Day 1: Fundamental data and statistical literacy

Data science, statistical reasoning, and policy-making

Simon Munzert
Hertie School

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Willkommen!

Vorstellungen

Über Mich

Ich bin Simon Munzert [si'mən munsɜrt], oder Simon [saɪmən].

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Professor für Data Science und Public Policy | Direktor des Data Science Labs

Über Sie

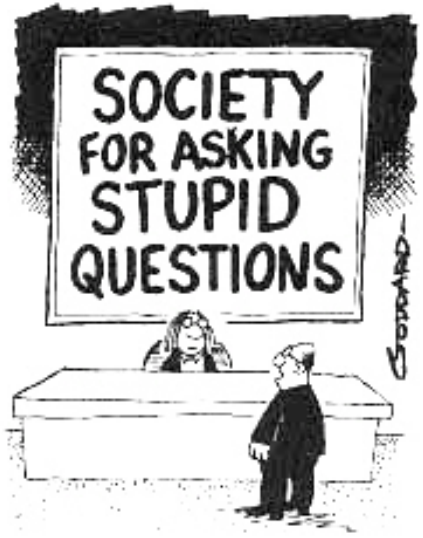
Wie heißen Sie und was ist Ihre Position?

Welche Erfahrungen haben Sie mit Datenwissenschaft und Statistik gemacht?

Haben Sie in Ihrer Position Berührungspunkte mit quantitativer Evidenz?

Workshop etiquette

- Wir haben viel gemeinsam vor. Ich habe eine Menge Material mitgebracht, aber letztlich müssen Sie **signalisieren, wo Ihre Interessen und Bedürfnisse liegen**. Ich bin gerne bereit, Themen zu vertiefen, abzuschweifen oder die Aufmerksamkeit auf andere Themen und Beispiele zu lenken (solange sie sich in meiner Komfortzone befinden).
- Natürlich bin ich alles andere als ein Experte für Ihre individuelle Behörde oder Ihre aktuellen Themen. Für eine fundierte, evidenzbasierte Argumentation in Bezug auf die Politik ist Fachwissen der Schlüssel und ist explizit Teil vieler der datenbasierten Werkzeuge und Methoden, die wir diskutieren werden. Bitte **bringen Sie Ihr eigenes Wissen und Ihre Erfahrung mit**.
- Bitte nutzen Sie die Gelegenheit, **jederzeit Fragen zu stellen**. Einige der Themen könnten Sie aus Ihrer Komfortzone herausführen. Aber es gibt keine schlechten Fragen, also stellen Sie sie bitte.



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

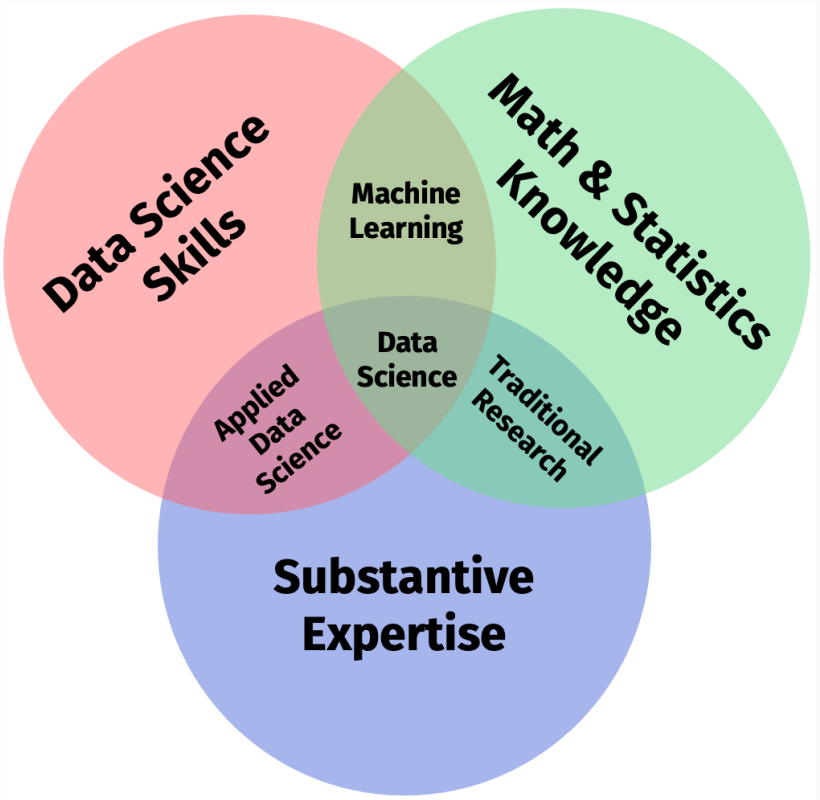
Was ist Data Science?

Was ist Data Science?

> "Data Science ist ein interdisziplinäres Wissenschaftsfeld, welches wissenschaftlich fundierte Methoden, Prozesse, Algorithmen und Systeme zur Extraktion von Erkenntnissen, Mustern und Schlüssen sowohl aus strukturierten als auch unstrukturierten Daten ermöglicht." - Wikipedia
>
> "Data Science ist ein Konzept, das Statistik, Datenanalyse, Informatik und die damit verbundenen Methoden vereint, um aktuelle Phänomene anhand von Daten zu verstehen und zu analysieren." - Chikio Hayashi

Insgesamt gibt es **keinen Konsens** - es ist schließlich ein Modewort. Wir werden mit der Arbeitsdefinition von Conway fortfahren.

A working definition



`Source` Drew Conway, 2010 (adapted)

Arten von datengestützter Forschung und ihre Rolle für die Politik

1. Beschreibung

- Wie ist der Zustand der Welt?
- Was sind die Trends im Laufe der Zeit?
- Was sind die Unterschiede zwischen den Gruppen?

Der Wert für die Politikgestaltung

- Im Zentrum des **Monitorings**
- „Wie viele Menschen konsumieren Fehlinformationen im Internet?“
- „Wie viele Menschen sind in einem bestimmten Bezirk arbeitslos?“
- „Wie ist die Einkommensverteilung in den verschiedenen Bildungssegmenten der Bevölkerung?“

2. Erklärung

- Welche Auswirkungen hat eine Maßnahme?
- Ist die Wirkung je nach Gruppe unterschiedlich?
- Was sind die Mechanismen hinter dieser Wirkung?

Der Wert für die Politikgestaltung

- Im Mittelpunkt der **Evaluation**
- „Hat die Erhöhung des Mindestlohns zu einem Rückgang der Beschäftigung geführt?“
- „Wirkte sich die Kampagne bei verschiedenen Gruppen unterschiedlich auf die Verbreitung von Falschinformationen aus?“
- „Warum hat die Intervention nicht

3. Vorhersage

- Was ist der Weg eines Indikators?
- (Wann) werden zukünftige Ereignisse eintreten?
- Zu welcher Klasse gehört diese Beobachtung höchstwahrscheinlich?

Der Wert für die Politikgestaltung

- Steht im Mittelpunkt der **Vorhersage**, aber auch der **Zielsetzung** und **Messung**.
- „Wird es Konflikte geben?“
- „Wie viele Menschen werden nächstes Jahr in einem bestimmten Bezirk arbeitslos sein?“
- „Welche Personengruppen werden am ehesten von einer Maßnahme

Die Data Science Pipeline

Die Data Science Pipeline

Vorbereitung

- **Problemstellung** Vorhersage, Inferenz, Beschreibung
- **Design** Konzept erstellen, Datenerfassung aufsetzen
- **Datenerhebung** rekrutieren, sammeln, überwachen

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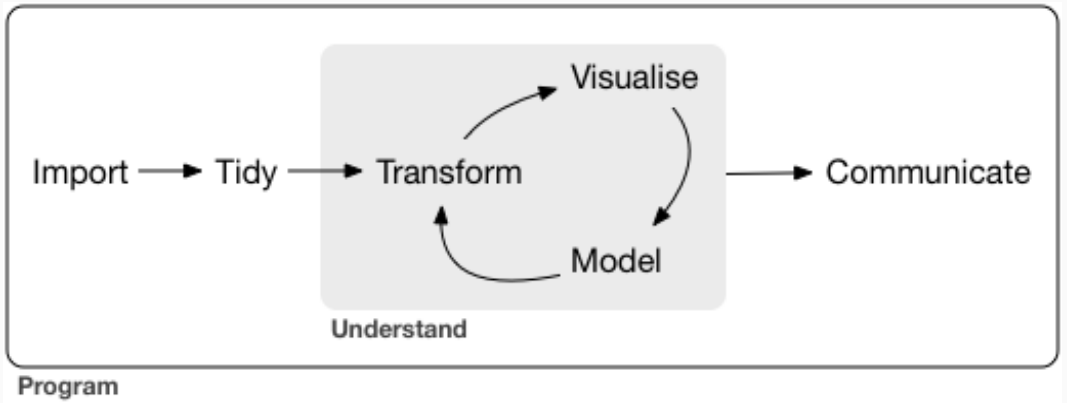
Datenverarbeitung



`Source` H. Wickham, M. Çetinkaya-Rundel, G. Gronemund: R for Data Science

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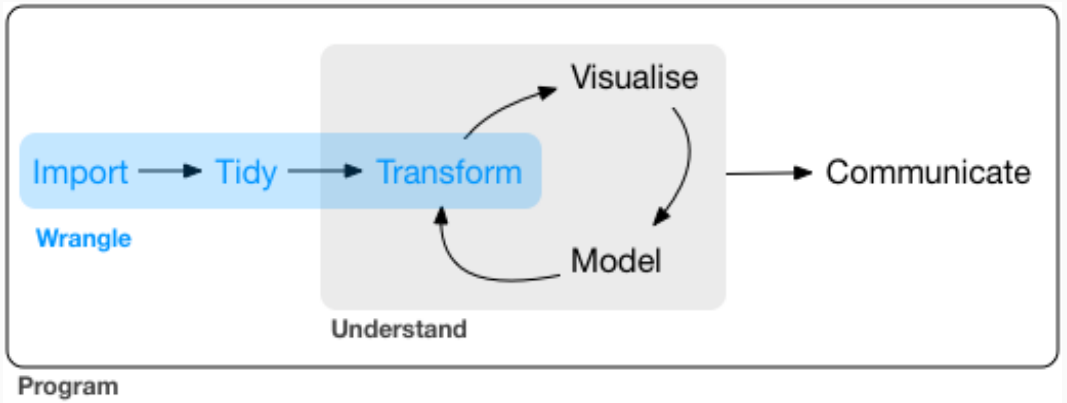

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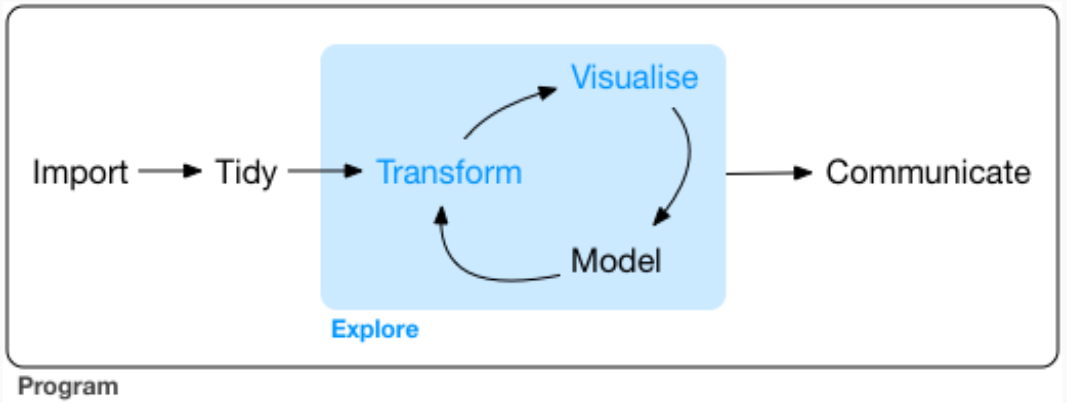

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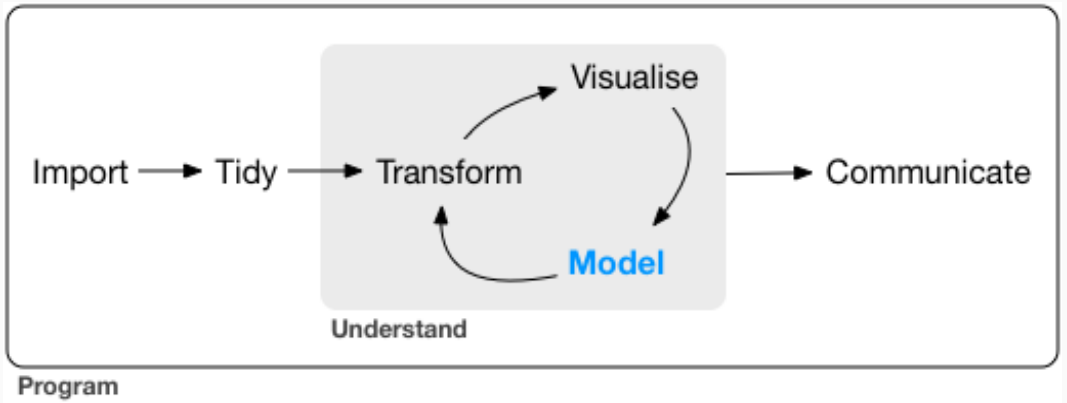

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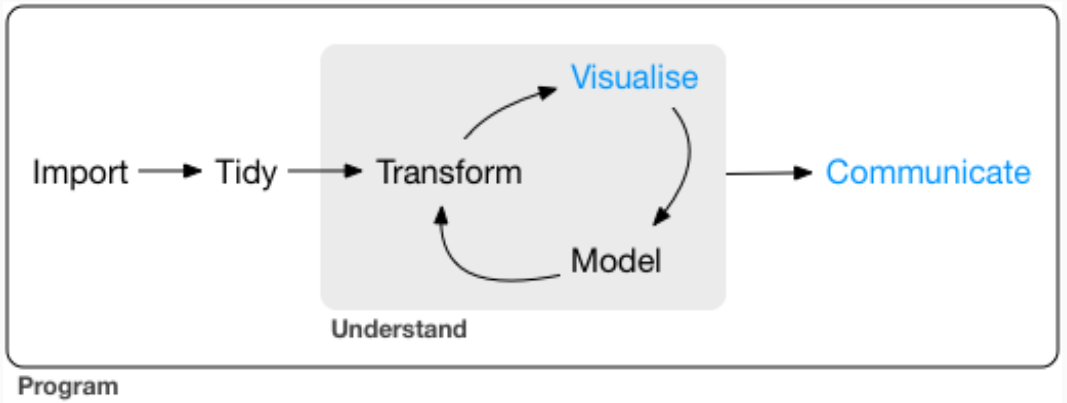
Verbreitung

- **Kommunikation**: an die Öffentlichkeit, Medien, politische Entscheidungsträger
- **Veröffentlichen**: Zeitschriften/Proceedings, Blogs, Software
- **Produktivieren**: nutzbar, robust, skalierbar machen



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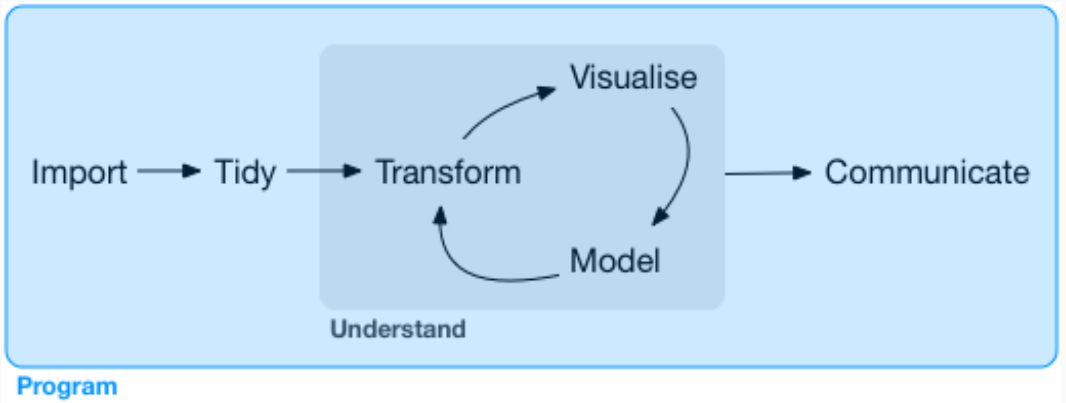
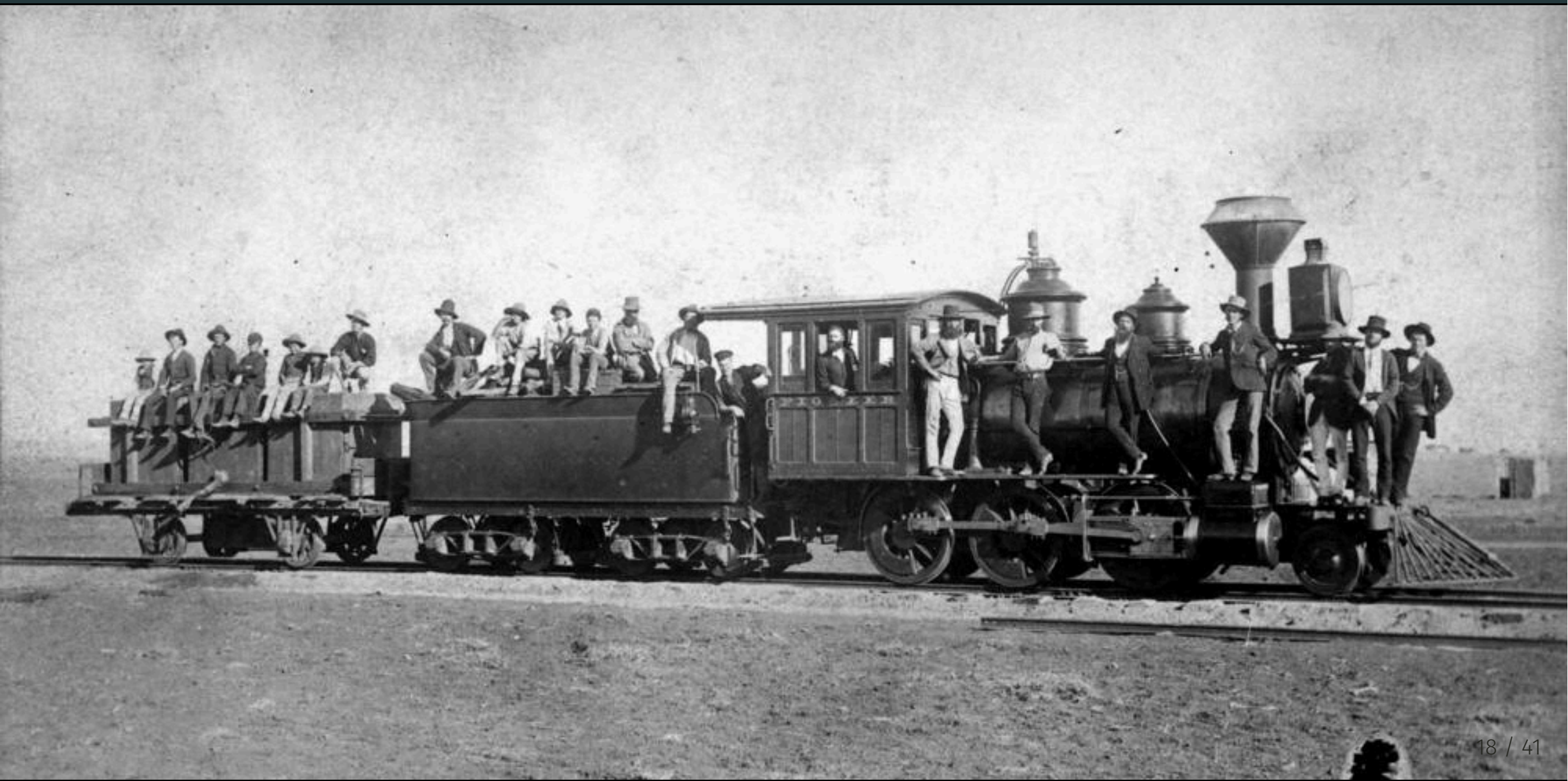


`Source` H. Wickham, M. Çetinkaya-Rundel, G. Gronemund: R for Data Science

(Data) Science für Public Policy

Einige Beispiele für politikrelevante datenwissenschaftliche Forschung



Das MIT-Milliarden-Preise-Projekt

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

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

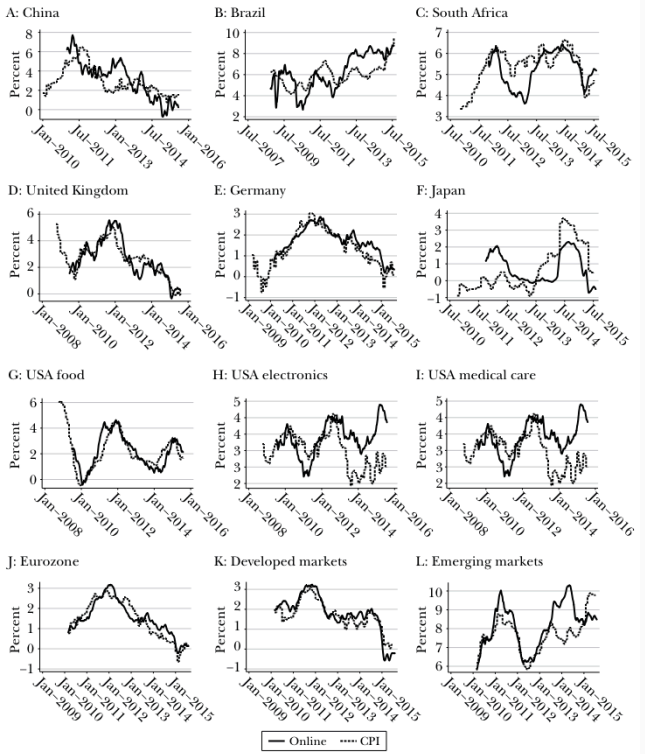
Alberto Cavallo and Roberto Rigobon

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.

Siehe auch: https://thebillionpricesproject.com/ und https://www.pricestats.com/

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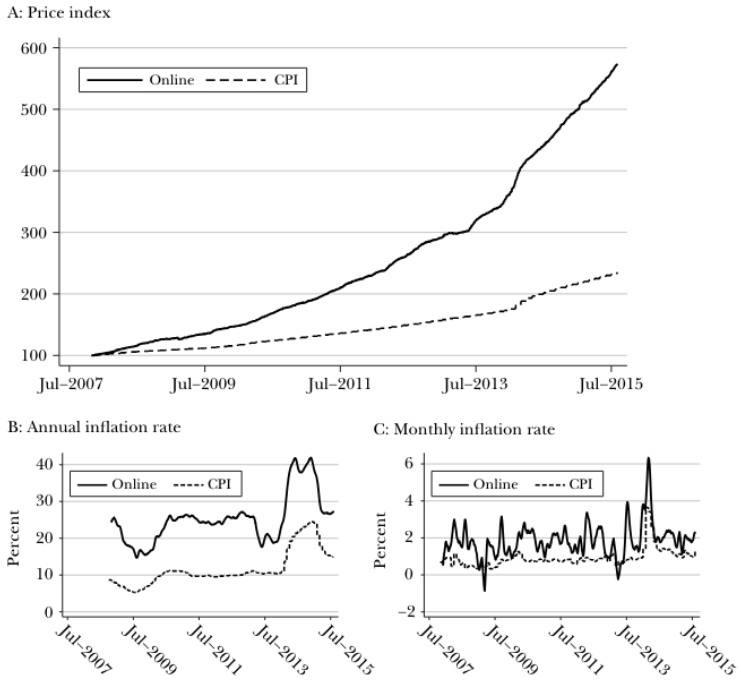
Figure 1
Argentina



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.

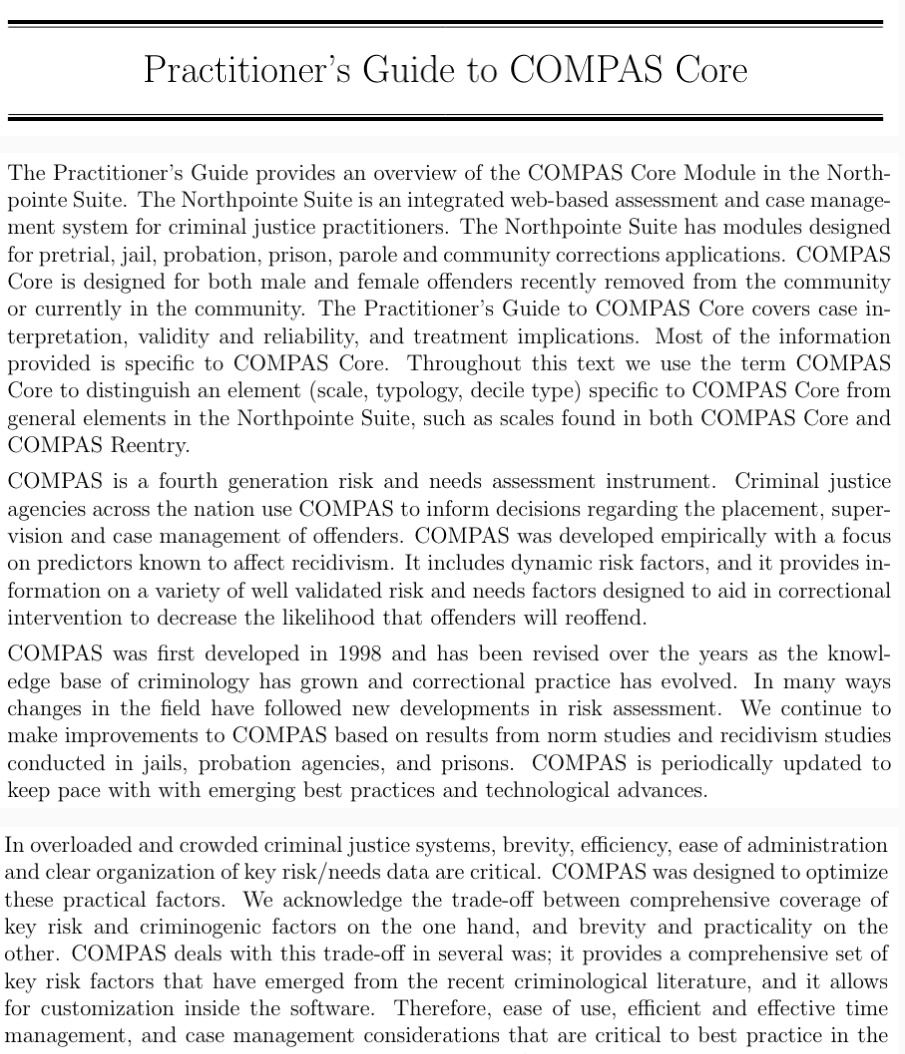
Siehe auch: https://thebillionpricesproject.com/ und https://www.pricestats.com/

Der COMPAS-Algorithmus zur Vorhersage der Rückfälligkeit von Straftätern

Hertie School

Hintergrund

- Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) ist ein von Northpointe (jetzt Equivant) entwickeltes Entscheidungshilfeinstrument, das von US-Gerichten zur **Bewertung der Rückfallwahrscheinlichkeit** eingesetzt wird.
- Erstellt mehrere Skalen (Risiko der vorzeitigen Entlassung, allgemeine Rückfälligkeit, gewalttätige Rückfälligkeit) auf der Grundlage von Faktoren wie Alter, Vorstrafen und Drogenmissbrauch
- Der Algorithmus ist urheberrechtlich geschützt und seine inneren Abläufe sind nicht öffentlich.



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

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Die ProPublica und andere Untersuchungen

- Im Jahr 2016 veröffentlichte ProPublica eine Untersuchung, die zeigte, dass COMPAS **voreingenommen gegenüber Afroamerikanern** war
- **Voreingenommenheit:** Der Algorithmus sagte bei Afroamerikanern mit höherer Wahrscheinlichkeit falsch voraus, dass Angeklagte wieder straffällig werden würden.
- **Genauigkeit:** Nur 20 % der Personen, denen Gewaltverbrechen vorhergesagt wurden, wurden tatsächlich straffällig (in einer späteren Studie wurde der Wert auf 65 % geschätzt, was immer noch schlechter ist als eine Gruppe von Menschen mit wenig Fachwissen)

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).

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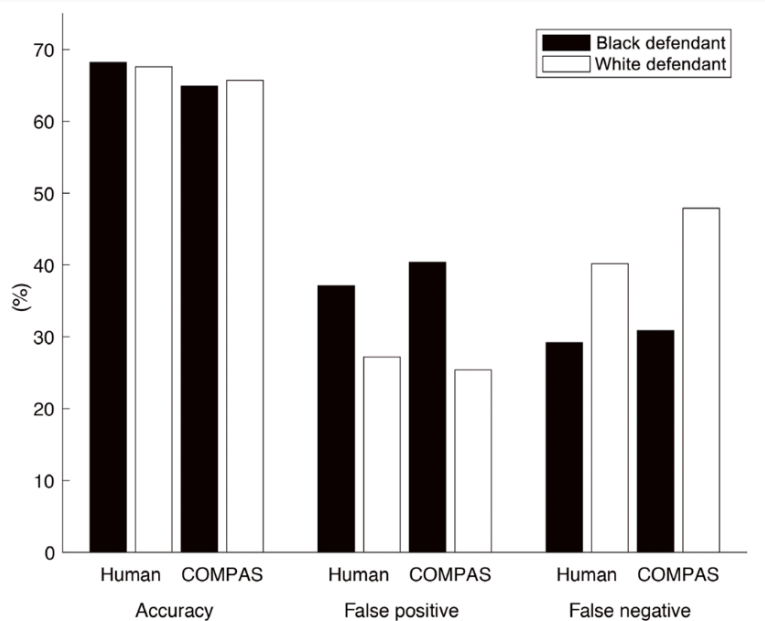
SCIENCE ADVANCES | RESEARCH ARTICLE

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.



Like-minded sources on Facebook are prevalent but not polarizing

https://doi.org/10.1038/s41586-023-06297-w

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Open access

Check for updates

Brendan Nyhan[1,25✉], Jaime Settle[2,25], Emily Thorson[3,25], Magdalena Wojcieszak[4,5,25], Pablo Barberá[6,25], Annie Y. Chen[7], Hunt Allcott[8], Taylor Brown[6], Adriana Crespo-Tenorio[6], Drew Dimmery[6,24], Deen Freelon[9], Matthew Gentzkow[10], Sandra González-Bailón[9], Andrew M. Guess[11,12], Edward Kennedy[13], Young Mie Kim[14], David Lazer[15], Neil Malhotra[16], Devra Moehler[6], Jennifer Pan[17], Daniel Robert Thomas[6], Rebekah Tromble[18,19], Carlos Velasco Rivera[6], Arjun Wilkins[6], Beixian Xiong[6], Chad Kiewiet de Jonge[6,26], Annie Franco[6,26], Winter Mason[6,26], Natalie Jomini Stroud[20,21,26] & Joshua A. Tucker[22,23,26]

Many critics raise concerns about the prevalence of 'echo chambers' on social media and their potential role in increasing political polarization. However, the lack of available data and the challenges of conducting large-scale field experiments have made it difficult to assess the scope of the problem[1,2]. Here we present data from 2020 for the entire population of active adult Facebook users in the USA showing that content from 'like-minded' sources constitutes the majority of what people see on the platform, although political information and news represent only a small fraction of these exposures. To evaluate a potential response to concerns about the effects of echo chambers, we conducted a multi-wave field experiment on Facebook among 23,377 users for whom we reduced exposure to content from like-minded sources during the 2020 US presidential election by about one-third. We found that the intervention increased their exposure to content from cross-cutting sources and decreased exposure to uncivil language, but had no measurable effects on eight preregistered attitudinal measures such as affective polarization, ideological extremity, candidate evaluations and belief in false claims. These precisely estimated

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.

Asymmetric ideological segregation in exposure to political news on Facebook

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

Does Facebook enable ideological segregation in political news consumption? We analyzed exposure to news during the US 2020 election using aggregated data for 208 million US Facebook users. We compared the inventory of all political news that users could have seen in their feeds with the information that they saw (after algorithmic curation) and the information with which they engaged. We show that (i) ideological segregation is high and increases as we shift from potential exposure to actual exposure to engagement; (ii) there is an asymmetry between conservative and liberal audiences, with a substantial corner of the news ecosystem consumed exclusively by conservatives; and (iii) most misinformation, as identified by Meta's Third-Party Fact-Checking Program, exists within this homogeneously conservative corner, which has no equivalent on the liberal side. Sources favored by conservative audiences were more prevalent on Facebook's news ecosystem than those favored by liberals.

The Meta US 2020 Wahlstudie

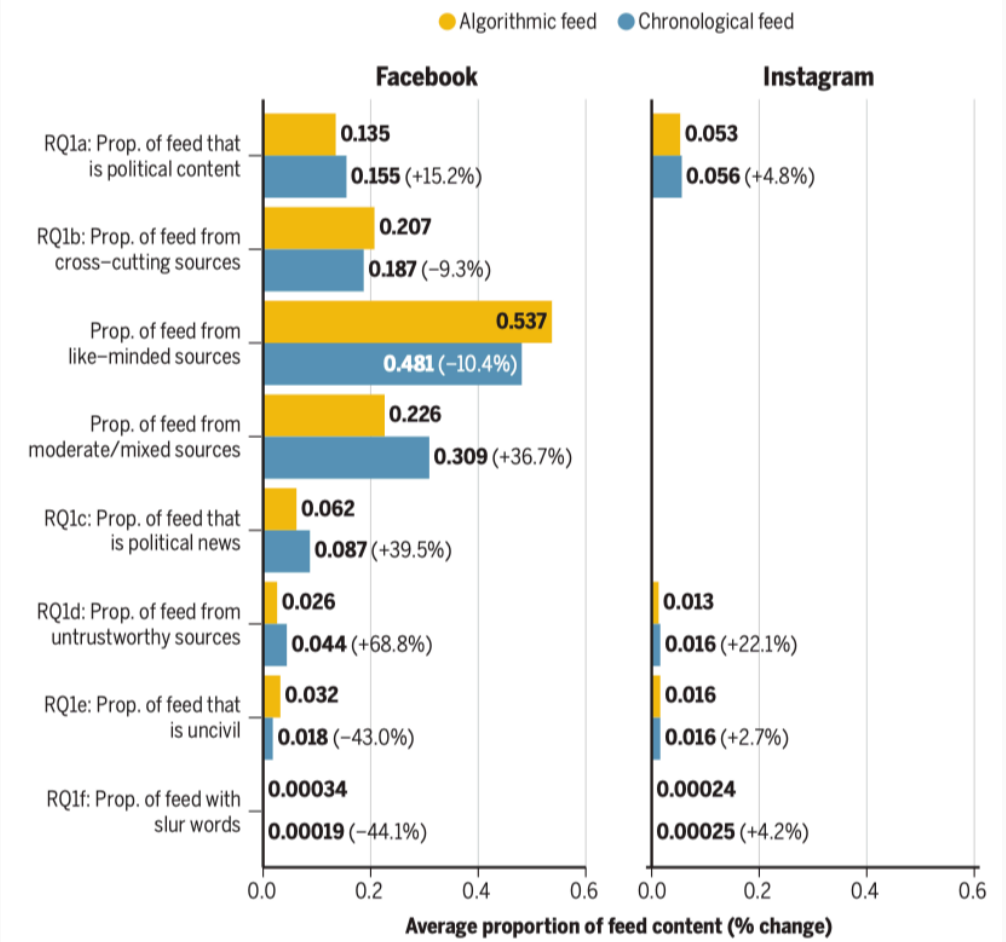

Fig. 2. Estimated changes in prevalence of feed content on both Facebook and Instagram. (**Left**) Facebook. (**Right**) Instagram. Values are average unweighted proportions within each group, with percent changes relative to the Algorithmic Feed control group in parentheses. All differences are significant 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 Wahlstudie

Hertie School

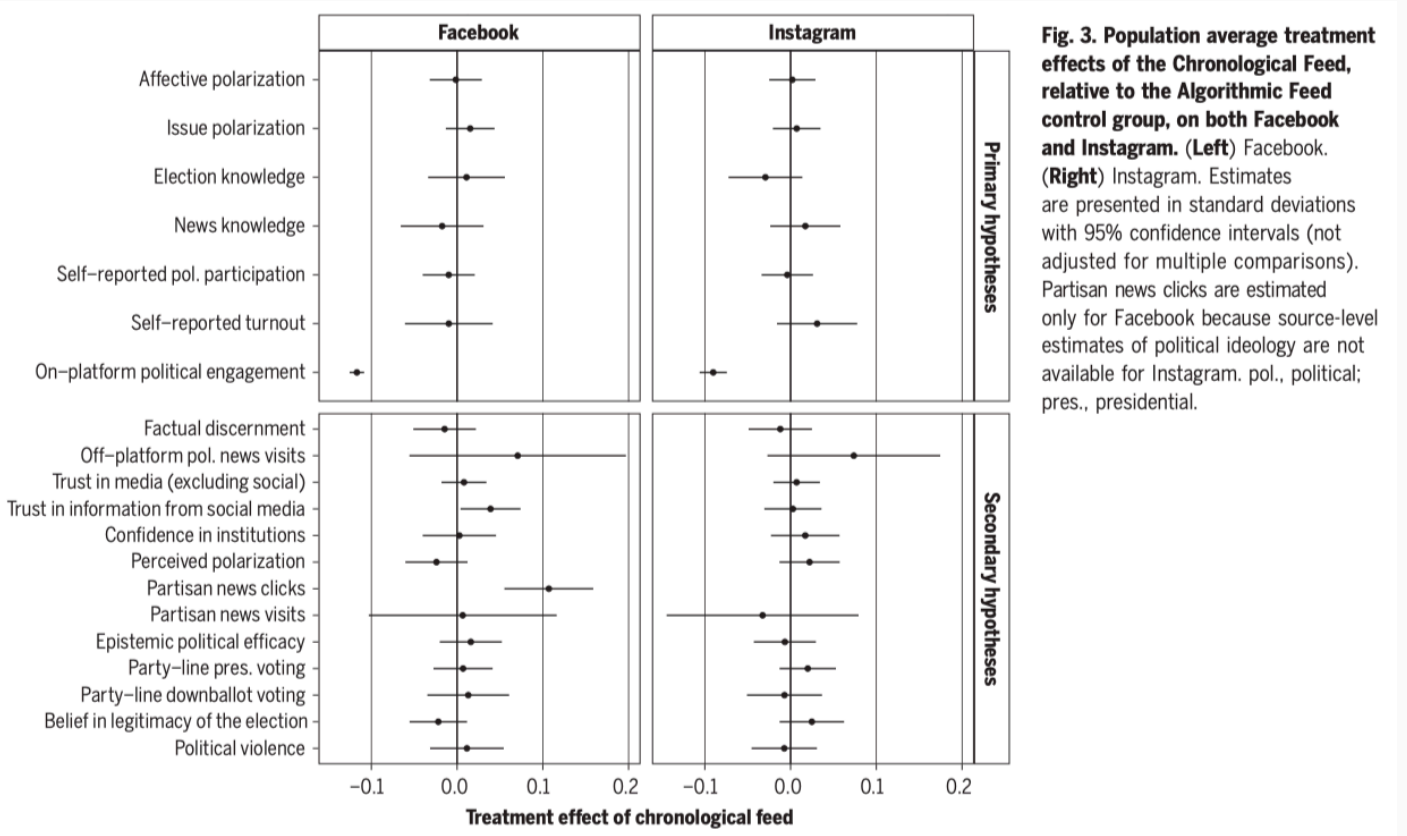

Fig. 3. Population average treatment effects of the Chronological Feed, relative to the Algorithmic Feed control group, on both Facebook and Instagram. (**Left**) Facebook. (**Right**) Instagram. Estimates are presented in standard deviations with 95% confidence intervals (not adjusted for multiple comparisons). 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

Förderung von guter Data Science für gute Public Policy

Hertie School

Vertrauen in Wissenschaft

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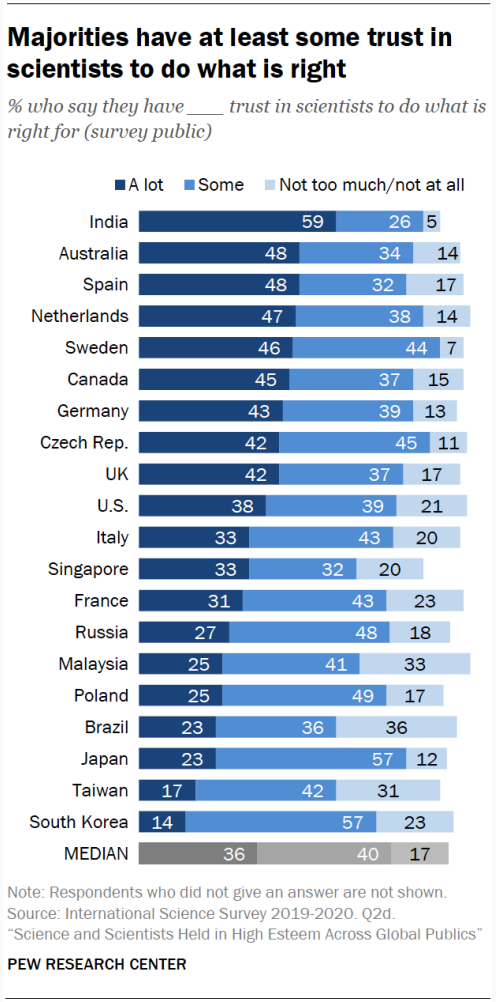

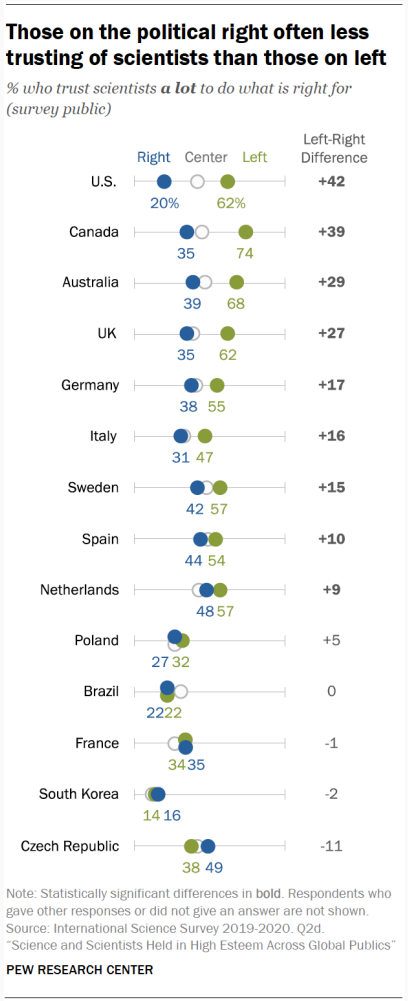

Quelle Pew 2020

Vertrauen in Wissenschaft

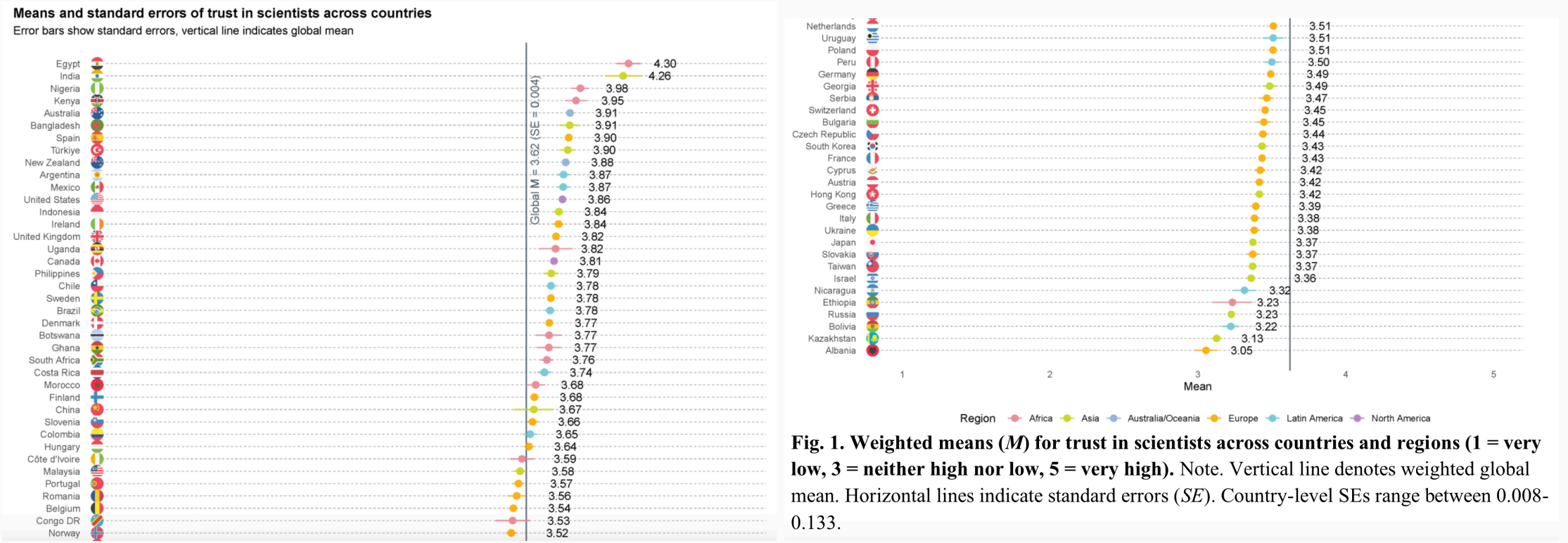

Fig. 1. Weighted means (*M*) for trust in scientists across countries and regions (1 = very low, 3 = neither high nor low, 5 = very high). Note. Vertical line denotes weighted global mean. Horizontal lines indicate standard errors (*SE*). Country-level SEs range between 0.008-0.133.

`Source` Cologna et al. 2024

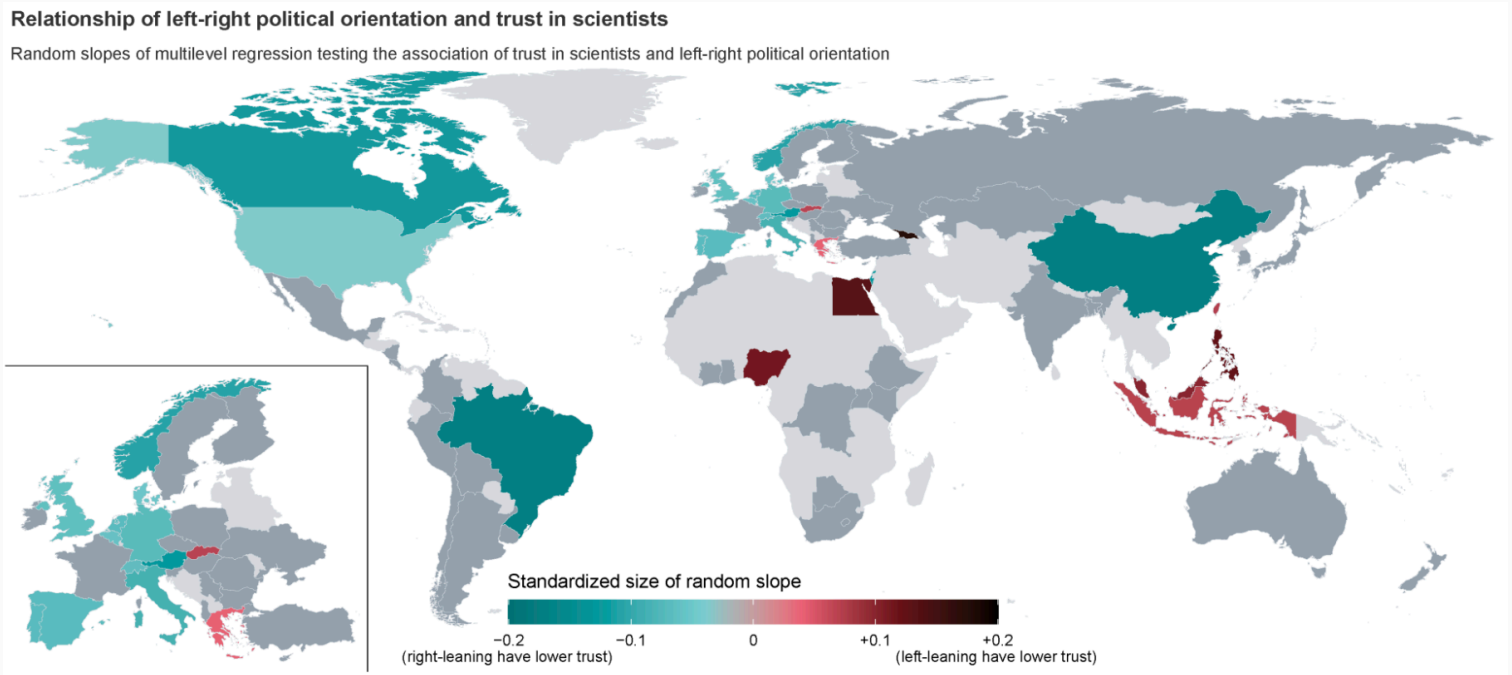

Fig. 3. Relationship of left-right political orientation and trust in scientists. Figure visualises standardised random slopes for political orientation (1 = left – 5 = right), which were extracted from a weighted linear multilevel regression model that explained trust in scientists (1 = very low, 3 = neither high nor low, 5 = very high) across countries and contained random intercepts and slopes of political orientation across countries. Countries with significant effects ($p < .05$) are displayed in colours: Countries coloured in shades of blue show a positive association of left-leaning orientation and trust in scientists (i.e., right-leaning have lower trust). Countries coloured in shades of red show a positive association of right-leaning orientation and trust in scientists (i.e., left-leaning have lower trust) Countries with non-significant effects are shaded in dark grey. Countries with no available data are shaded in light grey.

`Quelle` Cologna et al. 2024

Vertrauen in Wissenschaft

Data scientists have the potential to help save the world

By Leo Borrett May 17, 2017

With an untold number of crises emerging every year, big data is becoming increasingly important for helping aid organisations respond quickly to chaotic and evolving situations.

HOW DATA SCIENCE IS SAVING LIVES

AVINASH N Sep 29 · 2 min read

For all the people first priority is about their life. Life is one of the most precious thing in the world. Can Data Science techniques save life, is it possible? Yes, using Data Science techniques to analyze large data sets today has a huge impact on saving lives.

Health

Artificial intelligence and covid-19: Can the machines save us?

Analytics And Data Science

Data Scientist: The Sexiest Job of the 21st Century

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and D.J. Patil

From the Magazine (October 2012)

How AI Will Save Thousands of Lives

Sepsis is the problem; data are the cure

Drew Smith, PhD Jan 10, 2020 · 5 min read ★

STUDENTS

Data Science: Why It Matters and How It Can Make You Rich

Vertrauen in Data Science?

The Cambridge Analytica case: What's a data scientist to do?

The Cambridge Analytica controversy has highlighted data ethics issues especially dear to early career stage data scientists

Researchers just released profile data on 70,000 OkCupid users without permission

By Brian Resnick | @B_resnick | brian@vox.com | May 12, 2016, 6:00pm EDT

An Algorithm That 'Predicts' Criminality Based on a Face Sparks a Furor

Its creators said they could use facial analysis to determine if someone would become a criminal. Critics said the work recalled debunked "race science."

Data Failed the Election, But There's Still Hope for Business

Everyone is blaming data for failing to predict Trump's win. But it's the data handlers who need the real reexamination.

Die Replicationskrise

Hertie School

Worum geht es bei der Krise?

- Die Feststellung, dass sich viele wissenschaftliche Studien nur schwer oder gar nicht reproduzieren lassen.
- Reproduzierbarkeit ist ein Eckpfeiler der Wissenschaft als Unternehmen der Wissensgenerierung → schlecht.

Faktoren, die die Reproduktionskrise anheizen

- Einzelne, isolierte Forscher, die sich auf kleine Stichproben beschränken
- Falsche Anreize in der Wissenschaft
- Keine Vorabregistrierung der zu prüfenden Hypothesen
- Post-hoc-Auswahl der Hypothesen mit den besten P-Werten
- Nur P < .05 erforderlich
- Keine Replikation
- Keine Datenveröffentlichung

`Quelle` Ioannidis 2005/PLOS Medicine

Open access, freely available online

Essay

Why Most Published Research Findings Are False

John P. A. Ioannidis

Summary

There is increasing concern that most current published research findings are false. The probability that a research claim is true may depend on study power and bias, the number of other studies on the same question, and, importantly, the ratio of true to no relationships among the relationships probed in each scientific field. In this framework, a research finding is less likely to be true when the studies conducted in a field are smaller; when effect sizes are smaller; when there is a greater number and lesser preselection of tested relationships; where there is greater flexibility in designs, definitions, outcomes, and analytical modes; when there is greater financial and other interest and prejudice; and when more teams are involved in a scientific field in chase of statistical significance. Simulations show that for most study designs and settings, it is more likely for a research claim to be false than true. Moreover, for many current scientific fields, claimed research findings may often be simply accurate measures of the prevailing bias. In this essay, I discuss the implications of these problems for the conduct and interpretation of research.

Published research findings are sometimes refuted by subsequent evidence, with ensuing confusion and disappointment. Refutation and controversy is seen across the range of research designs, from clinical trials and traditional epidemiological studies [1–3] to the most modern molecular research [4,5]. There is increasing concern that in modern research, false findings may be the majority or even the vast majority of published research claims [6–8]. However, this should not be surprising. It can be proven that most claimed research findings are false. Here I will examine the key factors that influence this problem and some corollaries thereof.

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

Modeling the Framework for False Positive Findings

Several methodologists have pointed out [9–11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a p-value less than 0.05. Research is not most appropriately represented and summarized by p-values, but, unfortunately, there is a widespread notion that medical research articles

It can be proven that most claimed research findings are false.

should be interpreted based only on p-values. Research findings are defined here as any relationship reaching formal statistical significance, e.g., effective interventions, informative predictors, risk factors, or associations. "Negative" research is also very useful. "Negative" is actually a misnomer, and the misinterpretation is widespread. However, here we will target relationships that investigators claim exist, rather than null findings.

As has been shown previously, the probability that a research finding is indeed true depends on the prior probability of it being true (before doing the study), the statistical power of the study, and the level of statistical significance [10,11]. Consider a 2×2 table in which research findings are compared against the gold standard of true relationships in a scientific field. In a research field both true and false hypotheses can be made about the presence of relationships. Let R be the ratio of the number of "true relationships" to "no relationships" among those tested in the field. R is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among many that can be hypothesized) or the power is similar to find any of the several existing true relationships. The pre-study probability of a relationship being true is $R/(R + 1)$. The probability of a study finding a true relationship reflects the power $1 - \beta$ (one minus the Type II error rate). The probability of claiming a relationship when none truly exists reflects the Type I error rate, α. Assuming that c relationships are being probed in the field, the expected values of the 2×2 table are given in Table 1. After a research finding has been claimed based on achieving formal statistical significance, the post-study probability that it is true is the positive predictive value, PPV. The PPV is also the complementary probability of what Wacholder et al. have called the false positive report probability [10]. According to the 2×2 table, one gets $PPV = (1 - \beta)R/(R - \beta R + \alpha)$. A research finding is thus

Citation: Ioannidis JPA (2005) Why most published research findings are false. PLoS Med 2(8): e124.

Abbreviation: PPV, positive predictive value

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Competing Interests: The author has declared that no competing interests exist.

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Ziele dieses Workshops

1. Hartes Nachdenken über Kausalität

- Erarbeiten Sie Erwartungen, die überprüfbare Aussagen zu den Auswirkungen implizieren.
- Bevorzugen Sie Designs, die helfen, kausale Effekte zu isolieren.
- Achten Sie auf **interne Validität**.

2. Messen Sie die politischen Optionen und Ergebnisse, über die Sie etwas erfahren möchten

- Finden Sie gute empirische Darstellungen der Konzepte, die Sie interessieren.
- Beobachten und/oder manipulieren Sie klug.
- Achten Sie auf die **Validität der Messung**.

3. Ziehen Sie Schlussfolgerungen über die reale Welt

- Verallgemeinern Sie mit Bedacht.
- Übertreiben Sie nicht und interpretieren Sie Ihre Ergebnisse nicht falsch.

Lernziele für diesen Workshop

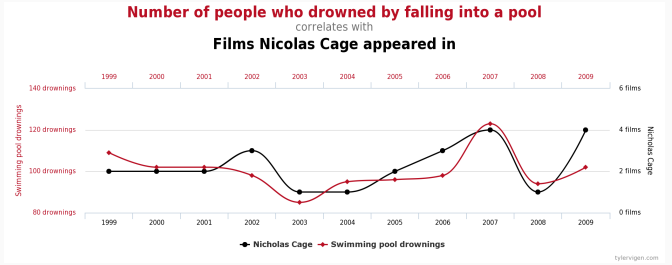
Hertie School

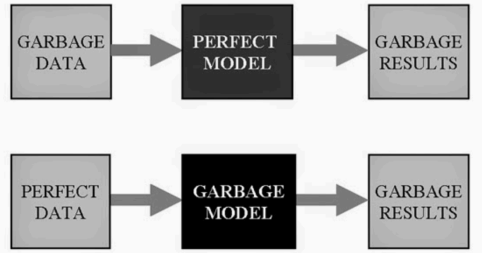
	Data science literacy					
Day	Statistical literacy	Causal reasoning	Data literacy	AI literacy	Evidence consumption	Ethical reasoning
1 - Fundamental data and statistical literacy	✅	✅	✅		✅	
2 - Policy evaluation and impact assessment	✅	✅			✅	
3 - AI and big data for policy-making			✅	✅		✅
4 - Informed consumption of evidence	✅				✅	
5 - Data visualization and communication			✅		✅	
6 - Data management and ethics			✅	✅		✅

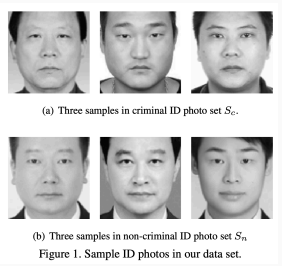
Schlechte Evidenz anprangern, wenn man sie sieht

1. Lernen Sie, sich nicht täuschen zu lassen von

- große Daten
- Datenmüll
- "Schrott-Modelle"
- seltsame Beispiele
- Behauptung der Allgemeingültigkeit
- statistische Signifikanz
- unplausibel große Effektgrößen
- hochpräzise Vorhersagen
- überangepasste Modelle (eng.: "overfitted")

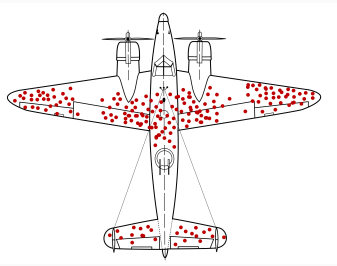


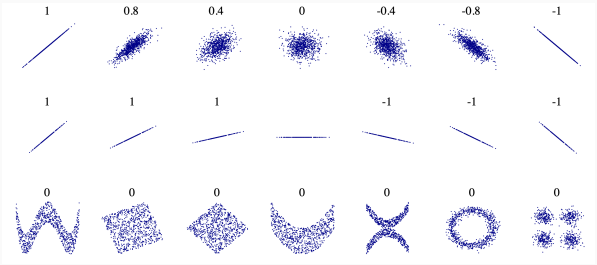



(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

Figure 1. Sample ID photos in our data set.





2. Effektives und effizientes Verarbeiten politikrelevanter Erkenntnisse

Was wir nicht behandeln werden

Programmierung

- Kenntnisse in Python, R, SQL usw. sind für die Datenwissenschaft unerlässlich
- Die Lernkurve ist steil und erfordert viel Übung
- Wir gewähren gerne einen Blick hinter die Kulissen, wenn dies von Interesse ist, und stellen zusätzliche Ressourcen zur Verfügung

Aktive Modellierung

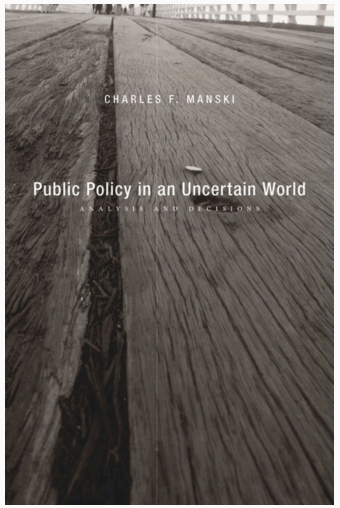
- Die Entwicklung von Designs und Modellen - erklärend und prädiktiv - erfordert mehr theoretisches und praktisches Wissen, als wir in diesem Workshop abdecken können.
- Die Konzentration auf die Grundsätze der statistischen und kausalen Argumentation sollte ausreichen, um Entwürfe und Modelle kritisch zu beurteilen.

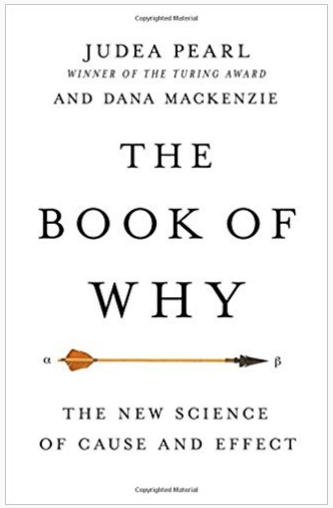
Fortgeschrittenes Maschinelles Lernen, NLP

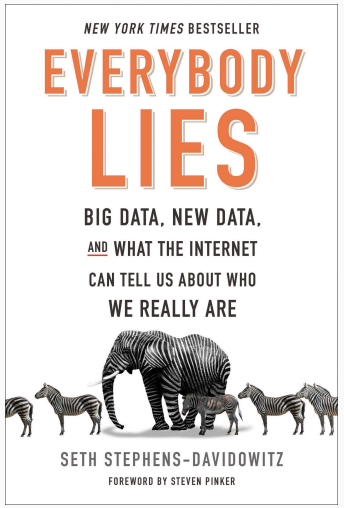
- ML, DL, NLP sind Technologien, die viele der spannendsten Anwendungen der Datenwissenschaft vorantreiben.
- Um zu verstehen, was unter der Haube passiert, ist eine solide Grundlage in Mathematik und Statistik erforderlich.
- Wir werden uns auf die grundlegenden Elemente der ML-basierten Forschung konzentrieren.

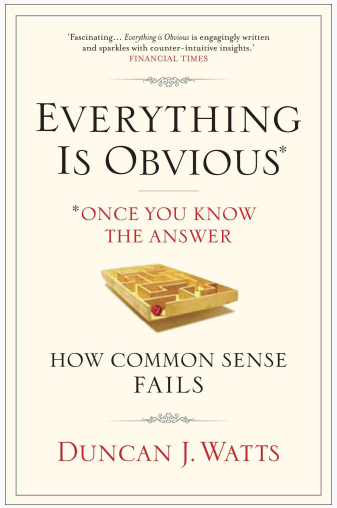
Weiterführende Literatur

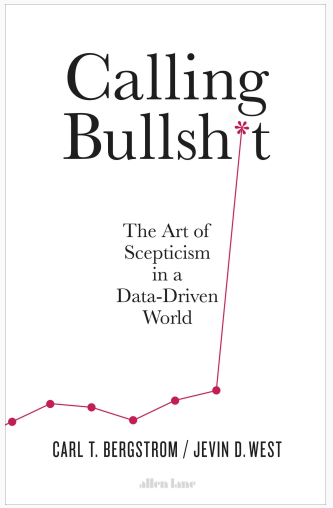
Hertie School

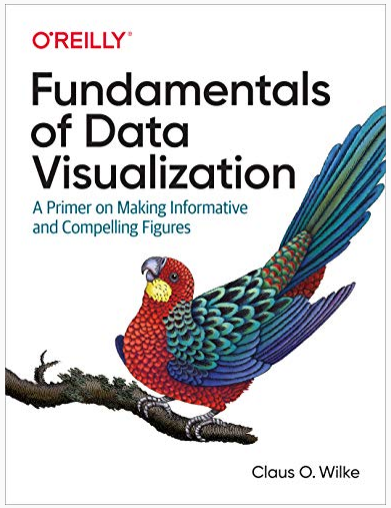


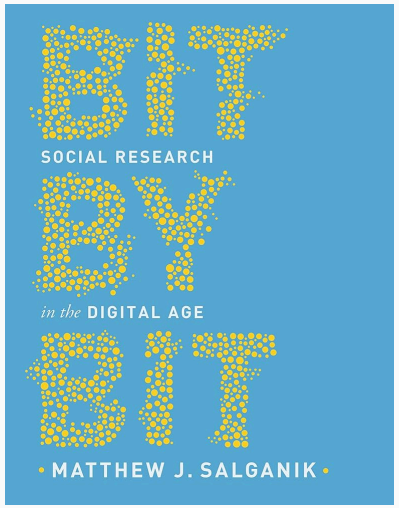


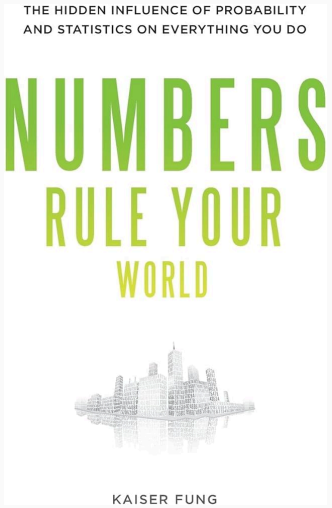


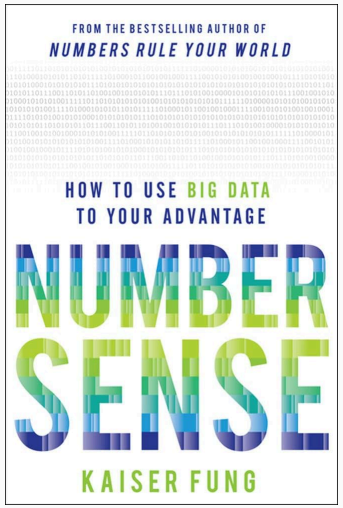


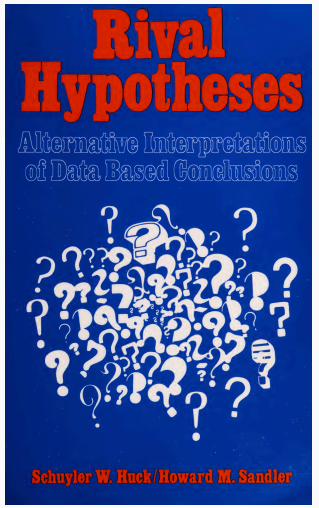


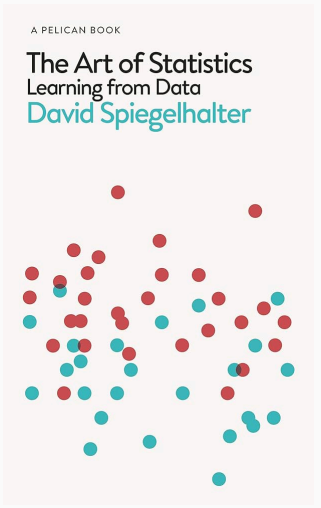


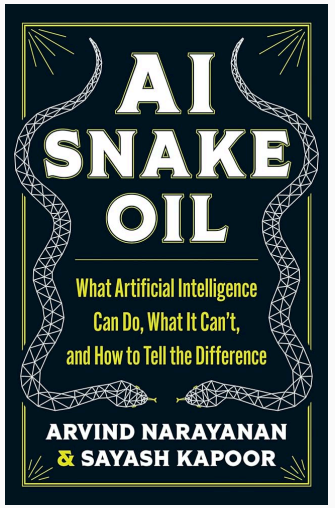




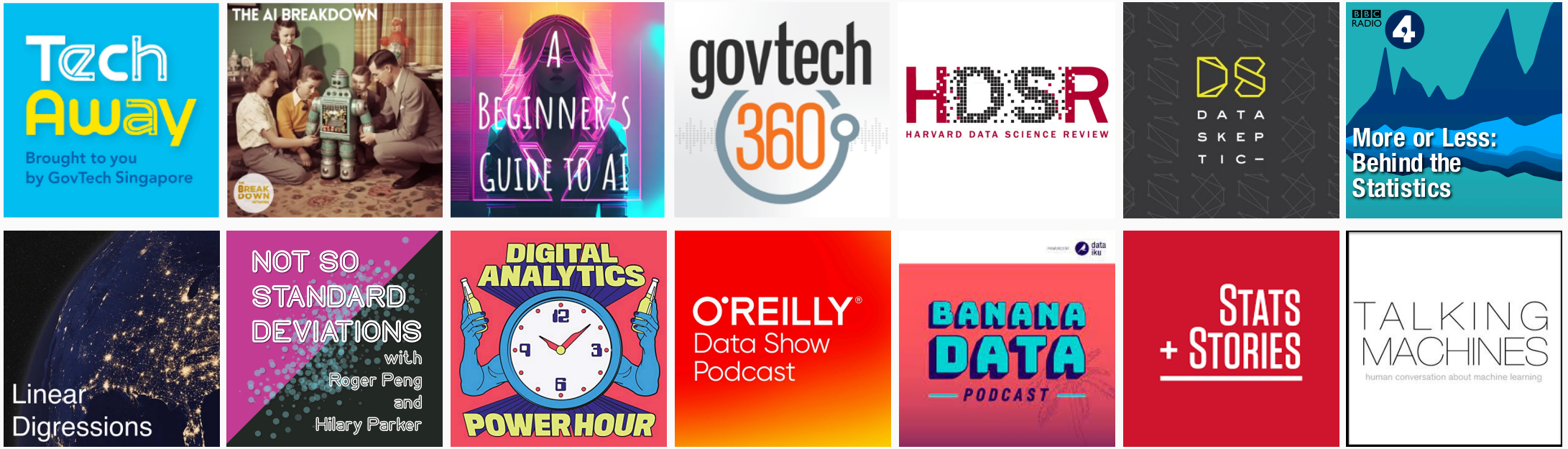








Weiterführende Podcasts



Material zum Ausbildungsprogramm

Hertie School

Besuchen Sie die Website mit Materialien unter

SCAN ME