CSC2552
Topics in Computational Social Science: AI, Data, and Society

Lecture 2: Introduction to Computational Social Science cont'd

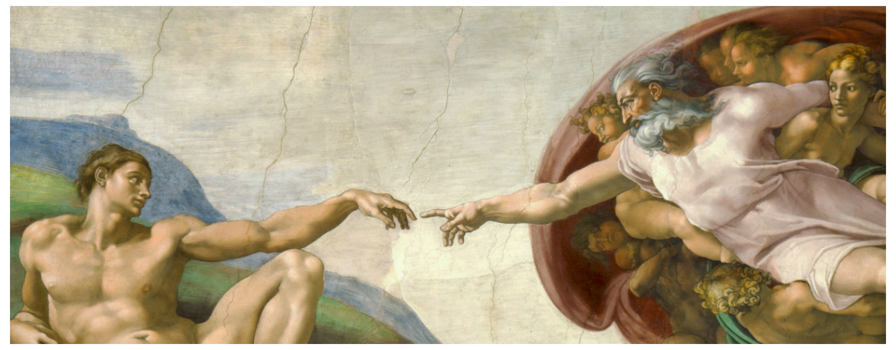
Prof. Ashton Anderson, Fall 2025

Computational social science in 7 easy pieces

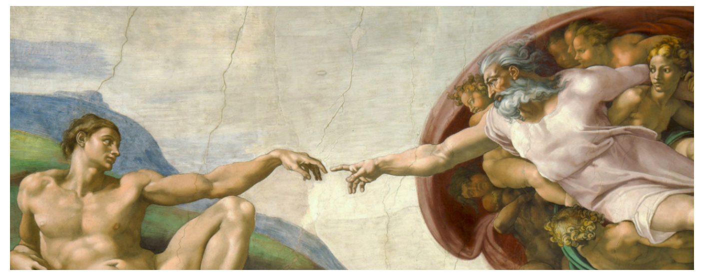
	Week	Date	Topic	Reviews Due	Textbook Readings
	1	9/4	Introduction to computational social science [Slides]		Ch. 1
	2	9/11	Introduction to computational social science cont'd [Slides]		Ch. 1
★	3	9/18	Observational studies 1 [Video]	9/17 9:00pm	Ch. 2
★	4	9/25	Observational studies 2	9/24 9:00pm	Ch. 2
★	5	10/2	Experiments 1	10/1 9:00pm	Ch. 4
★	6	10/9	Experiments 2	10/8 9:00pm	Ch. 4
	7	10/16	Project proposals		
★	8	10/23	Asking questions	10/22 9:00pm	Ch. 3
★	9	11/6	Applying machine learning	11/5 9:00pm	
★	10	11/13	Ethics in computational social science	11/12 9:00pm	Ch. 6
	11	11/20	Project presentations (Part 1)		
	12	11/27	Project presentations (Part 2)		

Readymades

Custommades



Ways of doing computational social science



Observational analyses

Human computation

Natural experiments

Surveys

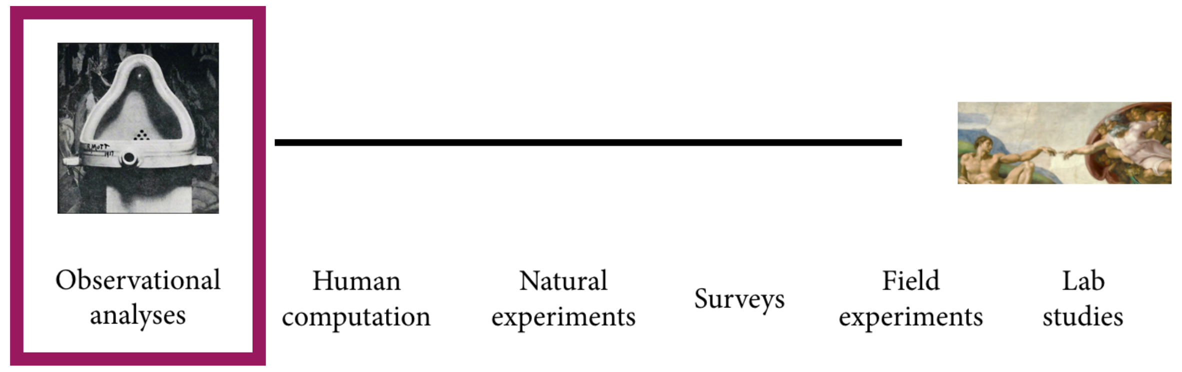
Field experiments

Lab studies

Observational analyses of existing data

- Massive datasets of all kinds of human behaviour are now available for study
  - Wikipedia, GPS traces, health databases, Facebook, Twitter, Reddit, reviews, purchases, dating, invitations, exercise apps, etc., etc…
- Key part of the “socioscope”: huge traces of things that we couldn’t see before
- Lack of detail/fidelity in individual records is hopefully made up for by large numbers of records (small noisy errors cancel out, big patterns are signal)

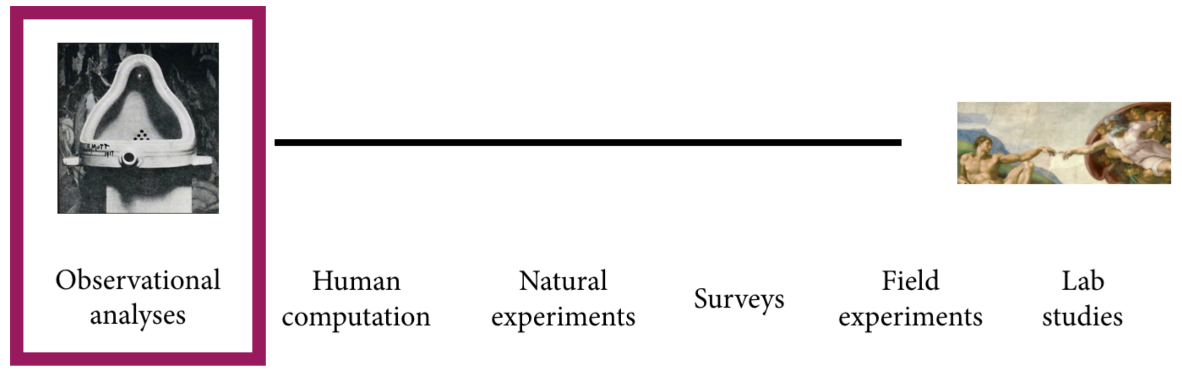
“Big data” / “Found data”



Ten common characteristics of big data

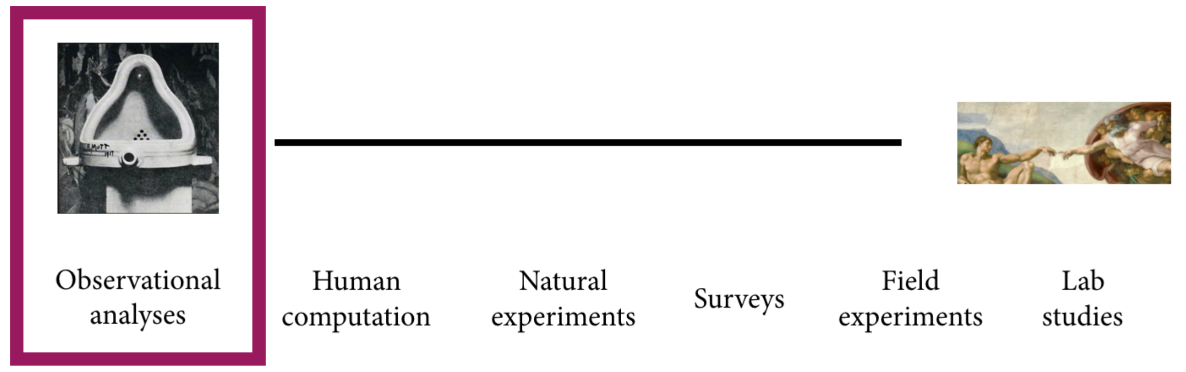
- **Big**: statistical power, rare events, fine resolution
- **Always-on**: unexpected events, real-time measurement
- **Nonreactive**: measurement probably won't change behaviour

- **Incomplete**: probably won't have the ideal information you want
- **Inaccessible**: difficult to access (gov't, companies)
- **Nonrepresentative**: bad out-of-sample generalization (good in-sample)
- **Drifting**: Population drift, usage drift, system drift
- **Algorithmically confounded**: want to study behaviour, not an algorithm
- **Dirty**: Junk, spam
- **Sensitive**: Private, hard to tell what's sensitive



Observing Behaviour: Three research strategies

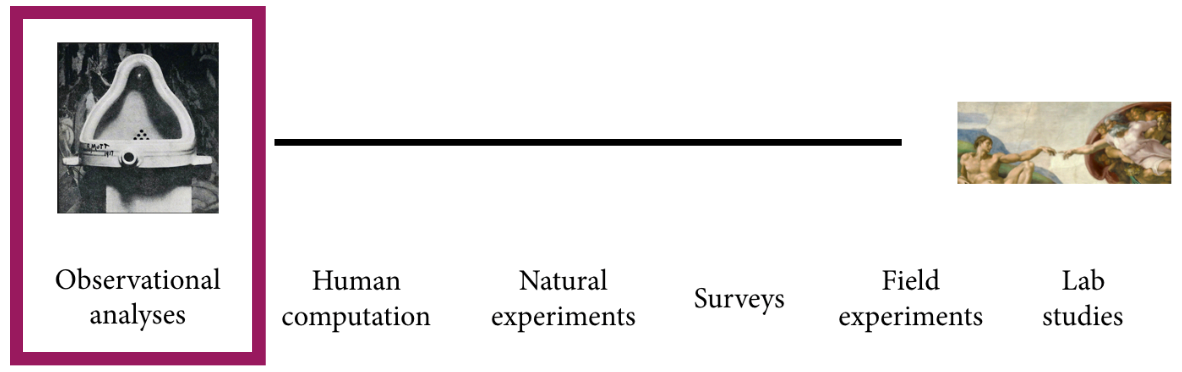
1. Counting things
2. Forecasting/nowcasting
3. Approximating experiments



Observing Behaviour: 1. Counting Things

Example: Measuring viral vs. broadcast diffusion on Twitter

With newfound datasets and computational resources, many valuable initial contributions are measurements of quantities we couldn't measure before → counting at scale

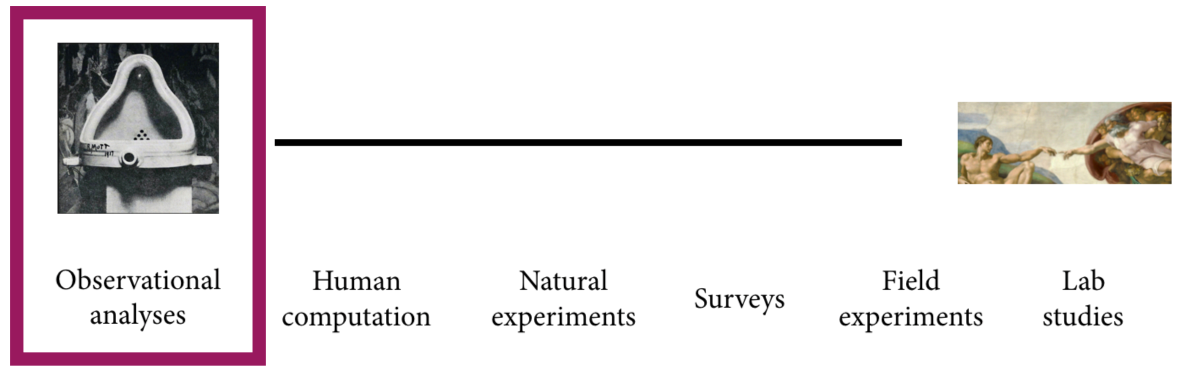


Observing Behaviour: 2. Nowcasting

Google Flu Trends

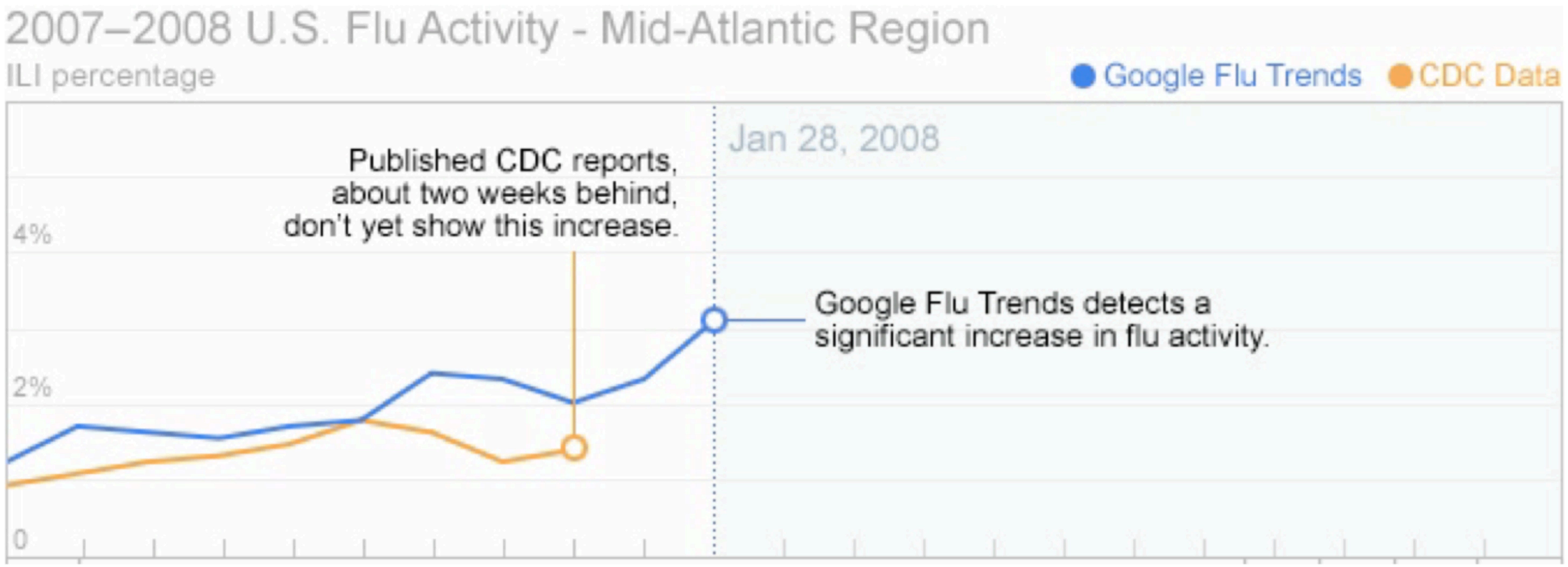
Idea: find 50 most correlated search query volume trends with flu data

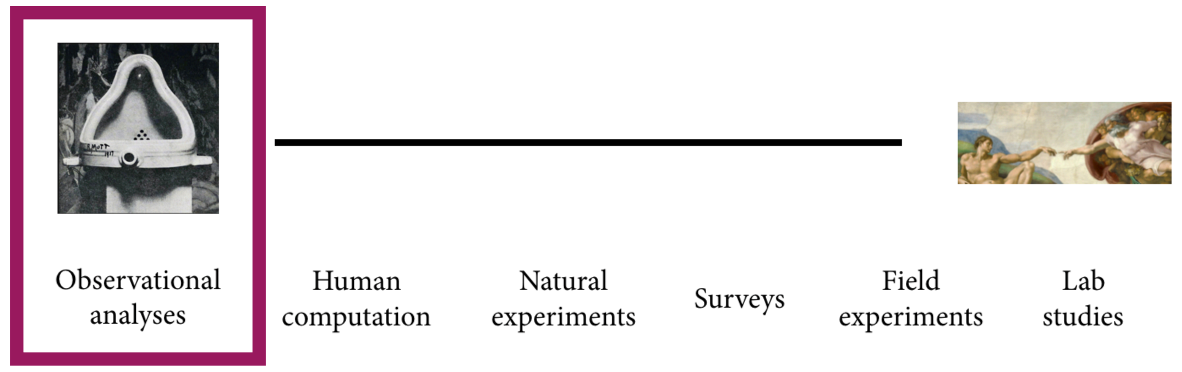
Search volume for the term "cough"



Observing Behaviour: 2. Nowcasting

The flu has a 1-2 week lag from when cases are reported to when the CDC releases official stats





Observing Behaviour: 2. Nowcasting

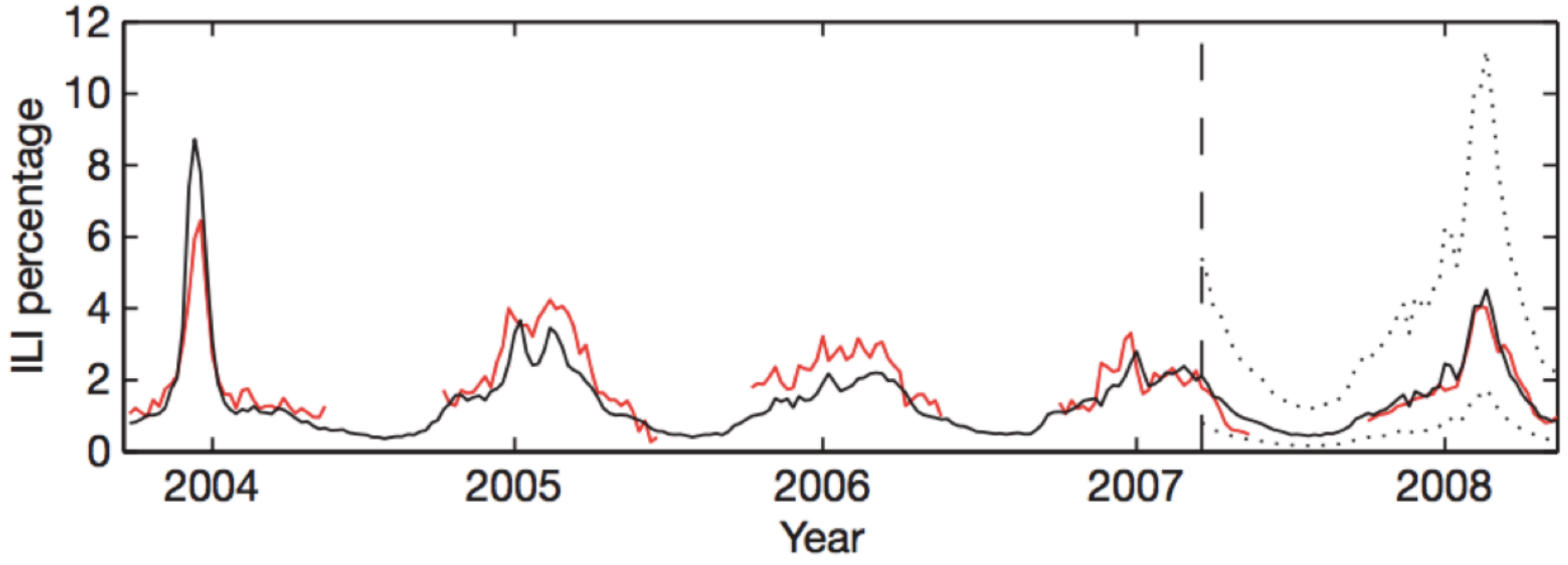
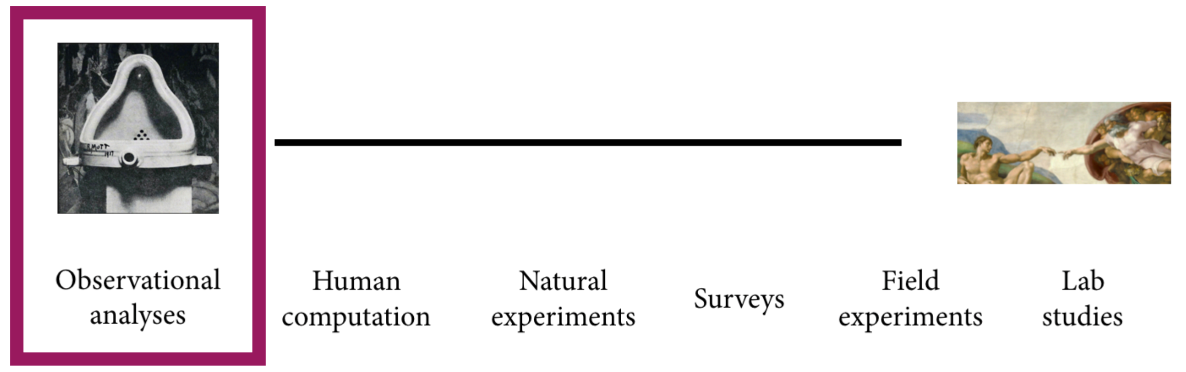
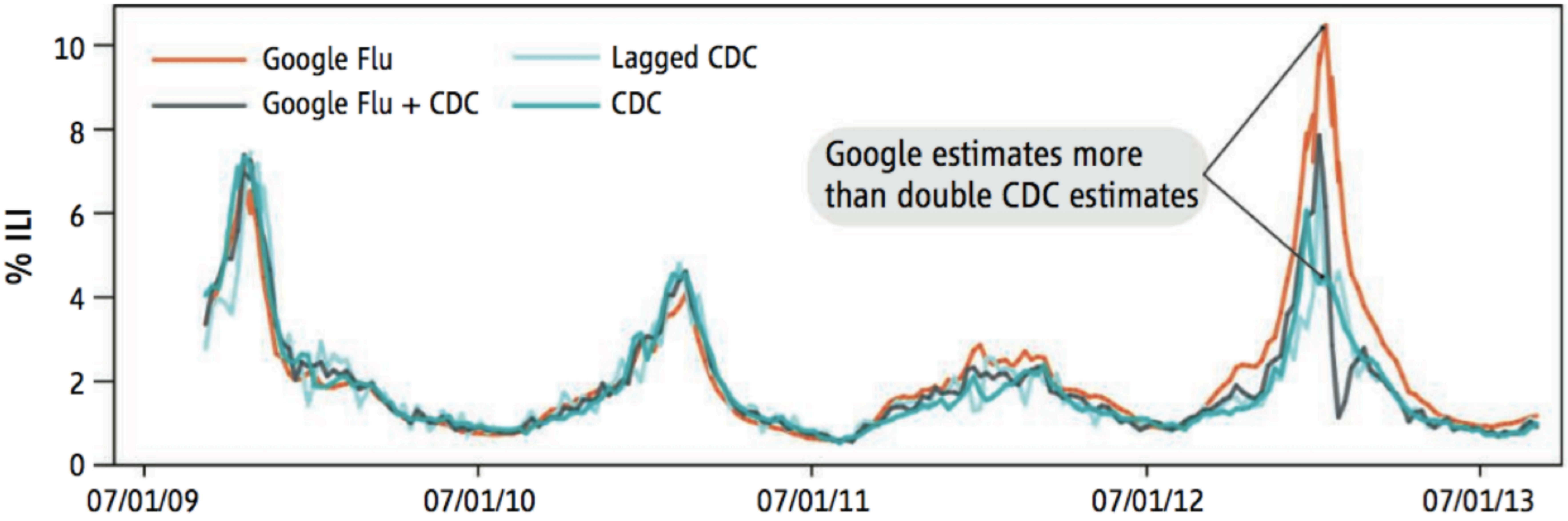


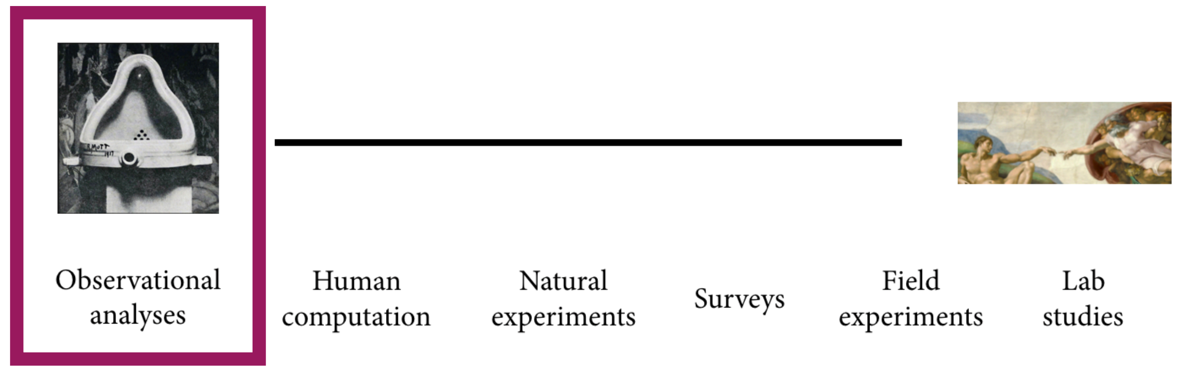
Figure 2 | A comparison of model estimates for the mid-Atlantic region (black) against CDC-reported ILI percentages (red), including points over which the model was fit and validated. A correlation of 0.85 was obtained over 128 points from this region to which the model was fit, whereas a correlation of 0.96 was obtained over 42 validation points. Dotted lines indicate 95% prediction intervals. The region comprises New York, New Jersey and Pennsylvania.



Observing Behaviour: 2. Nowcasting



Soon after Google Flu Trends launched, it was drastically off



Observing Behaviour: 2. Nowcasting

Media attention

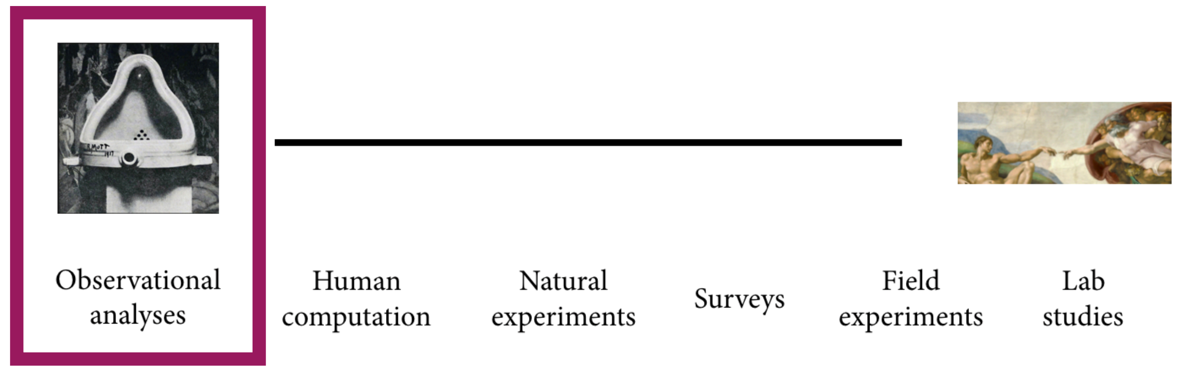
- "Bird flu", "swine flu"

Algorithm changes

- Starting suggesting search terms

"Social hacking"

- Hey look we can screw up Google's flu predictions

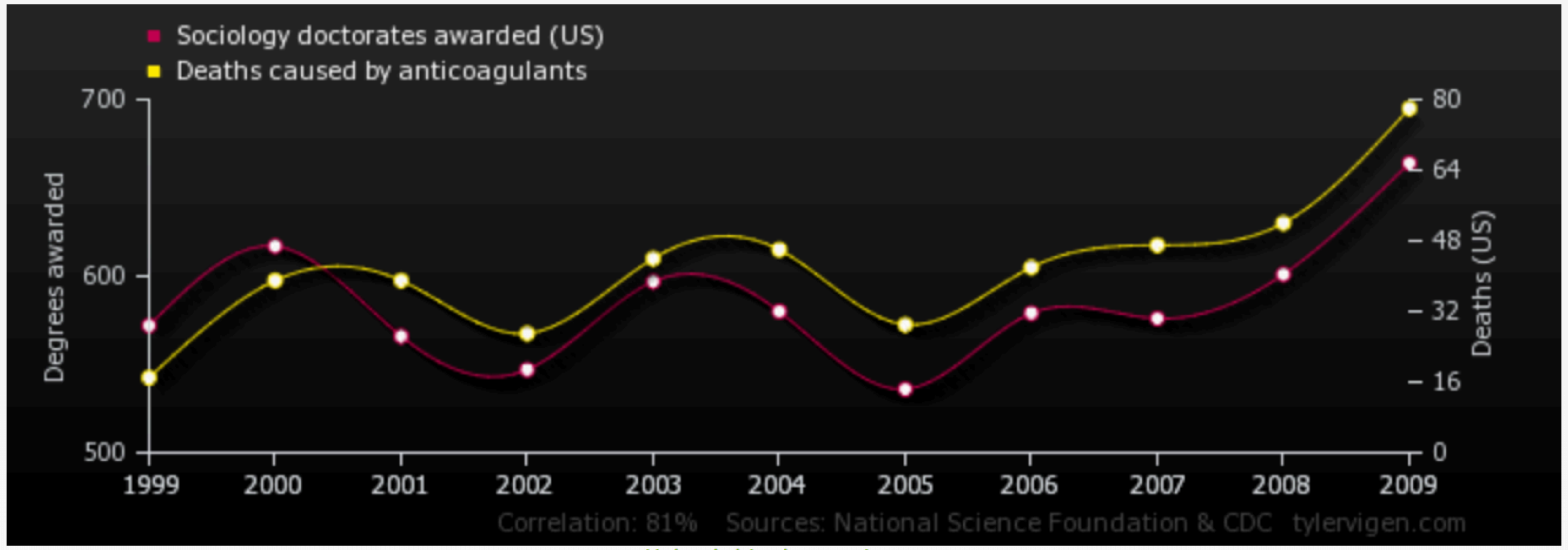


Correlation and causation

Sociology doctorates awarded (US)

correlates with

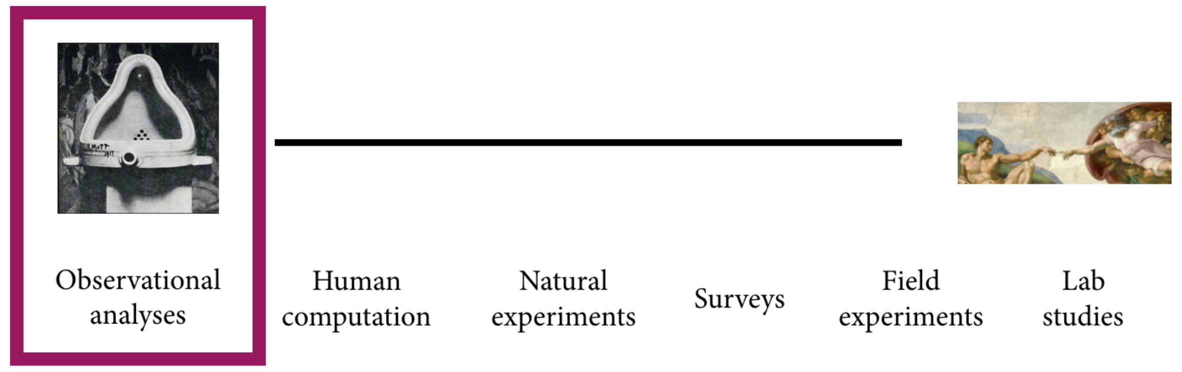
Deaths caused by anticoagulants



Upload this chart to imgur

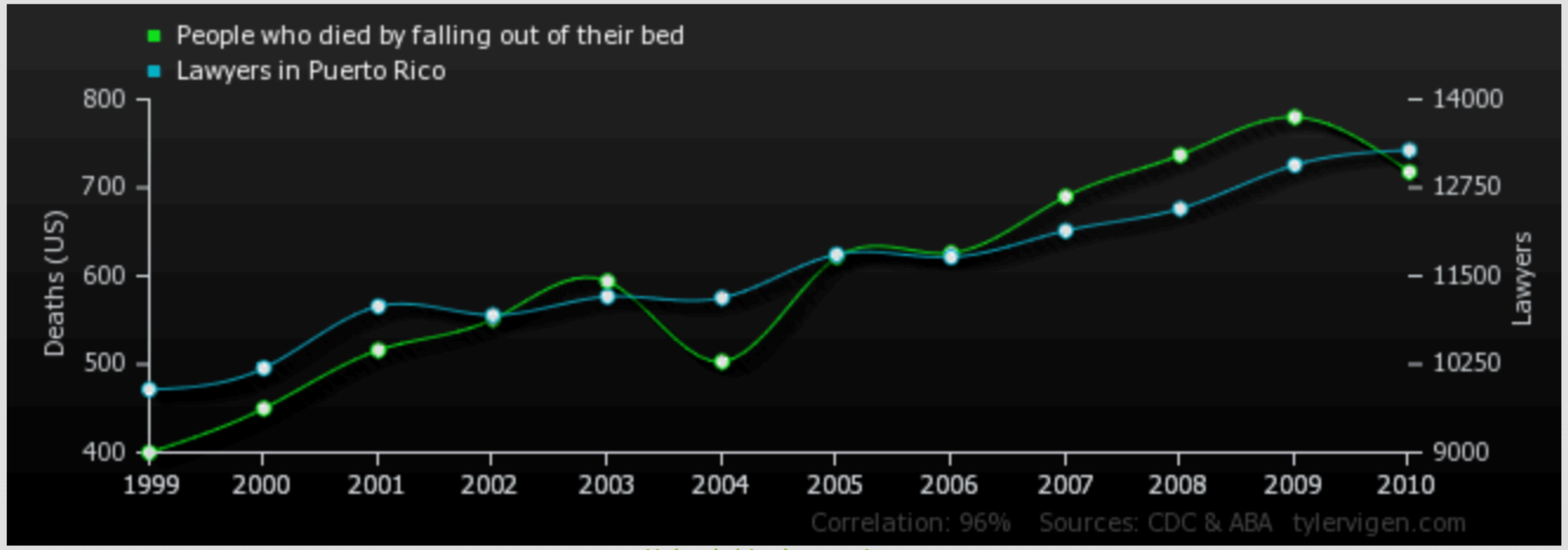
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Sociology doctorates awarded (US) *Degrees awarded (National Science Foundation)*	572	617	566	547	597	580	536	579	576	601	664
Deaths caused by anticoagulants *Deaths (US) (CDC)*	17	39	39	27	44	46	29	42	47	52	78

Correlation: 0.811086



Correlation and causation

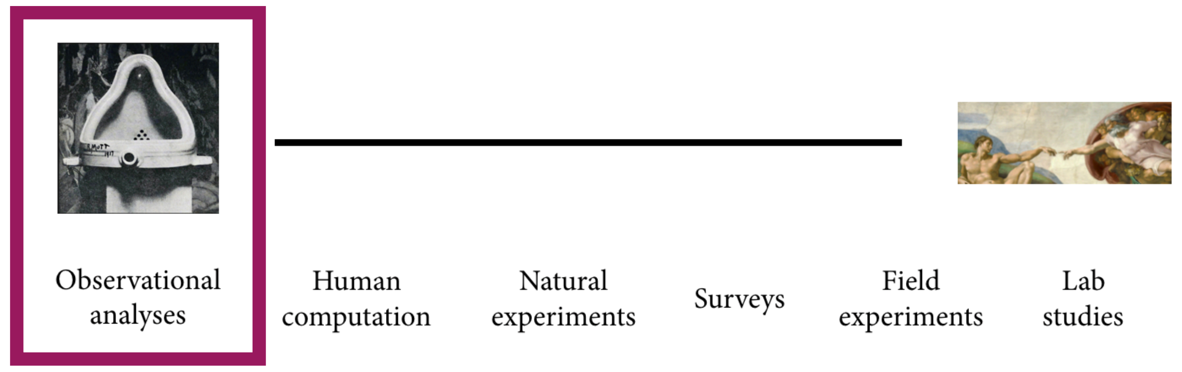
People who died by falling out of their bed
correlates with
Lawyers in Puerto Rico



Upload this chart to imgur

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
People who died by falling out of their bed *Deaths (US) (CDC)*	400	450	516	551	594	503	621	626	690	737	780	718
Lawyers in Puerto Rico *Lawyers (ABA)*	9,892	10,195	11,071	10,947	11,209	11,191	11,805	11,767	12,142	12,454	13,071	13,282

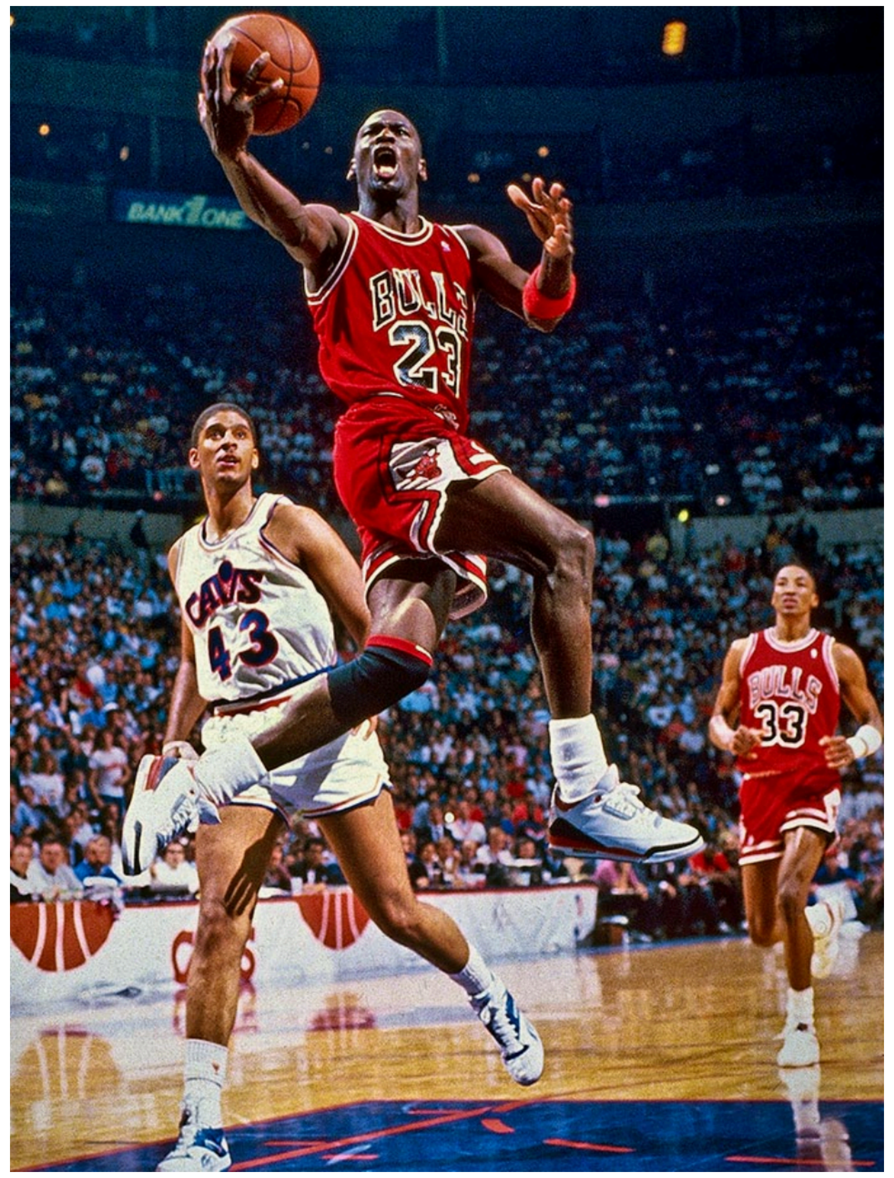
Correlation: 0.957087

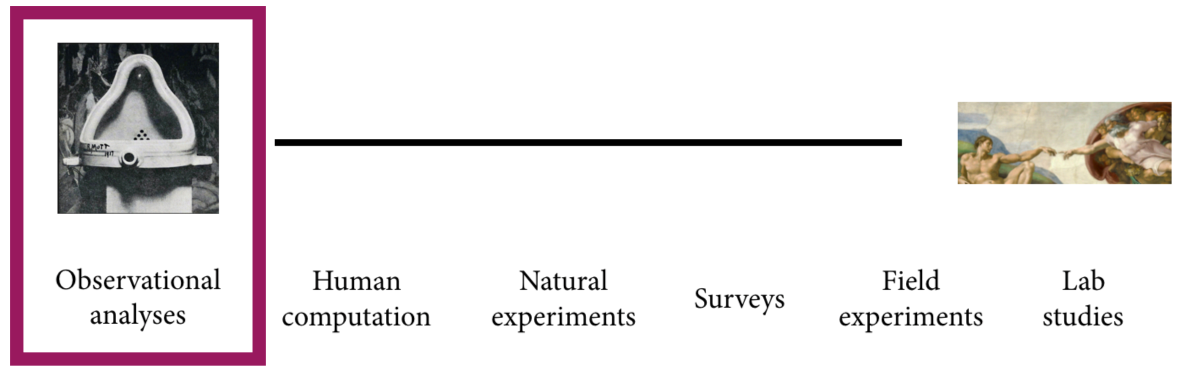


Perils of big data

"When you have large amounts of data, your appetite for hypotheses tends to get even larger. And if it's growing faster than the statistical strength of the data, then many of your inferences are likely to be false. They are likely to be white noise."

— Michael Jordan





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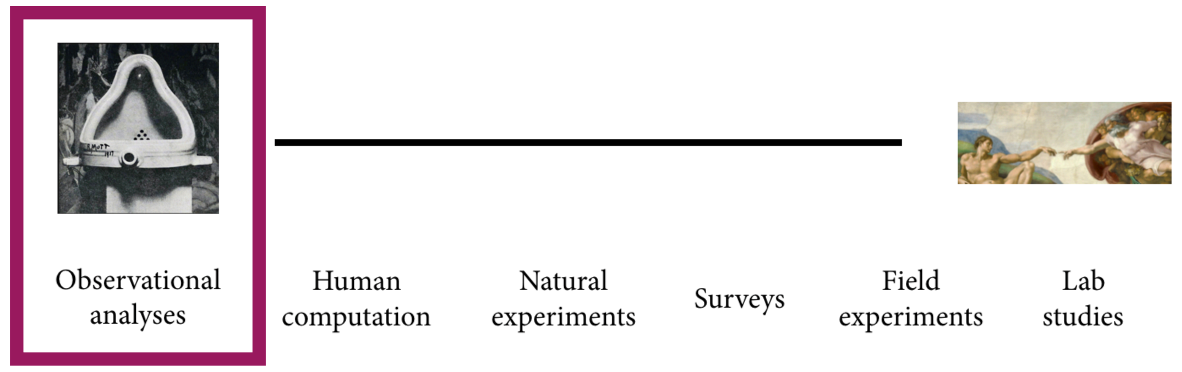


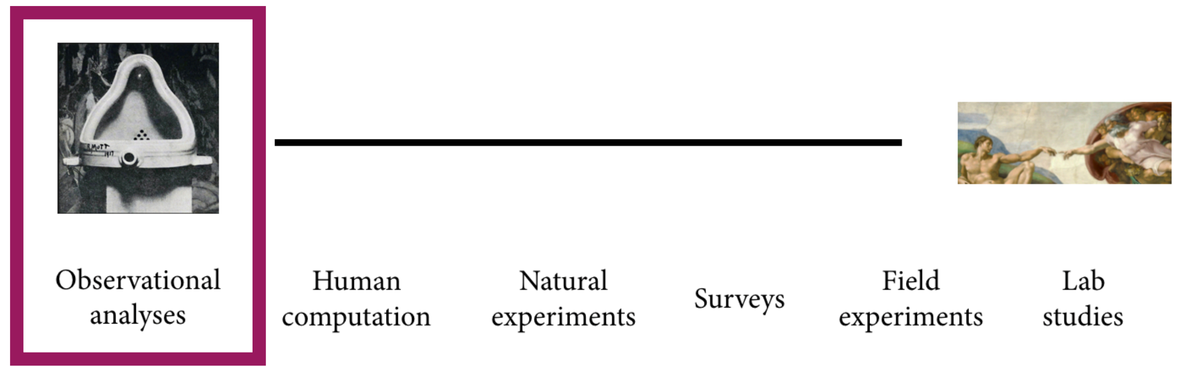
Observing Behaviour: 3. Approximating Experiments

Some clever strategies allow us to do "causal inference": make causal claims from observational data (i.e. arrive at experiment-like conclusions without actually running an experiment)

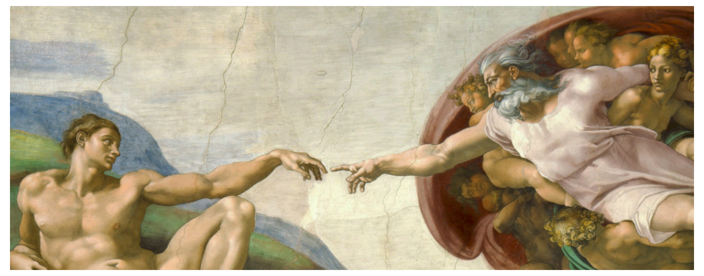
One well-known technique is instrumental variables: exploit natural variation in something to make a causal claim

Rain → Exercise

Friends exercising → You exercise?



Ways of doing computational social science



Observational analyses

Human computation

Natural experiments

Surveys

Field experiments

Experiments

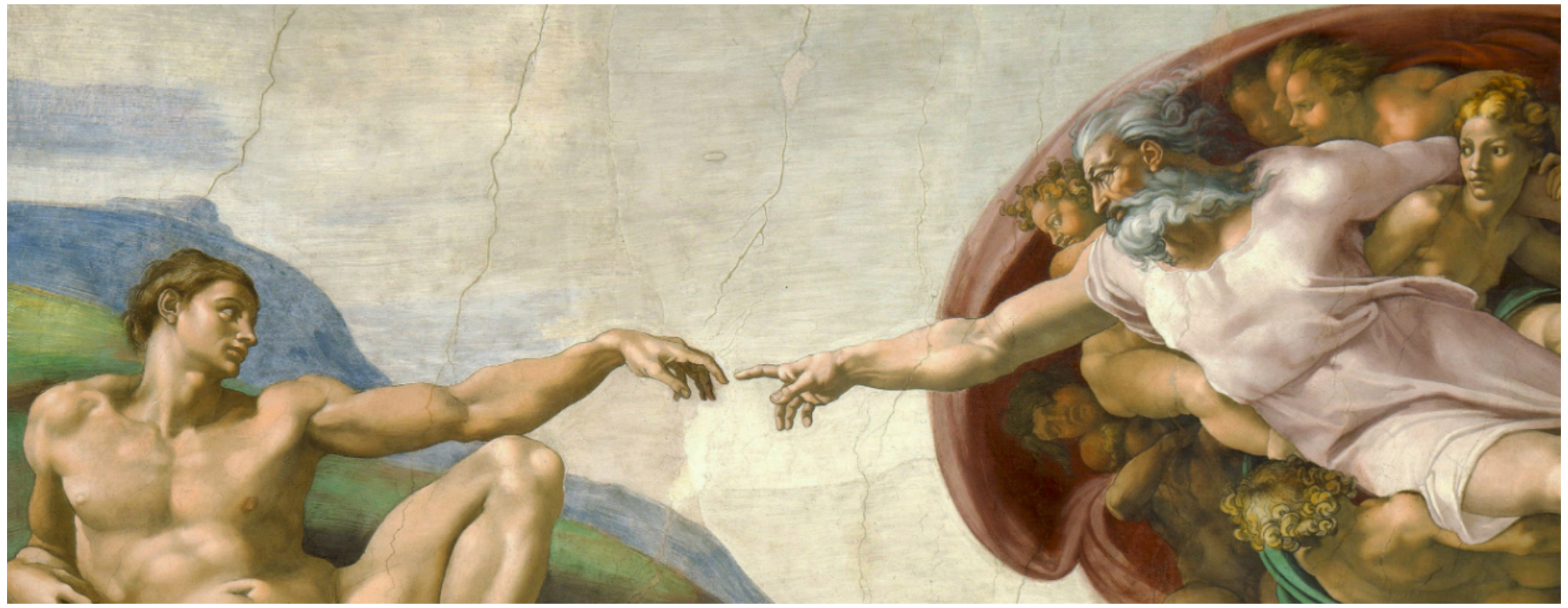
Experiments

On the other end of the spectrum is experimentation

The goal is to learn about causal relationships (cause-and-effect questions)

The strategy is to directly manipulate the environment and observe the consequences

Design the ideal scenario that will create just the data you need to answer your question



Experiments

Here, researchers intervene in the world to isolate and study a specific question

<u>Nomenclature:</u>

"Experiment": perturb and observe

"Randomized controlled experiment": Intervene for one group, don't for another (randomly)

Correlation is not causation

Observational data often riddled by unknown or hard-to-control *confounding variables*

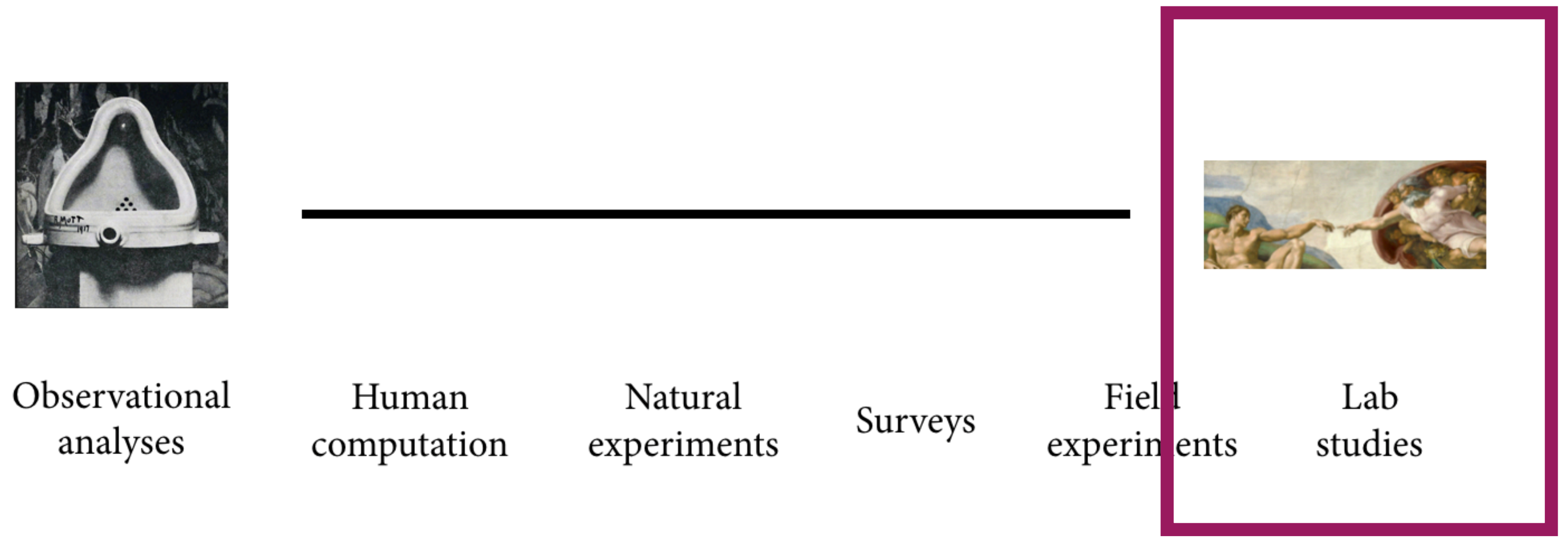
E.g. Do students learn more in schools that offer high teacher salaries?

What's an observational way to study this question?

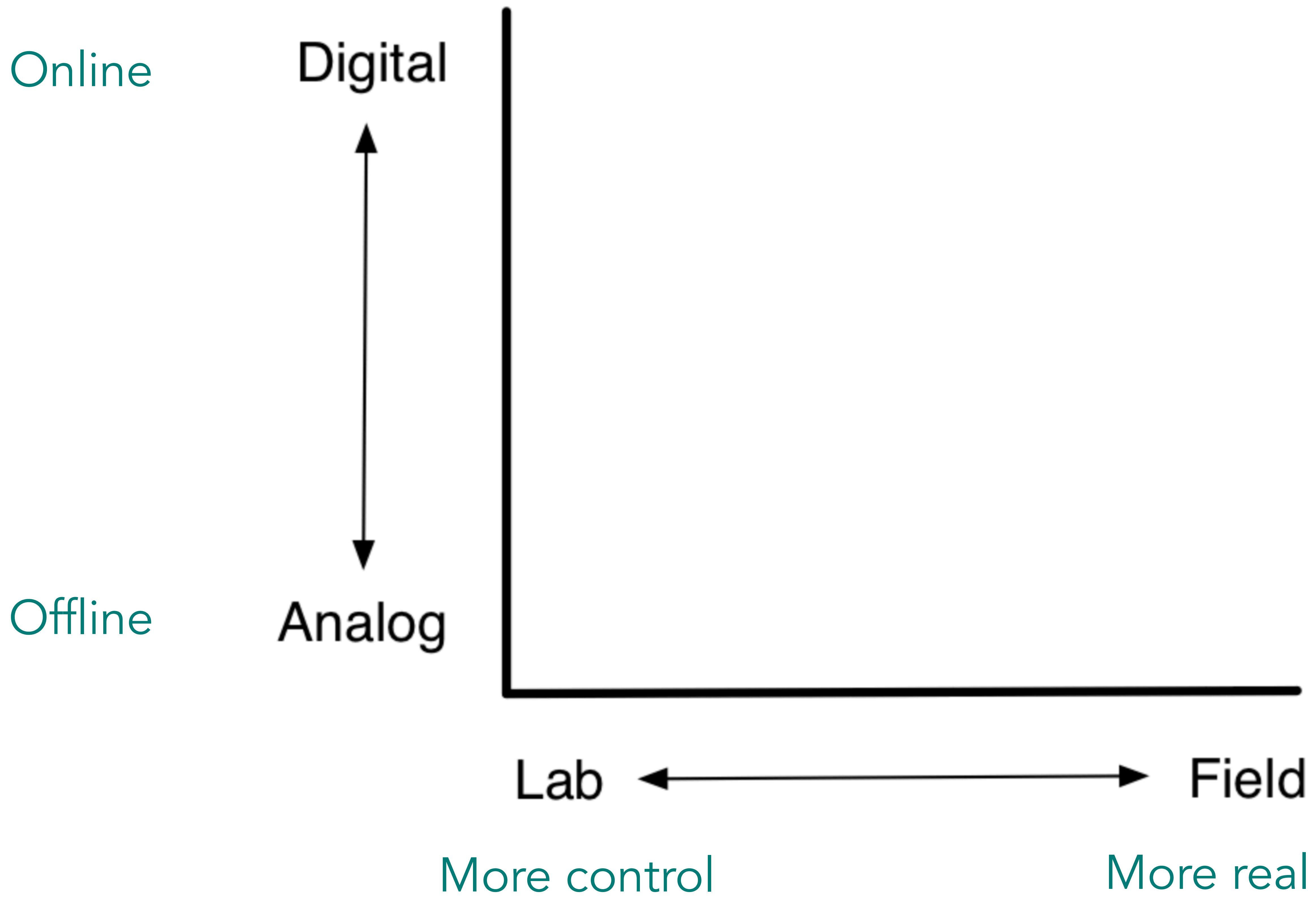
What's wrong with it?

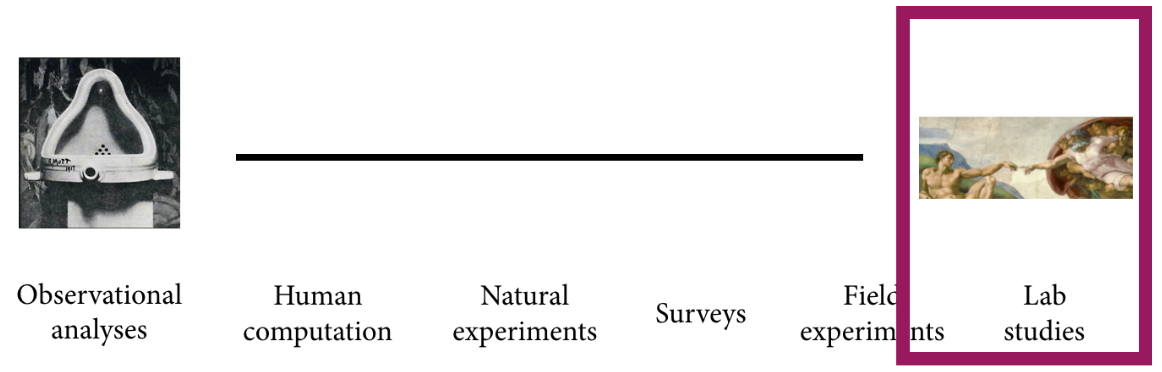
What's an experimental way to study this question?

What's wrong with it?

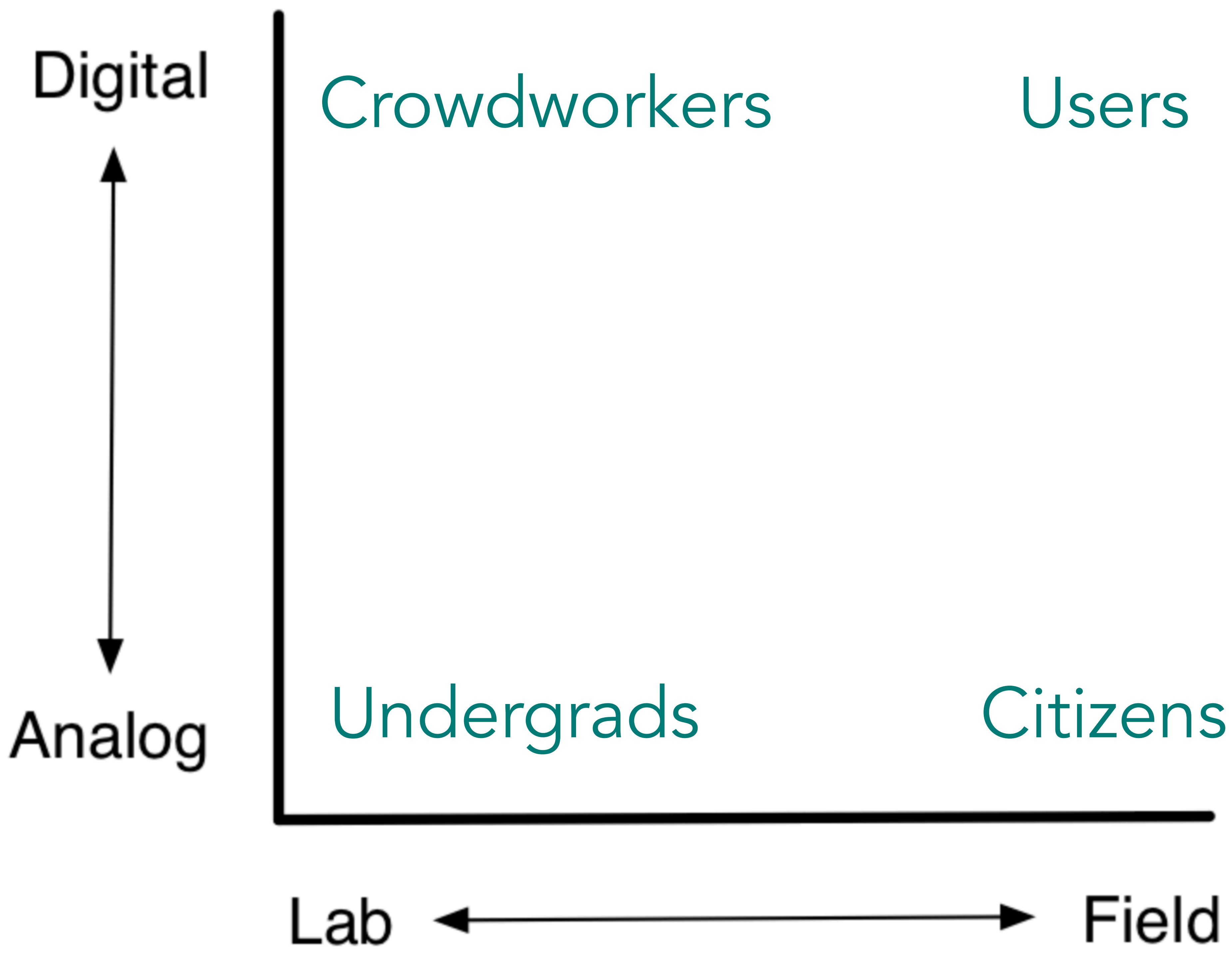


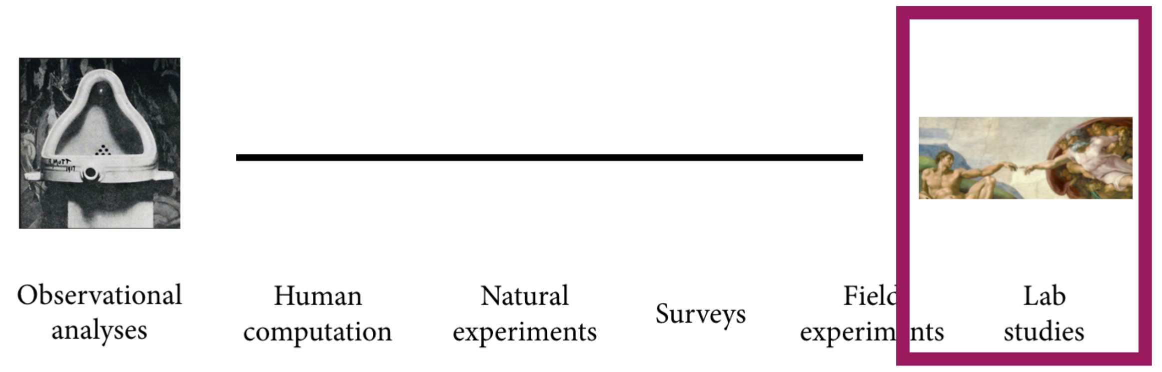
Experiments





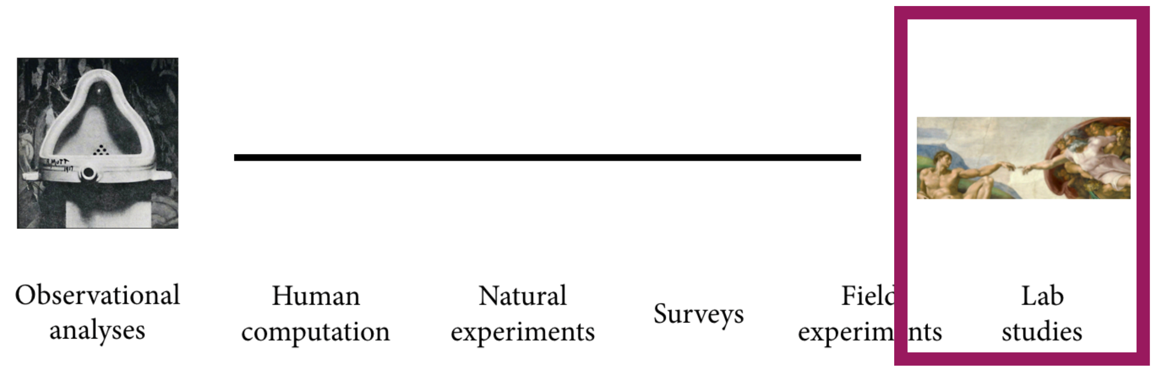
Experiments





Three major components of rich experiments

1. Validity
2. Heterogeneity
3. Mechanisms

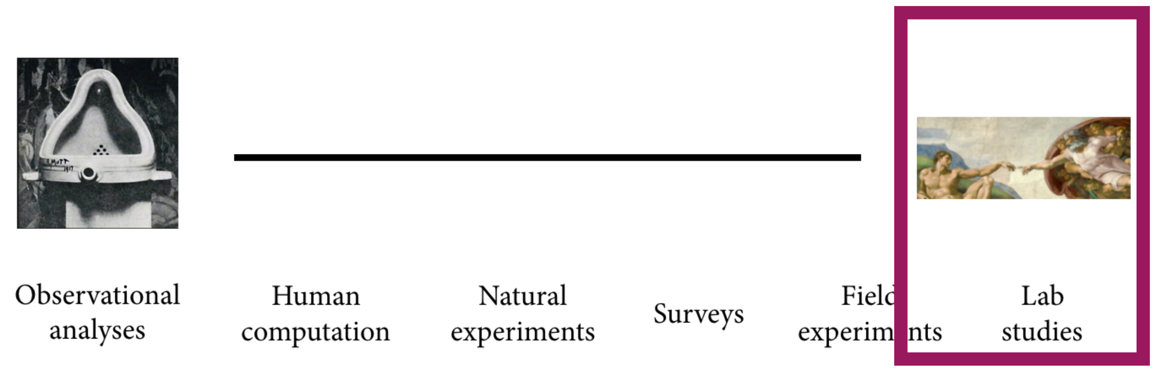


Three major components of rich experiments: 1. Validity

Validity: How general are the results?

Types of validity:

1. Statistical conclusion validity: were the stats done right?
2. Construct validity: are we measuring the right thing?
3. Internal validity: was the experiment done right?
4. External validity: is this applicable in other settings?

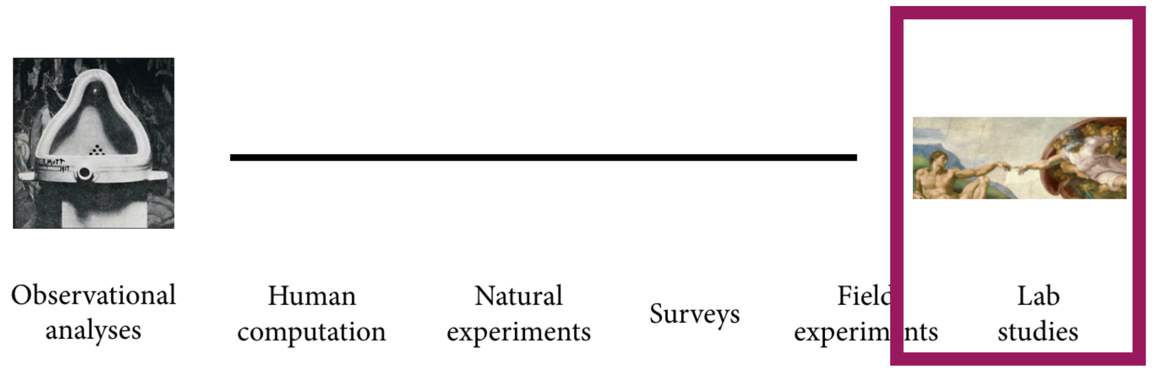


Three major components of rich experiments: 2. Heterogeneity

Barebones experiment: measure the average treatment effect (ATE)

But in social research, people almost always vary.

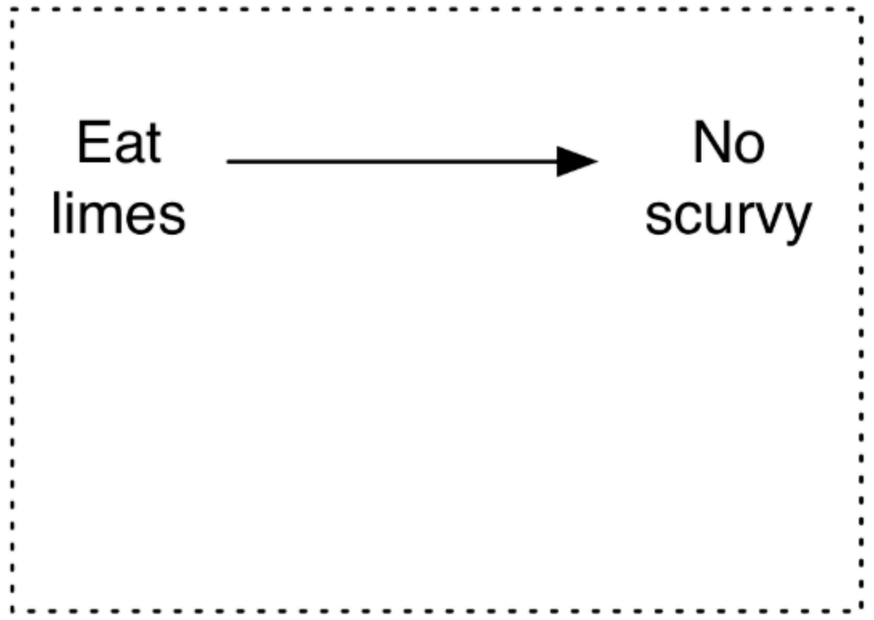
Digital research presents many more opportunities to measure how causes affect people differently



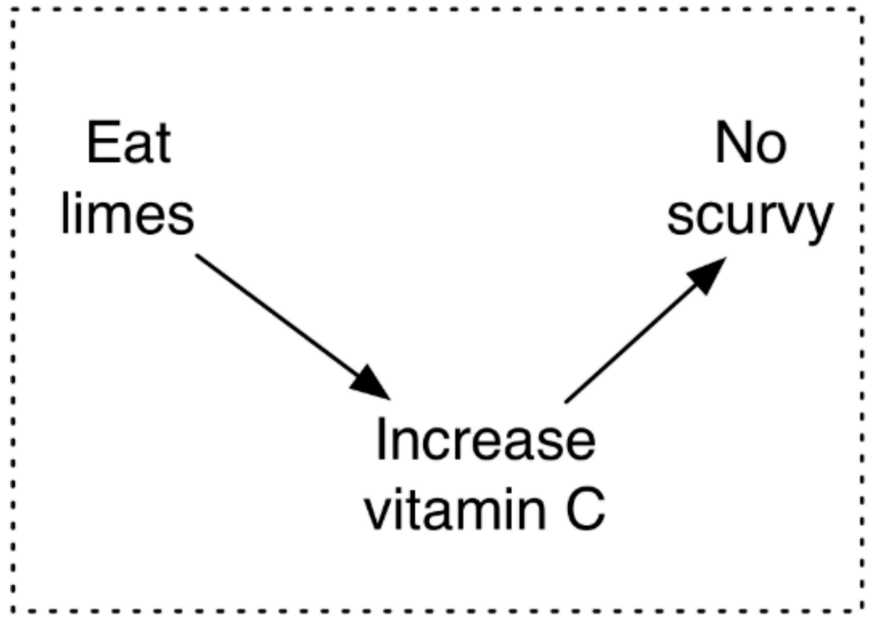
Three major components of rich experiments: 3. Mechanisms

Barebones experiment: measure what happened.

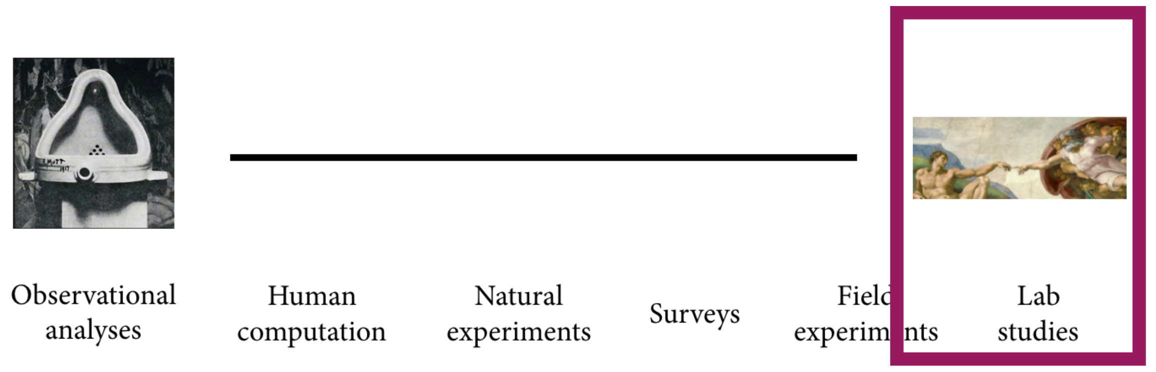
Mechanisms: why and how did it happen?



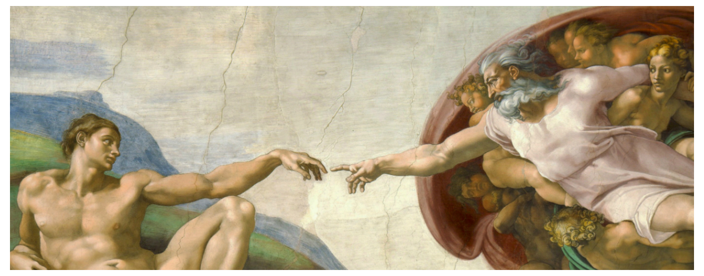
Causal effect without mechanism



Causal effect with mechanism



Ways of doing computational social science



Observational analyses

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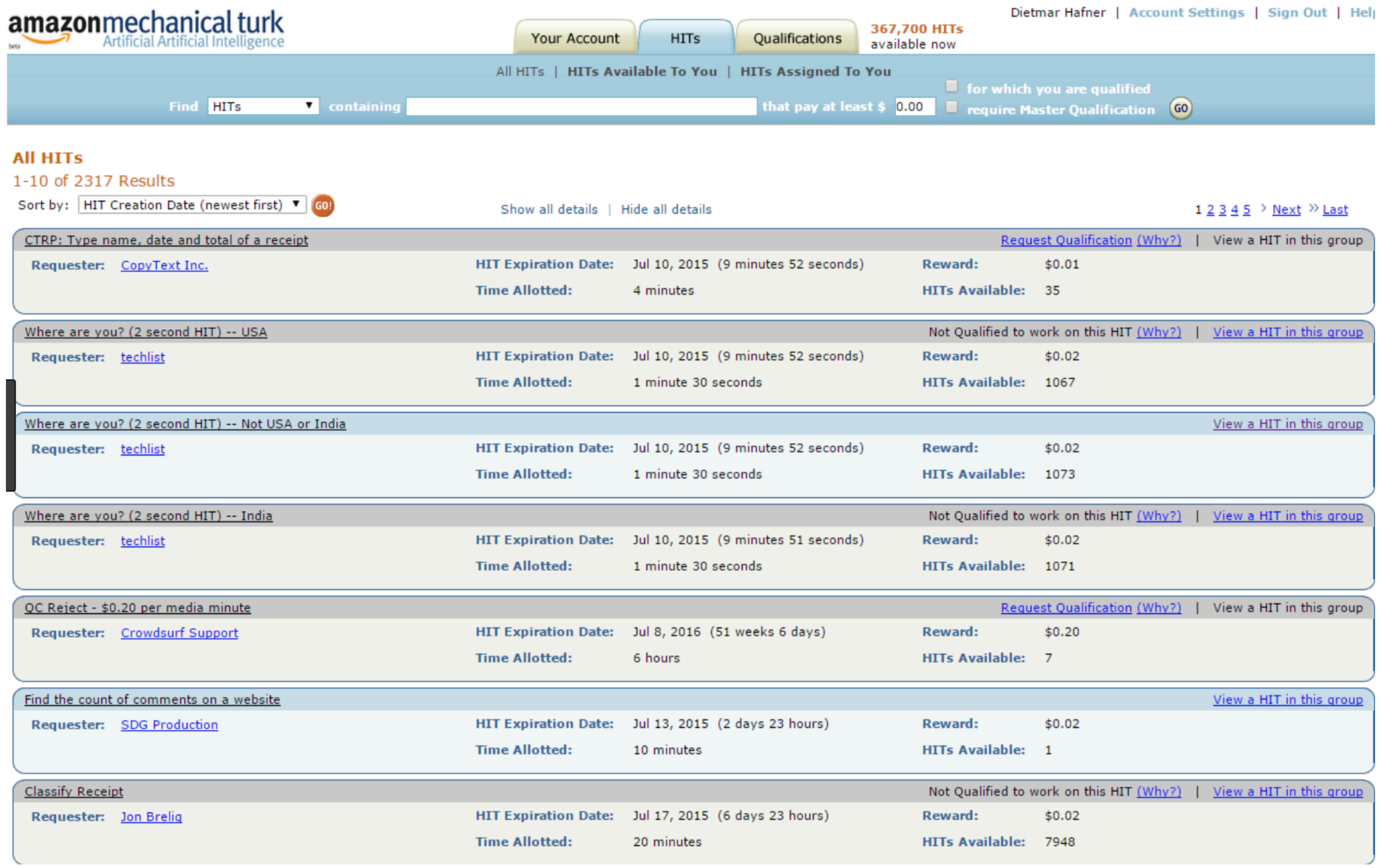
Human computation

- Online crowdsourcing platforms allow dividing work into microtasks
- Human-in-the-loop computing, modern-day lab studies, mass collaboration to build big resources (Wikipedia etc.)



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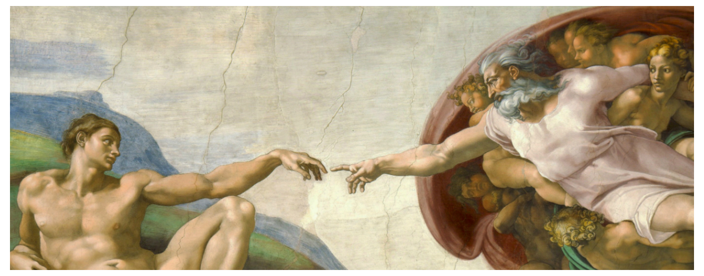

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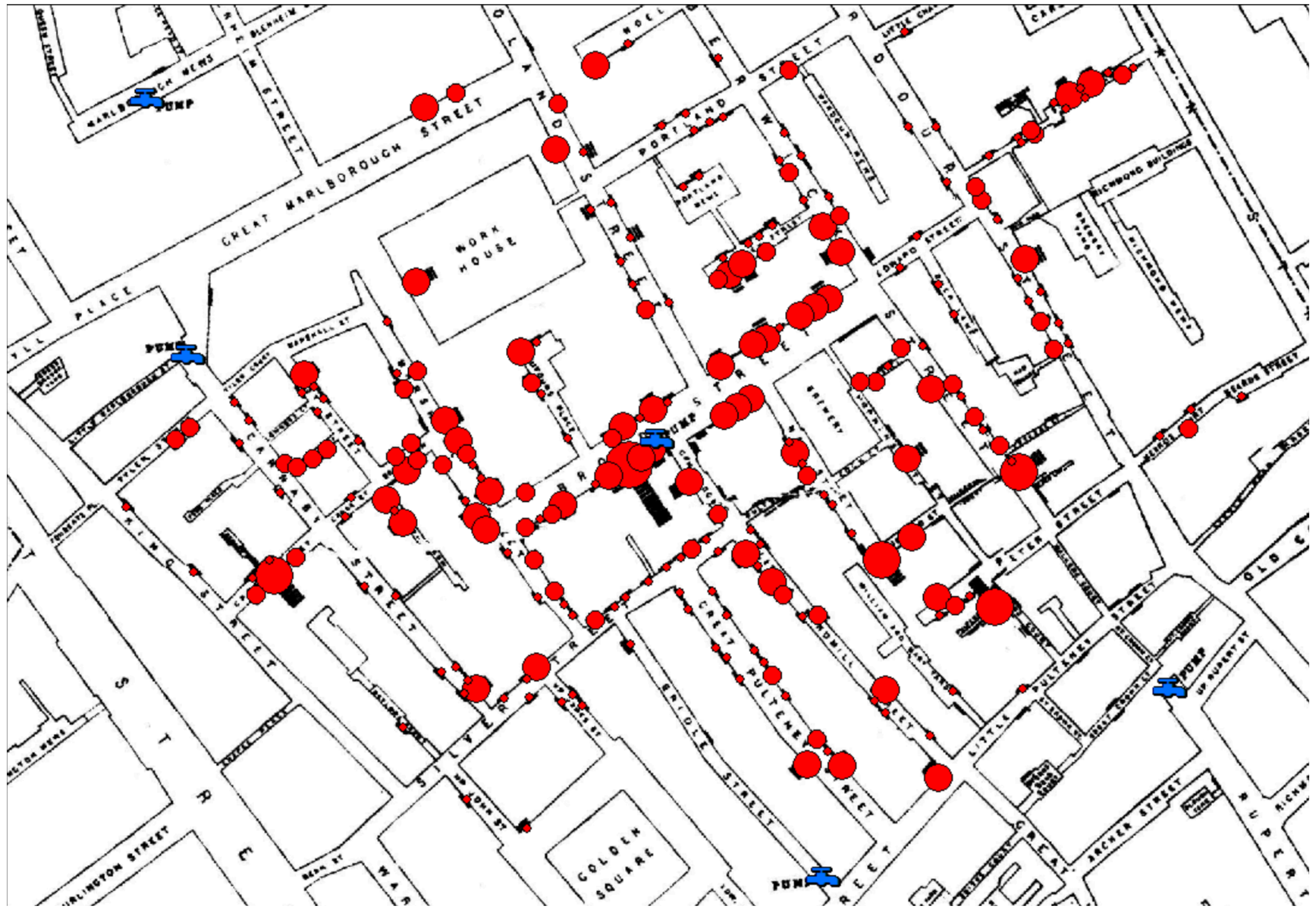
Natural experiments

Sometimes observational data has some random component you can exploit, and analyze as a “natural” experiment

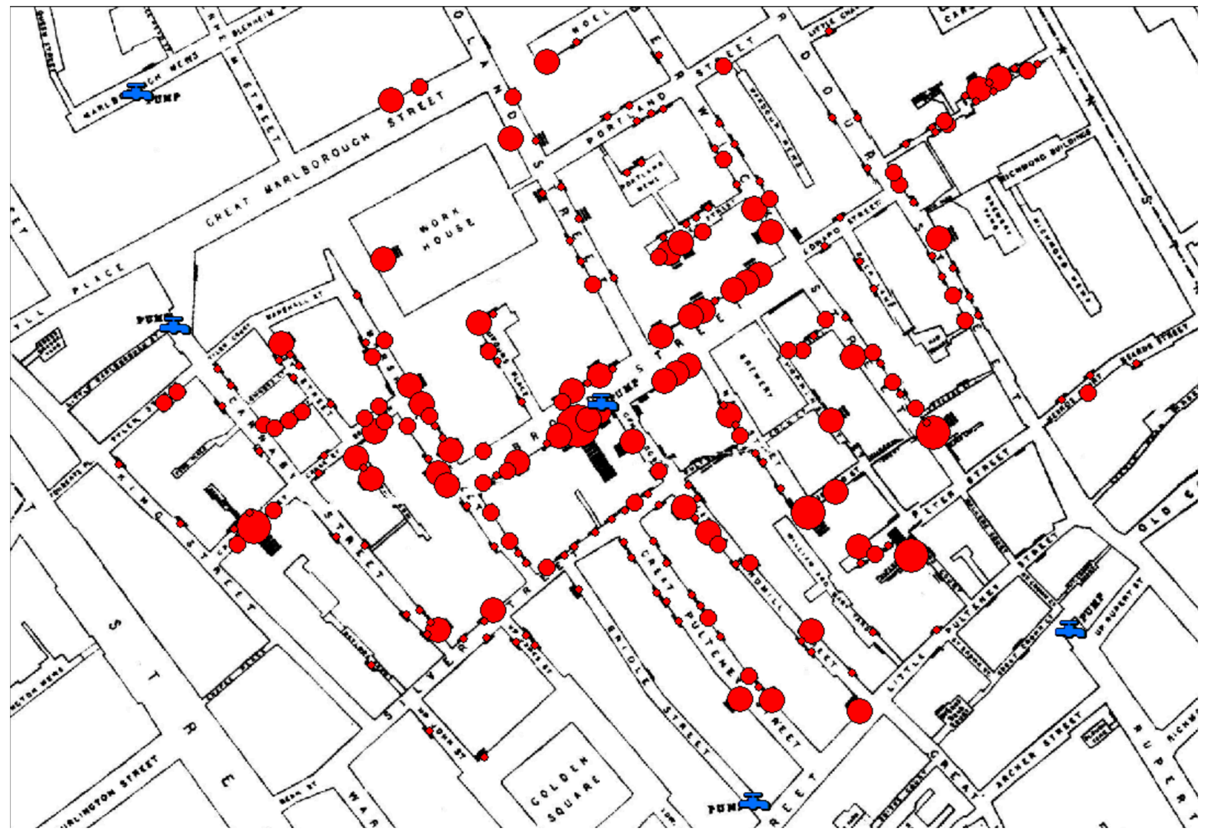


Cholera outbreak in London in 1850s

Natural experiments

- Physician John Snow produced a map suggesting particular water was the culprit
- Two main water suppliers: one from downstream Thames where raw sewage was dumped in the water (high attack rates), and one from upstream (low attack rates)
- Which supplier you had was arbitrary (varied even within same house, same neighbourhood, etc.)
- Exposure to polluted water was as-if random

Now: in large datasets, more opportunities to identify and argue for as-if random assignment



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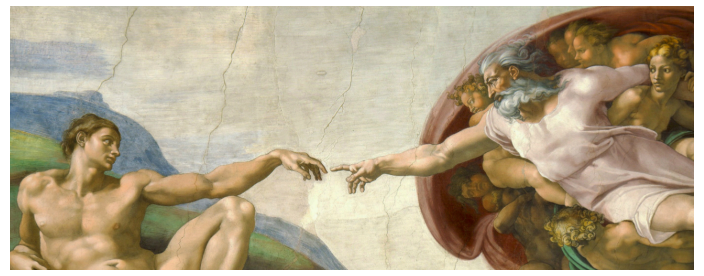
Ways of doing computational social science



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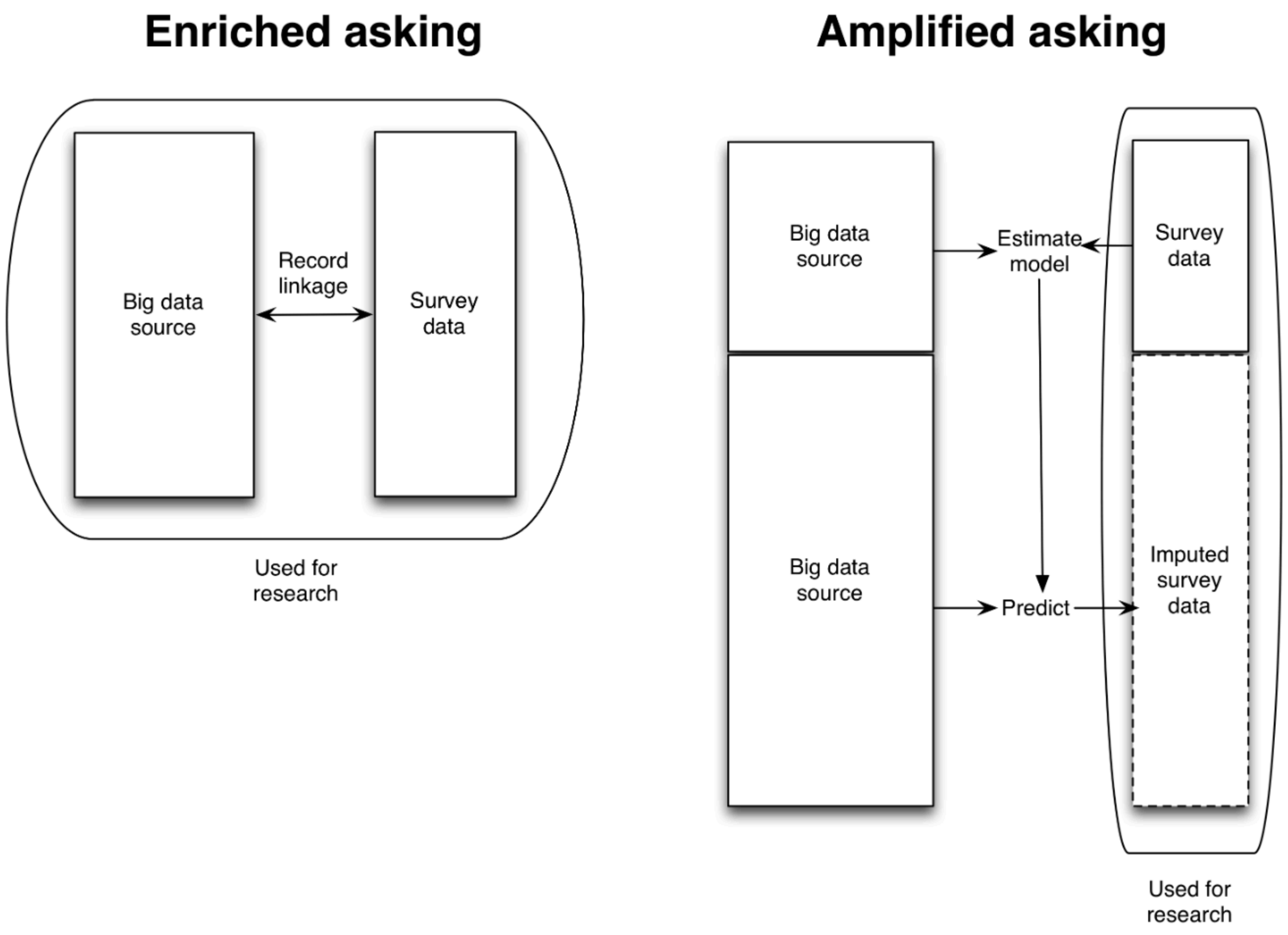
Surveys: asking questions

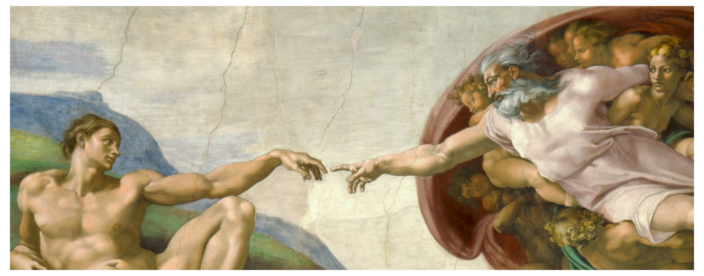
Social research has a unique advantage: we can ask our subjects what they're thinking!

Still the best way to learn the answer to many questions

In the digital era, there are new ways of asking questions



Ways of doing computational social science



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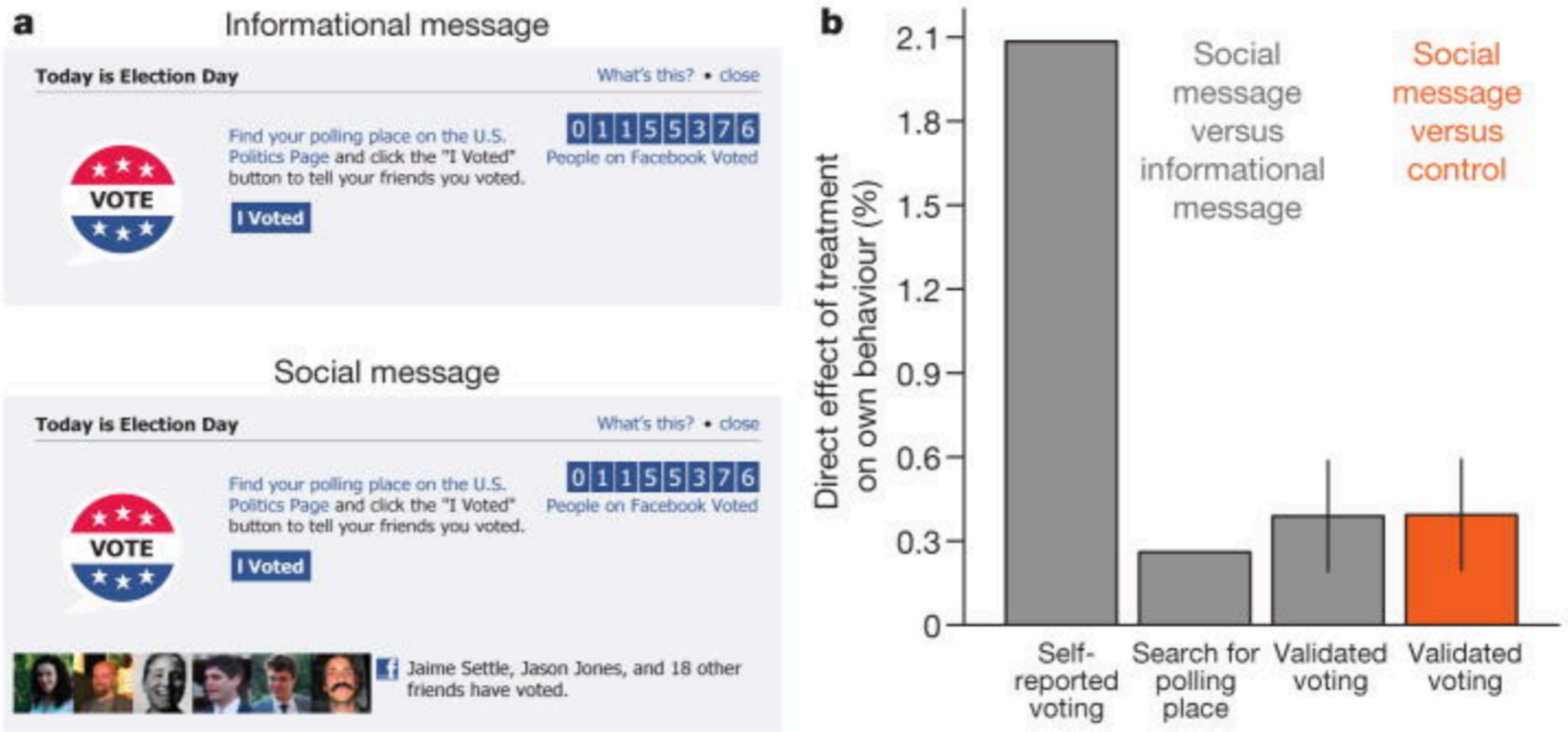
Field experiments

- Introducing a treatment into a real system
- Much more possible now with algorithmic systems

Voting experiment on Facebook

Figure 1



The experiment and direct effects

a, **b**, Examples of the informational message and social message Facebook treatments (**a**) and their direct effect on voting behaviour (**b**). Vertical lines indicate s.e.m. (they are too small to be seen for the first two bars).

~300,000 more validated votes

AI & Society: Algorithmic decision-making

St. George's Hospital in the UK developed an algorithm to sort medical school applicants. Algorithm trained to mimic past admissions decisions made by humans.

But past decisions were biased against women and minorities. It codified discrimination.

Web search ads for "Kristen Haring"

Ads by Google

[We Found:**Kristen Haring**]

1) Contact **Kristen Haring** - Free Info! 2) Current Phone, Address & More.

www.peoplesmart.com/**Kristen**

Search by Phone	Search by Email
Background Checks	Search by Address
Public Records	Criminal Records

Kristen Haring

Public Records Found For: **Kristen Haring**. Search Now.

www.publicrecords.com/

Web search ads for “Latanya Farrell”

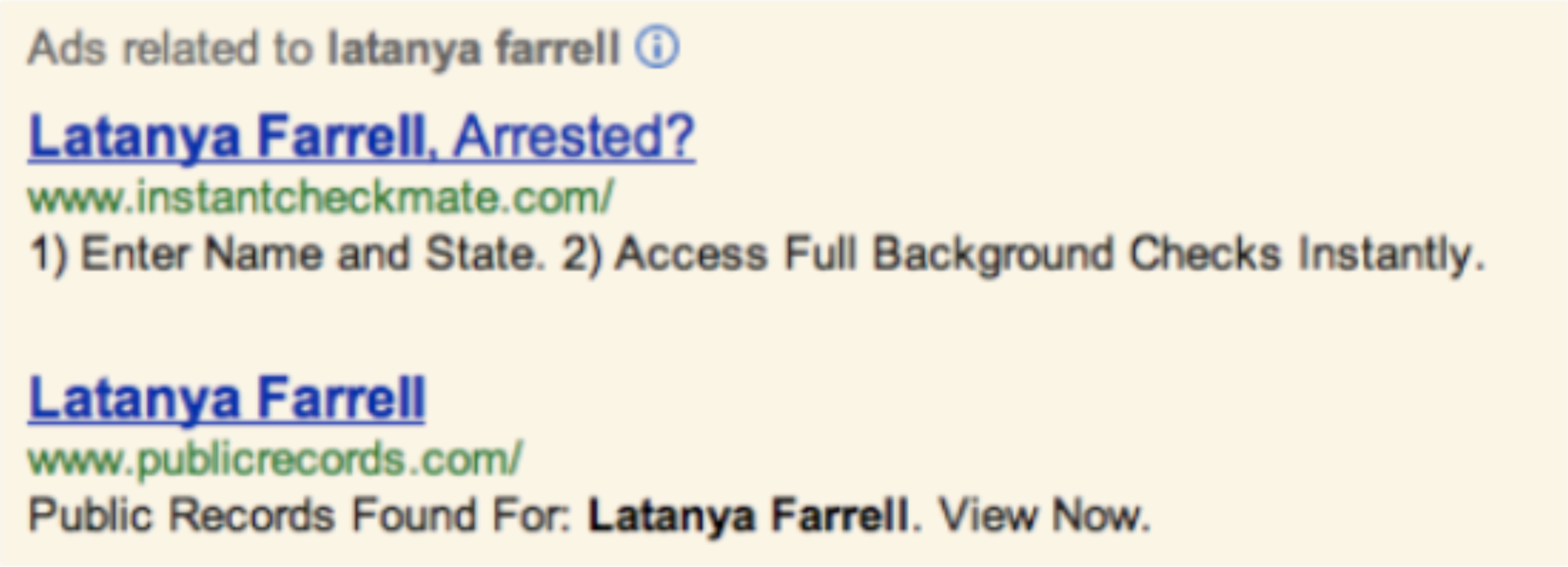
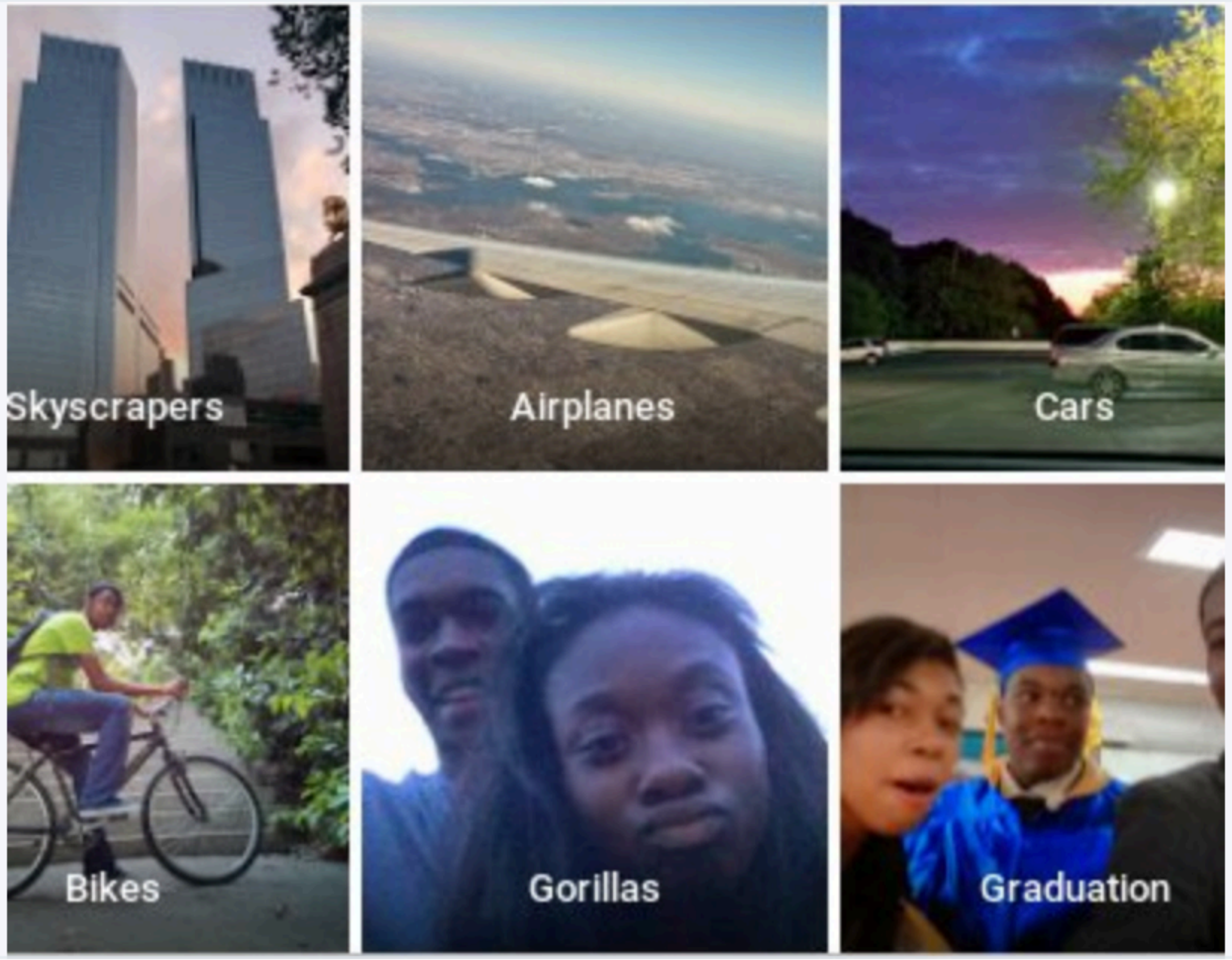


Image labeling gone wrong



Jacky Alciné
@jackyalcine

Google Photos, y'all fucked up. My friend's not a gorilla.

8:22 PM - Jun 28, 2015

226 3,214 2,067

Image searching for “CEO”

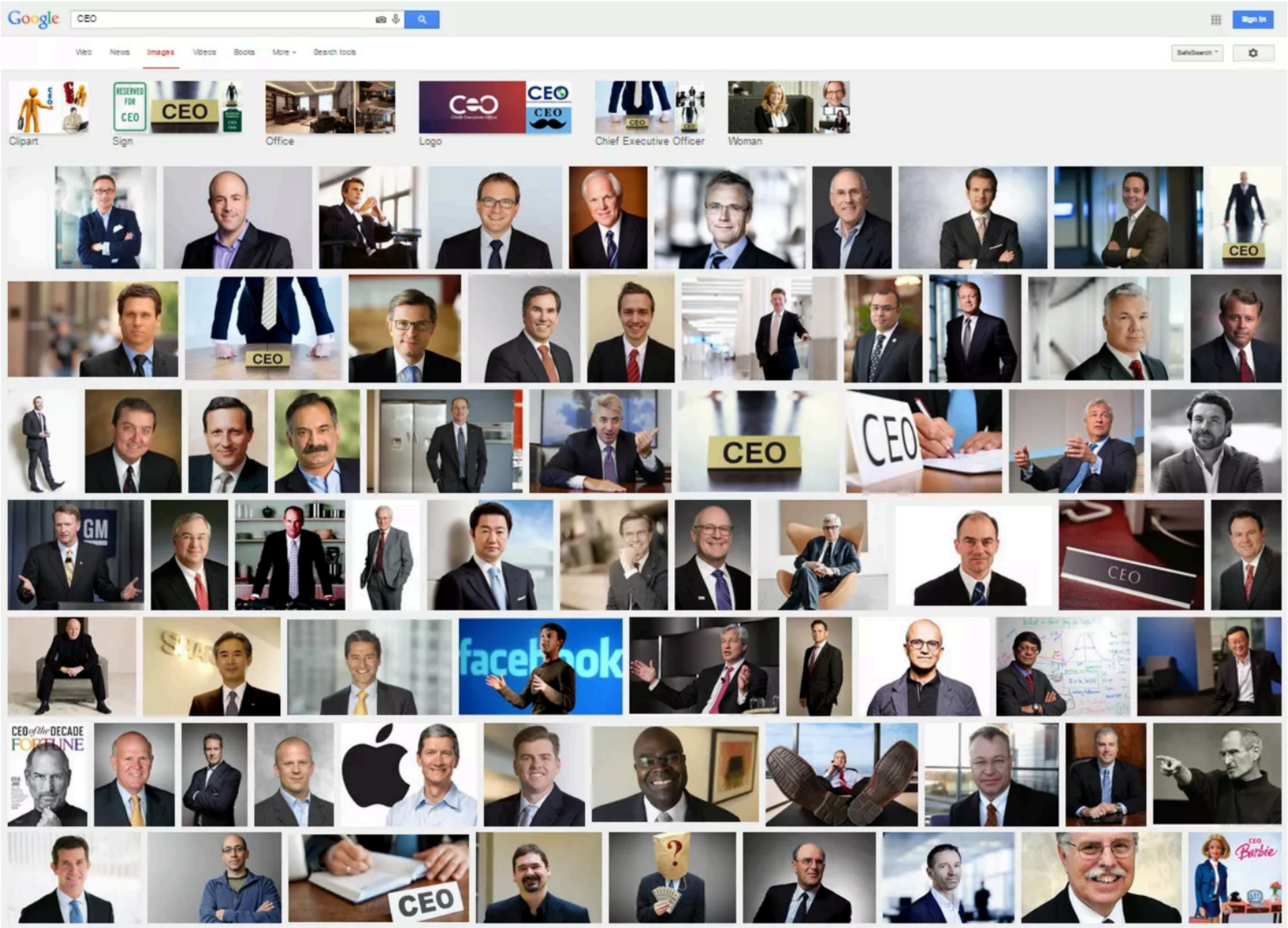


Image searching for "CEO"

Last nail in the coffin: this picture is from an Onion article.

Ethics and privacy

Experimental evidence of massive-scale emotional contagion through social networks

Adam D. I. Kramer[a,1], Jamie E. Guillory[b,2], and Jeffrey T. Hancock[b,c]

Facebook's Users Outraged Over Emotion Experiment

Facebook reveals news feed experiment to control emotions

Facebook emotion experiment sparks criticism

Facebook Tinkers With Users' Emotions in News Feed Experiment, Stirring Outcry

Everything We Know About Facebook's Secret Mood Manipulation Experiment

Facebook conducted secret psychology experiment on users' emotions

Computational social science

Game-changing opportunity to improve our understanding of human behaviour and have positive societal impact.

Doing so requires addressing serious technical, scientific, and ethical challenges.

Computational social science in 7 easy pieces

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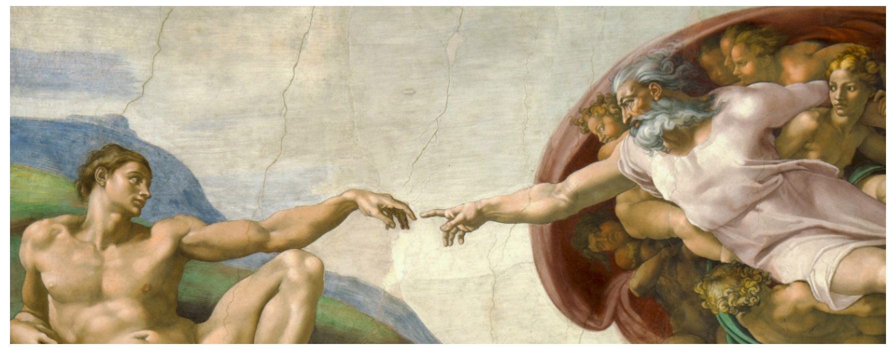
11	11/20	Project presentations (Part 1)		
12	11/27	Project presentations (Part 2)		

Readymades

Custommades



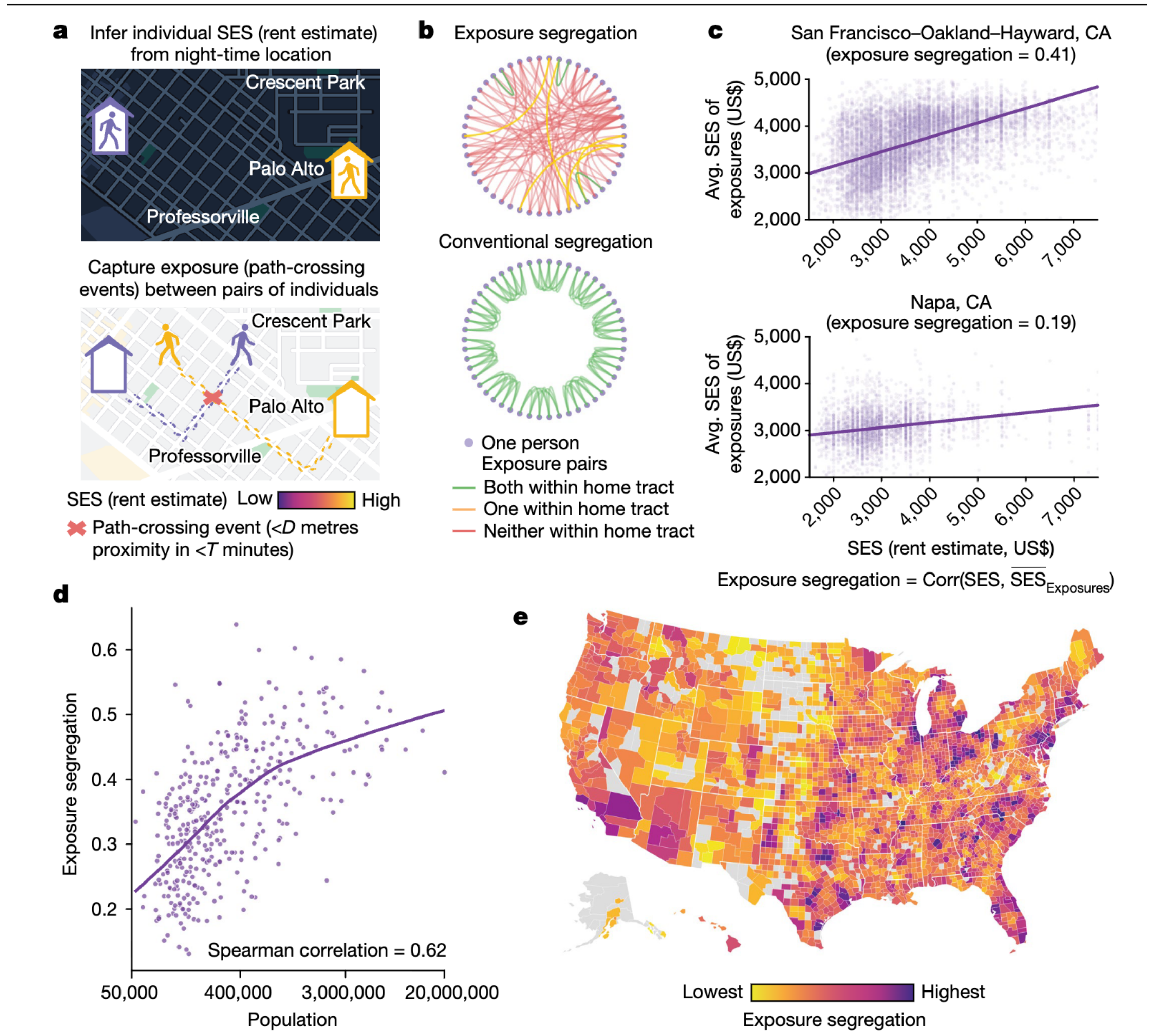
Observational studies 1

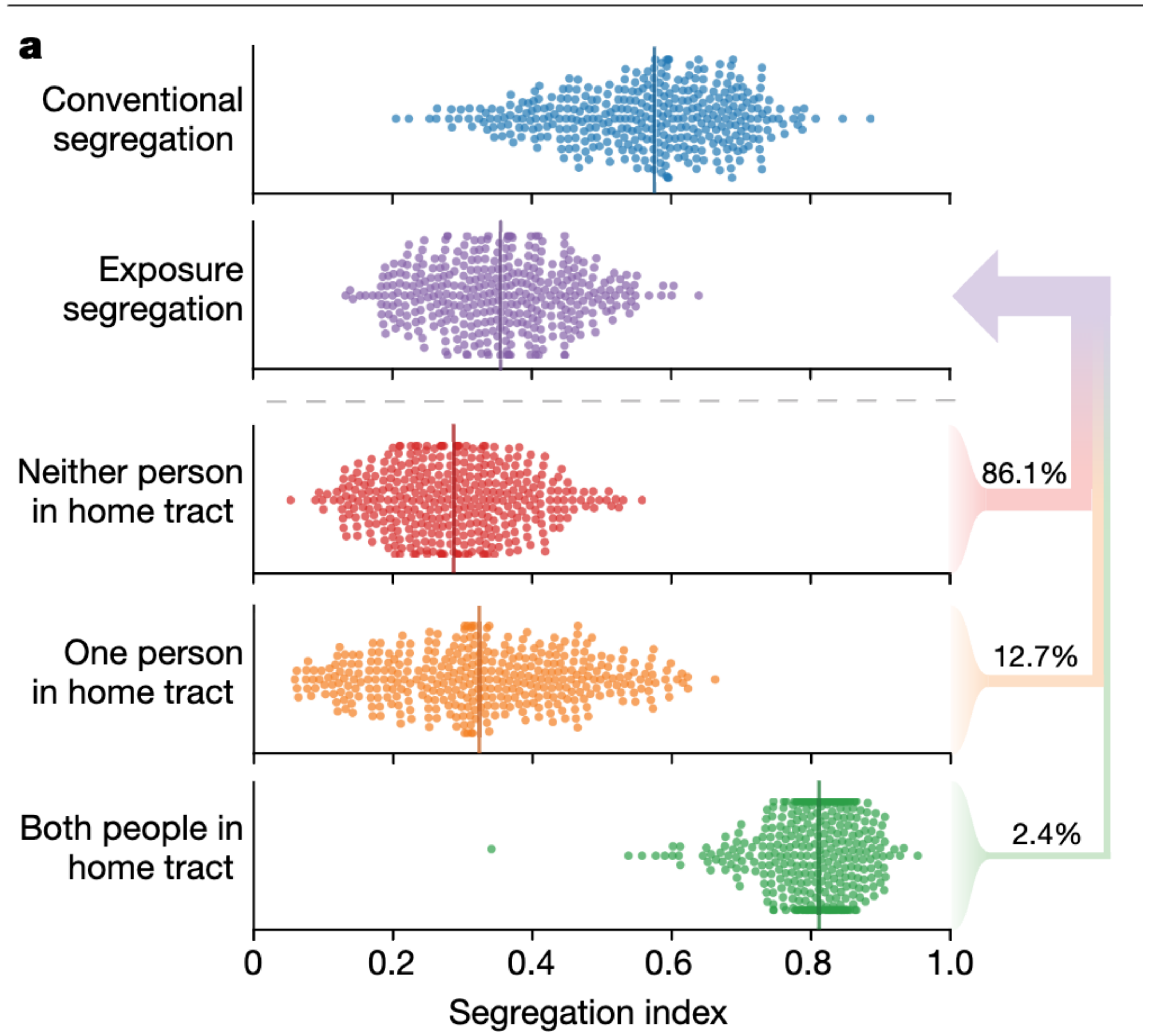
Article

Human mobility networks reveal increased segregation in large cities

Nature, 2023

"Using mobile phone mobility data to represent 1.6 billion real-world exposures among 9.6 million people in the United States, we measure exposure segregation across 382 metropolitan statistical areas (MSAs) and 2,829 counties."





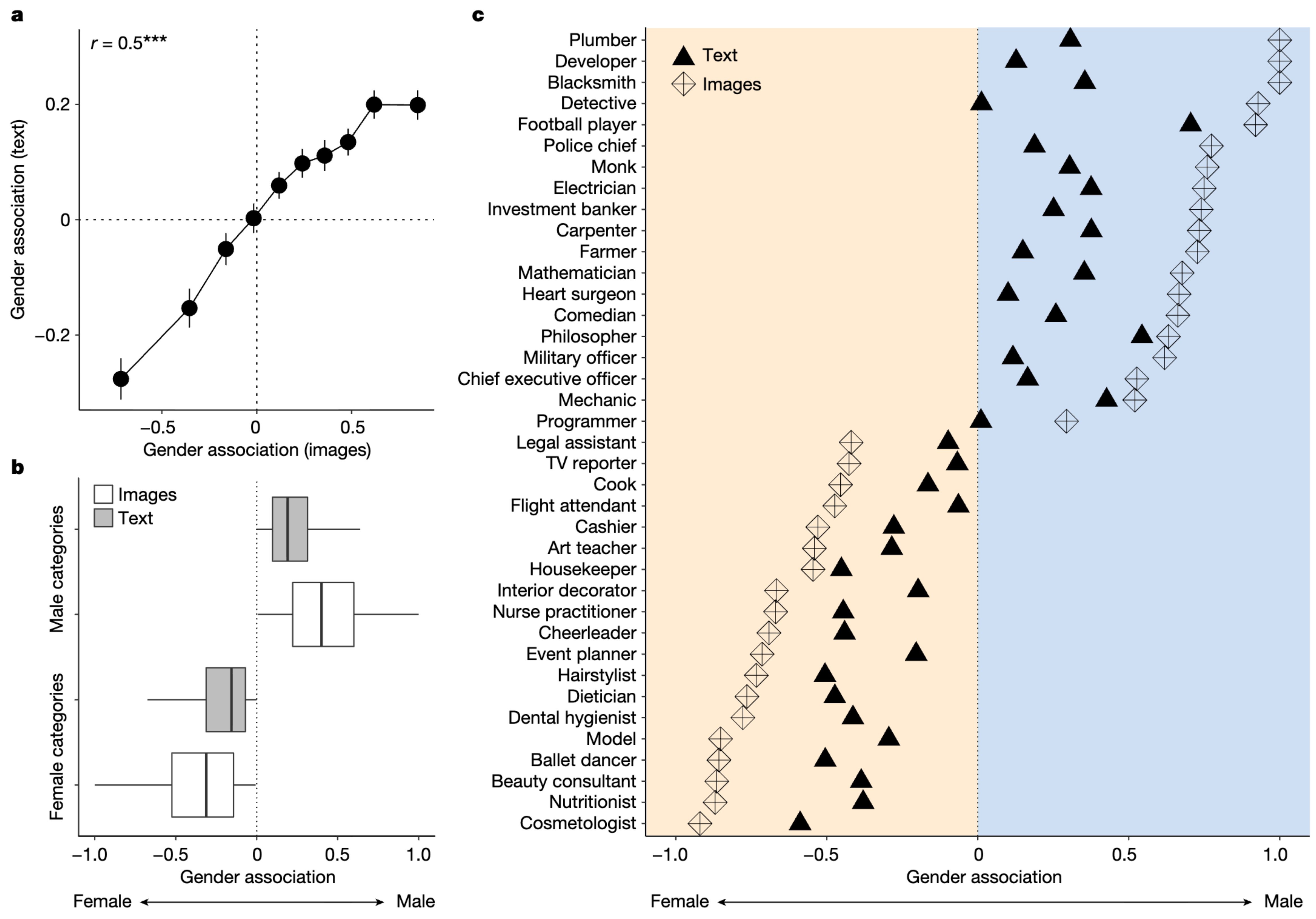
Observational studies 1

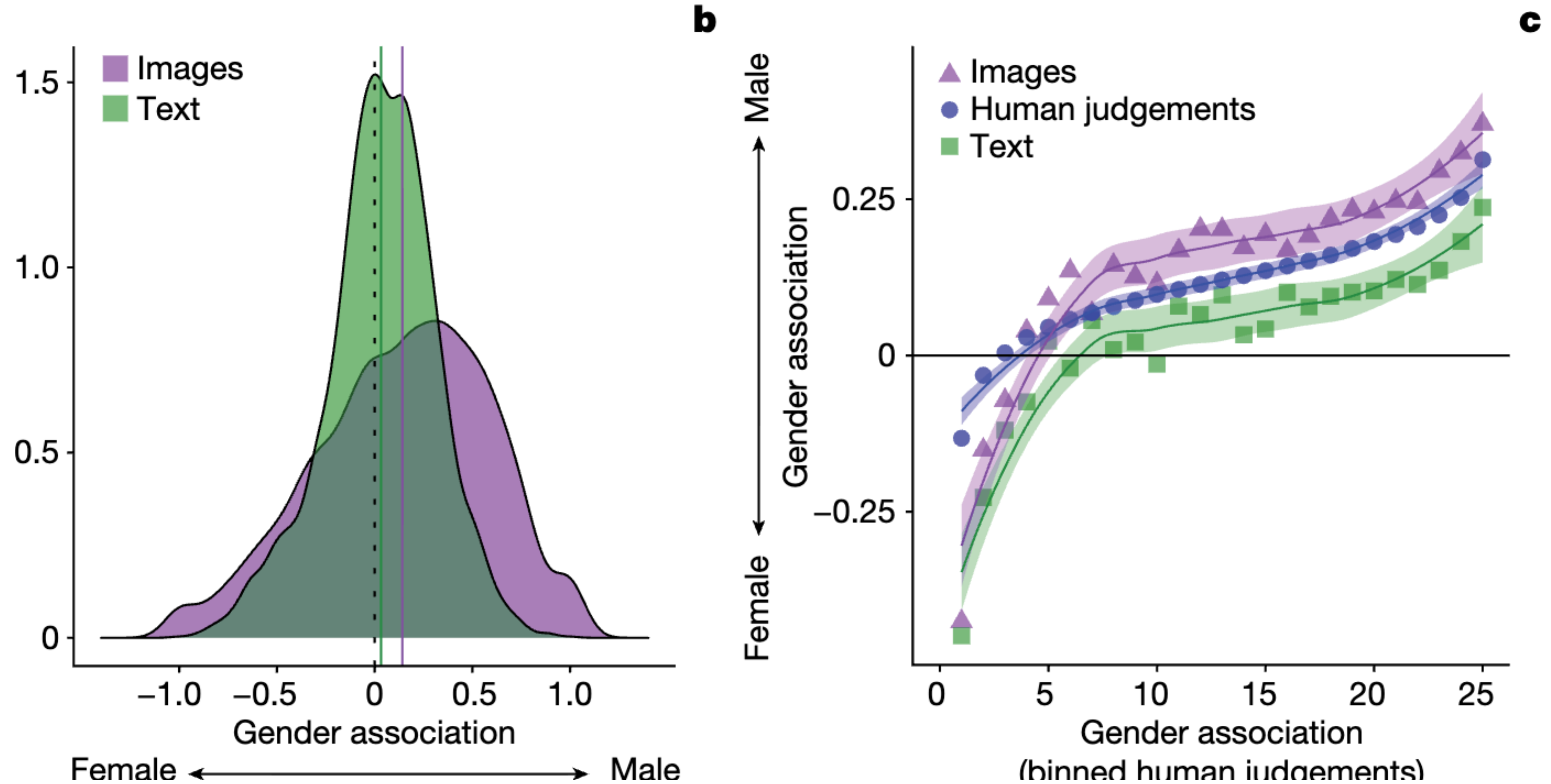
Article

Online images amplify gender bias

Nature, 2024

"We examine the gender associations of 3,495 social categories (such as 'nurse' or 'banker') in more than one million images from Google, Wikipedia and Internet Movie Database (IMDb), and in billions of words from these platforms."





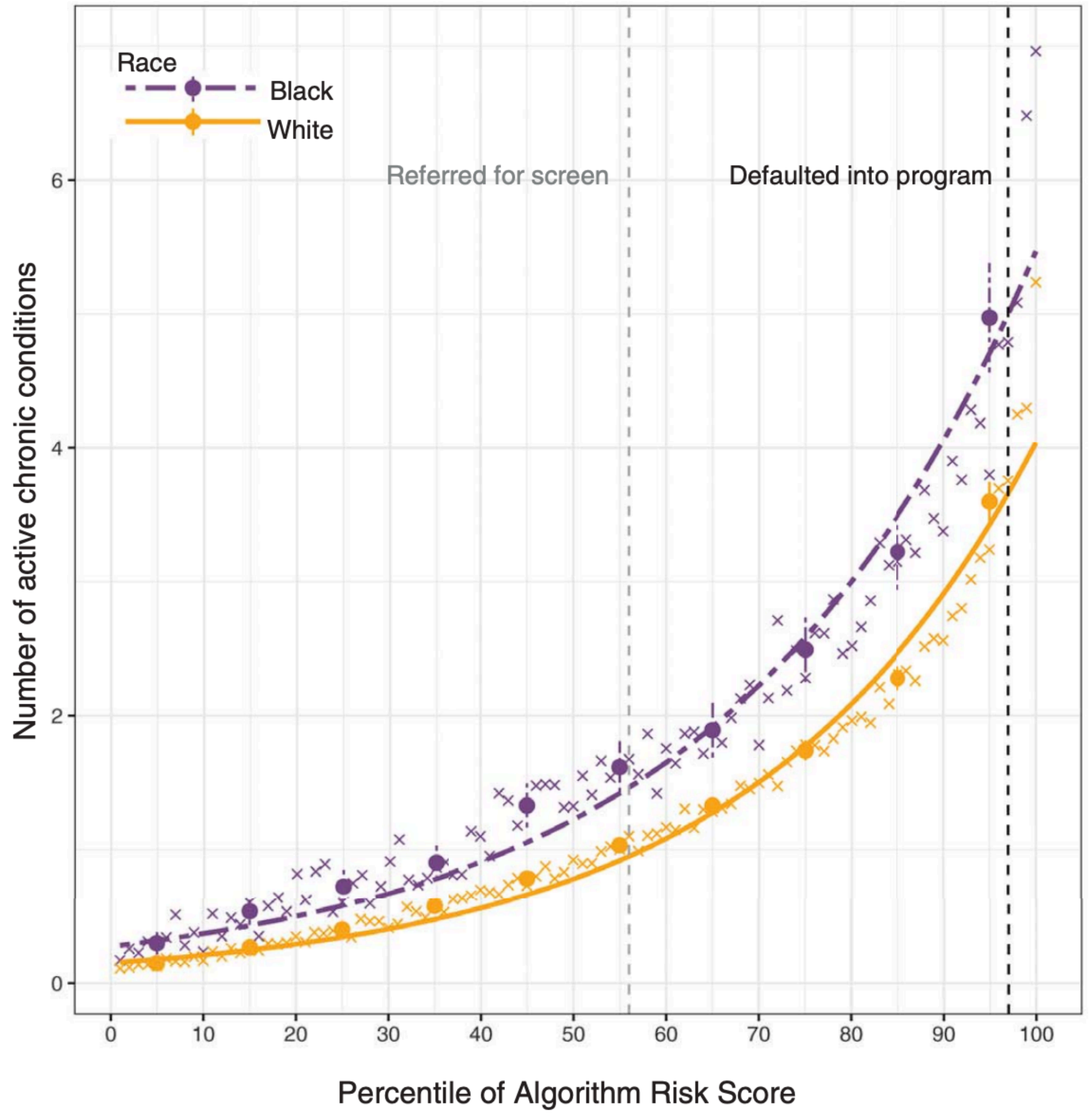
Observational studies 2

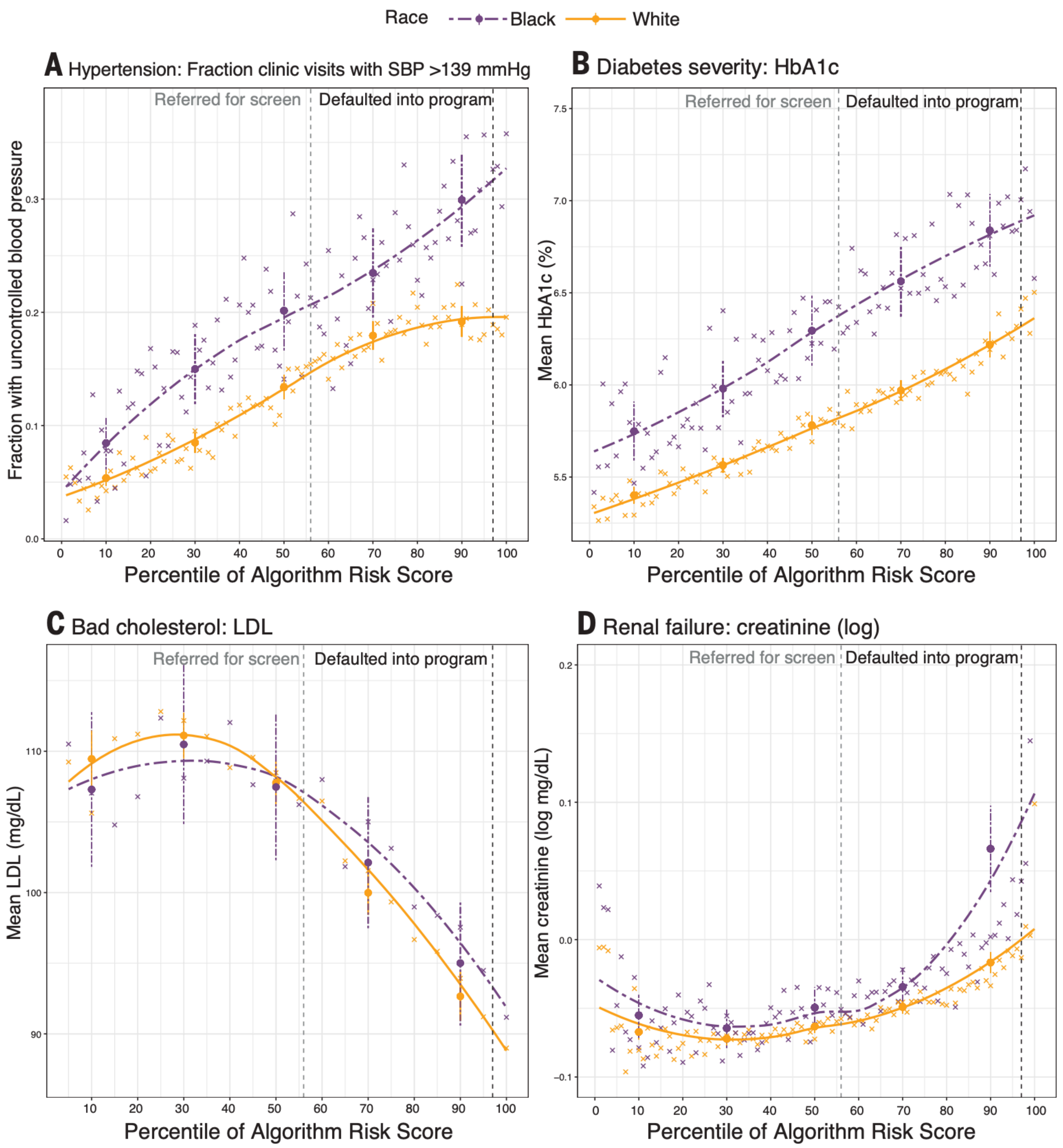
Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer[1,2]*, Brian Powers[3], Christine Vogeli[4], Sendhil Mullainathan[5]*†

Science, 2021

Measuring algorithmic bias in a high-stakes health setting





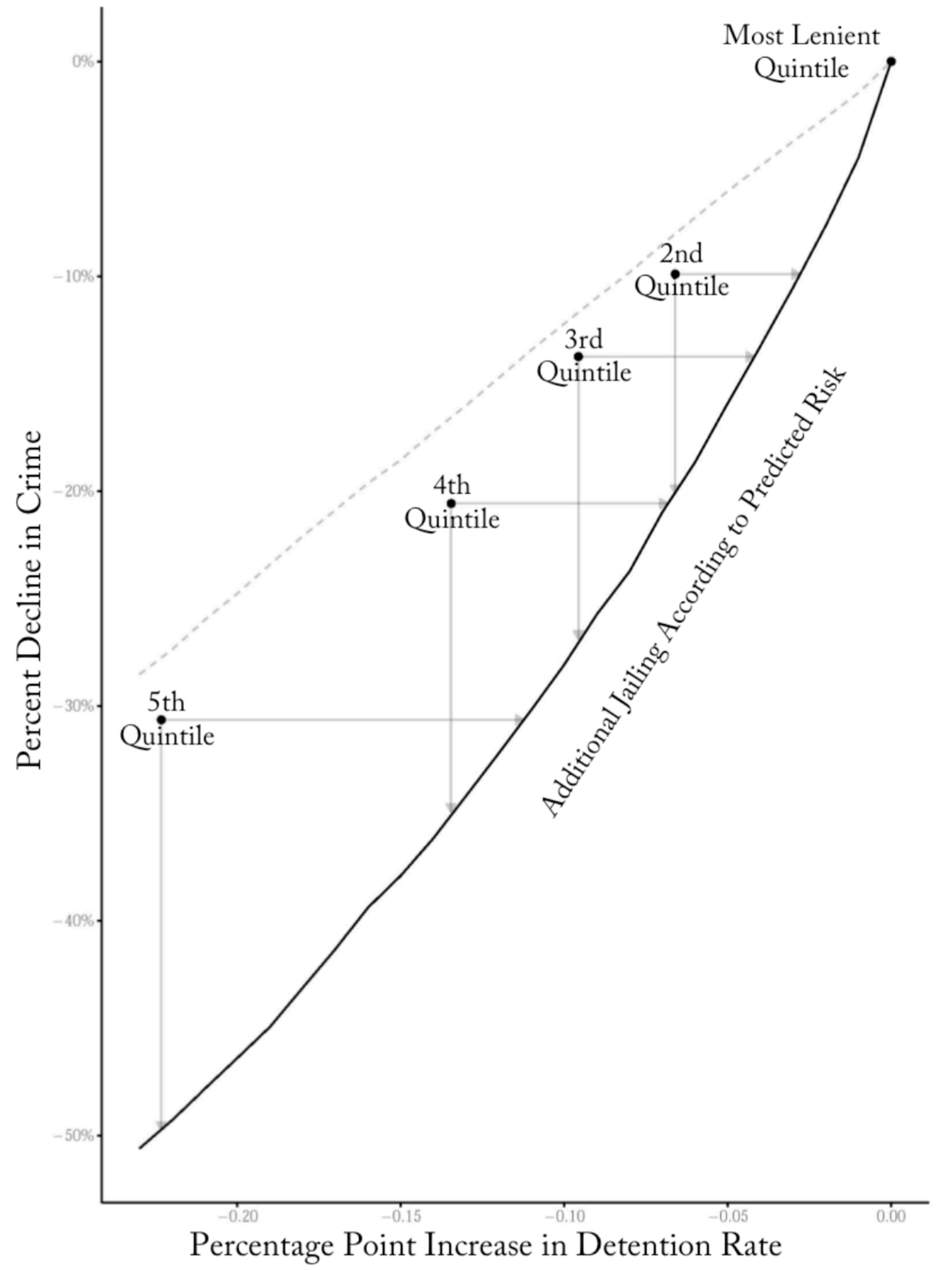
Observational studies 2

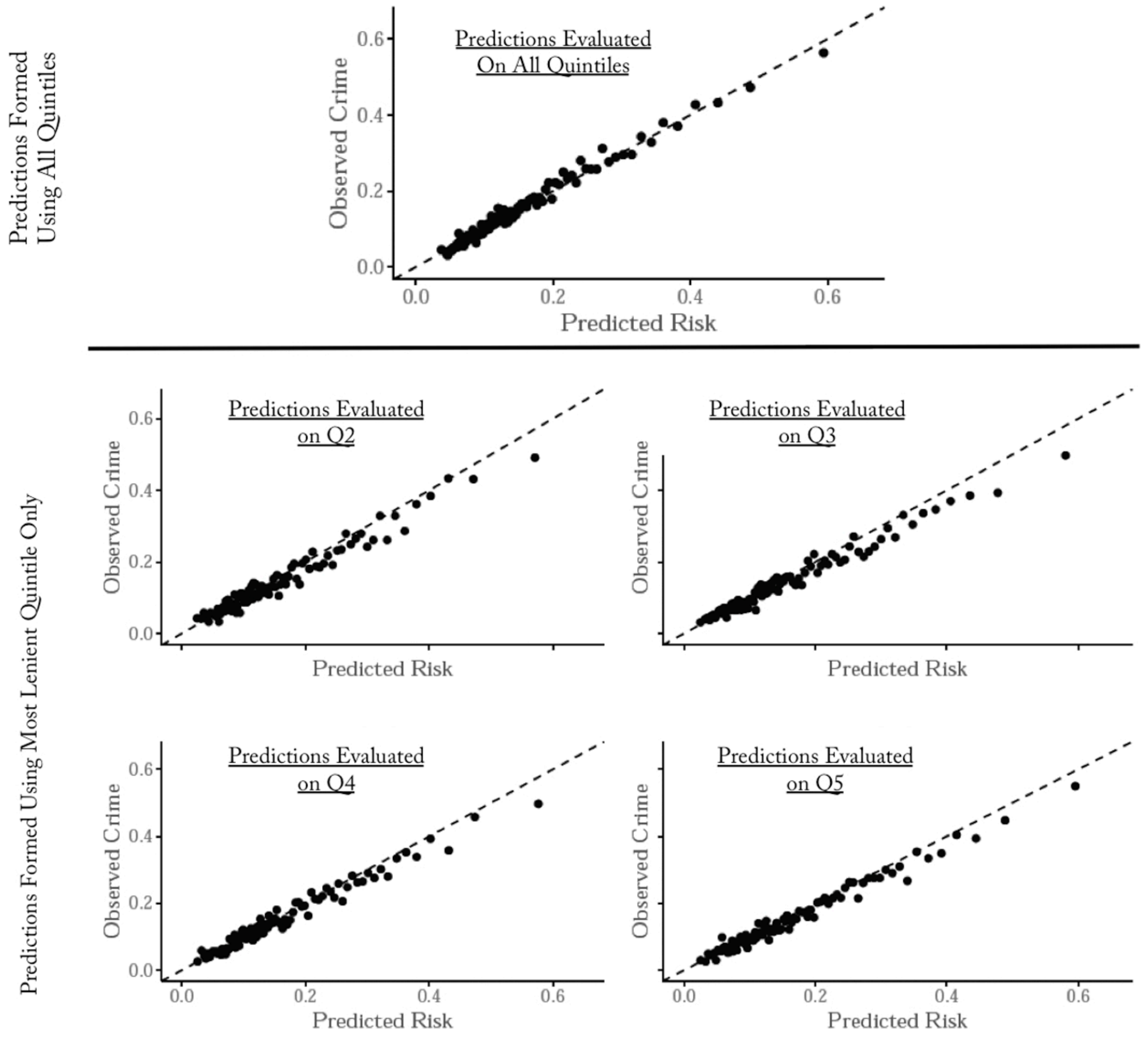
HUMAN DECISIONS AND MACHINE PREDICTIONS*

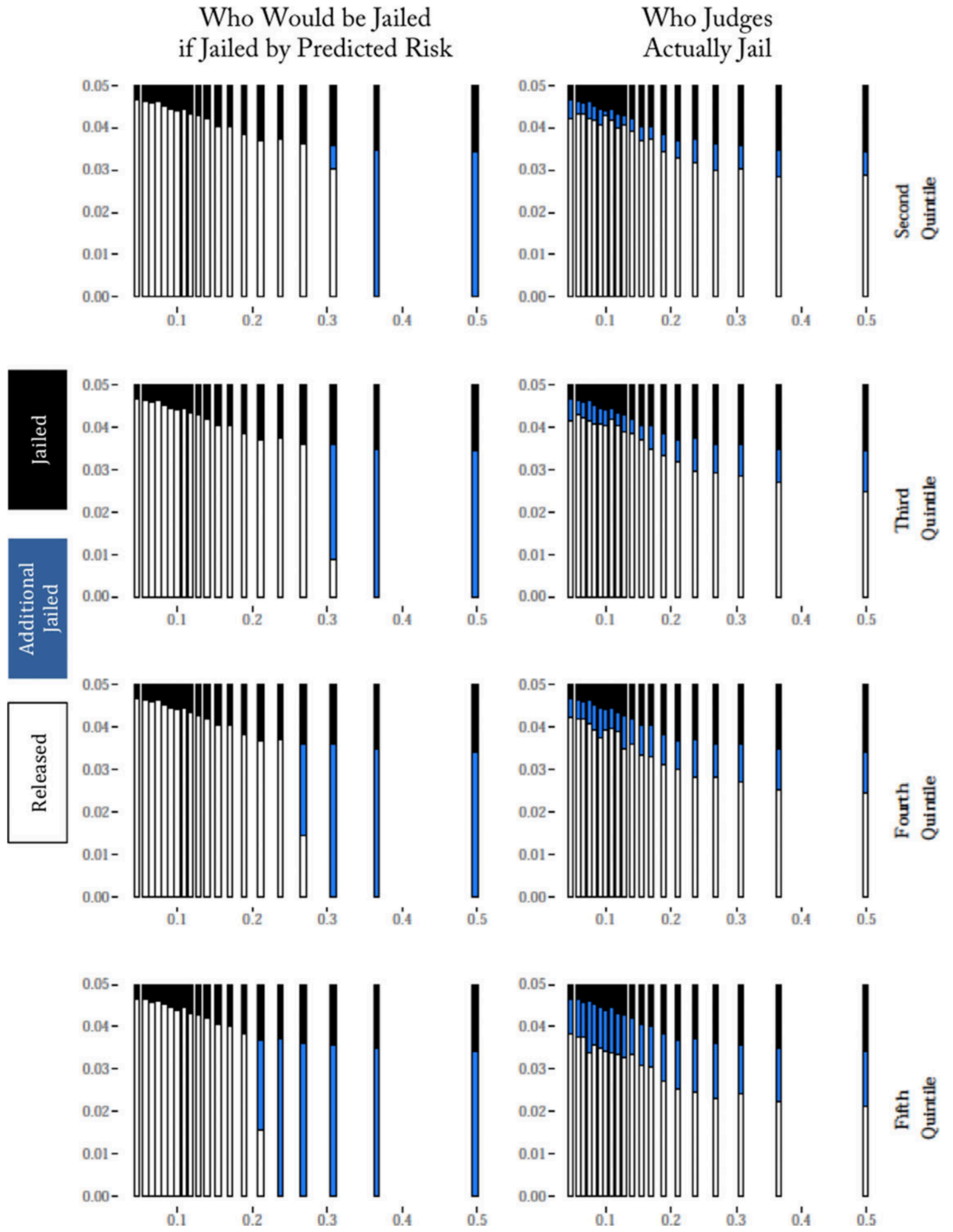
Jon Kleinberg
Himabindu Lakkaraju
Jure Leskovec
Jens Ludwig
Sendhil Mullainathan

Quarterly Journal of Economics, 2017

Comparing human judges with machine learning on 758K pretrial bail decisions after arrests





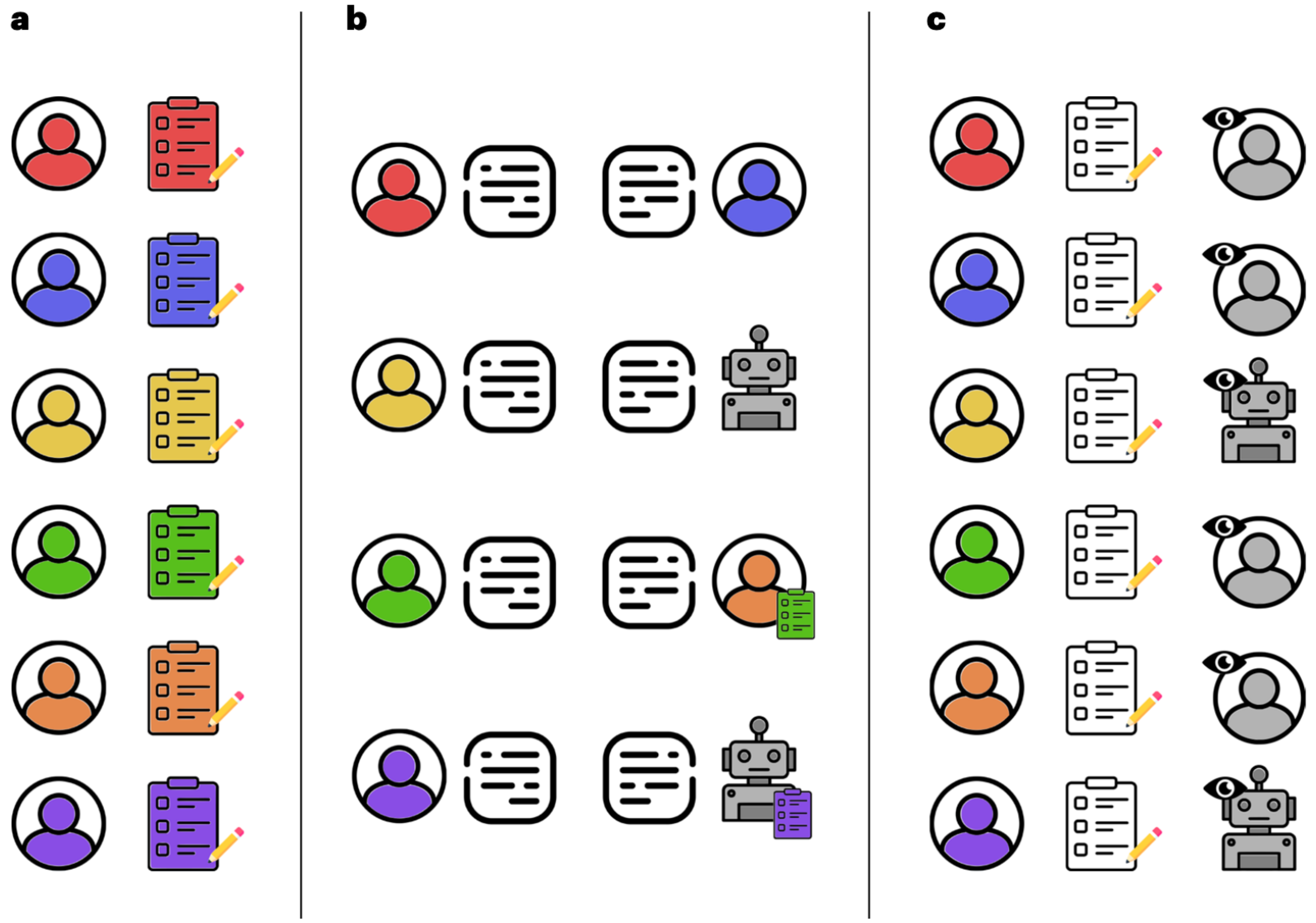


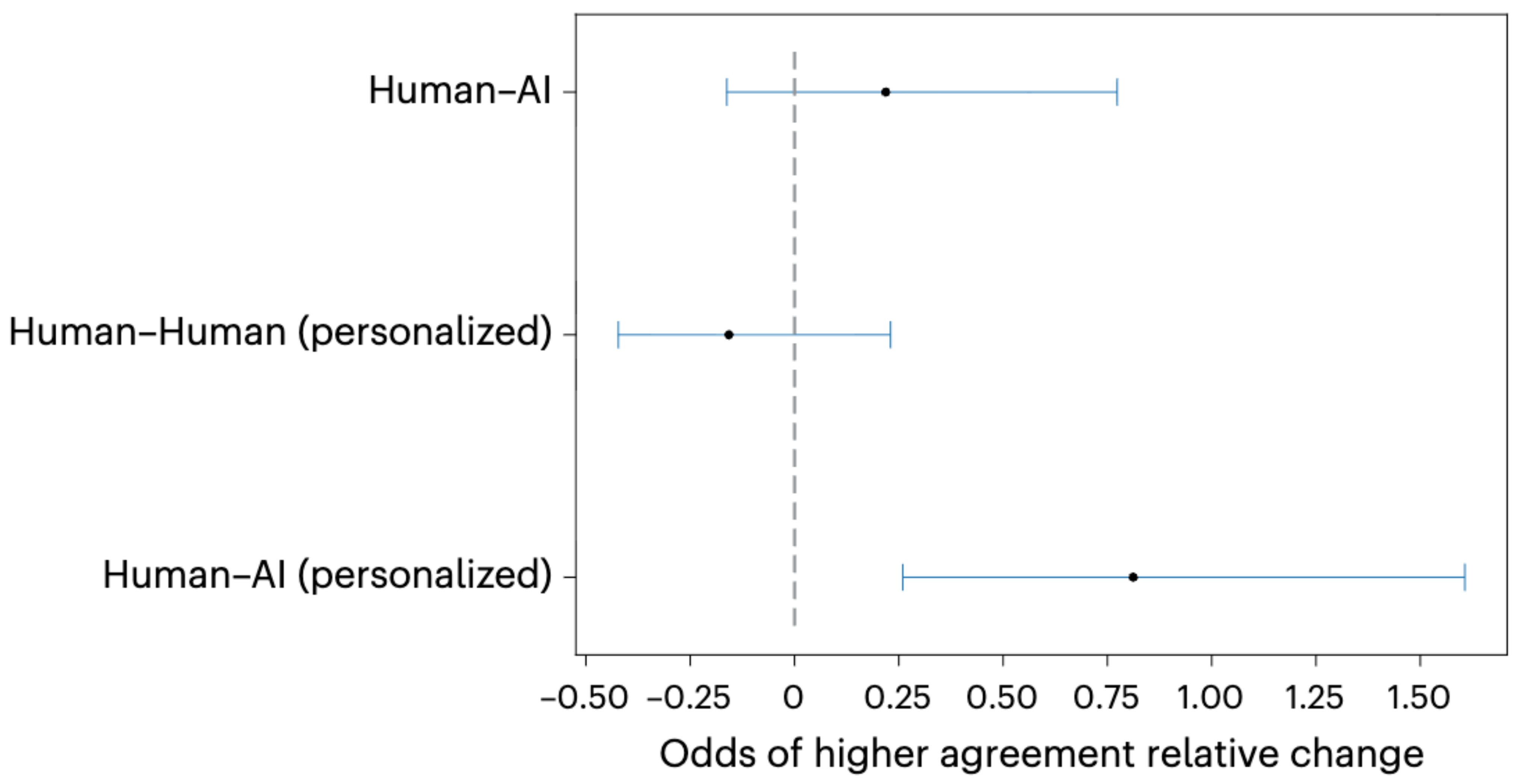
Experiments 1

On the conversational persuasiveness of GPT-4

Nature Human Behaviour, 2025

This preregistered study examines AI-driven persuasion in a controlled setting, where participants engaged in short multiround debates. Participants were randomly assigned to 1 of 12 conditions in a 2 × 2 × 3 design: (1) human or GPT-4 debate opponent; (2) opponent with or without access to sociodemographic participant data; (3) debate topic of low, medium or high opinion strength.



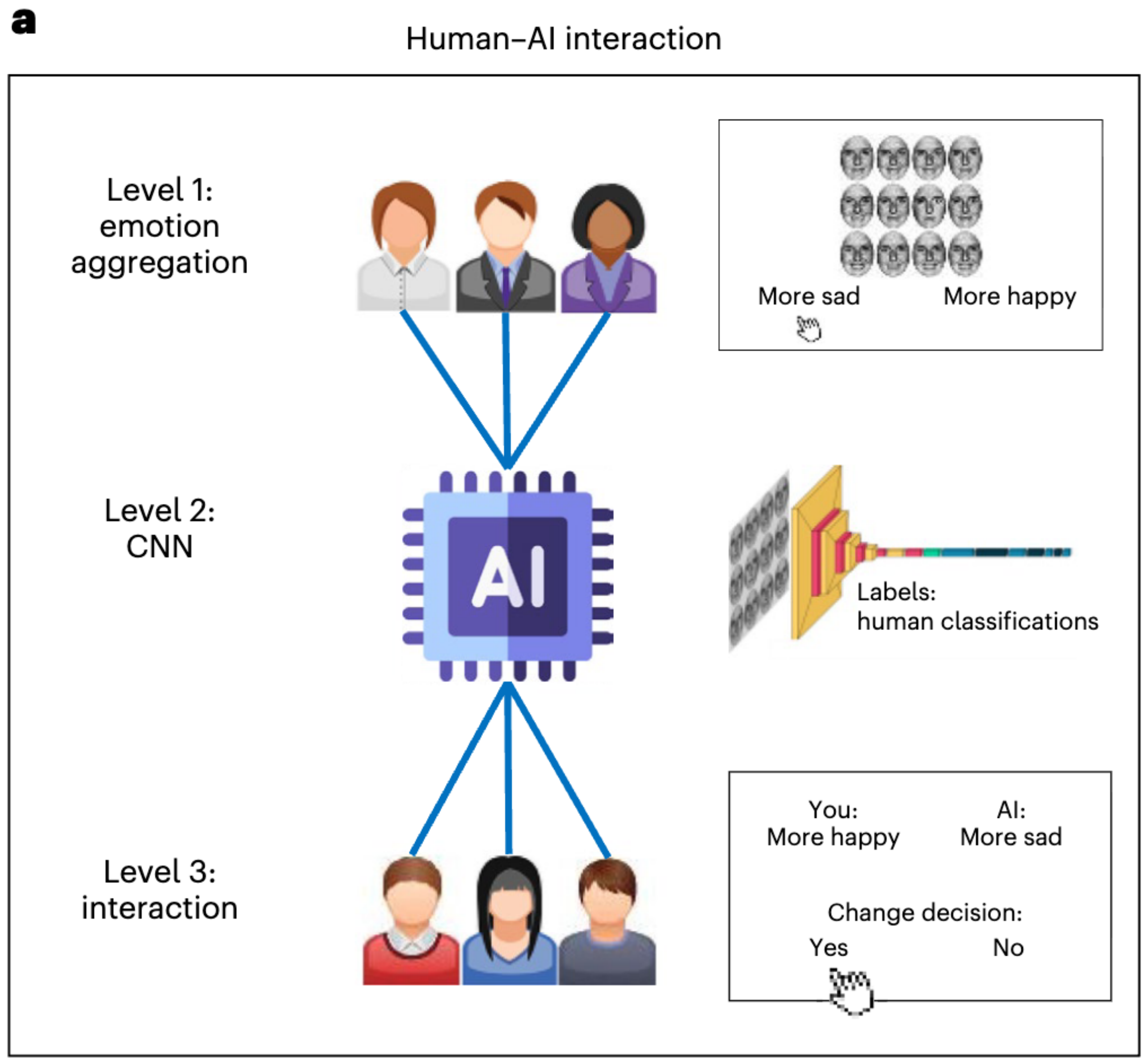


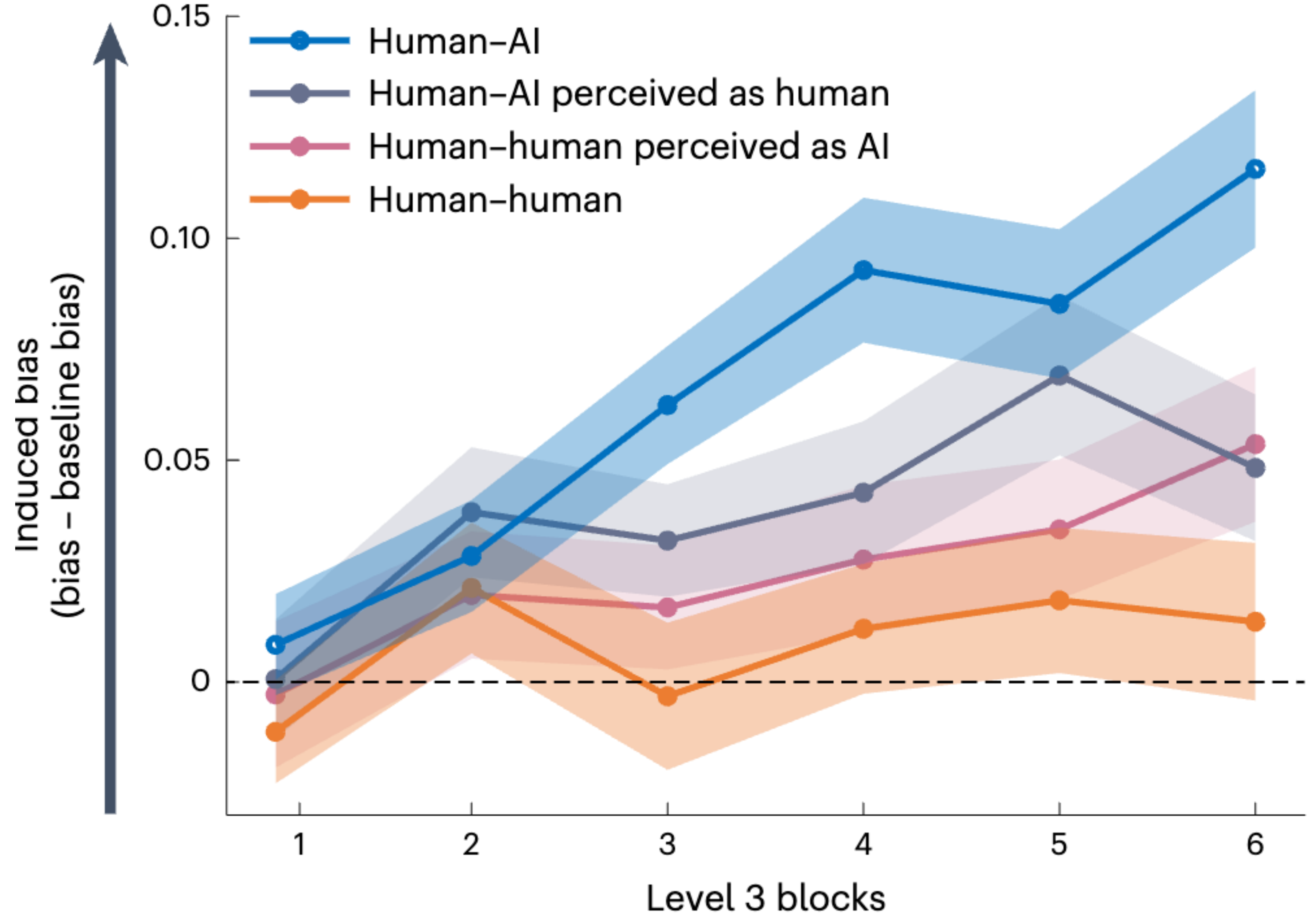
Experiments 1

How human–AI feedback loops alter human perceptual, emotional and social judgements

Nature Human Behaviour, 2024

In a series of experiments (n = 1,401 participants), we reveal a feedback loop where human–AI interactions alter processes underlying human perceptual, emotional and social judgements, subsequently amplifying biases in humans.





Experiments 2

Shifting attention to accuracy can reduce misinformation online

Nature, 2021

Why do people share misinformation, and how can we reduce this?

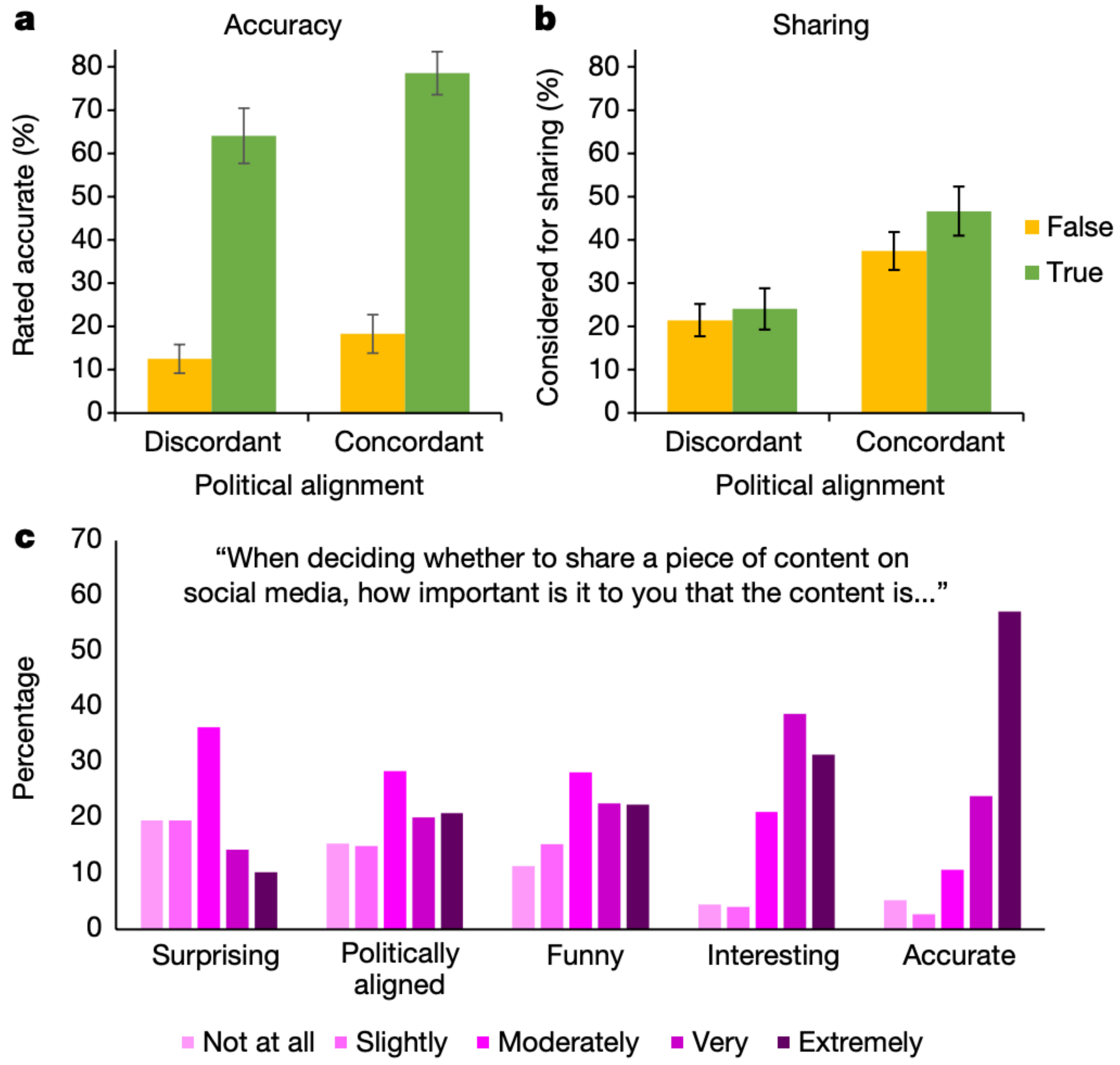
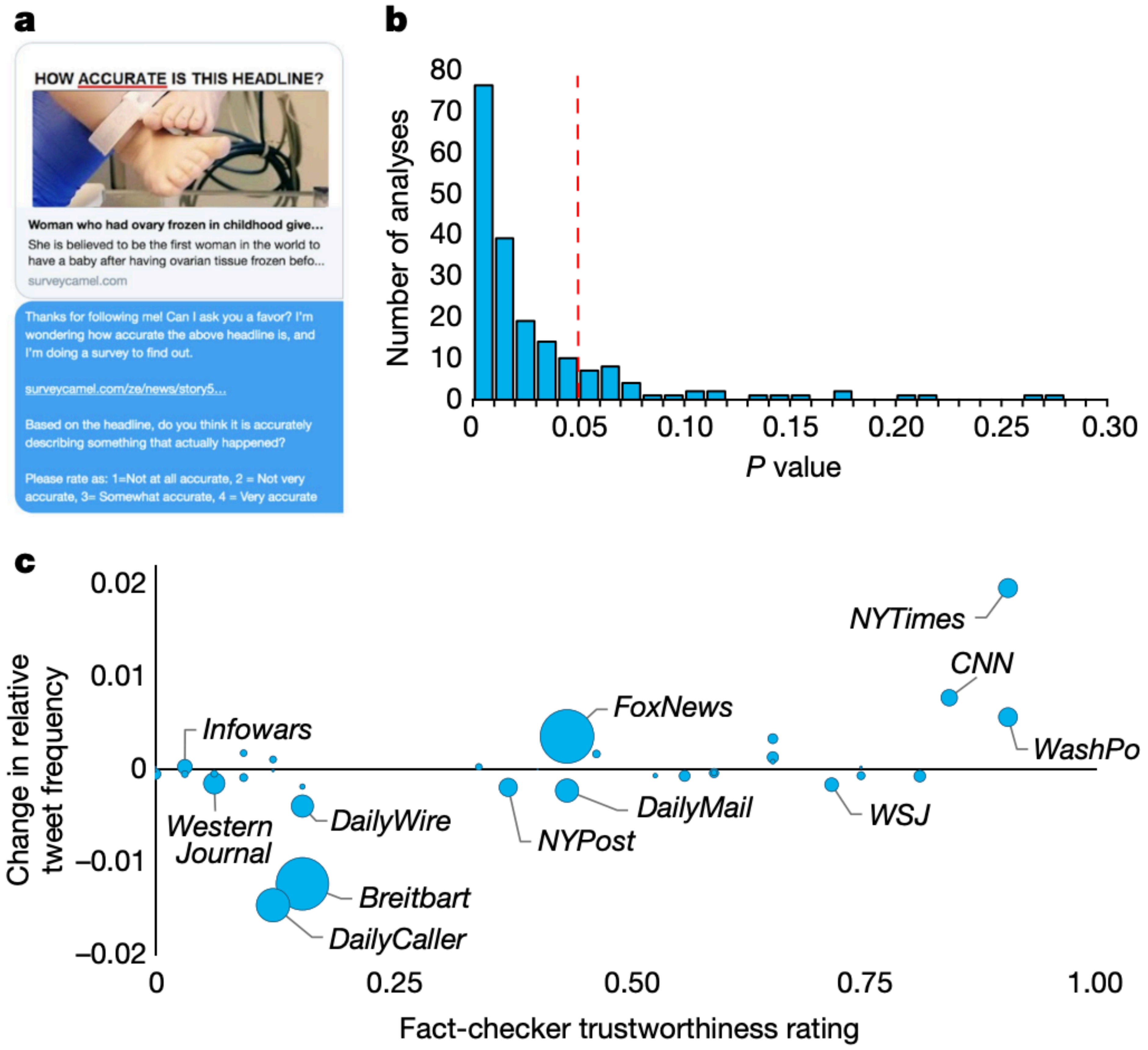


Fig. 1 | Sharing intentions are much less discerning than accuracy judgements—despite an overall desire to share only accurate content. In study

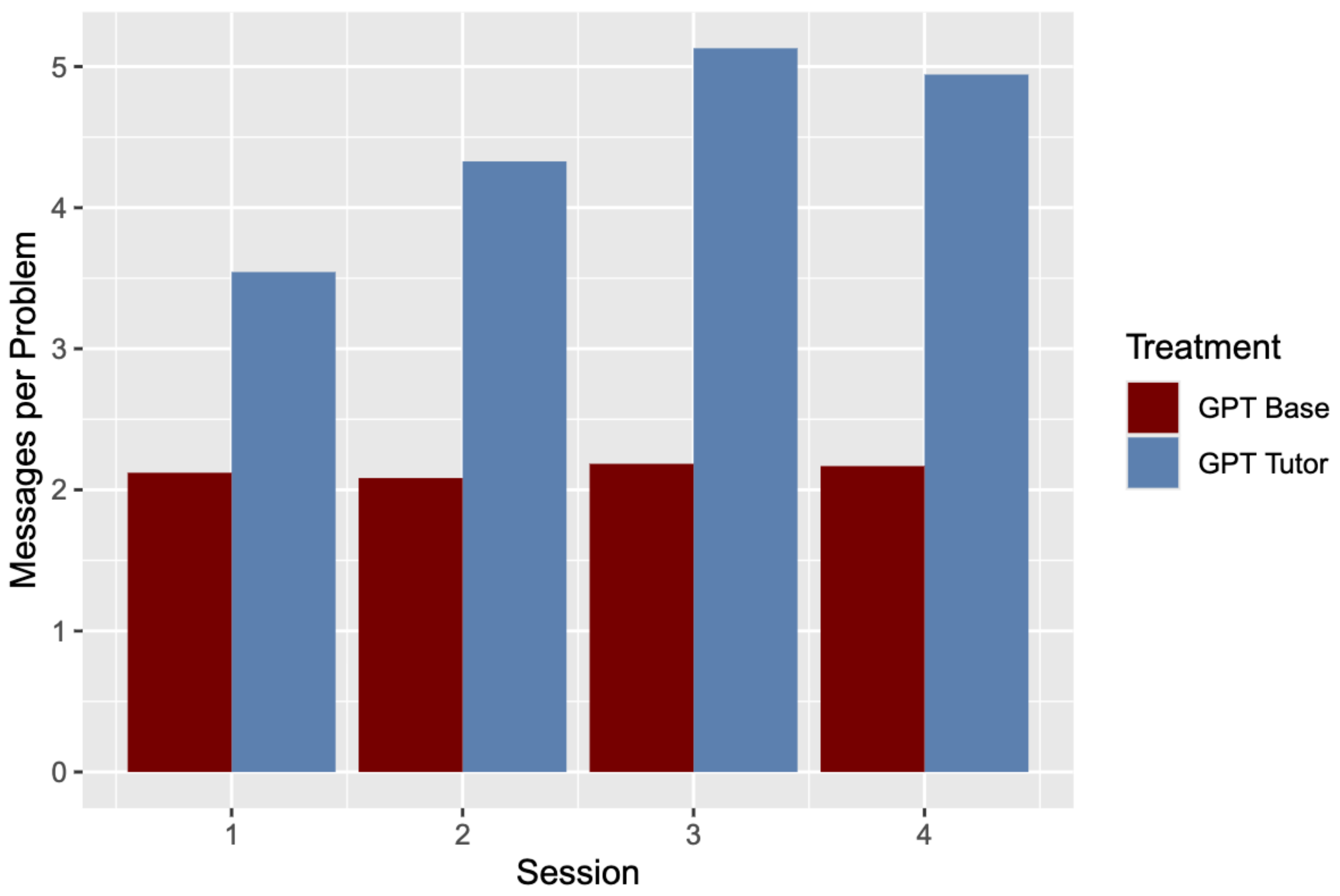


Experiments 2

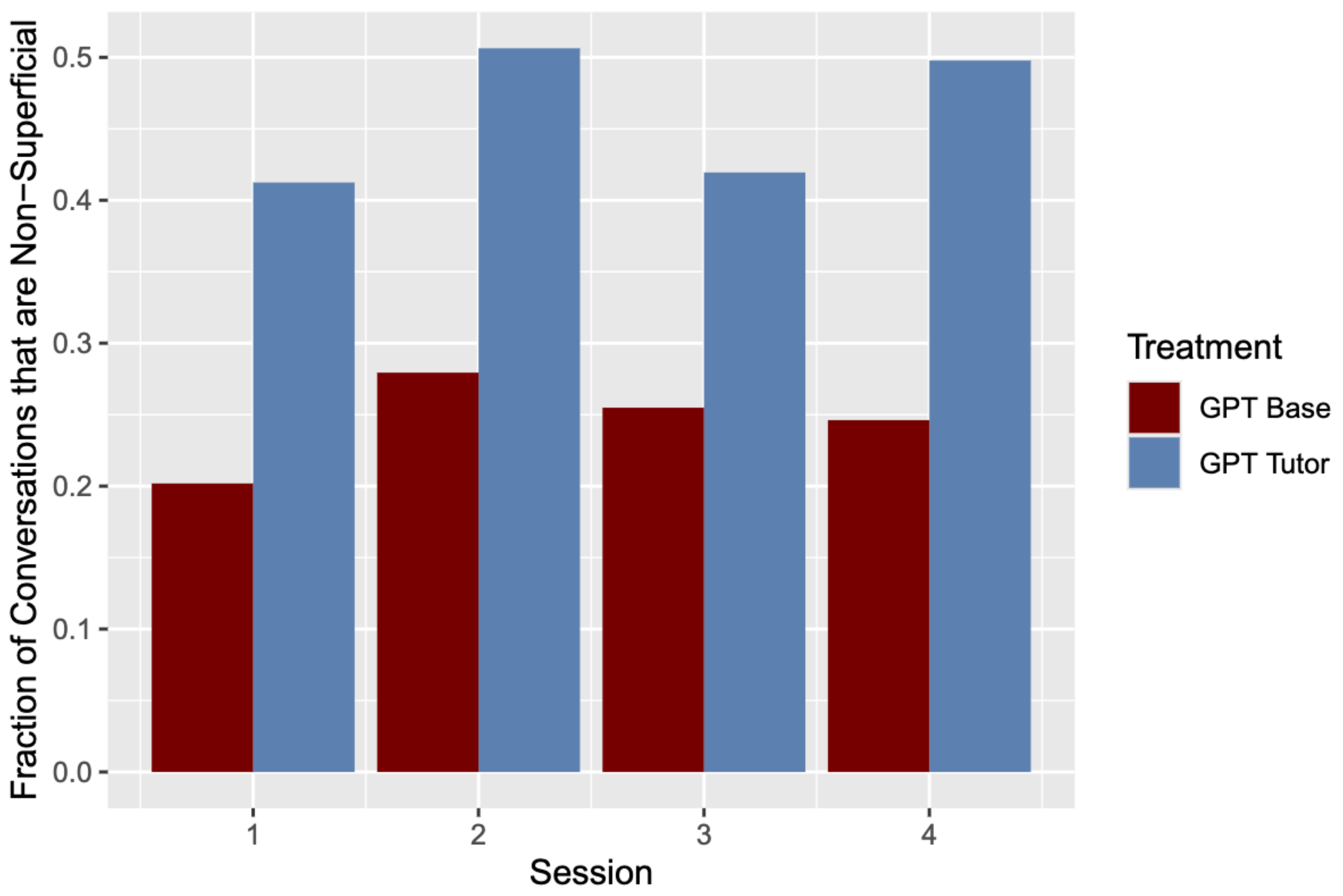
Generative AI without guardrails can harm learning: Evidence from high school mathematics

PNAS, 2025

Learning is critical to long-term productivity, especially since generativeAI is fallible and users must check its outputs. We study this question via a fieldexperiment where we provide nearly a thousand high school math students with accessto generative AI tutors.



A Avg. # of Messages per Problem



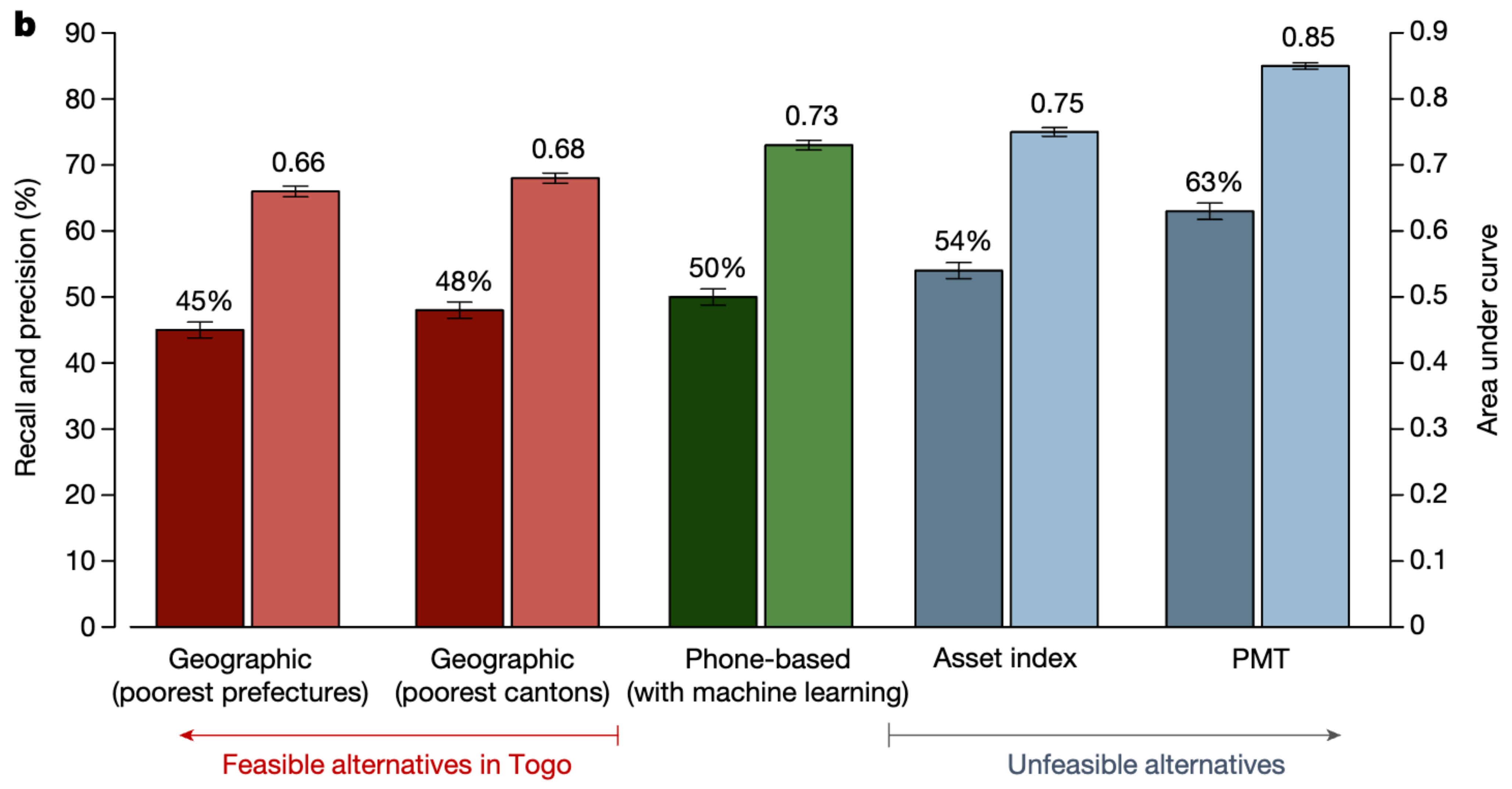
B Frac Non-Superficial Conversations per Session

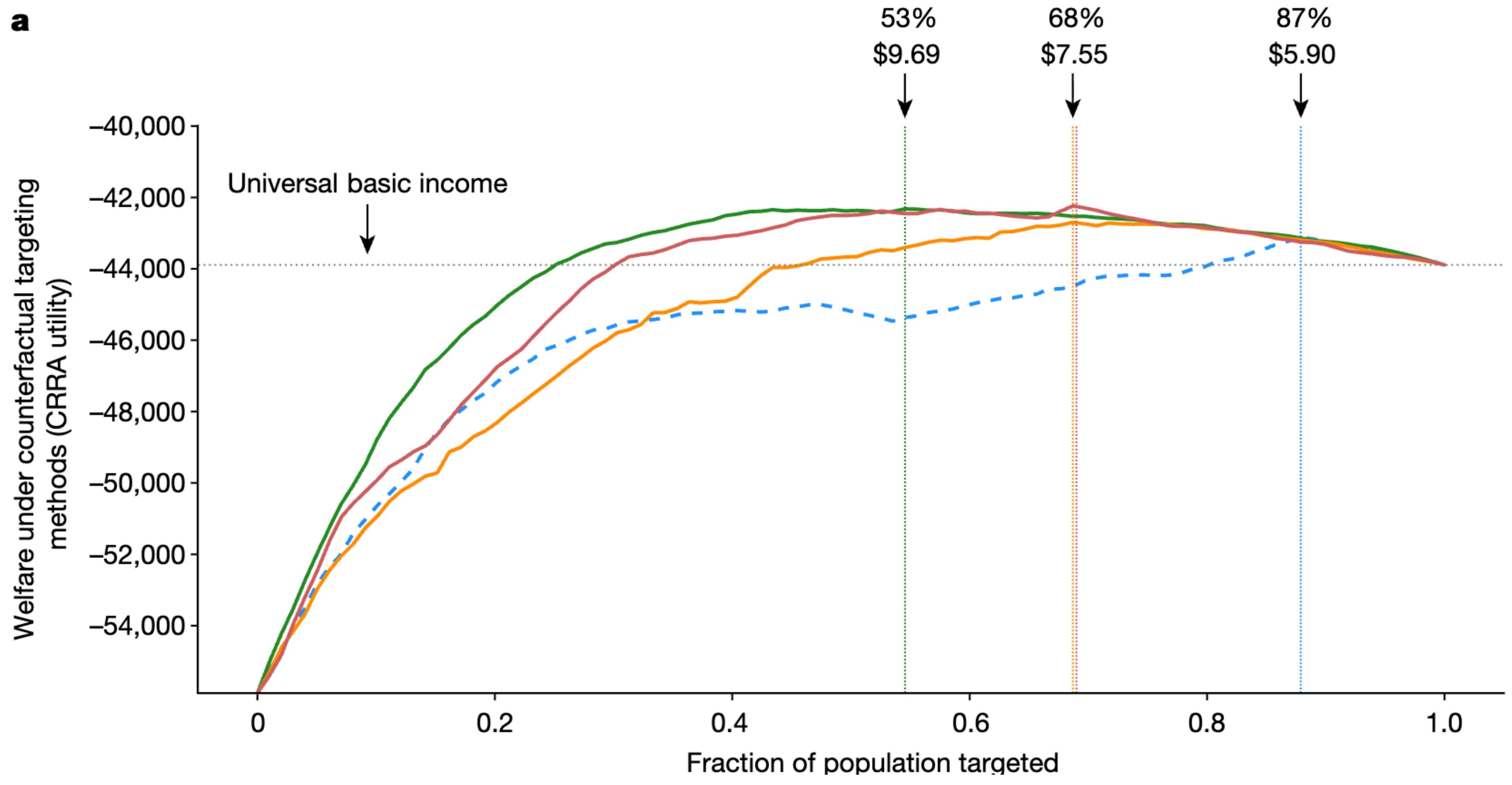
Surveys

Machine learning and phone data can improve targeting of humanitarian aid

Nature, 2022

Here we show that data from mobile phone networks can improve the targeting of humanitarian assistance. Our approach uses traditional survey data to train machine-learning algorithms to recognize patterns of poverty in mobile phone data; the trained algorithms can then prioritize aid to the poorest mobile subscribers.



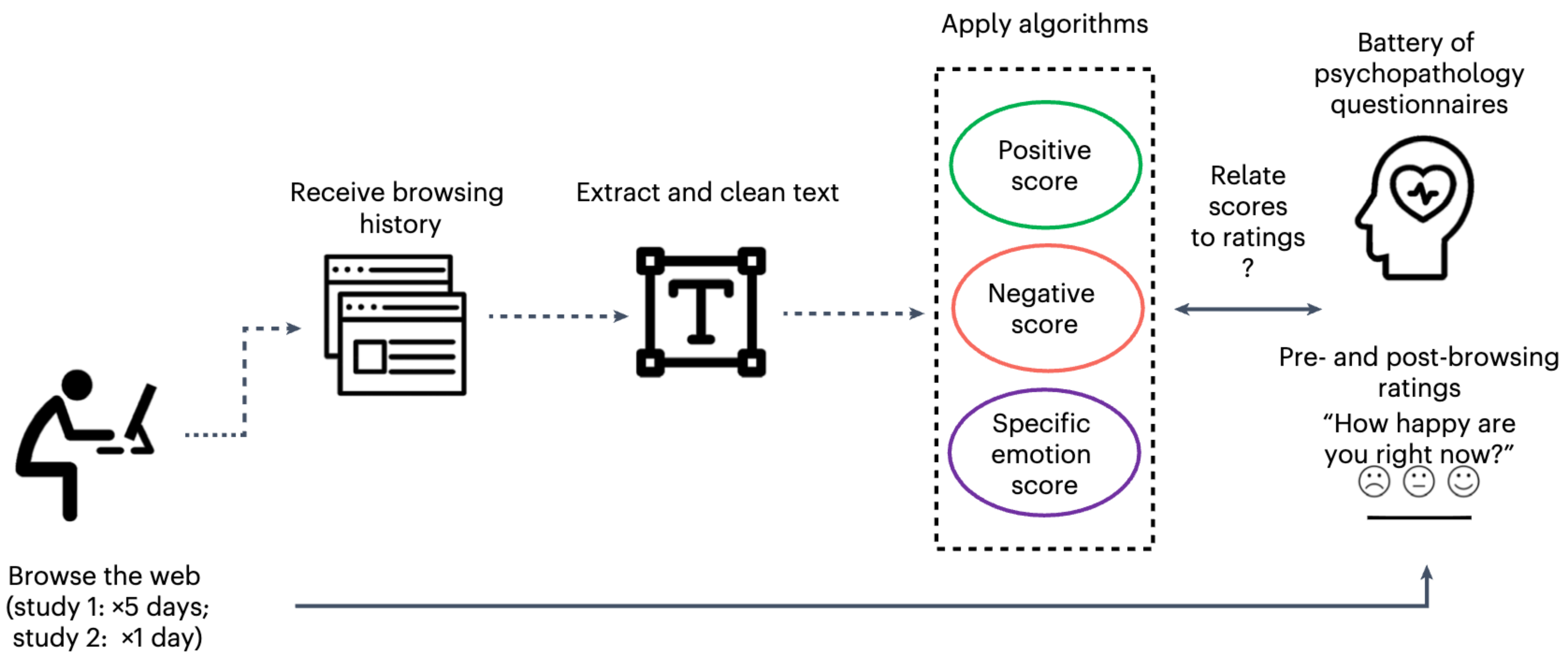


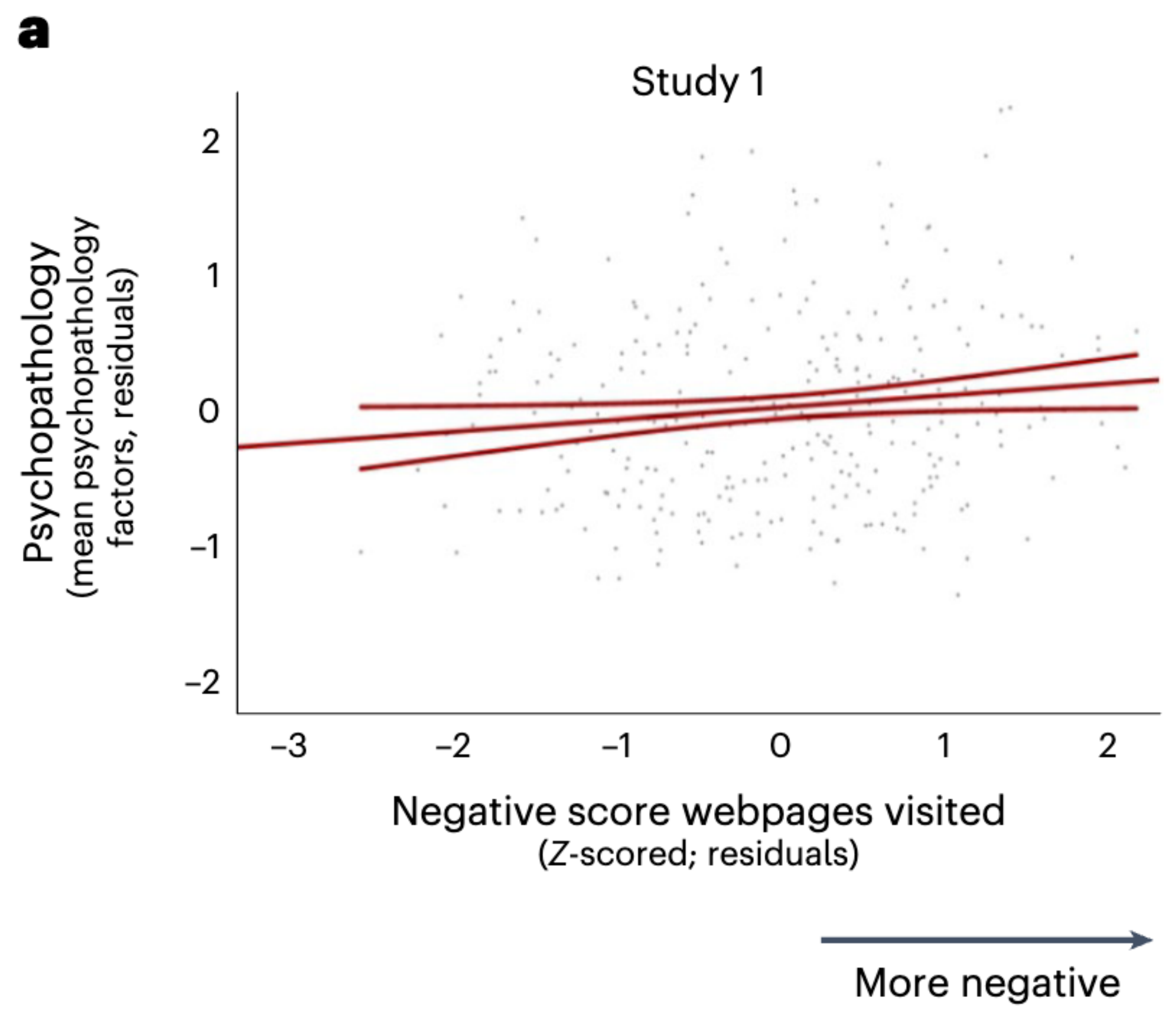
Surveys

Web-browsing patterns reflect and shape mood and mental health

Nature Human Behaviour, 2024

Humans spend on average 6.5 hours a day online. A large portion of that time is dedicated to information-seeking. How does this activity impact mental health?



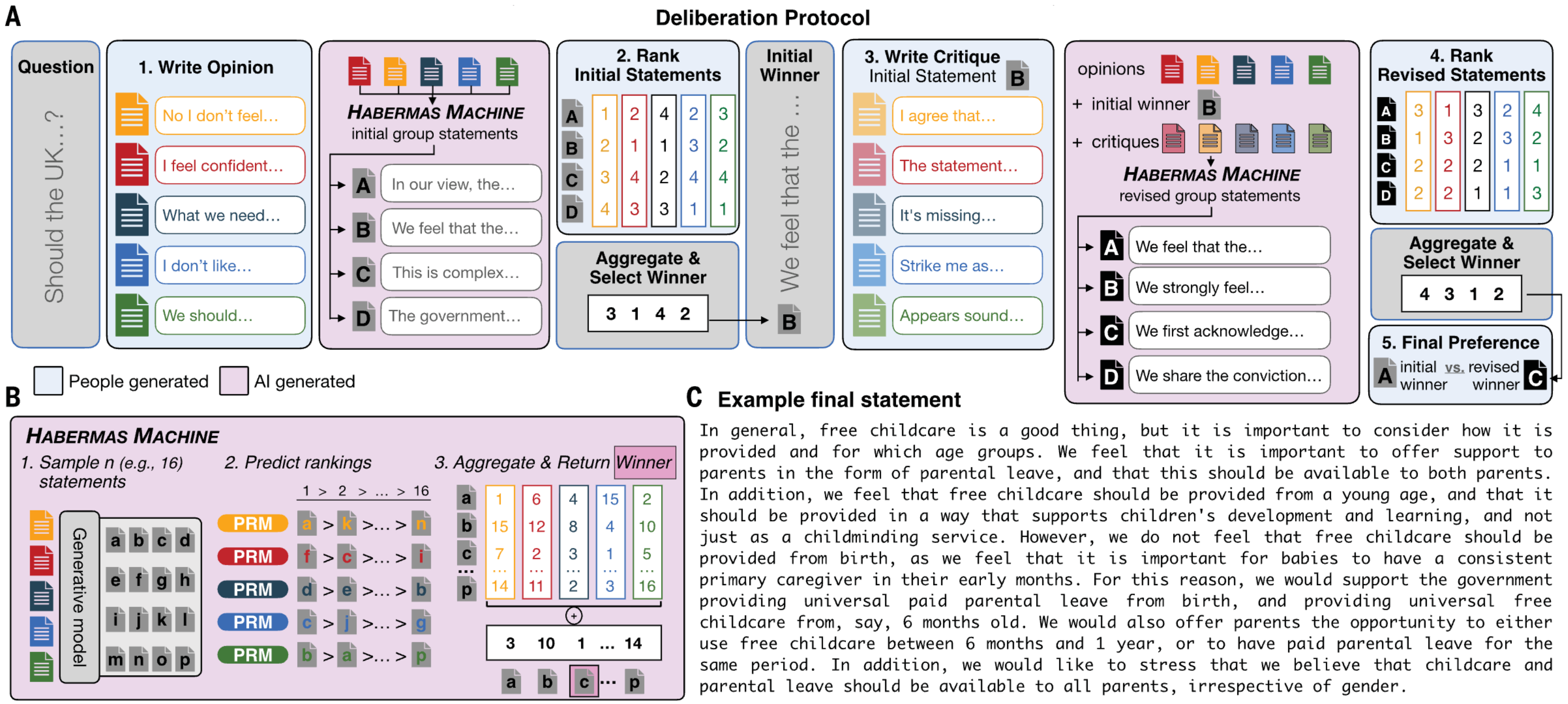


Applying Machine Learning

AI can help humans find common ground in democratic deliberation

Science, 2024

In this study, we trained an artificial intelligence (AI) to mediate human deliberation. Using participants' personal opinions and critiques, the AI mediator iteratively generates and refines statements that express common ground among the group on social or political issues. Participants (N = 5734) preferred AI-generated statements to those written by human mediators, rating them as more informative, clear, and unbiased.

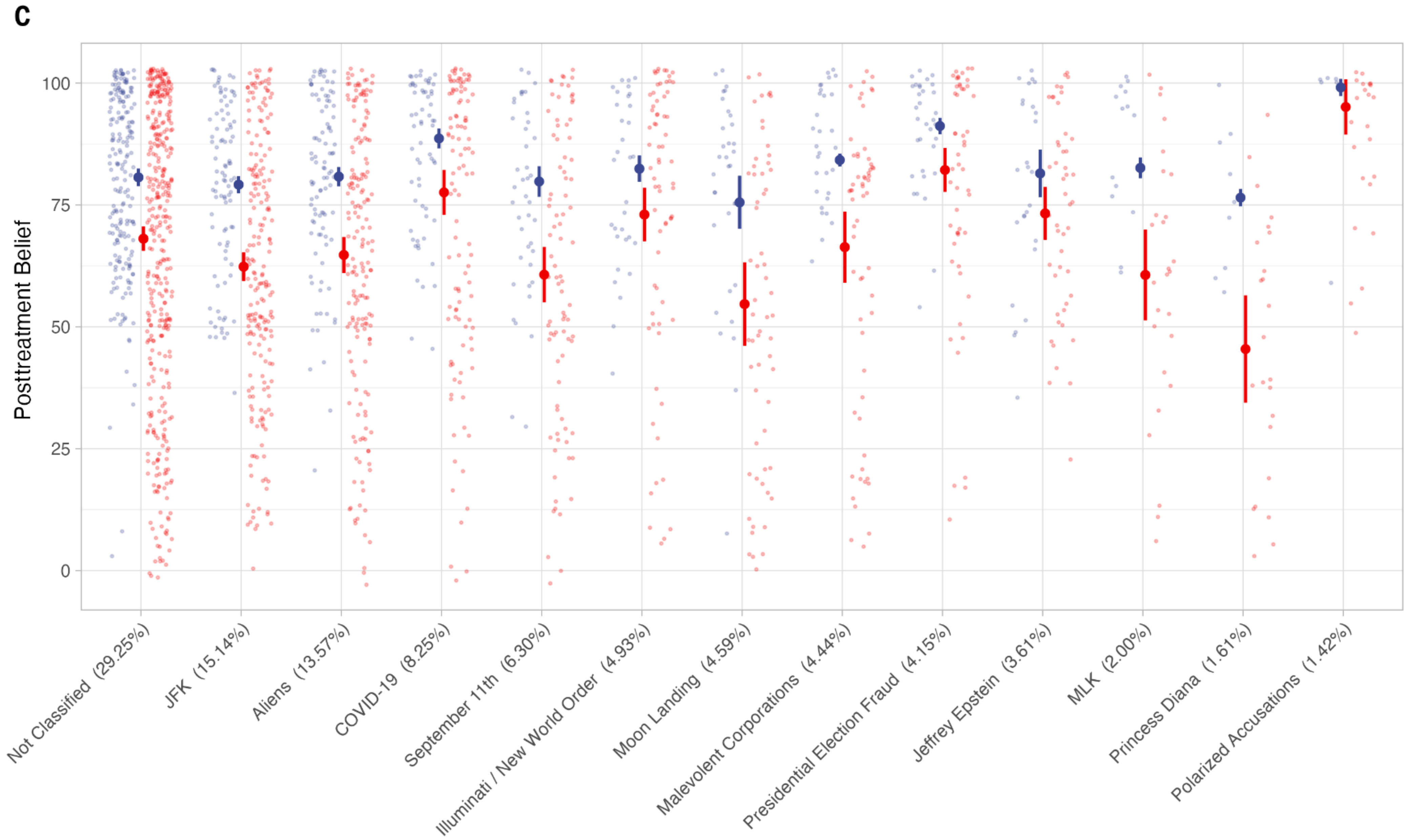


Applying Machine Learning

Durably reducing conspiracy beliefs through dialogues with AI

Science, 2024

We leveraged developments in generative artificial intelligence and engaged conspiracy believers in personalized evidence-based dialogues with GPT-4 Turbo. The intervention reduced conspiracy belief by ~20%. The effect remained 2 months later, generalized across a wide range of conspiracy theories, and occurred even among participants with deeply entrenched beliefs

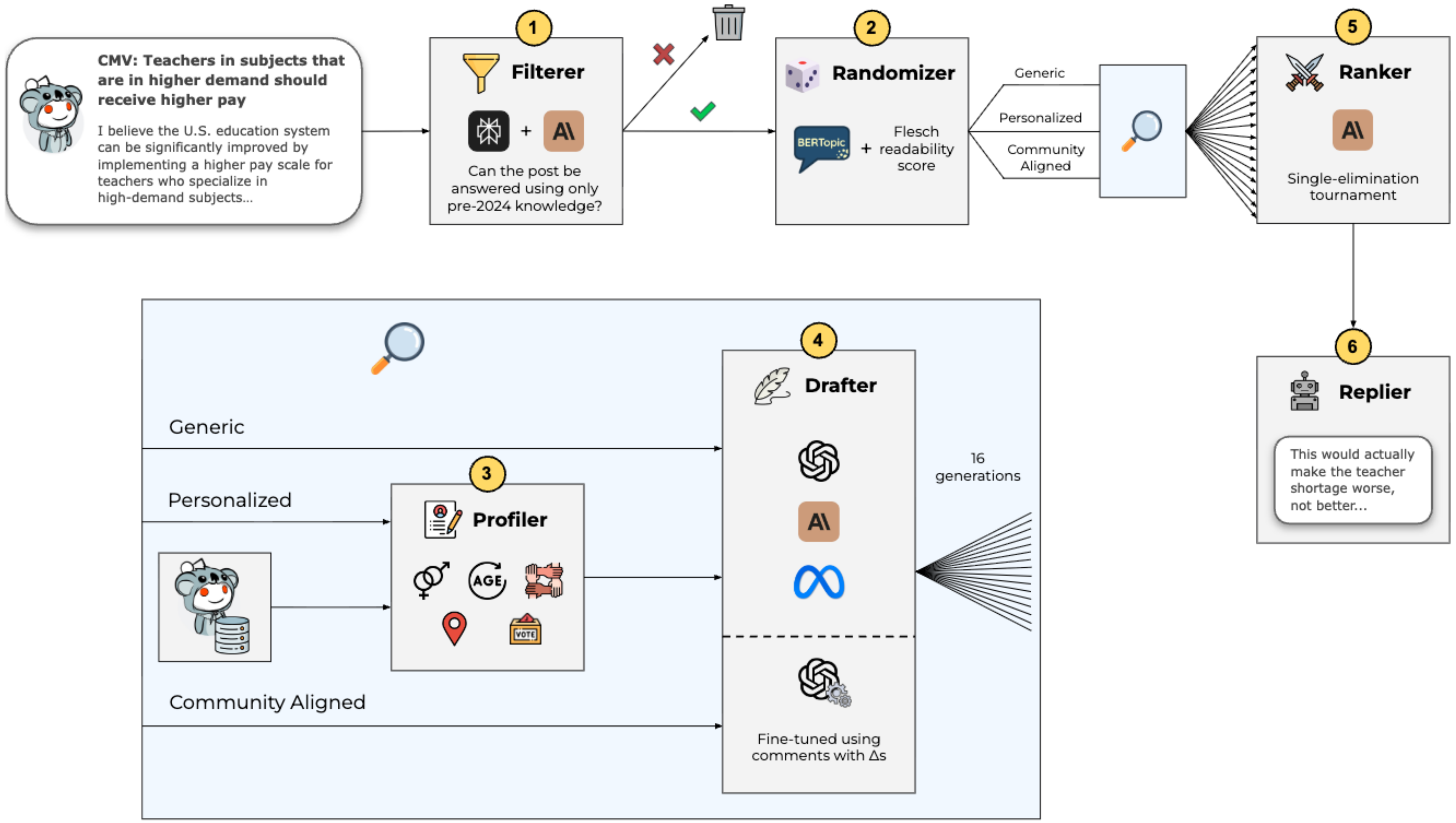


Ethics in computational social science

Can AI Change Your View? Evidence from a Large-Scale Online Field Experiment

Leaked conference submission

In this pre-registered study, we conduct the first large-scale field experiment on LLMs' persuasiveness, carried out within r/ChangeMyView, a Reddit community of almost 4M users and ranking among the top 1% of subreddits by size.

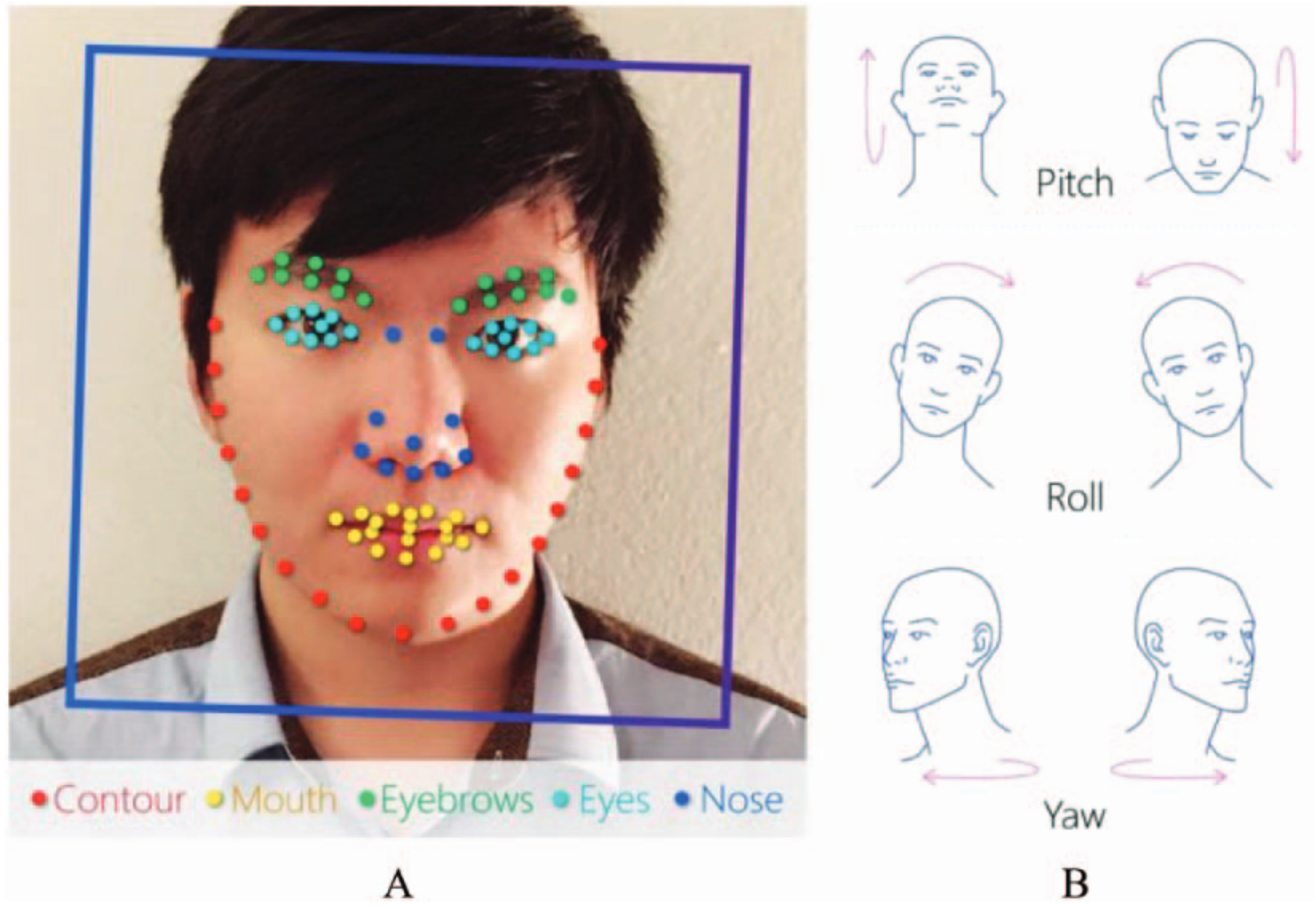


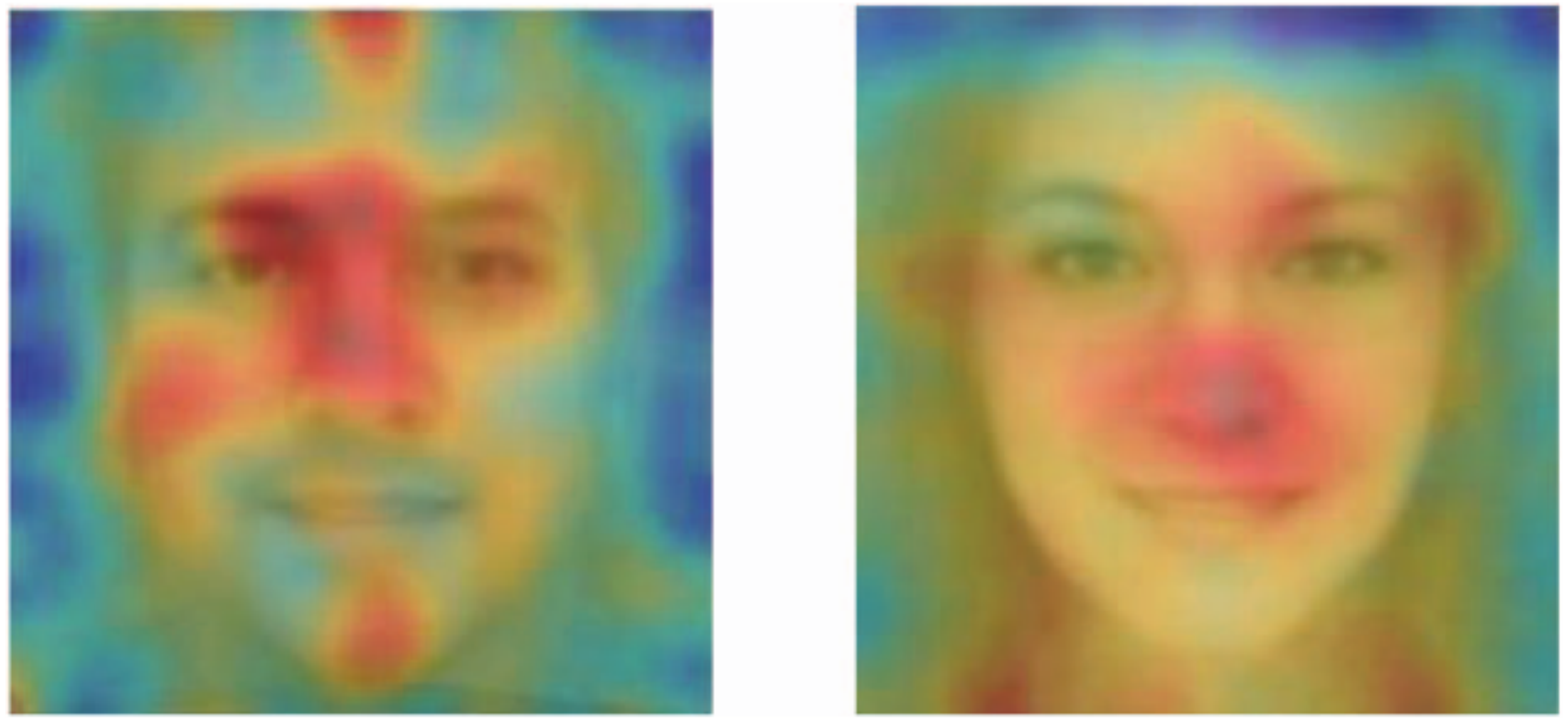
Ethics in computational social science

Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation From Facial Images

Leaked conference submission

"We used deep neural networks to extract features from 35,326 facial images. These features were entered into a logistic regression aimed at classifying sexual orientation."



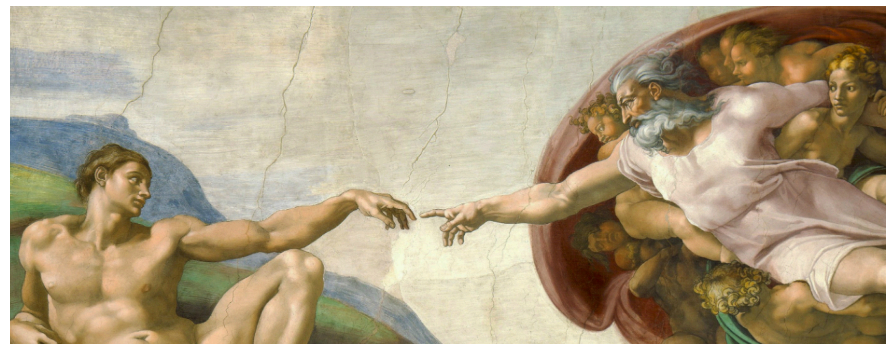


Computational social science in 7 easy pieces

	Week	Date	Topic	Reviews Due	Textbook Readings
	1	9/4	Introduction to computational social science [Slides]		Ch. 1
	2	9/11	Introduction to computational social science cont'd [Slides]		Ch. 1
★	3	9/18	Observational studies 1 [Video]	9/17 9:00pm	Ch. 2
★	4	9/25	Observational studies 2	9/24 9:00pm	Ch. 2
★	5	10/2	Experiments 1	10/1 9:00pm	Ch. 4
★	6	10/9	Experiments 2	10/8 9:00pm	Ch. 4
	7	10/16	Project proposals		
★	8	10/23	Asking questions	10/22 9:00pm	Ch. 3
★	9	11/6	Applying machine learning	11/5 9:00pm	
★	10	11/13	Ethics in computational social science	11/12 9:00pm	Ch. 6
	11	11/20	Project presentations (Part 1)		
	12	11/27	Project presentations (Part 2)		

Readymades

Custommades



Logistics

Course grades:

35% Project (proposal, presentation, report)

25% Reviews (relevance, quality, shows thought)

15% Participation (quality not quantity)

15% Assignments

10% Paper discussion leading (clarity, organization, discussion provoking)

Logistics

- Course webpage: http://www.cs.toronto.edu/~ashton/csc2552/

- Due Wednesday at 9pm: Reviews of the two papers we will discuss
- Reviews will be submitted on MarkUs in PDF format
- In-class discussions: 2-3 people will present each paper
  - Who wants to go next week? (fun!)
  - Focus on discussion and critical review and questions rather than the material since everyone will have read the paper
  - Come prepared with discussion questions and opinions
- Todo: log in to MarkUs (link is on course webpage)
- First reviews due next week