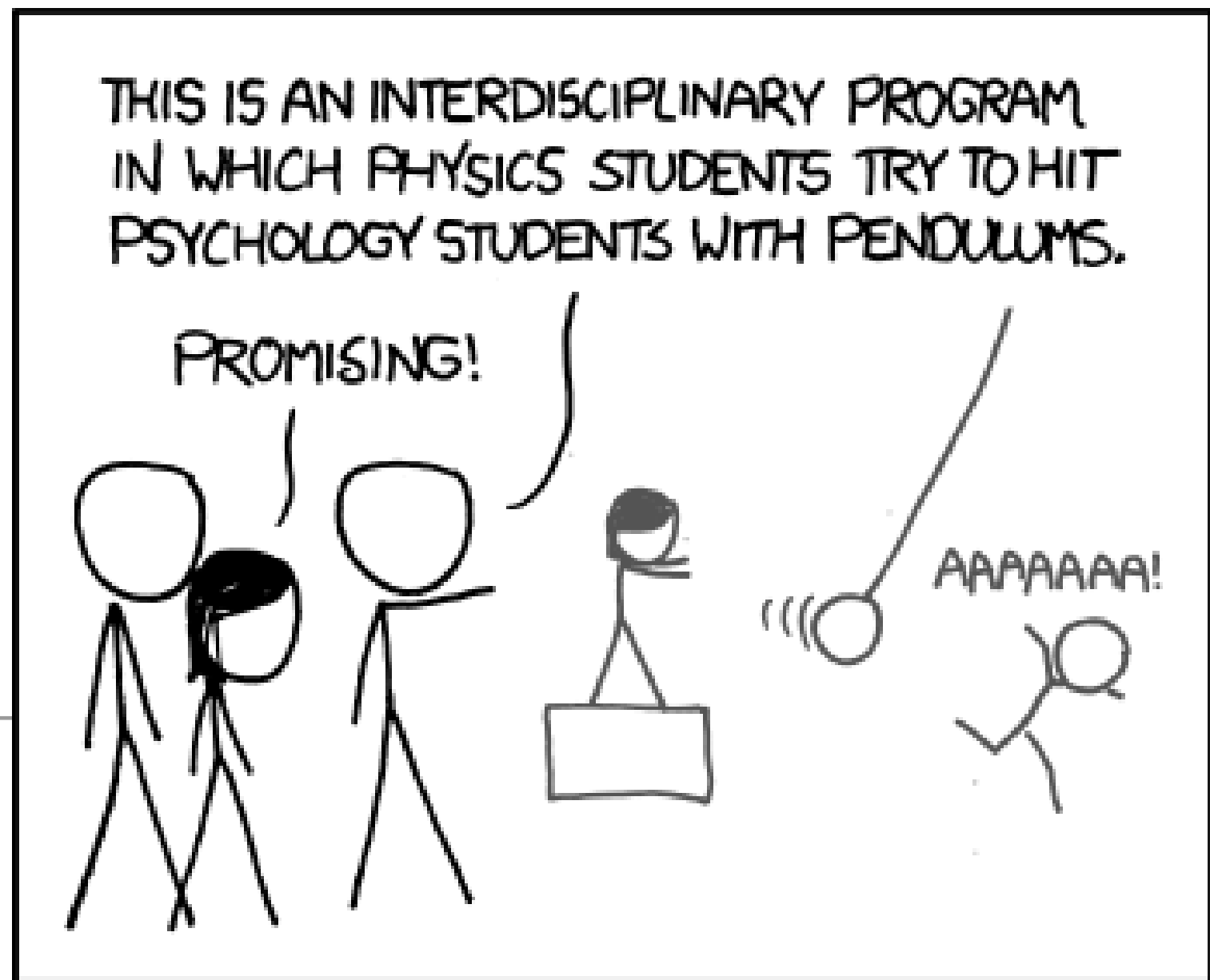


Interdisciplinary Ethics in Data Science

Jo Hardin
Pomona College
August 7, 2025



MY PROFESSORS HAD AN ONGOING COMPETITION TO GET THE WEIRDEST THING TAKEN SERIOUSLY UNDER THE LABEL "INTERDISCIPLINARY PROGRAM."

- Data science is interdisciplinary
- Engaging data science students in ethics is important

Guiding Principles



- Introduction to Data Science
- Introduction to Statistics
- Introduction to Computer Science
- Linear Algebra
- Ethics*
- Upper division elective class

**DS minor at
Pomona College**

* related to data science

- Introduction to Data Science
- Introduction to Statistics
- Introduction to Computer Science
- Linear Algebra
- Ethics*
- Upper division elective class

Capstone project:

- one semester
- not Stats/Math/CS
- advisor in the discipline
- meet w coordinator (me) once a week

**DS minor at
Pomona College**

* related to data science

Capstone Class

- new ethical data science quandary (5 of the meetings)
- students have pre-reading
- each week focuses on a different discipline
- guest colleague to provide disciplinary context

Interdisciplinary Ethics in Data Science

- History
- Linguistics
- Philosophy
- Psychology
- Economics

From Anthropometry to Algorithms: the historical roots of bias in data science

SCI
AM

Police Facial Recognition Technology Can't Tell Black People Apart

OPINION

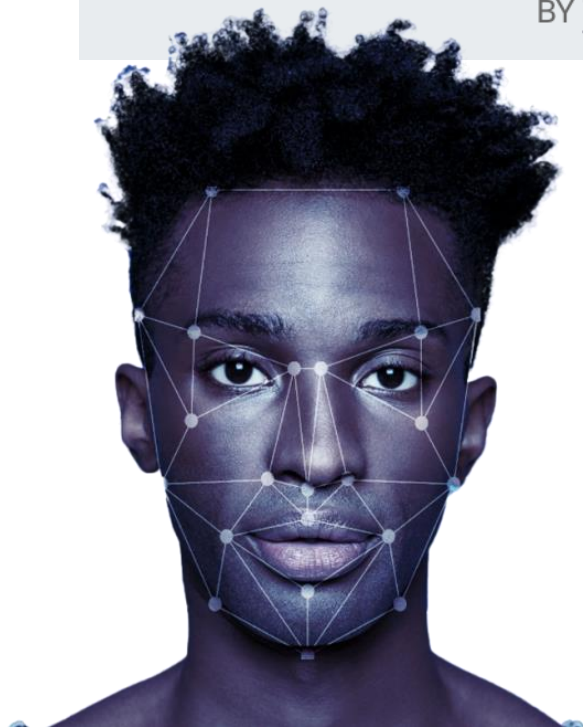
MAY 18, 2023 | 5 MIN READ

Police Facial Recognition Technology Can't Tell Black People Apart

AI-powered facial recognition will lead to increased racial profiling

BY THADDEUS L. JOHNSON & NATASHA N. JOHNSON

paper link: <https://www.scientificamerican.com/article/police-facial-recognition-technology-cant-tell-black-people-apart/>



History

image credit: <https://www.aclu-mn.org/en/news/biased-technology-automated-discrimination-facial-recognition>



Biometry against Fascism: Geoffrey Morant, Race, and Anti-Racism in Twentieth-Century Physical Anthropology

Iris Clever



PDF



PDF PLUS



Abstract



Full Text



More

Abstract

This essay introduces an anthropological practice that remains largely unexplored in the historical literature on racial science: biometrics. In the early twentieth century, biometricians analyzed skull measurements using novel statistical methods to demonstrate racial biological differences. Drawing on new archival material, the essay reveals how these biometric data practices challenged racist anthropology. Between 1934 and 1952, Geoffrey Morant, an expert on biometry and race in Karl Pearson's Biometric Laboratory in London, mobilized biometry to debunk Nazi racial theories. He informed the public about Nazism's fallacies in *The Races of Central Europe* (1939) and his UNESCO pamphlet *The Significance of Racial Differences* (1952). Unlike anti-racism campaigners such as Ashley Montagu, however, Morant did not dismiss the biological reality of race in his fight against Nazi racism. The essay shows that the coexistence of anti-racist and racializing practices was not paradoxical but, rather, an important feature of the anthropological study of human variation in the twentieth century.

paper link:

<https://www.journals.uchicago.edu/doi/abs/10.1086/723686>

Pre-class reading

How do social and cultural values shape scientific inquiry and its applications?

The 5 Cs of Historical Thinking:

1. Change over time
2. Context
3. Causality
4. Contingency
5. Complexity

What Does It Mean to Think
Historically?

paper link: <https://www.historians.org/perspectives-article/what-does-it-mean-to-think-historically-january-2007/>

In groups, explore historical anthropometry:

- What social institutions supported these practices?
- What were the cultural or scientific assumptions driving the studies?
- How do assumptions persist in modern technologies like facial recognition?
- Are there other parallels between your historical scenario and the use of AI today (e.g., facial recognition).

As a group come together to discuss the coexistence of anti-racist and racializing practices historically and today. How can understanding history inform ethical practices in data science? How should data scientists address the historical roots of bias in their work?

In class

Language does not equal human cognition.

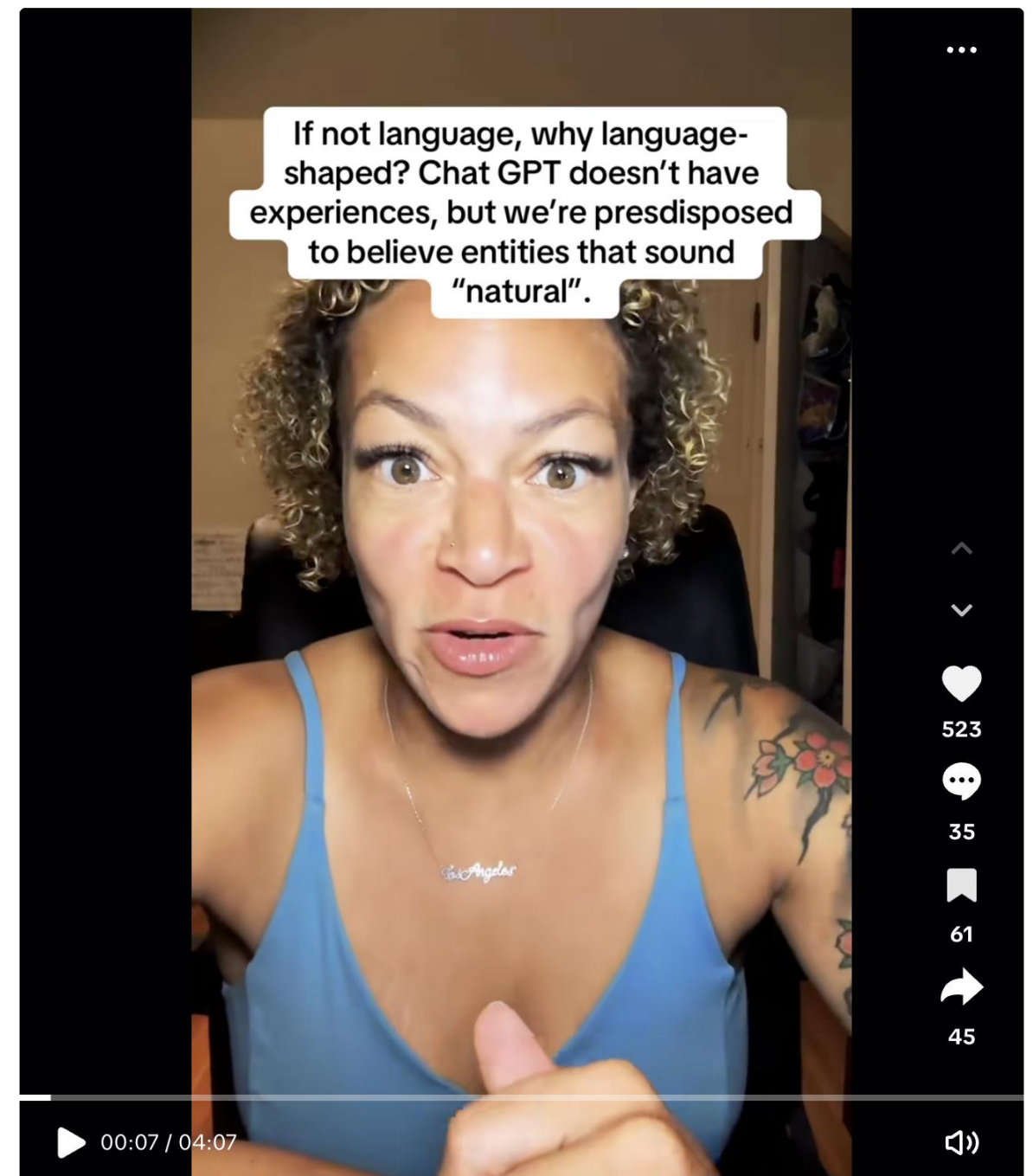
Linguistics

Chatbot Grok Doesn't Glitch—It Reflects X

GABRIELLE D. BEACKEN, MATTHIAS J. BECKER / JUL 28, 2025



Image credit: <https://www.techpolicy.press/chatbot-grok-doesnt-glitch-it-reflects-x/>



video credit: @mixedlinguist
<https://www.tiktok.com/@mixedlinguist/video/7517374618101992734>

On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?



Authors:  [Emily M. Bender](#),  [Timnit Gebru](#),  [Angelina McMillan-Major](#),  [Shmargaret Shmitchell](#) | [Authors Info & Claims](#)

[FAccT '21: Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency](#) • Pages 610 - 623
<https://doi.org/10.1145/3442188.3445922>

- What is language?
- Who can we say “speaks” that language?

Pre-class reading

Each student takes a different problematic aspect:

- environmental & financial costs
- lack of diversity in training data
- data changing social views
- encoding bias
- documentation & accountability

> ... we explore the ways in which the factors laid out in §4 and §5 present real-world risks of harm, as these technologies are deployed.

In class

Distributed Blame: moral responsibility in biased artificial intelligence

Philosophy

Insight - Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

October 10, 2018 5:50 PM PDT · Updated October 9, 2018

Aa



Image credit:
<https://www.reuters.com/article/world/insight-amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK0AG/>





Entry Contents

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Computing and Moral Responsibility

First published Wed Jul 18, 2012; substantive revision Thu Feb 2, 2023

Traditionally philosophical discussions on moral responsibility have focused on the human components of moral action. Accounts of how to ascribe moral responsibility usually describe human agents performing actions that have well-defined, direct consequences. In today's increasingly technological society, however, human activity cannot be properly understood without making reference to technological artifacts, which complicates the ascription of moral responsibility (Jonas 1984; Doorn & van de Poel 2012).^[1] As we interact with and through these artifacts, they affect the decisions that we make and how we make them (Latour 1992, Verbeek 2021). They persuade, facilitate and enable particular human cognitive processes, actions or attitudes, while constraining, discouraging and inhibiting others. For instance, internet search engines prioritize and present information in a particular order, thereby influencing what internet users get to see. As Verbeek points out, such technological artifacts are “active mediators” that “actively co-shape people's being in the world: their perception and actions, experience and existence” (2006, p. 364). As active mediators, they are a key part of human action and as a result they challenge conventional notions of moral responsibility that do not account for the active role of technology (Jonas 1984; Johnson 2001; Swierstra and Waelbers 2012).

Pre-class reading

paper link:
<https://plato.stanford.edu/archives/spr2023/entries/computing-responsibility/>

“most analysis of moral responsibility share at least the following three conditions:”

1. There should be a causal connection between the person and the outcome of actions. A person is usually only held responsible if they had some control over the outcome of events.
2. The subject has to have knowledge of and be able to consider the possible consequences of her actions. We tend to excuse someone from blame if they could not have known that their actions would lead to a harmful event.
3. The subject has to be able to freely choose to act in certain way. That is, it does not make sense to hold someone responsible for a harmful event if her actions were completely determined by outside forces.

- Each student takes a different role: data scientist, software developer, project manager, president of the company, etc.
- Address the following criteria:
 1. Is there a causal connection?
 2. Was there knowledge of the consequences?
Should there have been?
 3. Was there freedom of choice

In class

Representative data are hard to find

Psychology

Image credit:

Psychologists grow increasingly dependent on online research subjects

Scientists make greater use of online workers from Amazon Mechanical Turk, but practice raises concerns

7 JUN 2016 · BY JOHN BOHANNON



New studies suggest that volunteer research subjects for Amazon Mechanical Turk—an online crowdsourcing service—are less numerous and diverse than hoped. PEOPLEIMAGES/ISTOCK

Pre-class reading

paper link:

<https://www.science.org/content/article/psychologists-grow-increasingly-dependent-online-research-subjects>

Psychology looks at the processes, within and between a person and the environment, that affect behavior.

Data is needed to produce models which explain such processes.

[Home](#) | [JAMA Psychiatry](#) | [Vol. 78, No. 7](#)

Original Investigation

FREE

Racial/Ethnic Disparities in the Performance of Prediction Models for Death by Suicide After Mental Health Visits

R. Yates Coley, PhD^{1,2}; Eric Johnson, MS¹; Gregory E. Simon, MD, MPH¹; [et al](#)

Key Points

Question Could implementation of suicide prediction models reinforce and worsen racial/ethnic disparities in care?

Findings In this diagnostic/prognostic study, 2 prediction models for suicide within 90 days were developed and validated in a retrospective study of 13 980 570 outpatient mental health visits. Both models accurately predicted suicide risk for visits by White, Hispanic, and Asian patients, but performance was poor for visits by Black and American Indian/Alaskan Native patients and patients without race/ethnicity reported.

Meaning This study suggests that implementation of either suicide prediction model would disproportionately benefit White, Hispanic, and Asian patients compared with Black and American Indian/Alaskan Native patients and patients with unrecorded race/ ethnicity.

Pre-class reading

Pros and cons to different data gathering mechanisms:

- Mechanical Turks
- IRB consent filter
- Restricted access to vulnerable populations
- Recruitment bias
- WEIRD (Western, Educated, Industrialized, Rich, and Democratic) samples
- Convenience sampling
- Self-selection bias
- Non-valid instruments
- Data cleaning bias
- Dropout bias (attrition)
- Ecological validity (measuring people in the lab instead of the real world)
- Correspondence study (sending in 100s of fake resumes)

In class

Economics

Pre-class reading

paper link: <https://www.nytimes.com/2022/06/21/business/uber-lyft-antitrust-lawsuit.html>

Drivers' Lawsuit Claims Uber and Lyft Violate Antitrust Laws

They accuse the companies of depriving them of employee benefits while also denying them the freedoms of independent contractors.

Share full article



A protest in 2020 outside Uber's headquarters in San Francisco, urging voters to reject Proposition 22, which would have locked in the independent contractor status of drivers. Jim Wilson/The New York Times



By **Kellen Browning** and **Noam Scheiber**

June 21, 2022

Economics is about allocating resources by formalizing the objectives of everyone in the setting. How does each individual act (rationally?) to get to an allocation?

1. Cases where algorithms are used to **support or implement a pre-existing collusion**: in this situation, the parties to an anticompetitive agreement have already put in place (or agreed to put in place) a traditional collusive practice and the algorithm is only used to support the implementation of the agreement, for example its monitoring, enforcement or concealment;
2. The **use of the same third party's algorithm by different competitors**. In this case, leaving aside the situation where the competitors explicitly agree to use the same provider/software for the purpose of implementing pre-existing collusion (in that case we will be under case 1. above), an alignment of the competitive conditions applied by the rivals can occur, hypothetically without any direct contacts between them;
3. The **parallel use by competitors of distinct (pricing) self-learning/deep-learning algorithms that via their automatic, reciprocal interaction** can lead to the alignment of the (pricing) behaviour of the rivals or profit-maximisation cartels, although no (human) communications has taken place between them.

Pre-class reading

text credit: "Algorithmic Competition – Note by the European Union"
[https://one.oecd.org/document/DAF/COMP/WD\(2023\)17/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2023)17/en/pdf)

- What defines collusion?
 - A discussion / presentation on why collusion is bad for the whole.
 - In what ways is algorithmic collusion more destructive than traditional collusion?
-
- Which of the previous page's questions is (are) true in the Uber/Lyft case?

In class

DS 190: Capstone in Data Science

Capstone in Data Science supports each data science minor's capstone project. The project's topic is outside of statistics, mathematics, and computer science.

The Course

Art by @allison_horst

Capstone in Data Science

is a course that supports the data science minor capstone courses. The capstone project is outside of statistics, mathematics, and computer science, emphasizing work in aligned disciplines. The students will bring together the work they have done in data science with problems in other disciplines, and they will consider the ethical implications of their questions and their work.

Prerequisite: all DS minor core courses including statistics, linear algebra, computer science, data science, and ethics in data science.



Thank you!

jo.hardin@pomona.edu

<https://ds190-capstone.netlify.app/>

