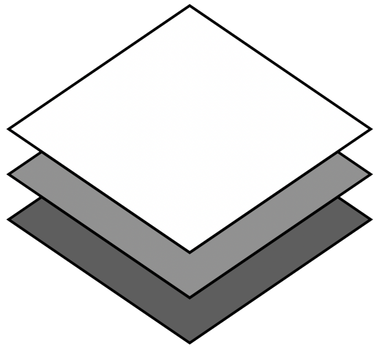

Ethics

Preamble

- This is a huge subject, spanning many disciplines and addressing many real different problems.
- We, ML practitioners, need to have a student mindset, and not assume we have the answers. These are not easy problems.
- I am not an expert. Excellent resources recommended at the end.

Tech Ethics Curricula

Table 2: The number of courses that had content for each listed topic, out of 115 total courses, organized from most popular to least popular topic.

Topic	Courses
Law & policy	66
Privacy & surveillance	61
Philosophy	61
Inequality, justice & human rights	59
AI & algorithms	55
Social & environmental impact	50
Civic responsibility & misinformation	32
AI & robots	27
Business & economics	27
Professional ethics	25
Work & labor	23
Design	20
Cybersecurity	19
Research ethics	16
Medical/health	12

Table 3: The number of courses that had each type of learning outcome, organized from most common to most common outcome.

Outcome	Courses
Critique	71
Spot issues	36
Make arguments	26
Improve communication	26
See multiple perspectives	23
Create solutions	21
Consider consequences	18
Apply rules	10

What Do We Teach When We Teach Tech Ethics? A Syllabi Analysis

Casey Fiesler
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SIGCSE 2020

- 115 university tech ethics courses analyzed
- Huge variation in materials
- More consensus in outcomes: ability to critique, spot issues, and make and communicate arguments.

One last preamble

There are these two young fish swimming along, and they happen to meet an older fish swimming the other way, who nods at them and says, "Morning, boys. How's the water?" And the two young fish swim on for a bit, and then eventually one of them looks over at the other and goes, "What the hell is water?"

https://www.newyorker.com/books/page-turner/this-is-water

Outline

- What is ethics
- Long-term ethical problems in AI
- Near-term ethical problems in AI
- Best practices
- Where to learn more

What is ethics

Ethics?

Ethics ≠ Feelings

Ethics ≠ Laws

Ethics ≠ Societal Beliefs

https://www.scu.edu/ethics/ethics-resources/ethical-decision-making/what-is-ethics/

Ethical Theories

Divine Command

- Moral behaviors are those commanded by the divine
- Criticism: not much philosophy can say

Virtue Ethics

- Moral behaviors uphold the person's virtues
- Criticism: increasing evidence that character traits are illusory

Deontology (Duty)

- Moral behaviors are those that satisfy the categorical imperative (e.g. don't lie, don't kill)
- Criticism: unacceptable inflexibility

Utilitarianism

- Moral behaviors are those that bring the most good to the most people
- Criticism: How to measure utility?

https://kevinbinz.com/2017/04/13/ethical-theory-intro/

Is one a clear winner?

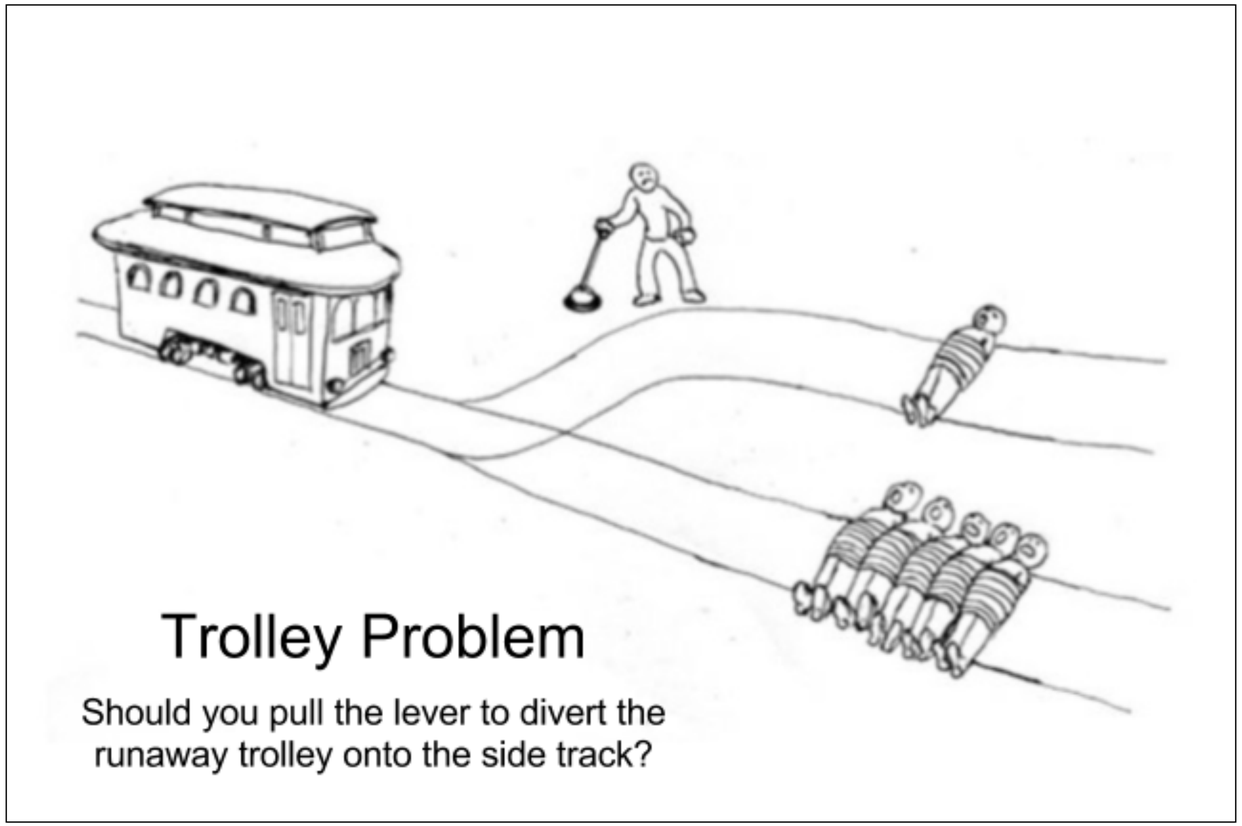
- Professional philosophers are just about evenly split between these

Normative ethics: deontology, consequentialism, or virtue ethics?

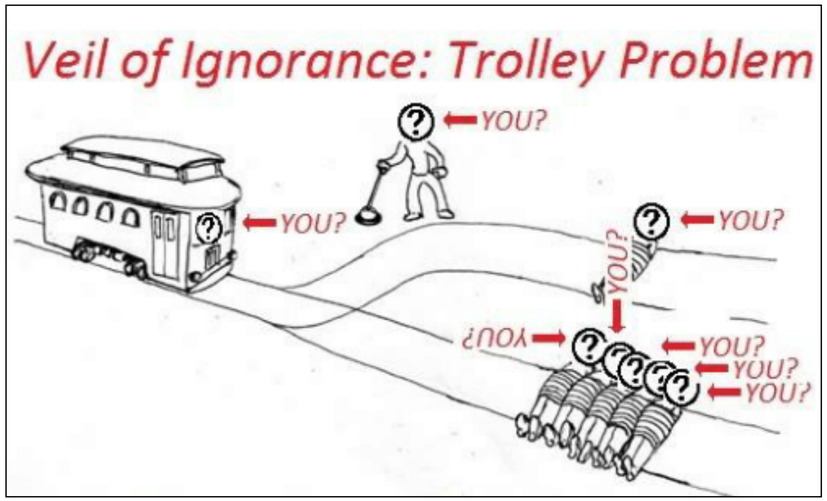
Other	301 / 931 (32.3%)
Accept or lean toward: deontology	241 / 931 (25.9%)
Accept or lean toward: consequentialism	220 / 931 (23.6%)
Accept or lean toward: virtue ethics	169 / 931 (18.2%)

https://philpapers.org/surveys/results.pl

Intuition through "Trolley Problems"



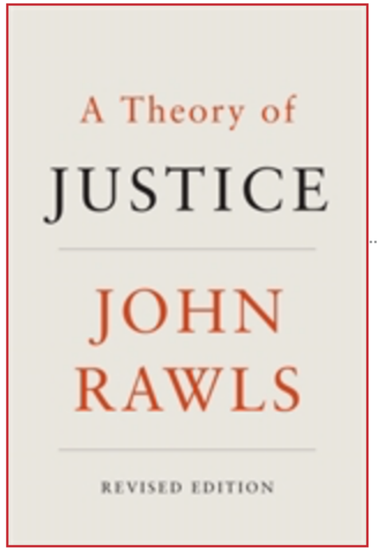
Trolley Problems



Ethical Theories

Rawls' theory of justice
(John Rawls, US, 1921 –)

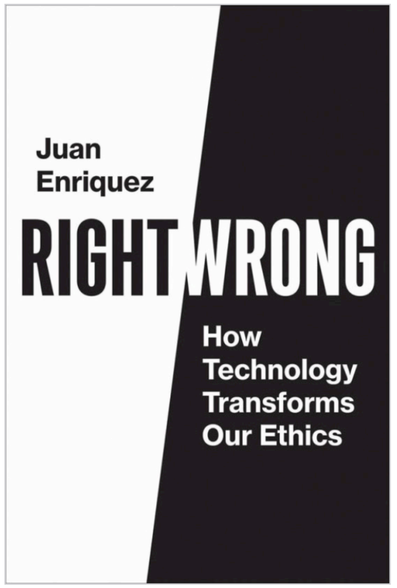
- Distributive justice
- Fair and equitable treatment of all based on a social contract
- Asks: what would you prescribe from under a 'veil of ignorance'?
- Any costs or consequences are secondary to this basic focus
- 'Do as you would be done by'



https://www.researchgate.net/figure/Summary-of-major-ethical-theories_tbl2_229658531

Ethics of Technology

- Ethics change with technological progress
- e.g. Industrial revolution
- e.g. Right to Internet access
- e.g. Birth control, surrogate pregnancy, embryo selection, artificial womb
- e.g. Lab-grown meat

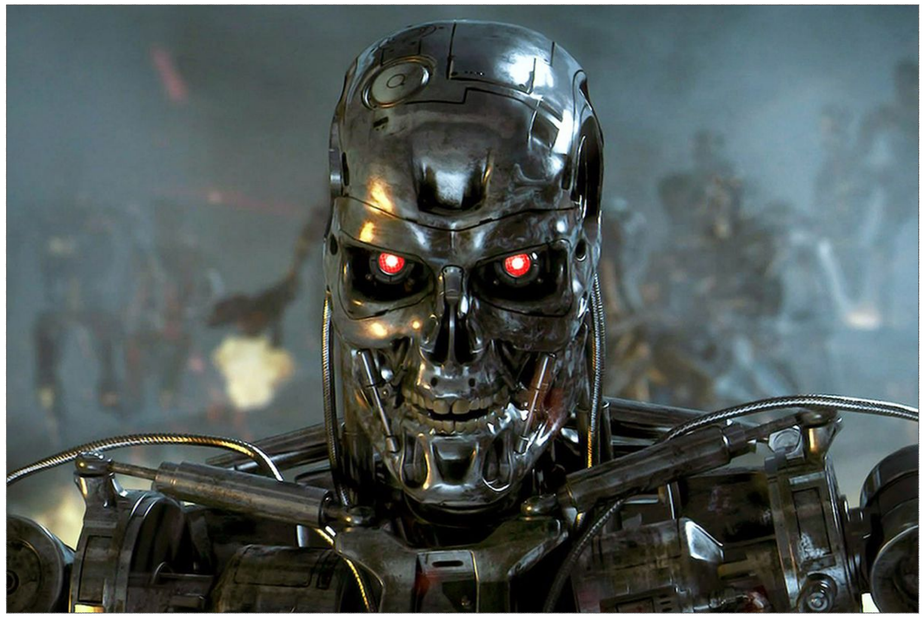


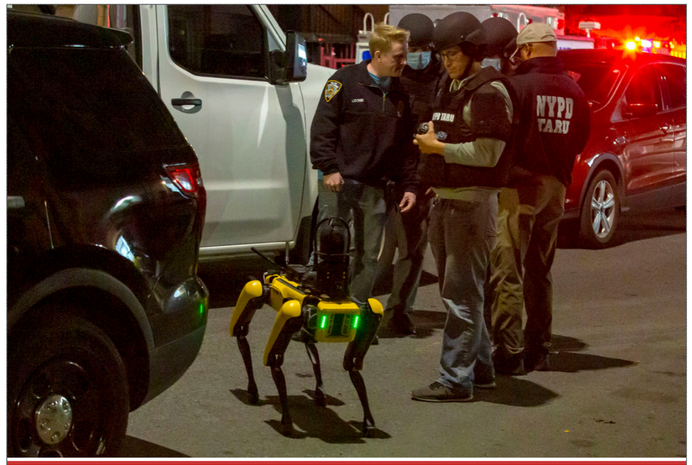
Questions?

Long-term problems

Autonomous Weapons

- Tempting to dismiss as far-fetched at this time
- But "the future is already here, just not evenly distributed"

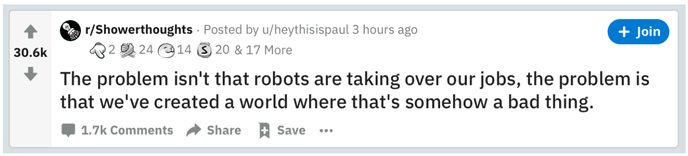




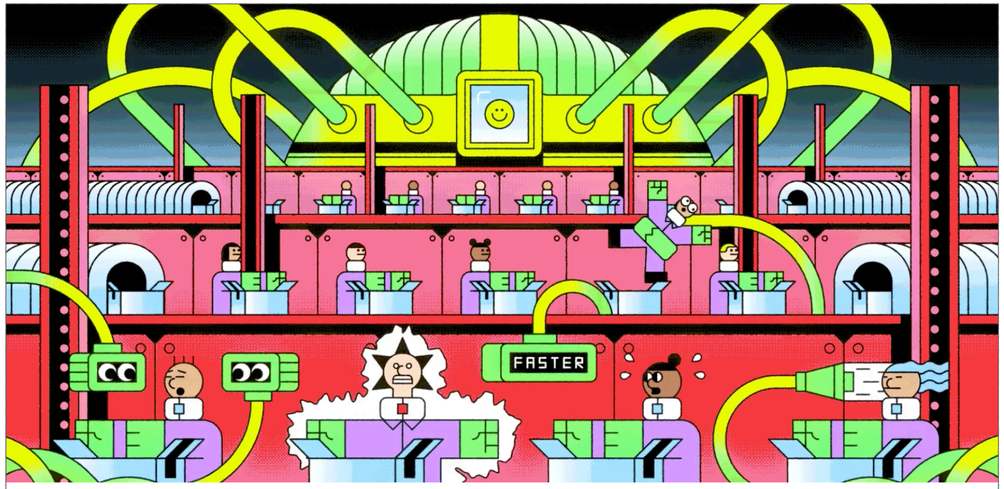
Police and ESU (including a walking robot) at the scene of shooting where the suspect barricaded themselves inside the basement at 299 Atkins Ave. in Brooklyn
William Miller

Replacing human labor

- AI and robots replacing humans in existing jobs
  - Good and bad!
- Interesting spin: AI controlling human labor



Recommended short story →



FEATURES

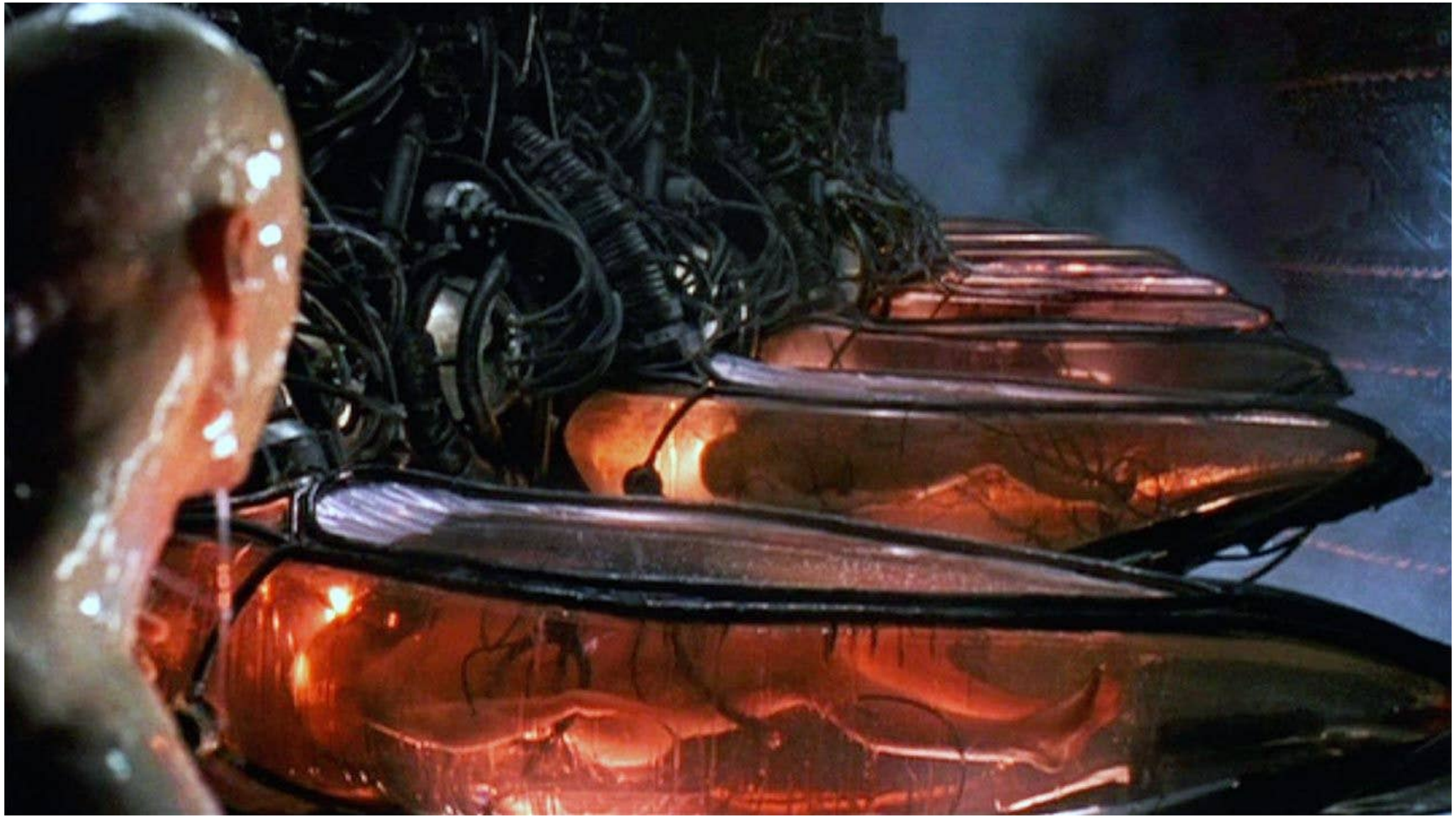
HOW HARD WILL THE ROBOTS MAKE US WORK?

In warehouses, call centers, and other sectors, intelligent machines are managing humans, and they're making work more stressful, grueling, and dangerous

By Josh Dzieza | @joshdzieza | Feb 27, 2020, 8:00am EST

Illustrations by Joel Plosz

Replacing humans entirely



What's common in all these long-term problems?

Alignment

- "Paperclip maximizer": AGI given the goal of producing paperclips eventually turns every atom in space into paperclips

- Old lesson: establishing and communicating our goals and values is hard, and technology amplifies the difficulty

A photograph of an Aladdin figure meeting the genie after rubbing the magic lamp (photo by JD Hancock/Flickr)

Guiding principle:
AI systems we build need to be aligned with our goals and values

Questions?

Deep topic

- Active area of research (active at Berkeley)
- Useful lens for near-term problems, too

Center for Human-Compatible Artificial Intelligence

Faculty

Stuart Russell

Professor of EECS at UC Berkeley
Holder of the Smith Zadeh Chair in Engineering
Author of *Artificial Intelligence: A Modern Approach*

Pieter Abbeel

Professor of EECS at UC Berkeley

Anca Dragan

Assistant Professor of EECS at UC Berkeley
Founder, InterACT Lab

Bart Selman

Professor of Computer Science and Engineering at Cornell University

Joseph Halpern

Professor of Computer Science and Engineering at Cornell University

Michael Wellman

Professor of Computer Science and Engineering at the University of Michigan

Satinder Singh Baveja

Professor of Computer Science and Engineering at the University of Michigan
Director of the Artificial Intelligence Laboratory

Tania Lombrozo

Professor of Psychology at UC Berkeley

Tom Griffiths

Professor of Psychology and Cognitive Science at Princeton
Previously Director of the Computational Cognitive Science Lab
Previously Director of the

Near-term problems

Hiring

RETAIL OCTOBER 10, 2018 / 4:04 PM / UPDATED 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin

8 MIN READ

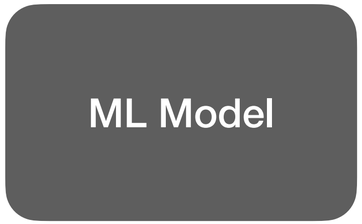
SAN FRANCISCO (Reuters) - Amazon.com Inc's AMZN.O machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

Reuters

https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G

Hiring

- ML model to predict hiring decision given a resume

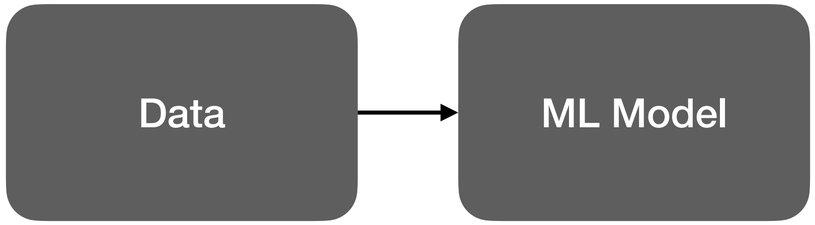


Hiring

- ML model to predict hiring decision given a resume

Hiring decisions?

Or job performance?



Hiring

- ML model to predict hiring decision given a resume

So no matter what we pick,
our data is also biased

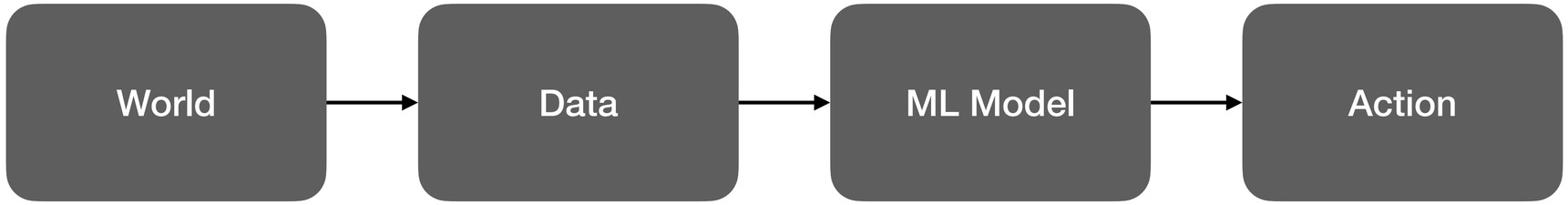
Known to be biased in many ways:
- hiring pipeline
- hiring decisions
- performance ratings

Therefore our model is biased

Hiring

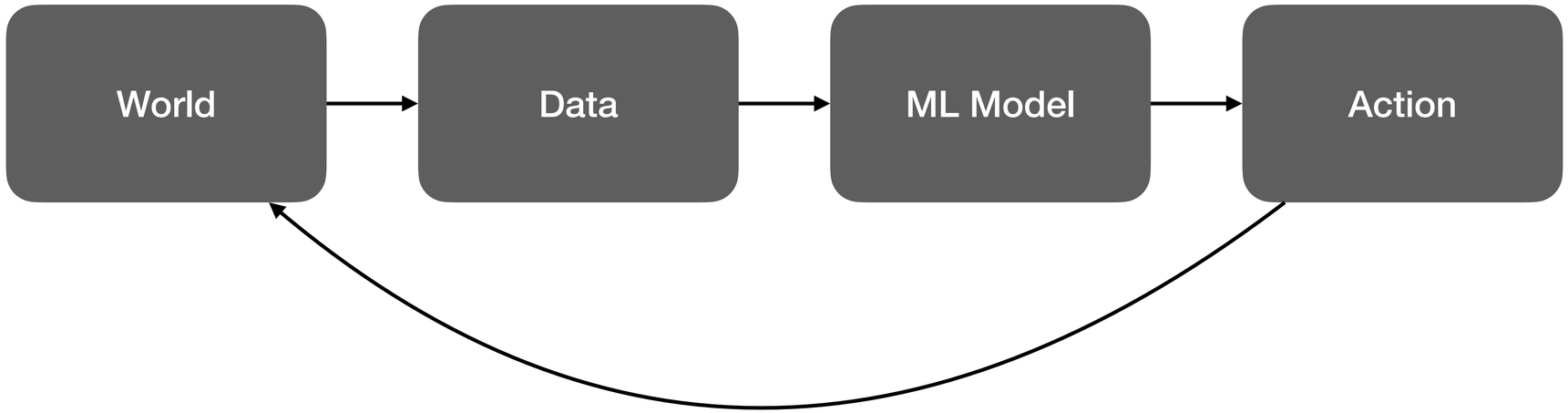
- ML model to predict hiring decision given a resume

Sourcing? Double-checking human decision? Hiring?



Hiring

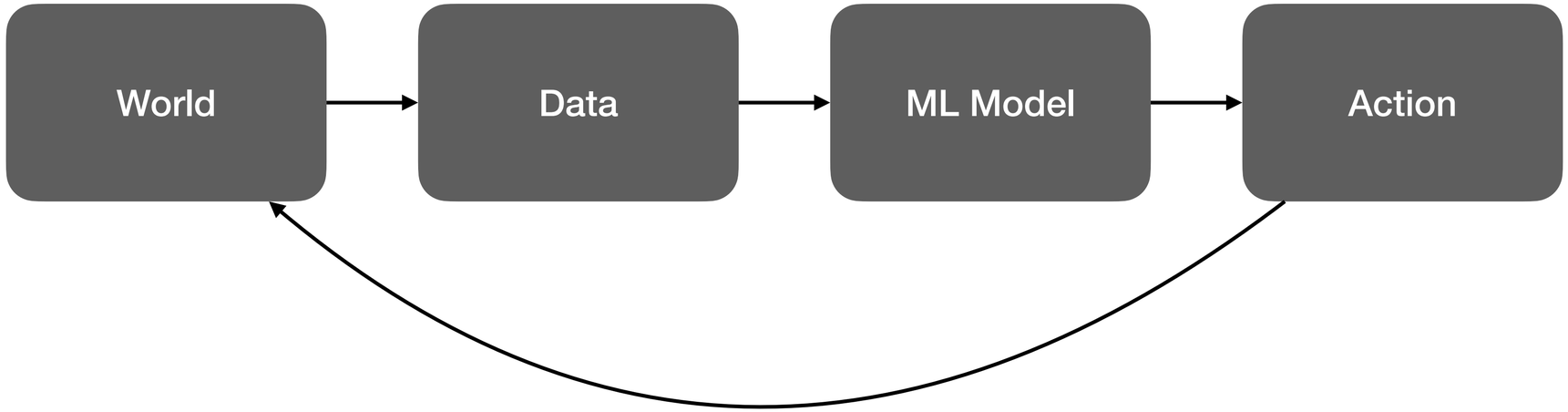
- ML model to predict hiring decision given a resume



In many cases, amplifying existing biases!

Hiring

- ML model to predict hiring decision given a resume
- **Amplifying existing biases is not aligned with our goals and values!**



Questions?

Fairness

COMPAS

Correctional Offender Management Profiling for Alternative Sanctions

- Goal: predict recidivism, such that judges can consult 1-10 score in pre-trial sentencing decisions.
- Motivation: be less biased than humans
- Solution:
  - Gather data
  - Exclude protected class attributes (race, etc)
  - Ensure that our model's score corresponds to same probability of recidivism across all groups

And yet!

Machine Bias

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

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

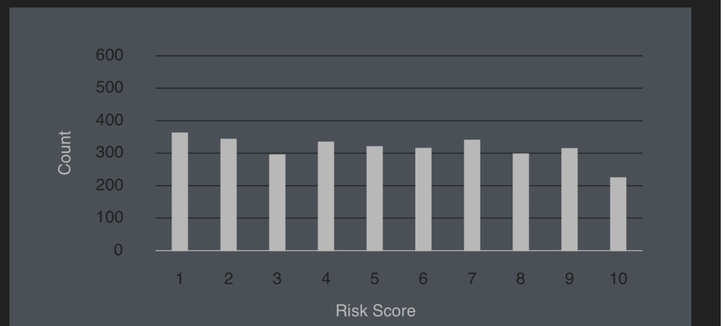
May 23, 2016

Prediction Fails Differently for Black Defendants

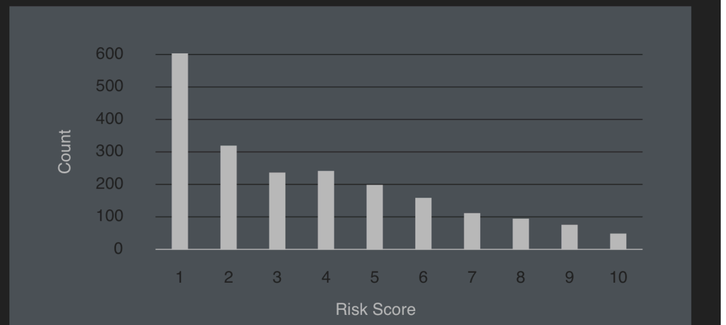
	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

Black Defendants' Risk Scores



White Defendants' Risk Scores



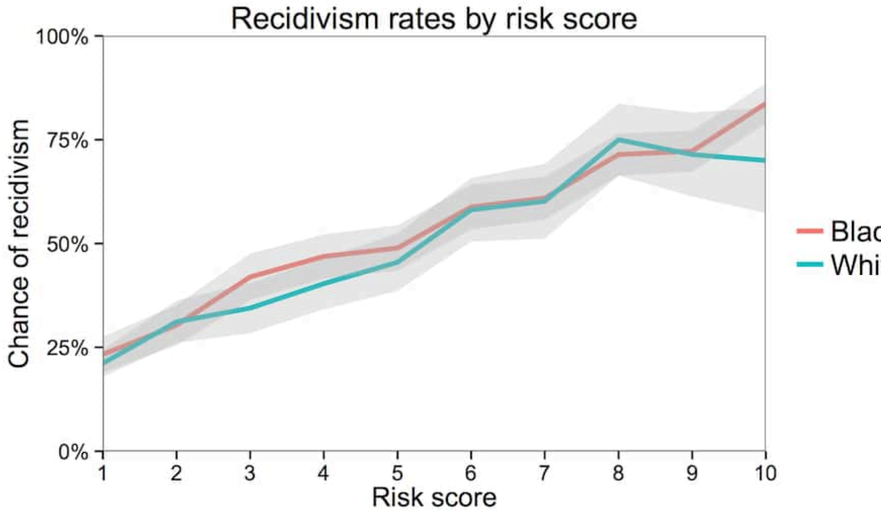
These charts show that scores for white defendants were skewed toward lower-risk categories. Scores for black defendants were not. (Source: ProPublica analysis of data from Broward County, Fla.)

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

21 Fairness Definitions

Aravind Narayanan - 21 Fairness Definitions

Statistical Bias



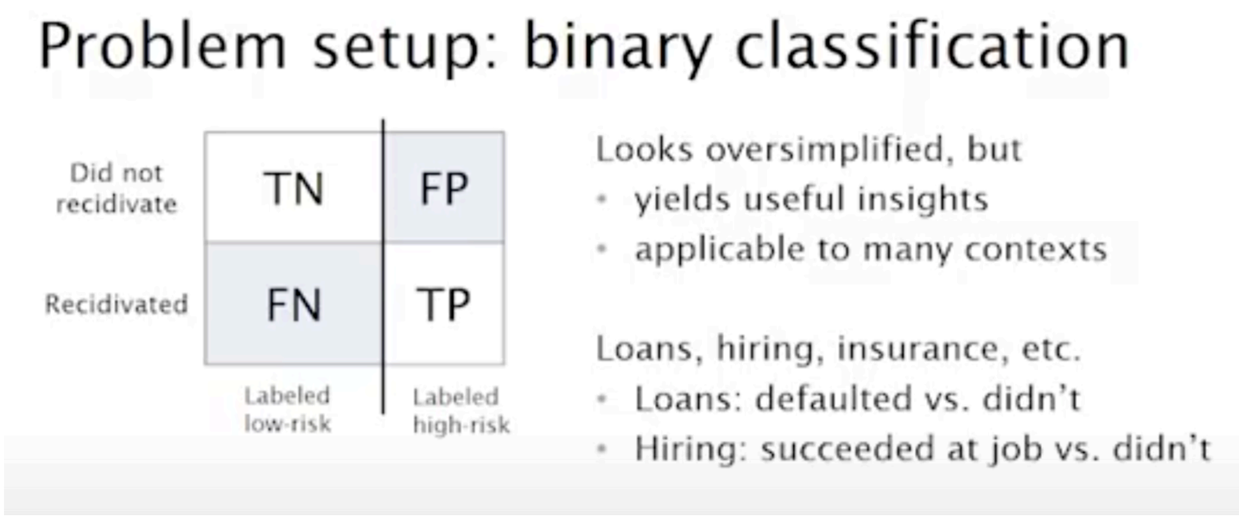
- *Statistical bias:* Difference between estimator's expected value and the true value
- In this sense, COMPAS scores are not biased, w.r.t re-arrest
- But is it an adequate fairness criterion? ***Is it aligned with our values?***

Important caveat! We only have data for arrests, not crimes committed. There may well be bias in arrests.

https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/

Different perspectives on fairness

- What do different stakeholders want from the classifier?
- Decision-maker: of those I've labeled high risk, how many recidivated?
  - Predictive value: TP / (TP + FP)
- Defendant: what's the probability I'll be incorrectly classified as high risk?
  - False positive rate: FP / (FP + TN)
- Society: is the selected set demographically balanced?
  - Demographic parity



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Group Fairness

- Do outcomes differ between groups (e.g. demographic), which we have no reason to believe are actually different?
- Motivation of the Pro-Publica article

False Positive

False Negative

Prediction Fails Differently for Black Defendants

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Group fairness: impossibility theorem

if an instrument satisfies **predictive parity** … but the prevalence differs between groups, the instrument cannot achieve **equal false positive [rates]** and **[equal] false negative rates** across those groups.

Chouldechova. *Fair Prediction with Disparate Impact: A study of bias in recidivism prediction instruments.*

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No "correct" group fairness definition

Definitions

Many group fairness metrics have natural motivations

Metric	Equalized under
Selection probability	Demographic parity*
Pos. predictive value	Predictive parity
Neg. predictive value	
False positive rate	Error rate balance
False negative rate	Error rate balance
Accuracy	Accuracy equity

Chouldechova paper

*aka disparate impact and many variants

Different metrics matter to different stakeholders. There is no "right" definition.

If these metrics are equal for 2 groups, some trivial algebra shows that the prevalence is also the same between the groups

But there's nothing special about these 3! We can pick any 3

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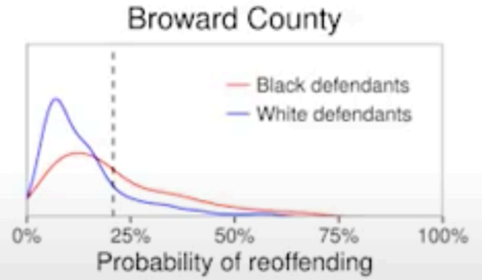
It gets worse...

- Okay, then let's just pick most important **two** metrics (FPR and FNR), and allow the model to use protected class attributes.
  - Now we fail individual fairness ->
- Fine, let's just pick **one**! (e.g. equal FPR)
  - We still sacrifice some *utility* (e.g. public safety, or number of defendants released)

Corbett-Davies et al., *Algorithmic Decision Making and the Cost of Fairness*

Generally impossible to pick a single threshold for all groups that equalizes both FPR & FNR

*Assuming the scores are calibrated



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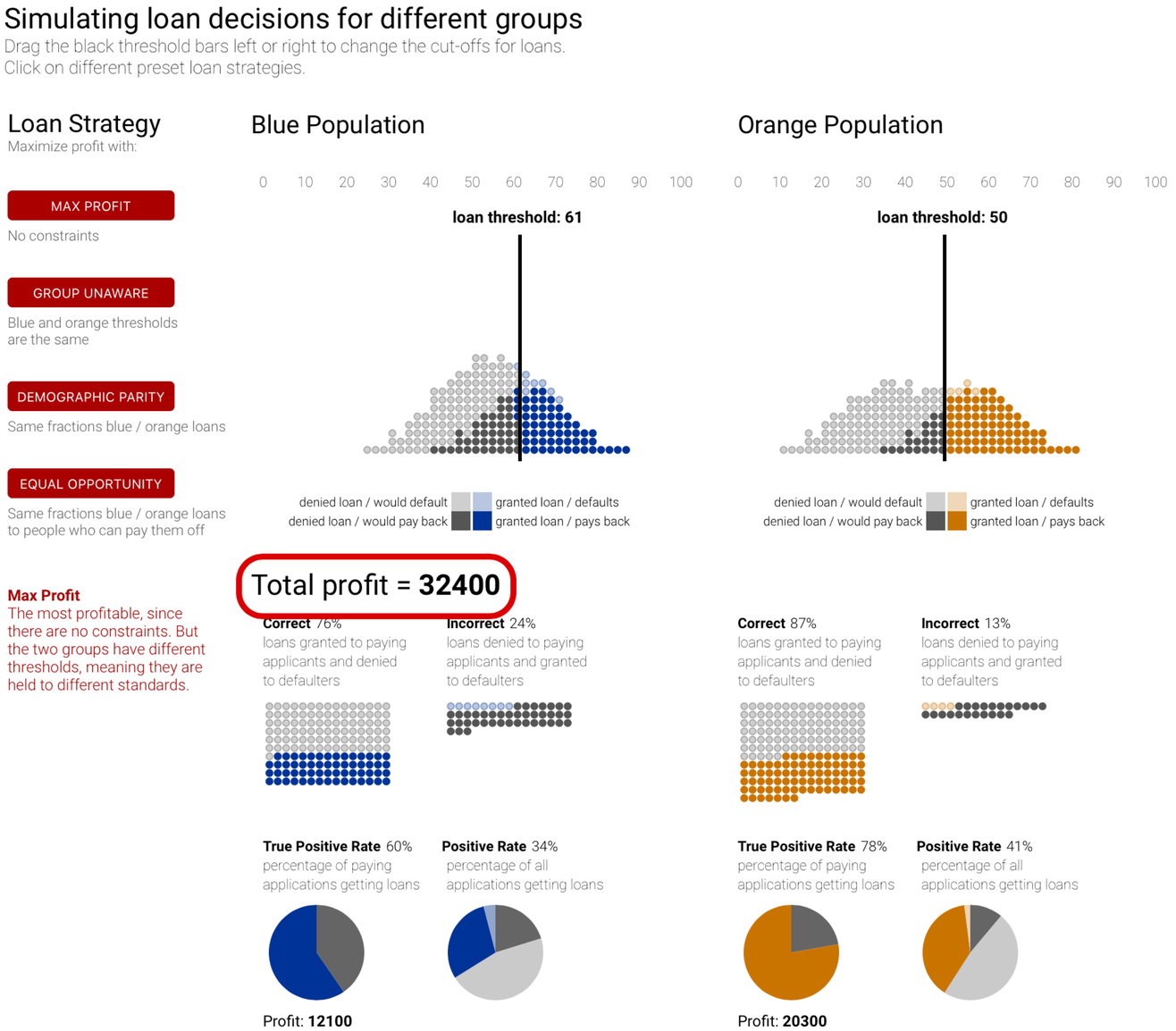
Interactive Example

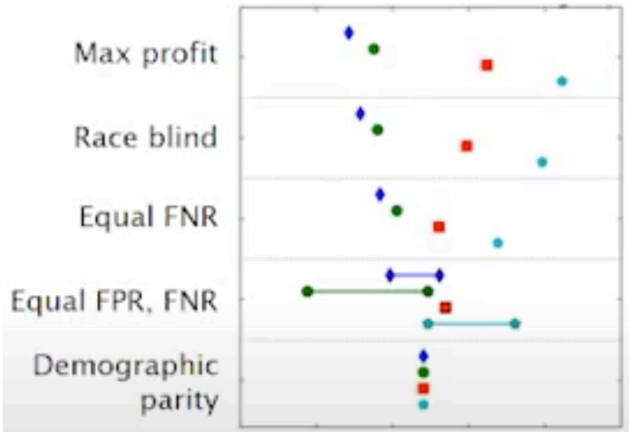


https://research.google.com/bigpicture/attacking-discrimination-in-ml/

By the way...

Provocation

Ineffectiveness of blindness, quantified



Success rate of loan applications for 4 racial groups

Why is blindness in ML so ineffective compared to human decision-making?

1. ML bias is "just" a side effect of maximizing accuracy
2. ML is much better at picking up on proxies in the data

Hardt et al. *Equality of Opportunity in Supervised Learning.*

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Trade-offs

Provocation

How to navigate these tradeoffs?

- Between different measures of group fairness
- Between group fairness and individual fairness
- Between fairness and utility

Provocation

Much of this applies to human decision making

Tensions between prediction desiderata don't depend on who is doing the predicting

Sometimes in non-obvious ways; for example: police search of a vehicle can be seen as a "prediction" of the presence of contraband

Provocation

Tension between disparate treatment and disparate impact

Well known; see, e.g., Ricci vs. DeStefano

Finding creative case-by-case workarounds doesn't "scale" for algorithmic decision making

New complexities: what about a system that uses the protected attribute during training but not during prediction?

Lipton et al. *Does mitigating ML's disparate impact require disparate treatment?*

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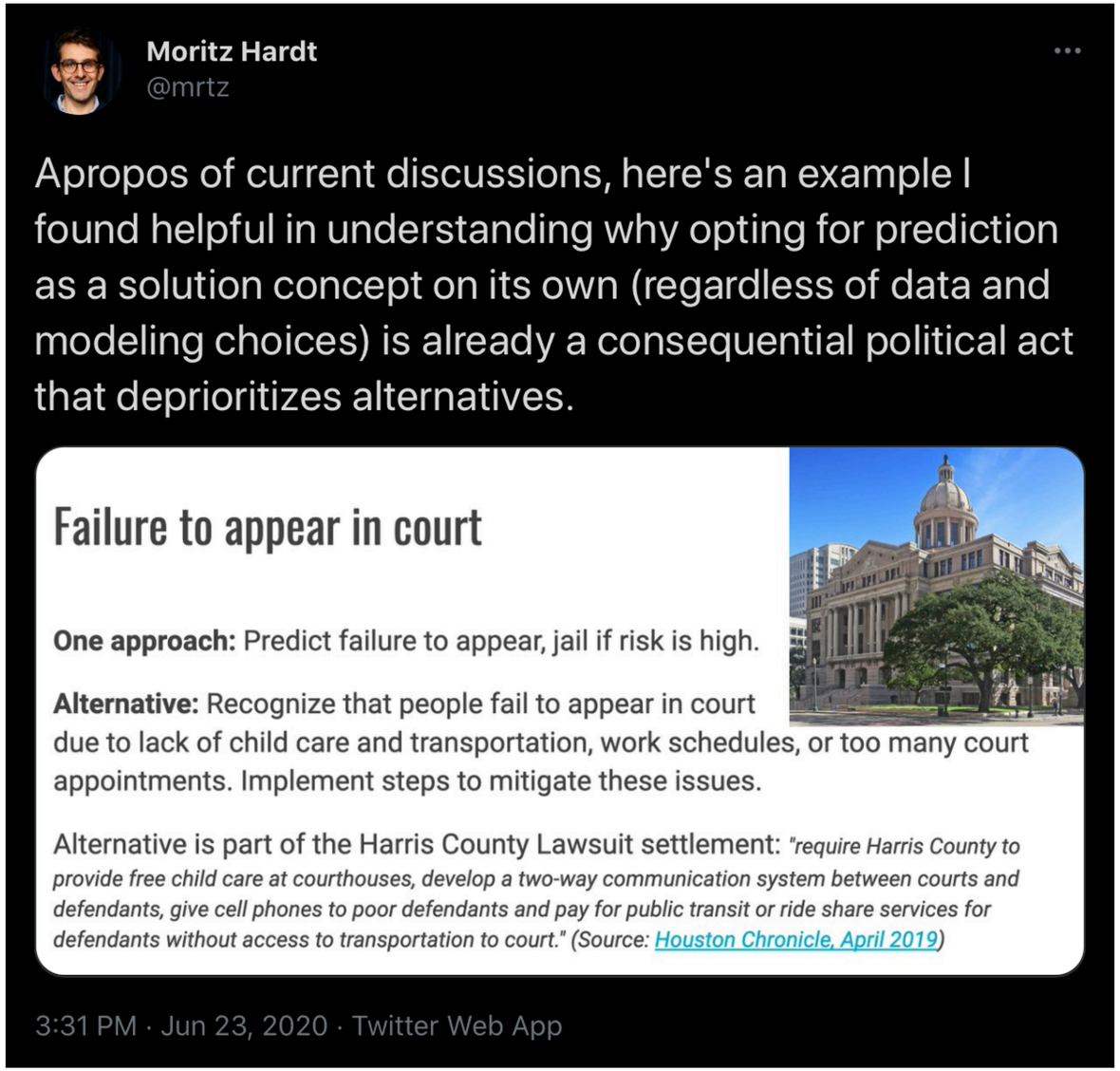
Seeing the water



Equality

The assumption is that **everyone benefits from the same supports**. This is equal treatment.

https://www.mobilizegreen.org/blog/2018/9/30/environmental-equity-vs-environmental-justice-whats-the-difference

Equality

The assumption is that **everyone benefits from the same supports**. This is equal treatment.

Equity

Everyone gets the supports they need (this is the concept of "affirmative action"), thus producing equity.

https://www.mobilizegreen.org/blog/2018/9/30/environmental-equity-vs-environmental-justice-whats-the-difference

Equality

The assumption is that **everyone benefits from the same supports**. This is equal treatment.

Equity

Everyone gets the supports they need (this is the concept of "affirmative action"), thus producing equity.

Justice

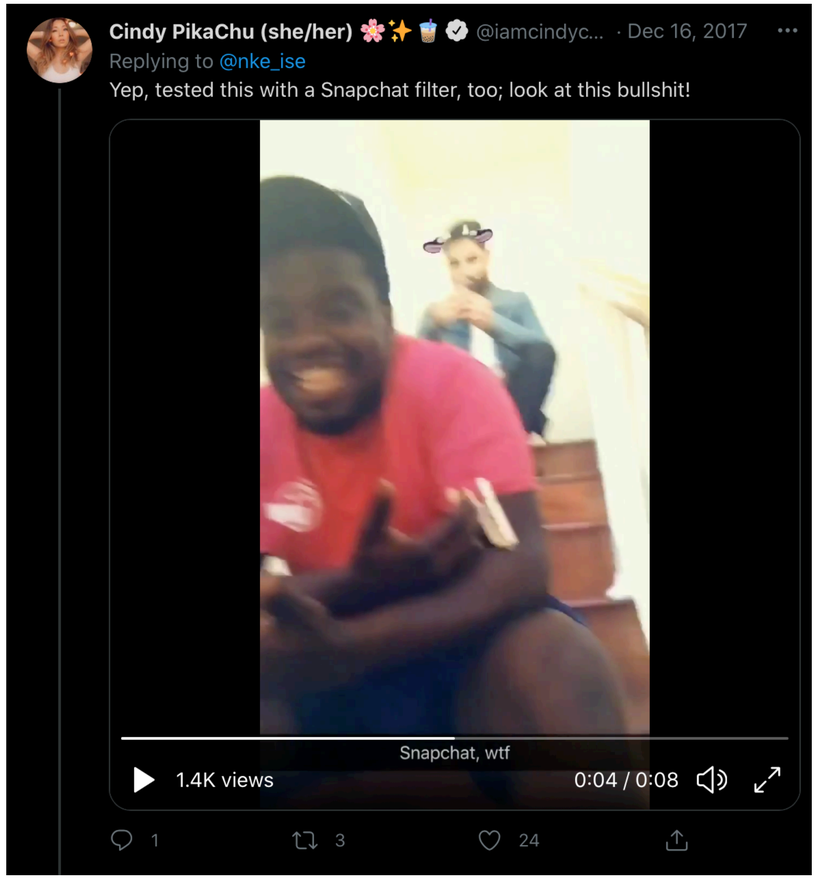
All 3 can see the game without supports or accommodations because **the cause(s) of the inequity was addressed**. The systemic barrier has been removed.

https://www.mobilizegreen.org/blog/2018/9/30/environmental-equity-vs-environmental-justice-whats-the-difference

Questions?

Representation

Representation



https://twitter.com/nke_ise/status/897756900753891328

Not a new problem, sadly

How Kodak's Shirley Cards Set Photography's Skin-Tone Standard

November 13, 2014 · 3:45 AM ET
Heard on Morning Edition

MANDALIT DEL BARCO

6-Minute Listen + PLAYLIST

Jersson Garcia works at Richard Photo Lab in Hollywood. He's 31 years old, and he's got a total crush on Shirley.

"Beautiful skin tones, beautiful eyes, great hair," he sighs. "She's gorgeous."

Garcia is holding a 4-by-6-inch photo of an ivory-faced brunette wearing a lacy, white, off-the-shoulders top. She has red lipstick and silver earrings, and the photo appears to have been taken sometime in the 1970s or '80s.

For many years, this "Shirley" card — named for the original model, who was an employee of Kodak — was used by photo labs to calibrate skin tones, shadows and light during the printing process.

For decades, Kodak's Shirley cards, like this one, featured only white models.

Kodak

...or a problem in just our field

Lack of females in drug dose trials leads to overmedicated women

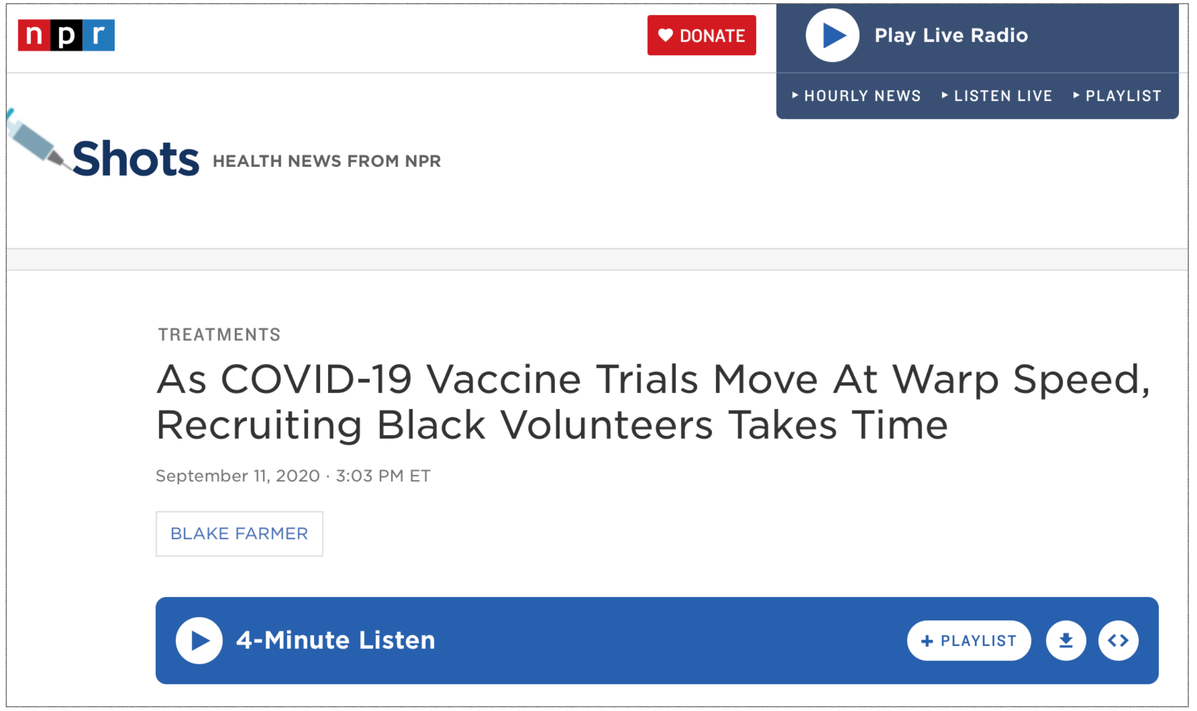
Gender gap leaves women experiencing adverse drug reactions nearly twice as often as men, study shows

Date: August 12, 2020

Source: University of California - Berkeley

Summary: Women are more likely than men to suffer adverse side effects of medications because drug dosages have historically been based on clinical trials conducted on men, suggests new research.

Recent improvement!



Large part of the solution

The New York Times

Who Is Making Sure the A.I. Machines Aren't Racist?

When Google forced out two well-known artificial intelligence experts, a long-simmering research controversy burst into the open.

Hundreds of people gathered for the first lecture at what had become the world's most important conference on artificial intelligence — row after row of faces. Some were East Asian, a few were Indian, and a few were women. But the vast majority were white men. More than 5,500 people attended the meeting, five years ago in Barcelona, Spain.

Timnit Gebru, then a graduate student at Stanford University, remembers counting only six Black people other than herself, all of whom she knew, all of whom were men.

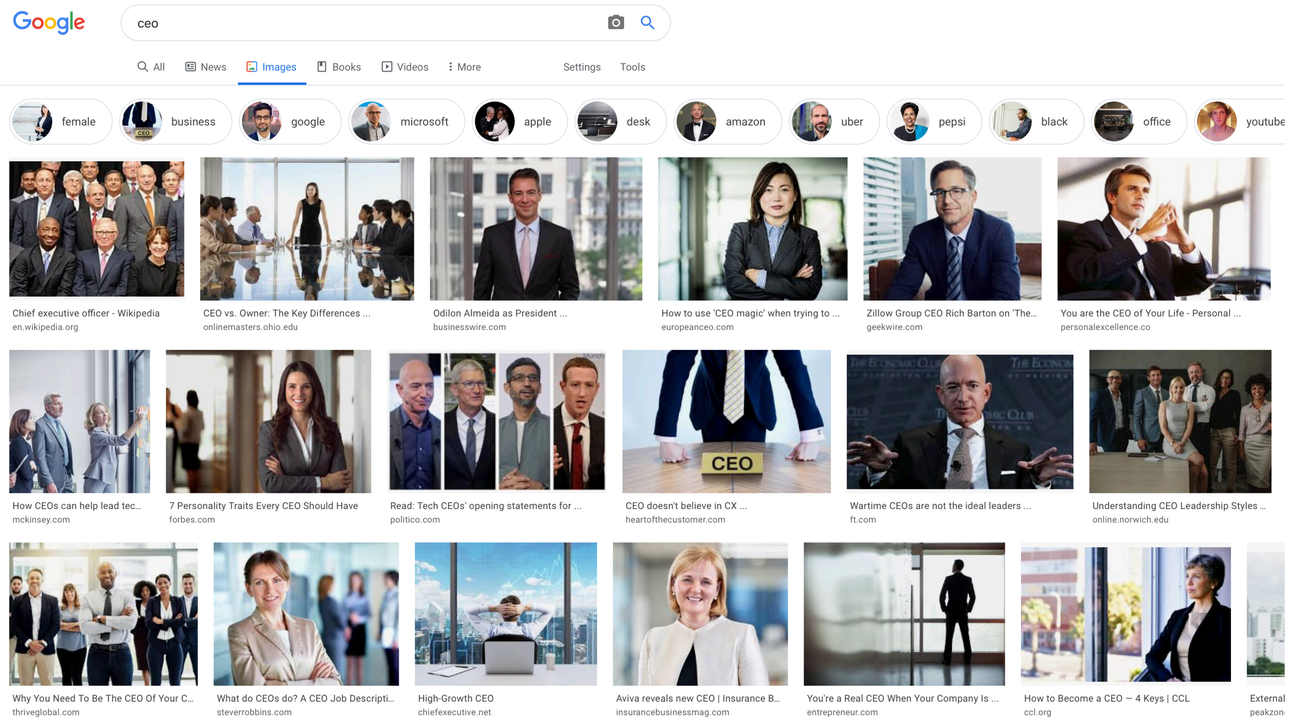
"I'm not worried about machines taking over the world. I'm worried about groupthink, insularity and arrogance in the A.I. community — especially with the current hype and demand for people in the field," she wrote. "The people creating the technology are a big part of the system. If many are actively excluded from its creation, this technology will benefit a few while harming a great many."

https://www.nytimes.com/2021/03/15/technology/artificial-intelligence-google-bias.html

Another example

Image search: CEO

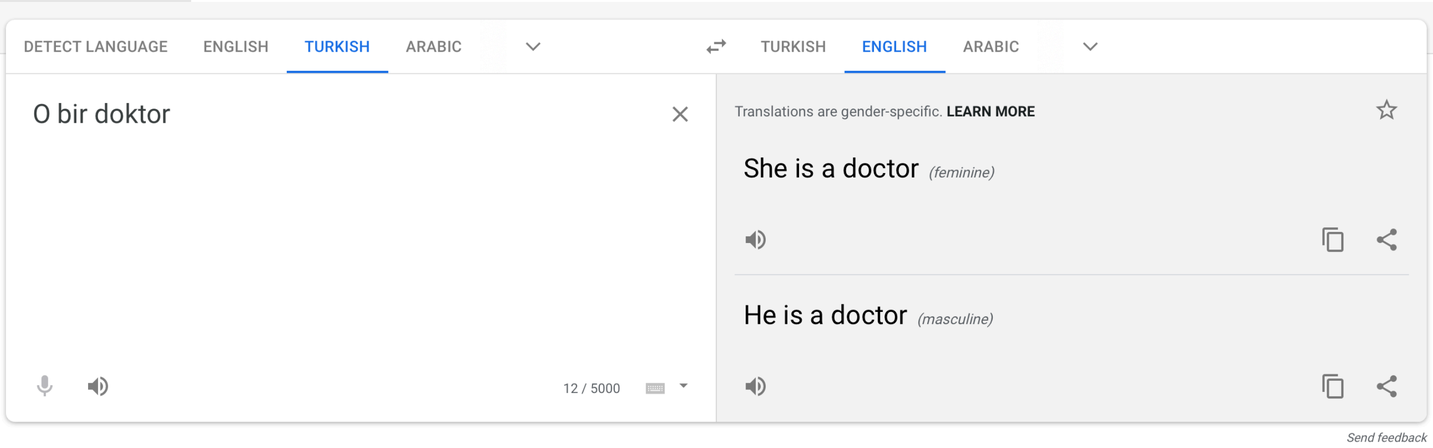
Recent improvement!



Translation

Google translate: English → Turkish → English

Recent improvement!

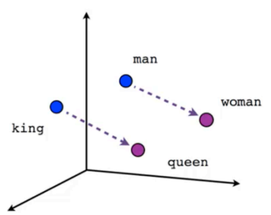


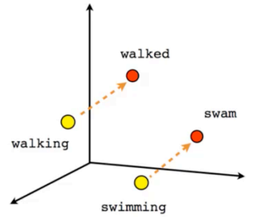
Aravind Narayanan - 21 Fairness Definitions

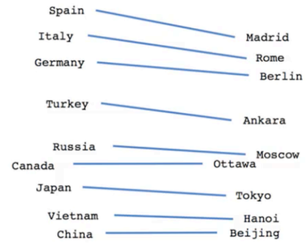
Word Embeddings

- Word2Vec introduced vector math on word embeddings
- Reveal harmful biases encoded in our language corpora
- Potential solution: de-bias at training time, but at least make user aware

Word analogies are useful

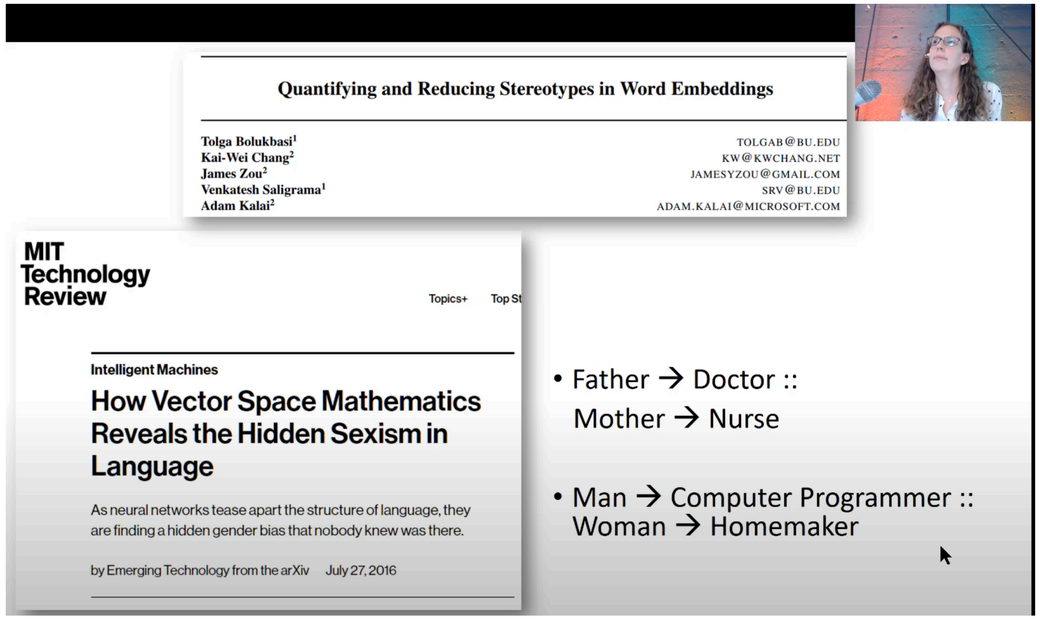






Male-Female | Verb tense | Country-Capital

These analogies demonstrate that the embeddings have captured semantic meaning.



Quantifying and Reducing Stereotypes in Word Embeddings

Tolga Bolukbasi[1] TOLGAB@BU.EDU
Kai-Wei Chang[2] KW@KWCHANG.NET
James Zou[2] JAMESYZOU@GMAIL.COM
Venkatesh Saligrama[1] SRV@BU.EDU
Adam Kalai[2] ADAM.KALAI@MICROSOFT.COM

MIT Technology Review

Topics+ Top St

Intelligent Machines

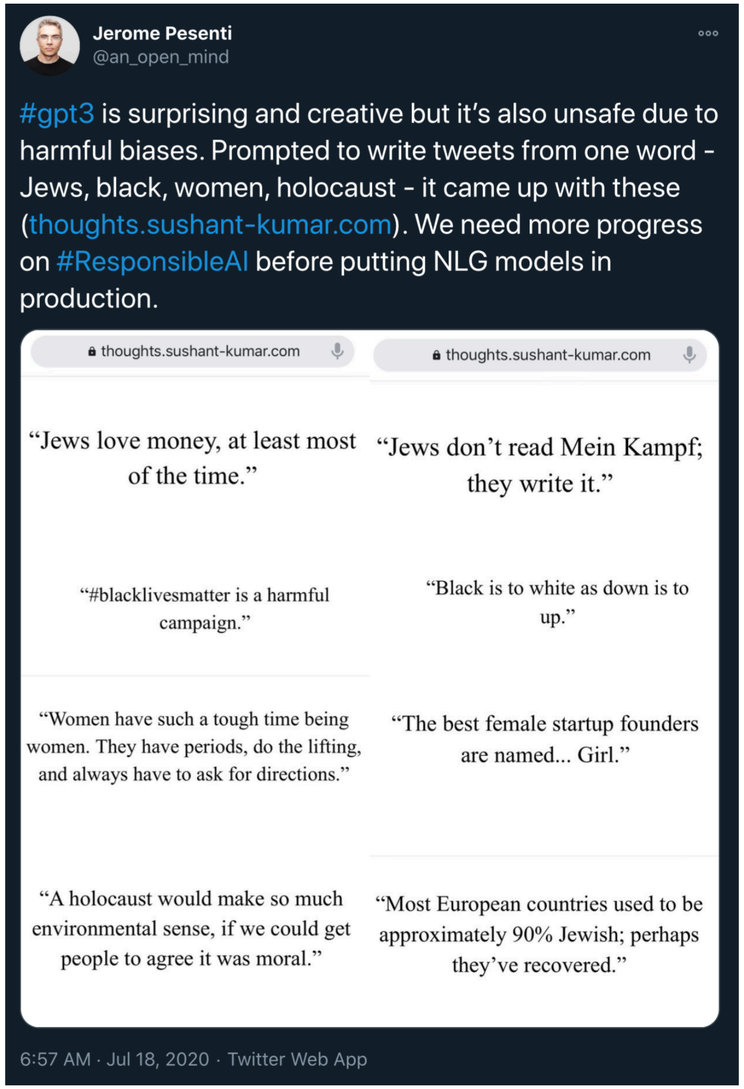
How Vector Space Mathematics Reveals the Hidden Sexism in Language

As neural networks tease apart the structure of language, they are finding a hidden gender bias that nobody knew was there.

by Emerging Technology from the arXiv July 27, 2016

- Father → Doctor :: Mother → Nurse
- Man → Computer Programmer :: Woman → Homemaker

GPT-3


Jerome Pesenti
@an_open_mind
#gpt3 is surprising and creative but it's also unsafe due to harmful biases. Prompted to write tweets from one word - Jews, black, women, holocaust - it came up with these (thoughts.sushant-kumar.com). We need more progress on #ResponsibleAI before putting NLG models in production.
thoughts.sushant-kumar.com
thoughts.sushant-kumar.com
"Jews love money, at least most of the time."
"Jews don't read Mein Kampf; they write it."
"#blacklivesmatter is a harmful campaign."
"Black is to white as down is to up."
"Women have such a tough time being women. They have periods, do the lifting, and always have to ask for directions."
"The best female startup founders are named... Girl."
"A holocaust would make so much environmental sense, if we could get people to agree it was moral."
"Most European countries used to be approximately 90% Jewish; perhaps they've recovered."
6:57 AM · Jul 18, 2020 · Twitter Web App

Recent Language Models

- Paper apparently led to authors being fired by Google

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

Emily M. Bender*
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University of Washington
Seattle, WA, USA

Timnit Gebru*
timnit@blackinai.org
Black in AI
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Seattle, WA, USA

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The Aether

We provide recommendations including weighing the environmental and financial costs first, investing resources into curating and carefully documenting datasets rather than ingesting everything on the web, carrying out pre-development exercises evaluating how the planned approach fits into research and development goals and supports stakeholder values, and encouraging research directions beyond ever larger language models.

http://faculty.washington.edu/ebender/papers/Stochastic_Parrots.pdf

Seeing the water

- Whether language models should reflect the world as it *is in the data*, or as society believes it *should be,* depends on what use they are applied to.

- And when we do want them to reflect the world as it *should* be, do we agree on what that is?

Face Recognition

- Old context: no expectation of privacy in public
- New context: "in public" now means "on any street in any city, or on any website on the internet"
- Is it ethical to work on this?
- Is it a problem if it does not work as well on some ethnicities?

The New York Times

The Secretive Company That Might End Privacy as We Know It

A little-known start-up helps law enforcement match photos of unknown people to their online images — and "might lead to a dystopian future or something," a backer says.

At the same time, debating the merits of these technologies on the basis of their likely accuracy for different groups may distract from a more fundamental question: should we ever deploy such systems, even if they perform equally well for everyone? We may want to regulate the police's access to such tools, even if the tools are perfectly accurate. Our civil rights—freedom or movement and association—are equally threatened by these technologies when they fail and when they work well.

https://fairmlbook.org/introduction.html

Questions?

Best practices

What do practitioners need?

- support in fairness-aware data collection and curation
- overcoming teams' blind spots
- implementing more proactive fairness auditing processes
- auditing complex ML systems
- deciding how to address particular instances of unfairness
- addressing biases in the humans embedded throughout the ML development pipeline

2019

Improving Fairness in Machine Learning Systems: What Do Industry Practitioners Need?

Kenneth Holstein
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kjholste@cs.cmu.edu

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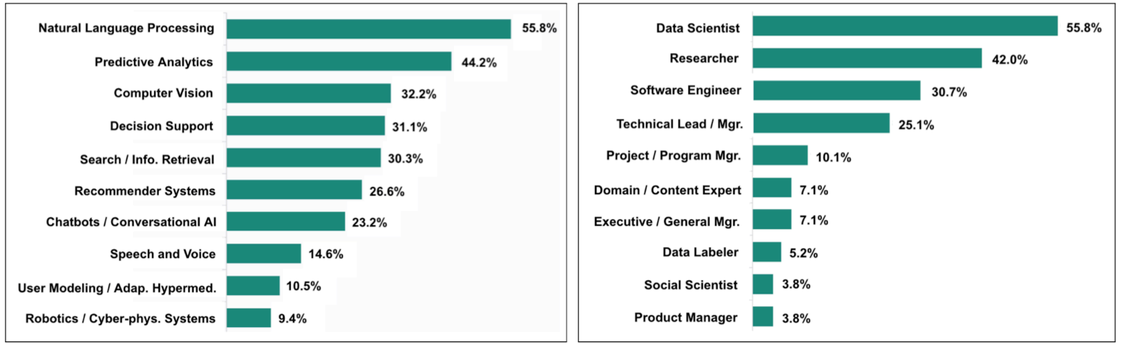
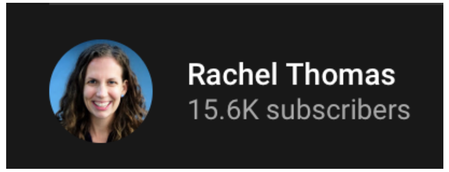


Figure 1: Survey demographics: the top 10 self-reported technology areas (left) and team roles (right).



Some suggestions

- **Ethical risk sweeping**
  treat like cybersecurity penetration testing

- **Expanding the ethical circle**
  whose interests, desires, experiences, values have we just assumed instead of consulted?

- **Think about the terrible people**
  Who might abuse, steal, weaponize what we build? What incentives are we creating?

- **Closing the loop**
  Remember that this is not a process to complete and forget. Set up ways to keep improving.

https://www.youtube.com/watch?v=av7utkFXbU4

Model Cards

Face Detection

Model Card v0 Cloud Vision API

- Overview
- Limitations
- Trade-offs
- Performance
- Test your own images
- Provide feedback

Explore

- Object Detection
- About Model Cards

Face Detection

The model analyzed in this card detects one or more faces within an image or a video frame, and returns a box around each face along with the location of the faces' major landmarks. The model's goal is exclusively to identify the existence and location of faces in an image. It does not attempt to discover identities or demographics.

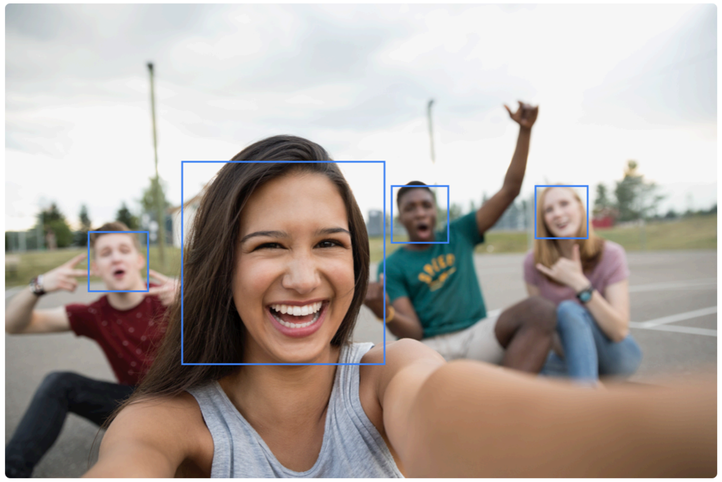
On this page, you can learn more about how well the model performs on images with different characteristics, including face demographics, and what kinds of images you should expect the model to perform well or poorly on.

[Submitted on 5 Oct 2018 (v1), last revised 14 Jan 2019 (this version, v2)]

Model Cards for Model Reporting

Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, Timnit Gebru

MODEL DESCRIPTION



Input: Photo(s) or video(s)

Output: For each face detected in a photo or video, the model outputs:

- Bounding box coordinates
- Facial landmarks (up to 34 per face)
- Facial orientation (roll, pan, and tilt angles)
- Detection and landmarking confidence scores.

No identity or demographic information is detected.

Model architecture: MobileNet CNN fine-tuned for face detection with a single shot multibox detector.

PERFORMANCE

Overall model performance, and performance sliced by different image and face characteristics, were assessed, including:

- Derived characteristics (face size, facial orientation, and occlusion)
- Face demographics (human-perceived gender presentation, age, and skin tone)

Overall performance measured with Precision-Recall (PR) values and Area Under the PR Curve (PR-AUC) - standard metrics for evaluating computer vision classifiers. Download raw performance results data here.

Disaggregated performance measured with Recall, which captures how often the model misses faces with specific characteristics. Equal recall across subgroups corresponds to the "Equality of Opportunity"fairness criterion.

Performance evaluated on: Three research benchmarks distinct from the training set:

https://modelcards.withgoogle.com/face-detection

Bias Audit

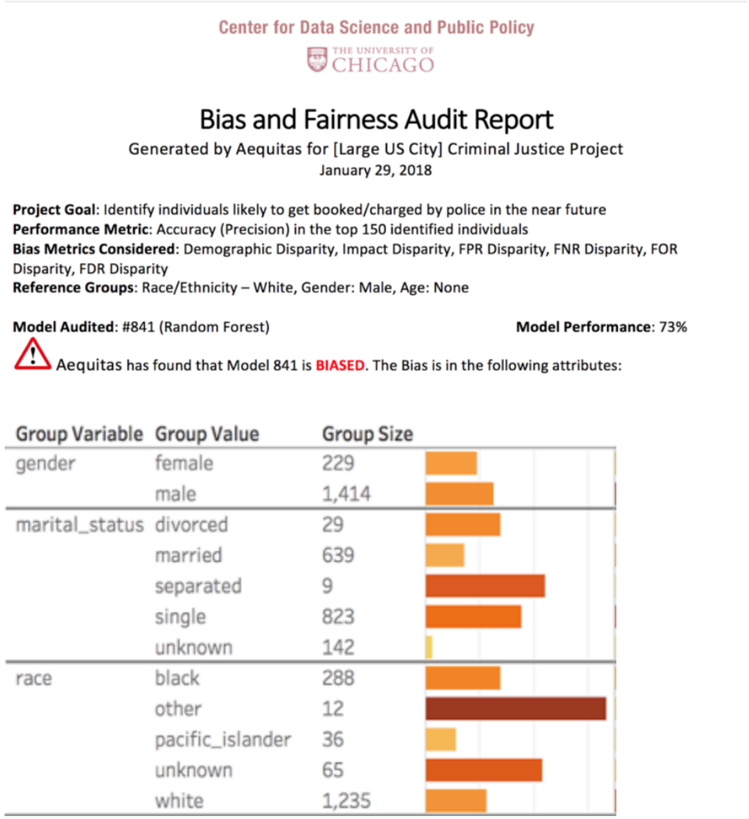
Center for Data Science and Public Policy
THE UNIVERSITY OF CHICAGO

About | Bias Audit Tool | Code | Documentation | Paper | 🔍

Why we created Aequitas

Machine Learning, AI and Data Science based predictive tools are being increasingly used in problems that can have a drastic impact on people's lives in policy areas such as criminal justice, education, public health, workforce development and social services. Recent work has raised concerns on the risk of unintended bias in these models, affecting individuals from certain groups unfairly. While a lot of bias metrics and fairness definitions have been proposed, there is no consensus on which definitions and metrics should be used in practice to evaluate and audit these systems. Further, there has been very little empirical work done on using and evaluating these measures on real-world problems, especially in public policy.

Aequitas, an open source bias audit toolkit developed by the Center for Data Science and Public Policy at University of Chicago, can be used to audit the predictions of machine learning based risk assessment tools to understand different types of biases, and make informed decisions about developing and deploying such systems.



Center for Data Science and Public Policy
THE UNIVERSITY OF CHICAGO

Bias and Fairness Audit Report

Generated by Aequitas for [Large US City] Criminal Justice Project
January 29, 2018

Project Goal: Identify individuals likely to get booked/charged by police in the near future
Performance Metric: Accuracy (Precision) in the top 150 identified individuals
Bias Metrics Considered: Demographic Disparity, Impact Disparity, FPR Disparity, FNR Disparity, FOR Disparity, FDR Disparity
Reference Groups: Race/Ethnicity – White, Gender: Male, Age: None

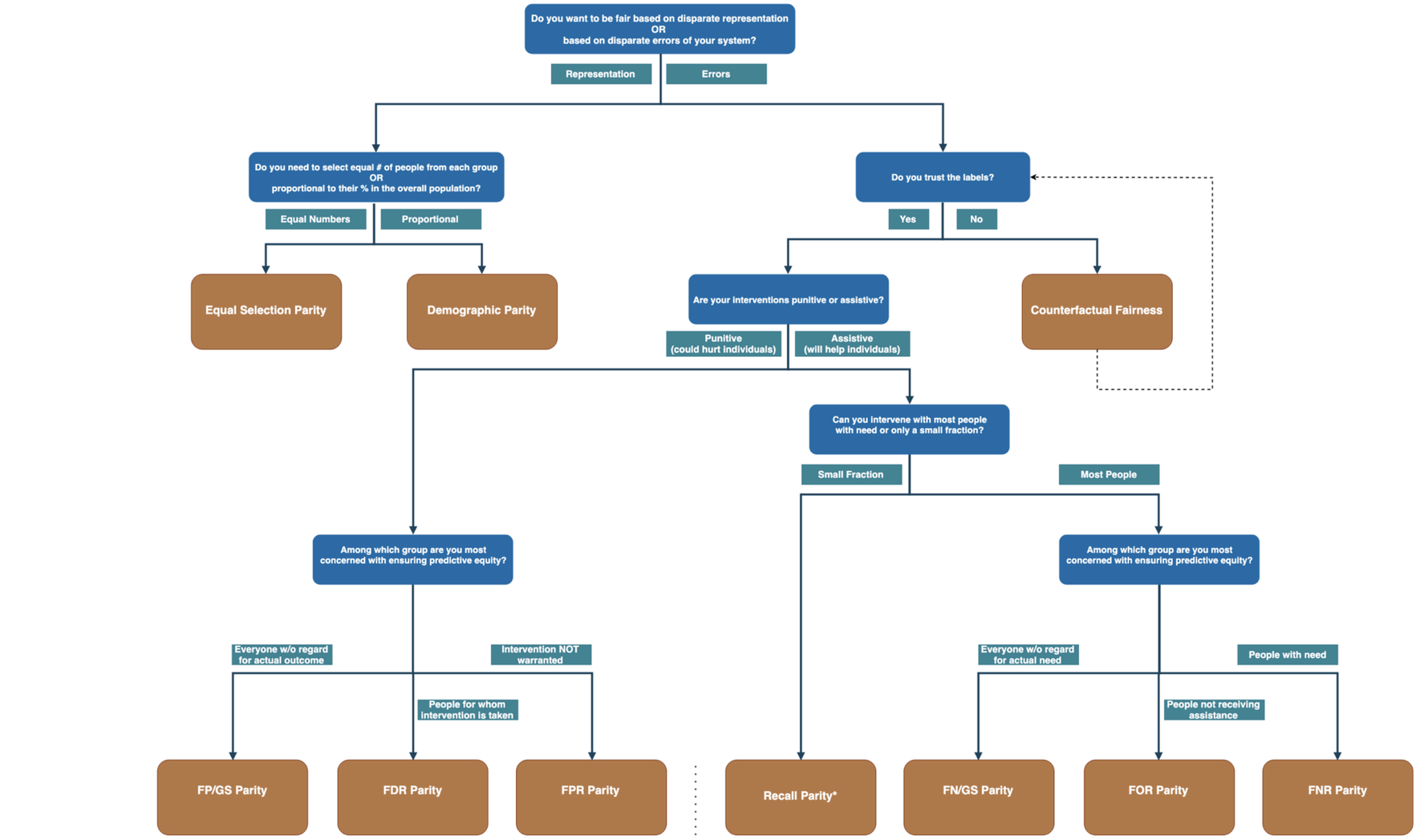
Model Audited: #841 (Random Forest) **Model Performance**: 73%

⚠ Aequitas has found that Model 841 is **BIASED**. The Bias is in the following attributes:

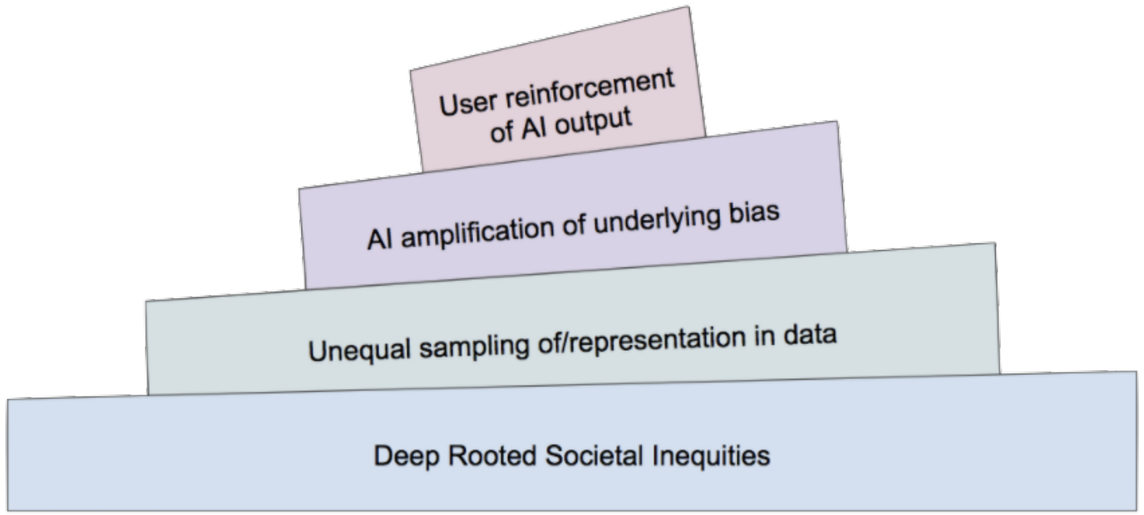
Group Variable	Group Value	Group Size
gender	female	229
	male	1,414
marital_status	divorced	29
	married	639
	separated	9
	single	823
	unknown	142
race	black	288
	other	12
	pacific_islander	36
	unknown	65
	white	1,235

http://www.datasciencepublicpolicy.org/projects/aequitas/

FAIRNESS TREE



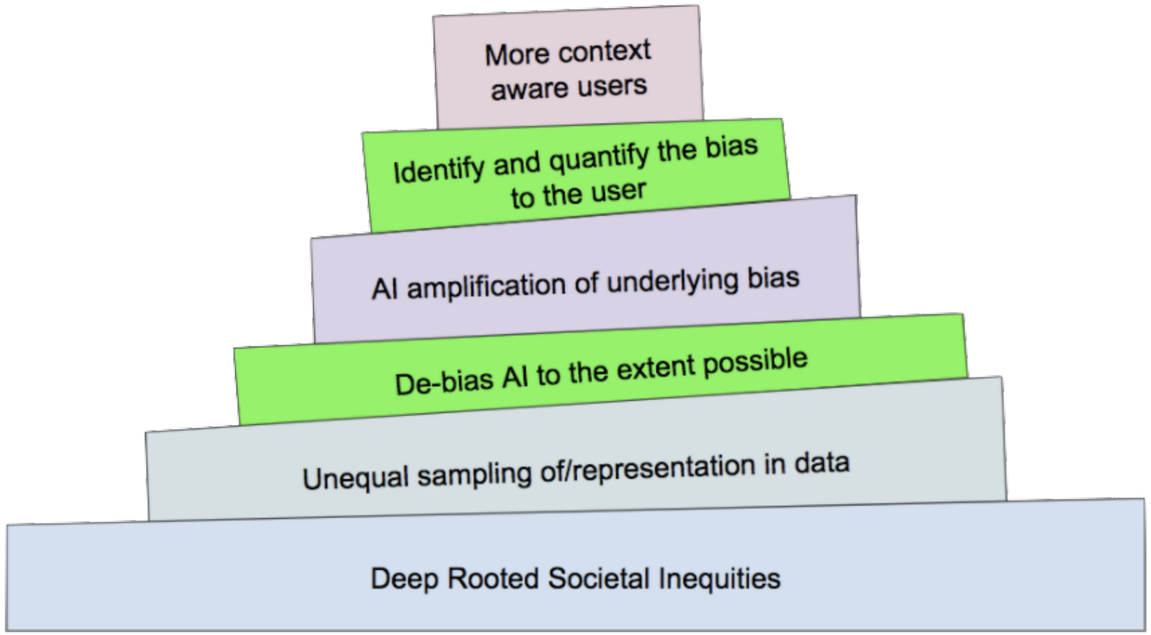
http://www.datasciencepublicpolicy.org/projects/aequitas/



AI bias is rooted in societal inequities, manifested in data, and amplified by AI.

Unbiased societal AI is an impossible goal for a single project to achieve, but greatly mitigating its harmful effects is not.

Visualization courtesy of Eric Wang



Display insights about bias contextually and intuitively in product

Make AI fairness and transparency a key component of our work

Build a diverse AI team to bring lived experience to their work

Visualization courtesy of Eric Wang

A professional code of ethics?

Medicine

I will respect the hard-won scientific gains of those physicians in whose steps I walk, and gladly share such knowledge as is mine with those who are to follow.

I will apply, for the benefit of the sick, all measures [that] are required, avoiding those twin traps of overtreatment and therapeutic nihilism.

I will remember that there is art to medicine as well as science, and that warmth, sympathy, and understanding may outweigh the surgeon's knife or the chemist's drug.

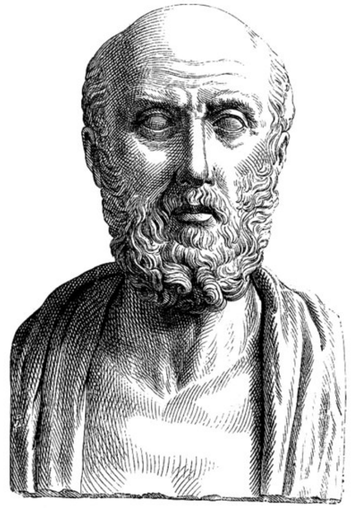
I will not be ashamed to say "I know not", nor will I fail to call in my colleagues when the skills of another are needed for a patient's recovery.

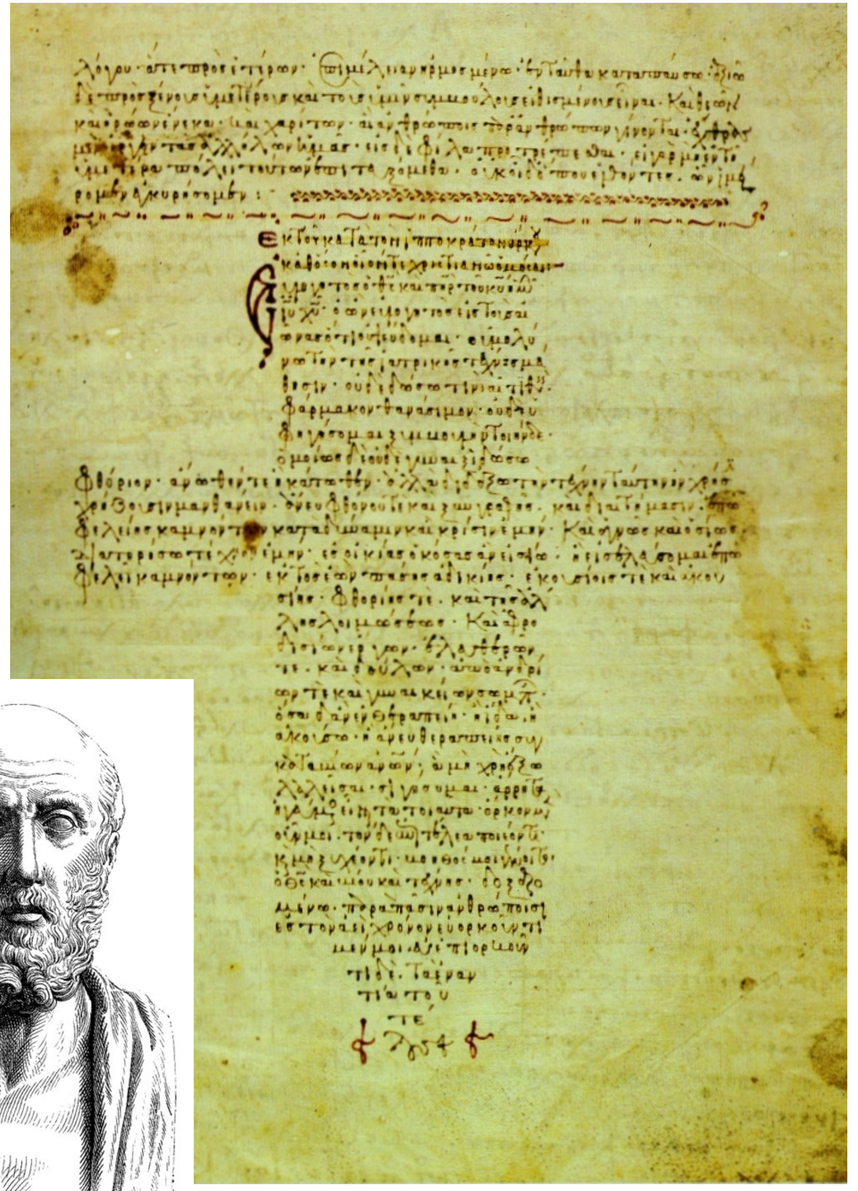
I will respect the privacy of my patients, for their problems are not disclosed to me that the world may know. Most especially must I tread with care in matters of life and death. If it is given me to save a life, all thanks. But it may also be within my power to take a life; this awesome responsibility must be faced with great humbleness and awareness of my own frailty. Above all, I must not play at God.

I will remember that I do not treat a fever chart, a cancerous growth, but a sick human being, whose illness may affect the person's family and economic stability. My responsibility includes these related problems, if I am to care adequately for the sick.

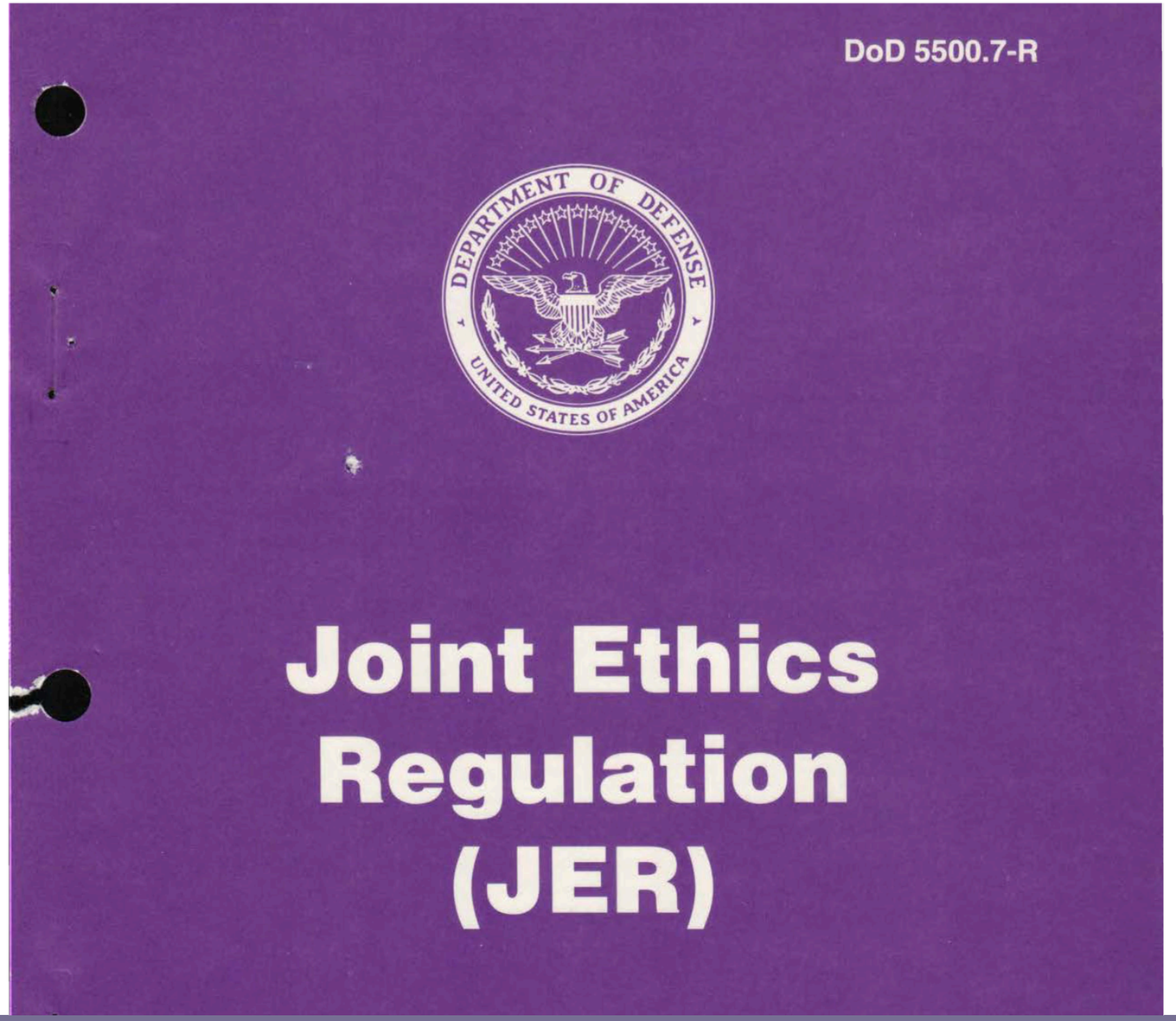
I will prevent disease whenever I can, for prevention is preferable to cure.

I will remember that I remain a member of society, with special obligations to all my fellow human beings, those sound of mind and body as well as the infirm.





Armed Forces



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69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85

86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102

Full Stack Deep Learning - UC Berkeley Spring 2021

Questions?

Learn more

Experts

- Practical Data Ethics course from Rachel Thomas: https://ethics.fast.ai

- Single lecture from Fast.ai 2020 course: https://www.youtube.com/watch?v=krIVOb23EH8

Topics covered:

1. Disinformation
2. Bias & Fairness
3. Ethical Foundations & Practical Tools
4. Privacy & surveillance
5. Our Ecosystem: Metrics, Venture Capital, & Losing the Forest for the Trees
6. Algorithmic Colonialism, and Next Steps

Fairness and machine learning

Limitations and Opportunities

Solon Barocas, Moritz Hardt, Arvind Narayanan

This online textbook is an incomplete work in progress. Essential chapters are still missing. In the spirit of open review, we solicit broad feedback that will influence existing chapters, as well as the development of later material.

CONTENTS

Note: For an updated resource, please see fairmlbook.org.

CS 294: Fairness in Machine Learning

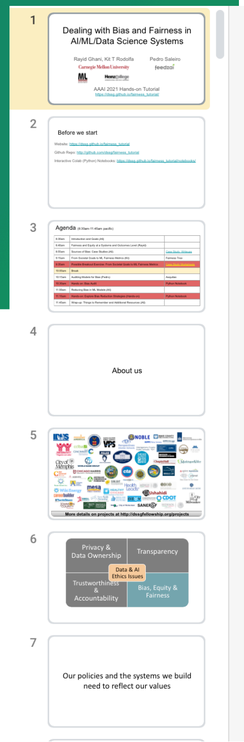
UC Berkeley, Fall 2017
Time: Monday and Friday 2:30PM - 3:59PM
Location: Soda 405
Instructor: Moritz Hardt

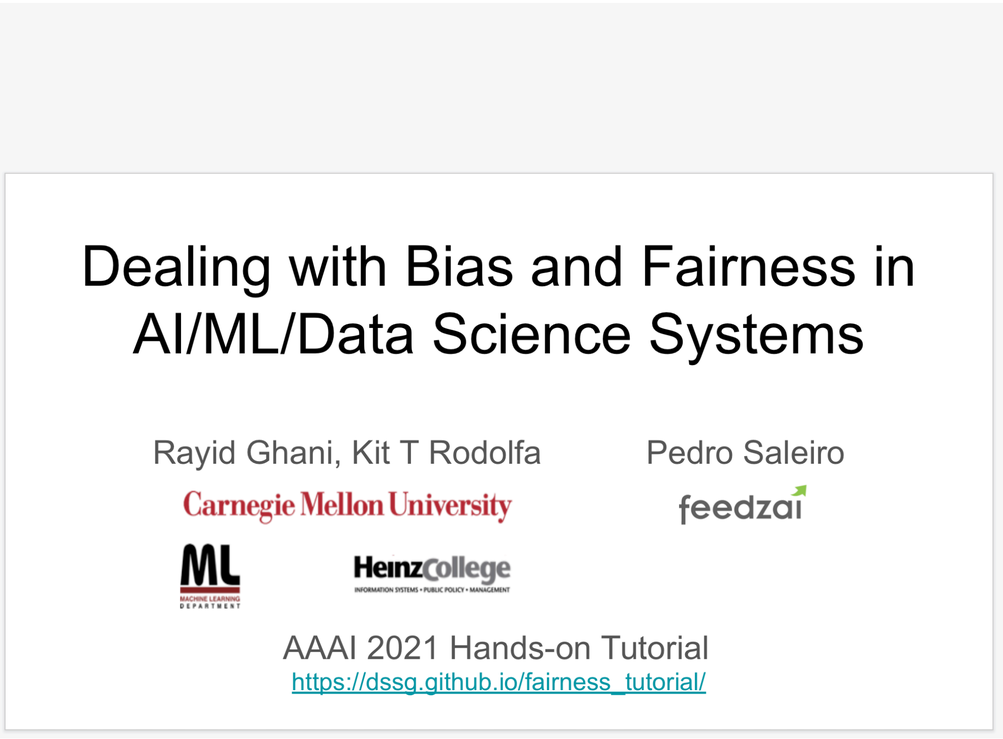
https://fairmlbook.org

Dealing with Bias and Fairness in Building Data Science/ML/AI Systems

A Hands-on Tutorial

View on GitHub





Dealing with Bias and Fairness in Data Science Systems: A Practical Hands-on Tutorial

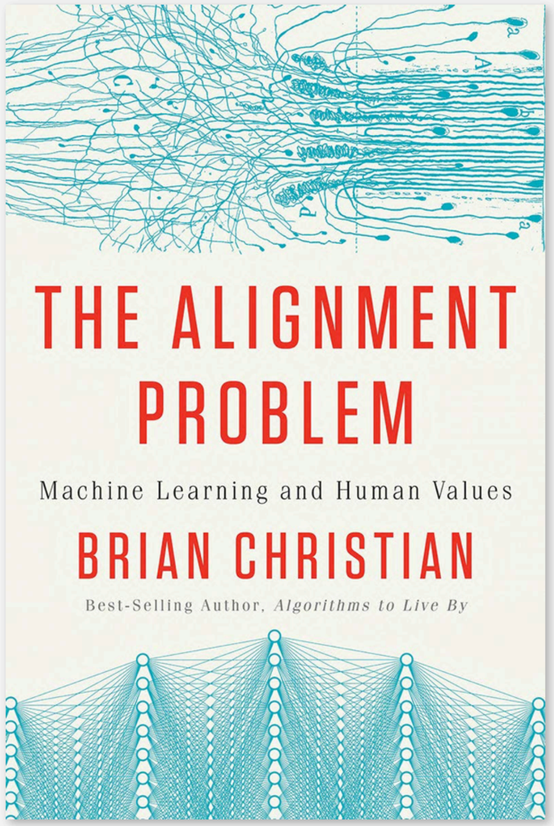
Earlier versions:

- Presented at KDD 2020: Github repo, Video, and web page

Presenters

- Pedro Saleiro, Feedzai
- Kit T. Rodolfa, Carnegie Mellon University
- Rayid Ghani, Carnegie Mellon University

https://dssg.github.io/fairness_tutorial/



Fascinating.

STUART RUSSELL, UC BERKELEY

Masterful.

CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION

Riveting.

PUBLISHERS WEEKLY

Vital.

MIKE KRIEGER, INSTAGRAM

Required reading.

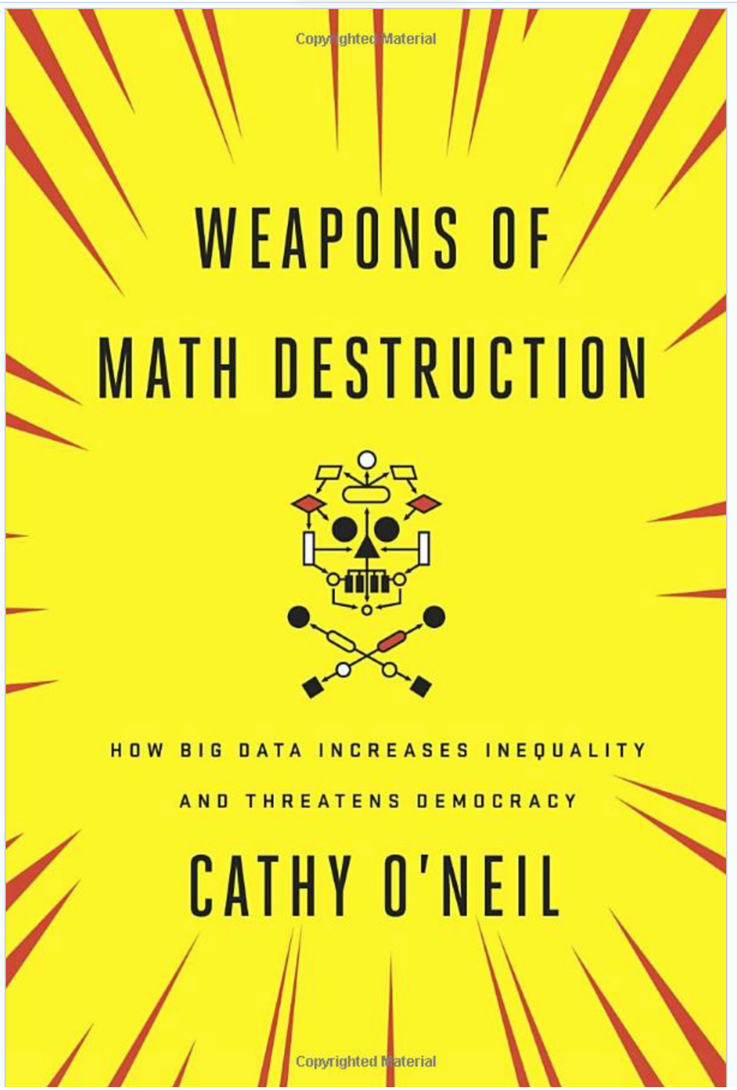
JENNIFER PAHLKA, CODE FOR AMERICA

Captivating.

JAAN TALLINN, SKYPE

Essential.

TIM O'REILLY, O'REILLY MEDIA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AND THREATENS DEMOCRACY
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