September 08
2	Programming I: Project management, coding etiquette, functions	H	September 15
3	Programming II: Iteration, automation, scheduling	Q	September 22
	Collecting data		
4	Web data and technologies	Q	~~September 29~~ October 1
5	Web scraping and APIs	H	October 06
6	Relational databases and SQL	Q	October 13
	Analyzing data		
7	Modeling	Q	October 20
	Fall break: no classes		
8	Visualization	H	November 03
	Communication and big picture		
9	Monitoring and communication	H	November 10
10	Data science ethics	Q	November 17
11	Towards open data science	-	November 24
12	Hackathon	-	December 01
	Final Exam Week: no classes		

Why R?

Why R and RStudio?

Data science positivism

- Alongside Python, R has become the *de facto* language for data science.
  - See: *The Impressive Growth of R*, *The Popularity of Data Science Software*
- Open-source (free!) with a global user-base spanning academia and industry.
  - "Do you want to be a profit source or a cost center?"

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Bridge to multiple other programming environments, with statistics at heart

- Already has all of the statistics support, and is amazingly adaptable as a “glue” language to other programming languages and APIs.
- The RStudio IDE and ecosystem allow for further, seemless integration.

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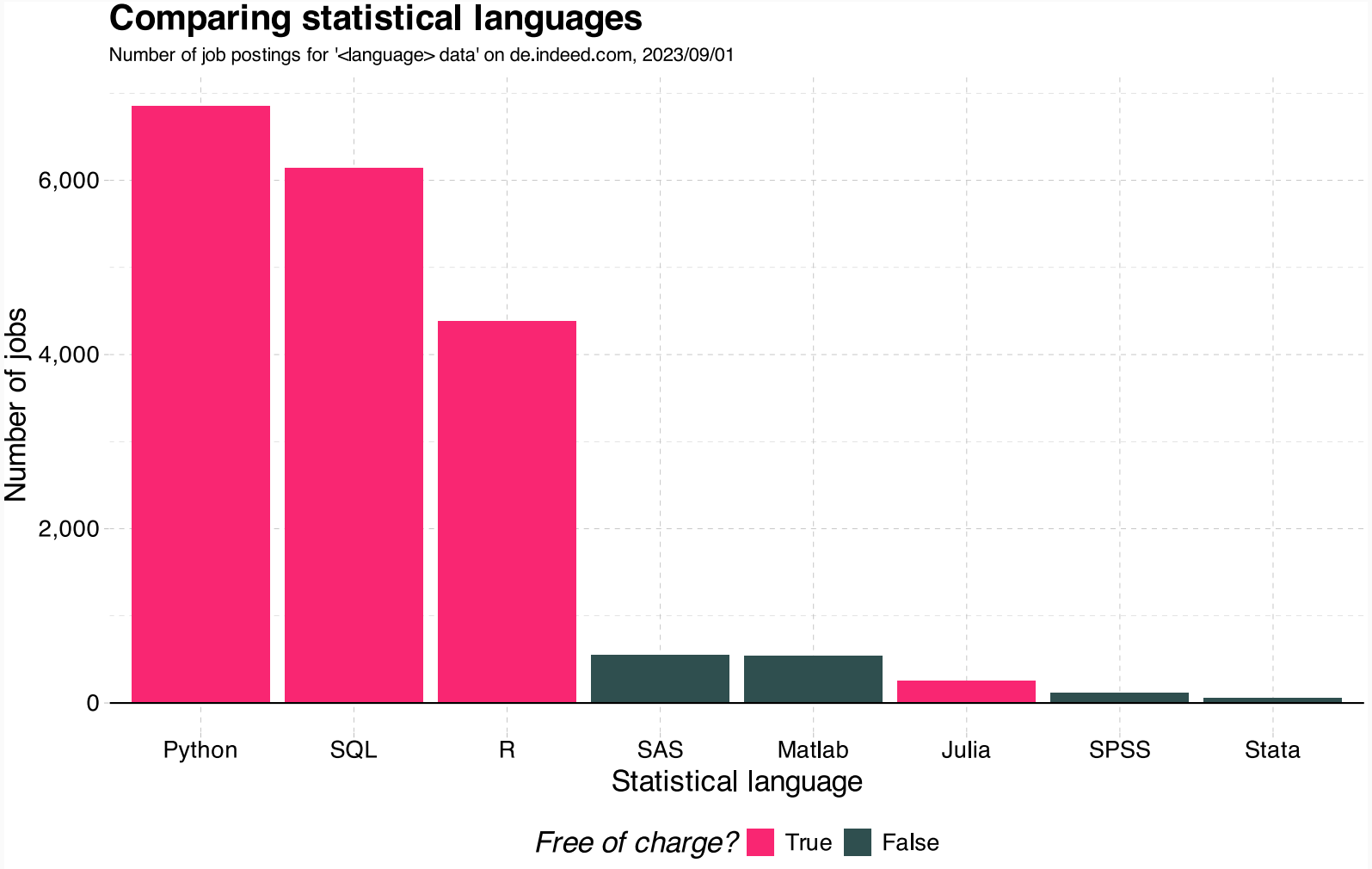
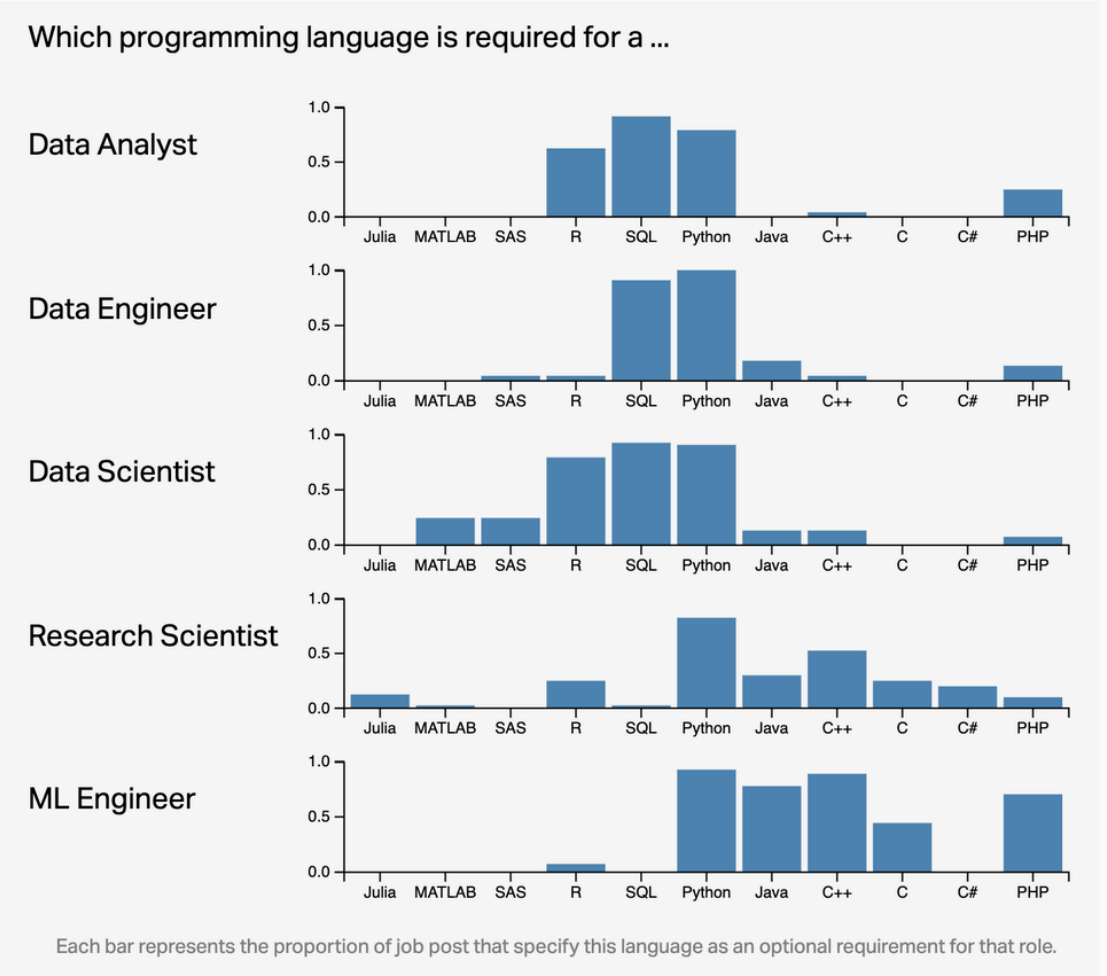
Path dependency

- It's also the language that I know best.
- (Learning multiple languages is a good idea, though.)

Why R and RStudio? (cont.)



Why R and RStudio? (cont.)



`Credit` Left_Ad8361/Reddit

Attendance

General rules

- You cannot miss more than two sessions. If you have to miss a session for medical reasons or personal emergencies, please **inform Examination Office** and they will inform me about your absence.
- I **don't want you to notify me about absences** in advance or ex post.
- We will check attendance on-site.

Office hours and advice

- If you want to discuss content from class, first do so in with your Lab TA.
- If you want to discuss something with the entire group, use the Moodle forum.
- If you want to discuss something with me, please sign up for a slot in my office hours (link on Moodle).
- For general technical advice, the Research Consulting Team at the Data Science Lab is there for you.

Assignments and grading

Component	Weight
3(4) × homework assignments	pass/fail
4(5) × online quizzes (5% each)	20%
1 × hackathon project	40%
1 × in-class coding exam	40%

Assignments and grading

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Homework assignments

- Your incentive to practice what you learn in class regularly!
- Each assignment is a mix of practical problems that are to be solved with R.
- The assignments are distributed via our own GitHub Classroom.
- You are encouraged to collaborate, but everyone will hand in a separate solution.
- There will be 4 assignments (one every ~2 weeks), and you'll have to submit 3 of them to pass the course.
- You'll have one week to work on each assignment (deadline: Tuesdays at 9:30am).
- You submit your solutions via GitHub.
- Grading: pass/fail + feedback. Your solutions don't have to be perfect, but we want to see an individual effort.

Assignments and grading

Component	Weight
3(4) × homework assignments	pass/fail
4(5) × online quizzes (5% each)	20%
1 × hackathon project	40%
1 × in-class coding exam	40%

Online quizzes

- The short online quizzes will test your knowledge about the topics covered in class.
- There will be 5 quizzes and the 4 best will contribute to the final grade.
- You'll have one week to work on each assignment (deadline: Tuesdays at 9:30am).
- Note that quizzes will employ light negative grading. Usually a question is multiple choice, with an unknown number of correct items. The rationale is that if you select all options with not all of them being correct, you should not receive full credit (otherwise, in the absence of negative grading, selecting all answers would be the dominant strategy).

Assignments and grading

Component	Weight
3(4) × homework assignments	pass/fail
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1 × hackathon project	40%
1 × in-class coding exam	40%

Hackathon project

- On December 1, 14-16h, there will be a hackathon hosted at Hertie.
- At the hackathon itself, I'll introduce the data and provide an environment that should facilitate you getting started with the project and form groups of 3-4 students.
- After the hackathon project, you will get instructions . You will then have 72 hours to submit your solutions.
- The task is similar to the homework assignments but puts more emphasis on creative problem-solving using the tools and techniques you have learned in class.

Assignments and grading

Component	Weight
3(4) × homework assignments	pass/fail
4(5) × online quizzes (5% each)	20%
1 × hackathon project	40%
1 × in-class coding exam	40%

In-class coding exam

- The in-class coding exam will take place in the final exam week (date tba).
- The exam will be open-book, open-internet, and open-R. Collaboration will not be allowed.
- The exam will be similar to the homework assignments but with a stronger emphasis on problem-solving under time constraints.
- You will have 90 minutes to solve the exam.

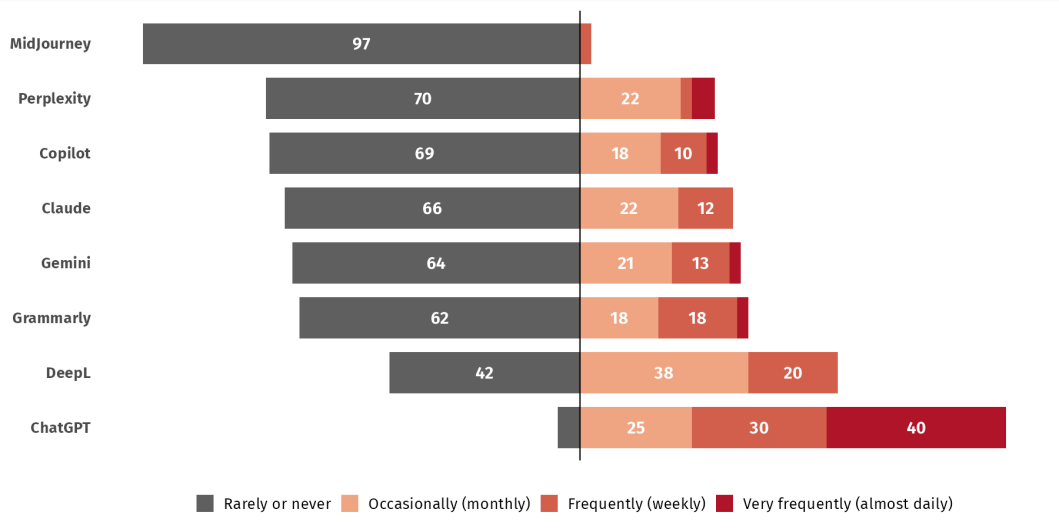
AI use in and for the course

Can AI tools (LLM-based coding assistants) be used for assignments?

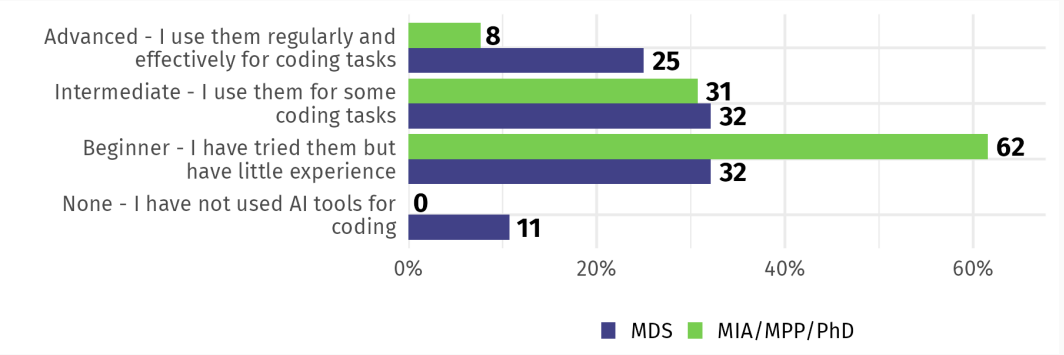
- Yes, but use them with care. You will not become an efficient programmer if you heavily rely on those tools without learning the basics.
- The Hertie School has a guideline in place that address the use of AI tools in education installed .
- Some key elements from the guidelines:
  - "Students are required to include a Statement of Authorship and AI Use at the end of each written assignment (...), which states their authorship including the use of AI and the absence of plagiarism."
  - "[A]ll AI tools that have been used need to be specified in the Statement of Authorship."
  - "Students are responsible for factual errors and false references in their assignments, even if these have been provided by AI tools that were properly disclosed. The assignment will receive a grade penalty in such instances."
- "Non-disclosed or non-permitted (...) use of AI in assignments (...) is a violation of good academic conduct."

AI use in and for the course (cont.)

Your use of AI tools



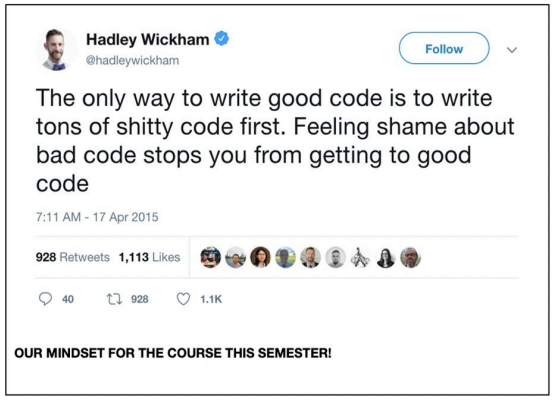
Your use of AI coding assistants



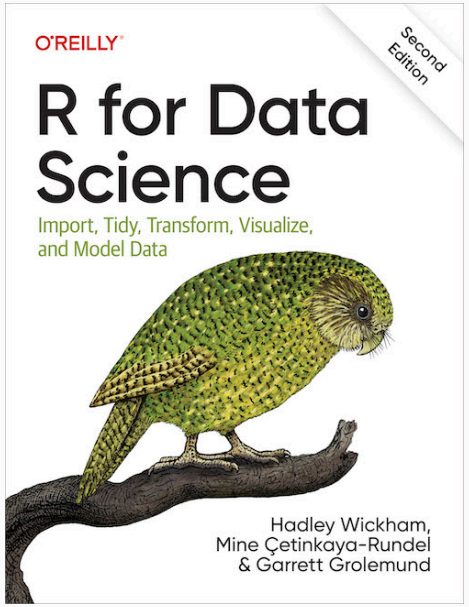
AI use in and for the course (cont.)

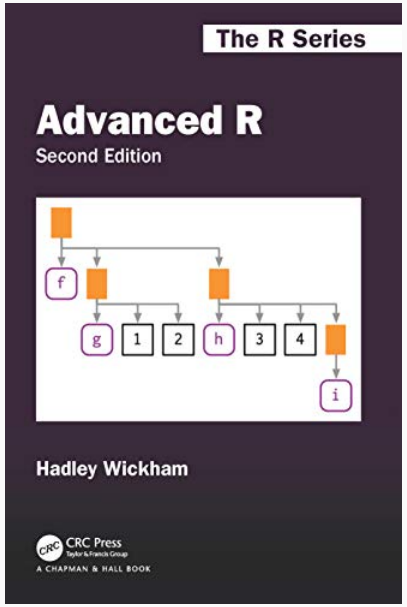
Should you use AI tools for this course?

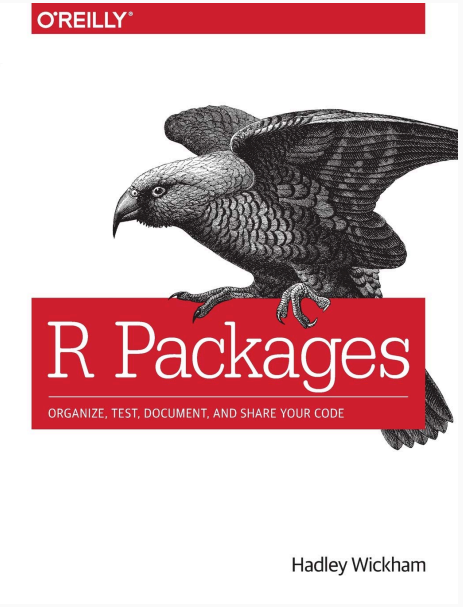
- You are a student at one of the leading policy schools in the world. You decided to invest a considerable amount of time and money to learn about data science and public policy here. I think you're at the right place to do so.
- However, the learning is still on you. What is key is that you want to *understand* what you are doing. That will require you to think hard and work hard. And that is ultimately what you need to excel in a data-based job.
- Or, you could just rely on some commercial language model to do the hard work for you. If you do that, you will notice that the muscles you wanted to train will not grow.
- That is not to say that AI is not useful for coding. It is incredibly powerful. But it also often fails spectacularly. You need to understand what is going on under the hood to make it work for you.
- I am not here to discipline and punish. I have no interest in that. What I can do is provide you with an environment that facilitates learning and sets the right incentives. If you want to learn, I will help you. If you don't, I can't.

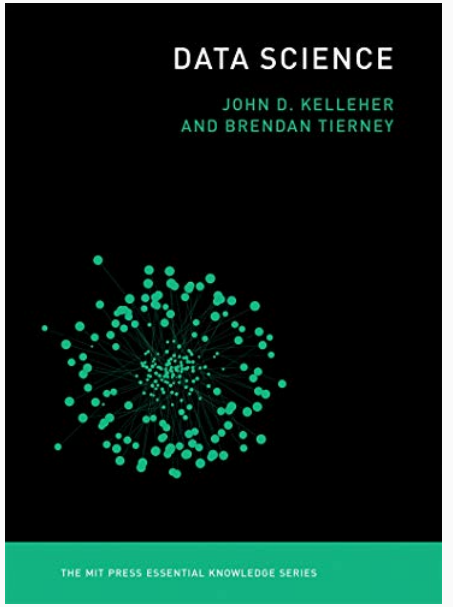


Core (and optional) readings

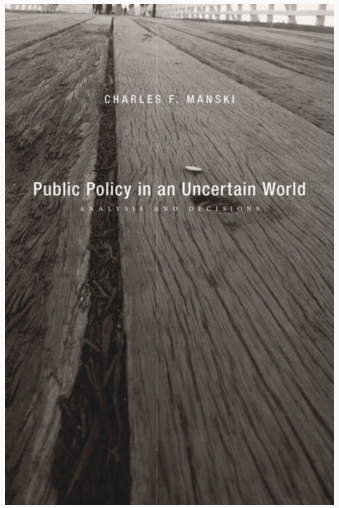


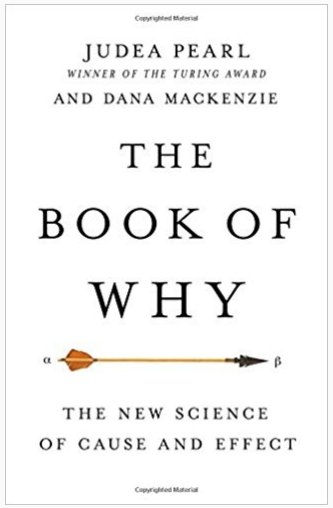


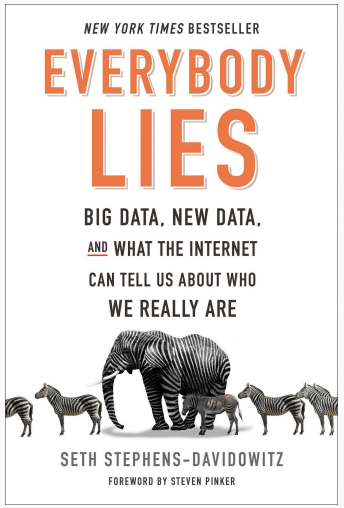


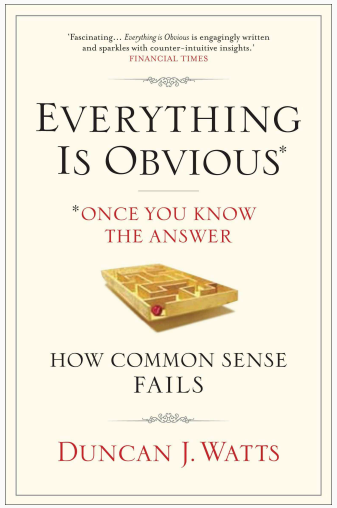


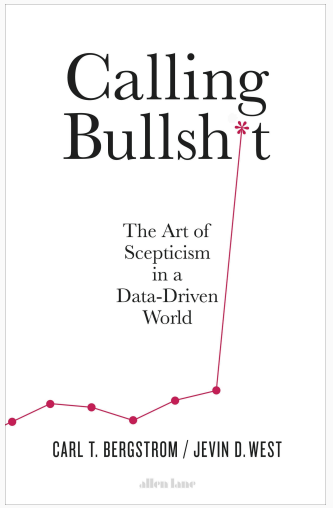
Further reading

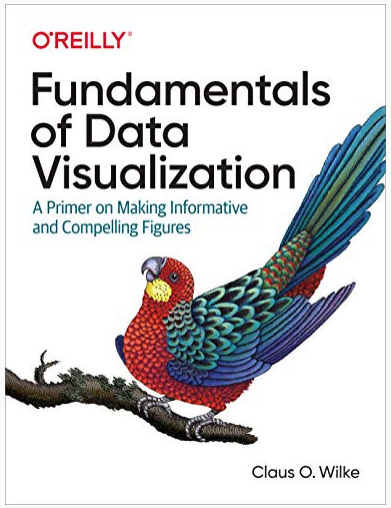


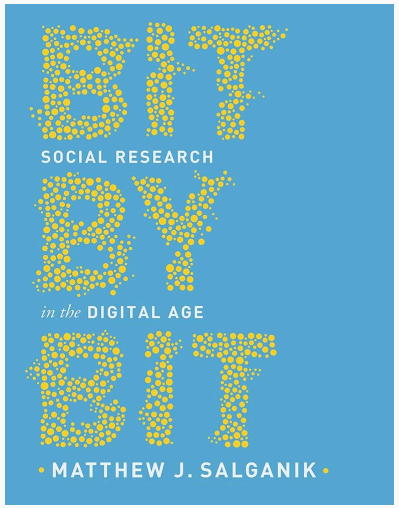


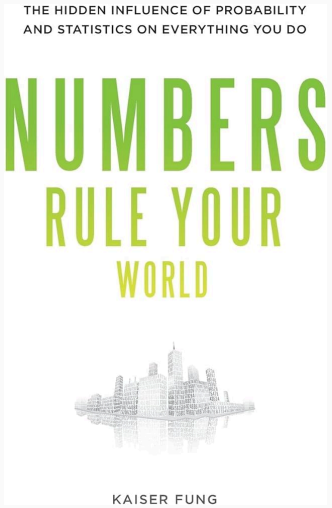


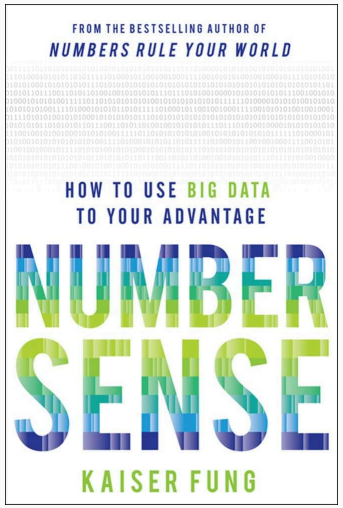


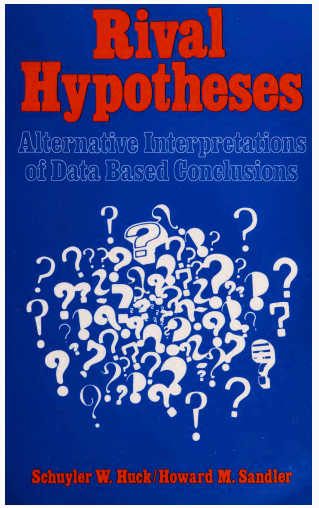


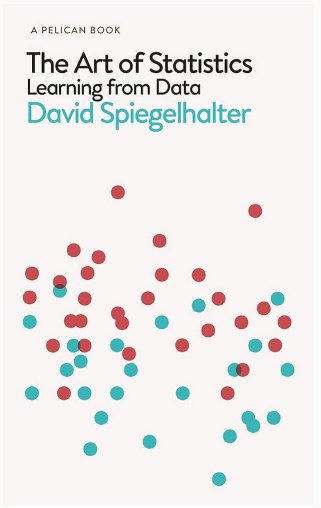


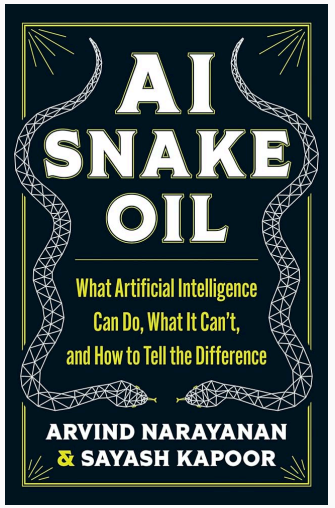




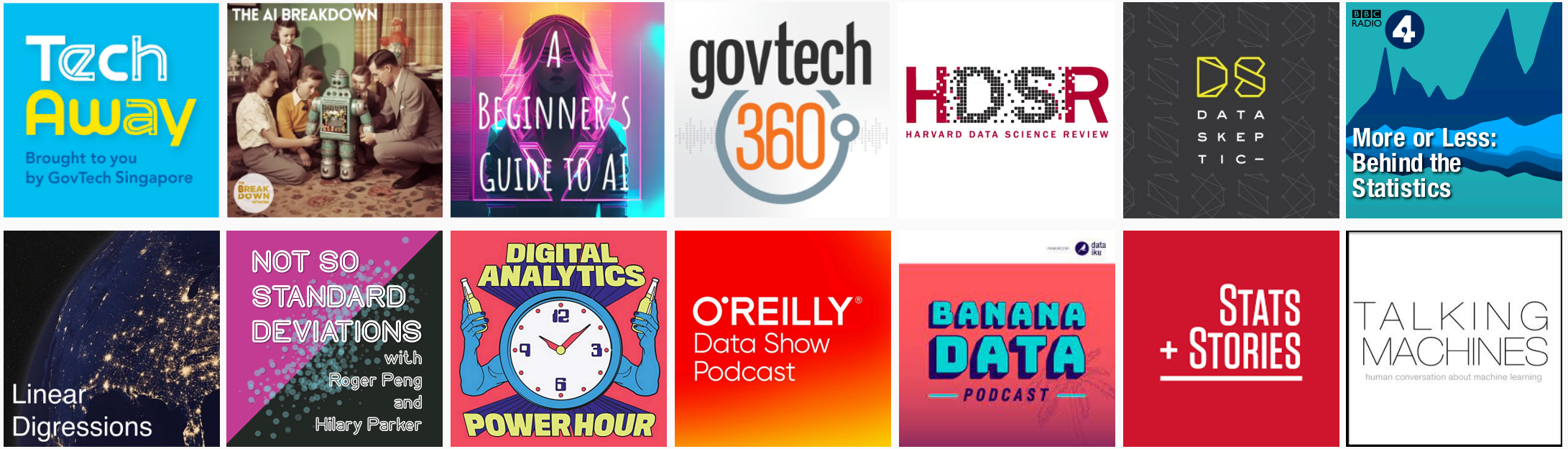




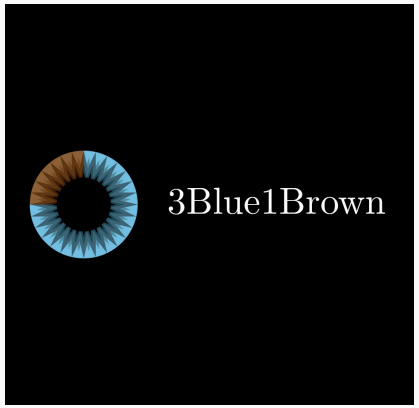


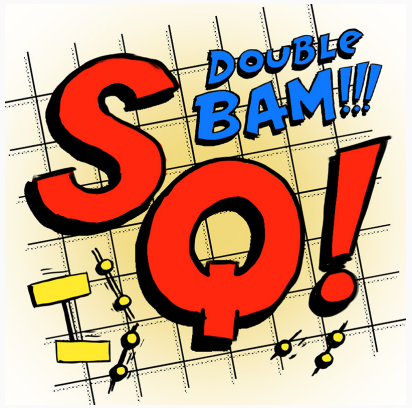


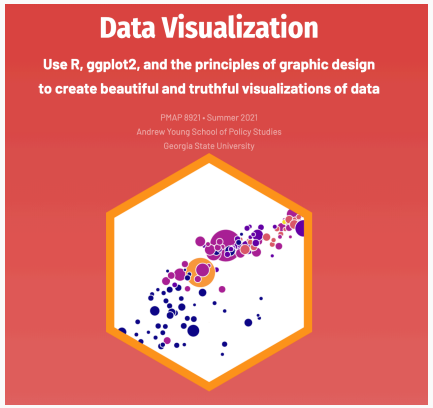
Further listening



Further watching







Coming up

The first lab session

Get to know Carol, Killian, R, and RStudio, four of your best friends for the next months!

Next lecture

Version control and project management