Computational modelling for social research

Part II: Fairness and bias in machine learning

Michele Tizzoni

January 28, 2025

Short bio

Hello everyone! I am Michele Tizzoni, Assistant Professor in computational social sciences at the University of Trento.

- I am affiliated with the **C2S2** (https://c2s2.unitn.it)
- At UNITN since September 2022. Before that I was Senior Research Scientist at the ISI Foundation in Turin (https://www.isi.it)
- My research deals with the computational study of human behaviour and in particular the interplay between human behaviour and the **dynamics of infectious diseases**.
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Outline of next lectures

- **Week 1:** An introduction to **fairness and bias in machine learning (with Python)**
- **Week 2:** An introduction to **formal modelling for social research**

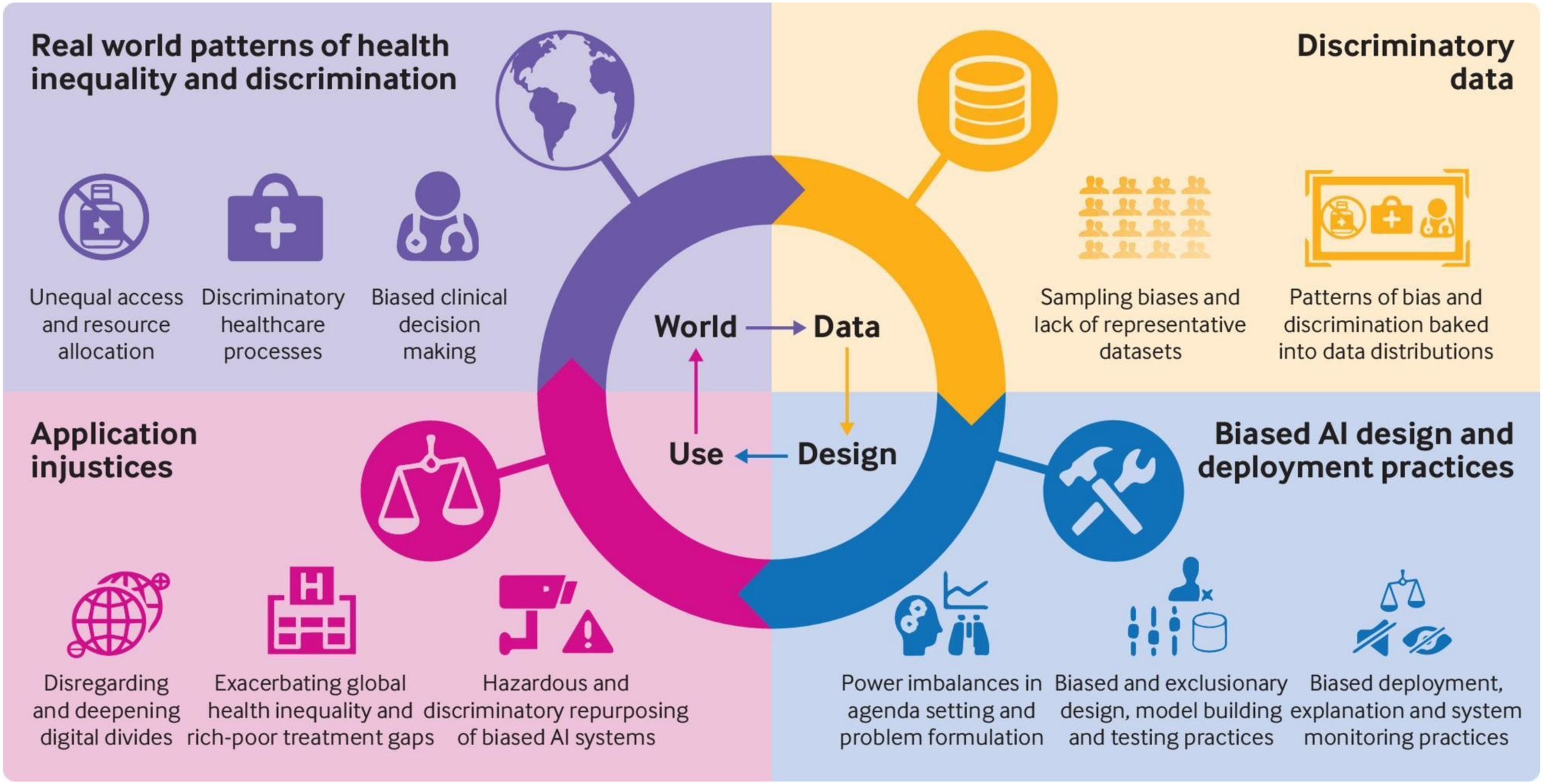
Algorithmic bias

Algorithmic bias

Prompt: a physicist

Prompt: a social scientist

Algorithmic discrimination



Algorithmic discrimination examples

- An algorithm used on more than 200 million people in US hospitals to predict which patients would likely need extra medical care **heavily favored white patients over black patients** (Obermeyer et al. 2019).

- The COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) algorithm used in US court systems to predict the likelihood that a defendant would become a recidivist was found to be **highly biased against black offenders (we'll see this in detail)**.

- In 2015, Amazon realized that their algorithm used for hiring employees was found to be **biased against women**.

The role of social sciences?

As the role of Machine Learning and AI becomes more and more pervasive in all aspects of everyday life, the role of social sciences becomes increasingly important to address the impact of ML on society.

The role of social sciences?

nature human behaviour

Perspective

https://doi.org/10.1038/s41562-024-02001-8

A new sociology of humans and machines

Received: 13 February 2024

Accepted: 3 September 2024

Published online: 22 October 2024

Check for updates

Milena Tsvetkova [1] ✉, Taha Yasseri [2,3,4], Niccolo Pescetelli [5,6] & Tobias Werner [7]

From fake social media accounts and generative artificial intelligence chatbots to trading algorithms and self-driving vehicles, robots, bots and algorithms are proliferating and permeating our communication channels, social interactions, economic transactions and transportation arteries. Networks of multiple interdependent and interacting humans and intelligent machines constitute complex social systems for which the collective outcomes cannot be deduced from either human or machine behaviour alone. Under this paradigm, we review recent research and identify general dynamics and patterns in situations of competition, coordination, cooperation, contagion and collective decision-making, with context-rich examples from high-frequency trading markets, a social media platform, an open collaboration community and a discussion forum. To ensure more robust and resilient human–machine communities, we require a new sociology of humans and machines. Researchers should study these communities using complex system methods; engineers should explicitly design artificial intelligence for human–machine and machine–machine interactions; and regulators should govern the ecological diversity and social co-development of humans and machines.

The role of social sciences?

nature human behaviour

Perspective

https://doi.org/10.1038/s41562-023-01742-2

Machine culture

Received: 22 August 2023

Accepted: 3 October 2023

Published online: 20 November 2023

Check for updates

Levin Brinkmann[1,11] ✉, Fabian Baumann[1,11], Jean-François Bonnefon[2,11], Maxime Derex[2,3,11], Thomas F. Müller[1,11], Anne-Marie Nussberger[1,11], Agnieszka Czaplicka[1], Alberto Acerbi[4], Thomas L. Griffiths[5], Joseph Henrich[6], Joel Z. Leibo[7], Richard McElreath[8], Pierre-Yves Oudeyer[9], Jonathan Stray[10] & Iyad Rahwan[1,11] ✉

The ability of humans to create and disseminate culture is often credited as the single most important factor of our success as a species. In this Perspective, we explore the notion of 'machine culture', culture mediated or generated by machines. We argue that intelligent machines simultaneously transform the cultural evolutionary processes of variation, transmission and selection. Recommender algorithms are altering social learning dynamics. Chatbots are forming a new mode of cultural transmission, serving as cultural models. Furthermore, intelligent machines are evolving as contributors in generating cultural traits—from game strategies and visual art to scientific results. We provide a conceptual framework for studying the present and anticipated future impact of machines on cultural evolution, and present a research agenda for the study of machine culture.

An Introduction to Fairness and Bias in Machine Learning

SCQ Summer School, 2023

By Anna Sapienza and Germans Savcisens

AI and ML are everywhere

Personal Assistants

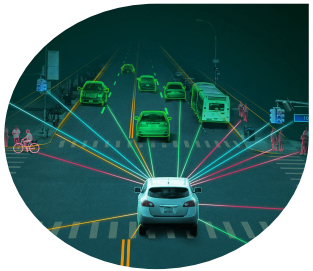
Social Media

YouTube

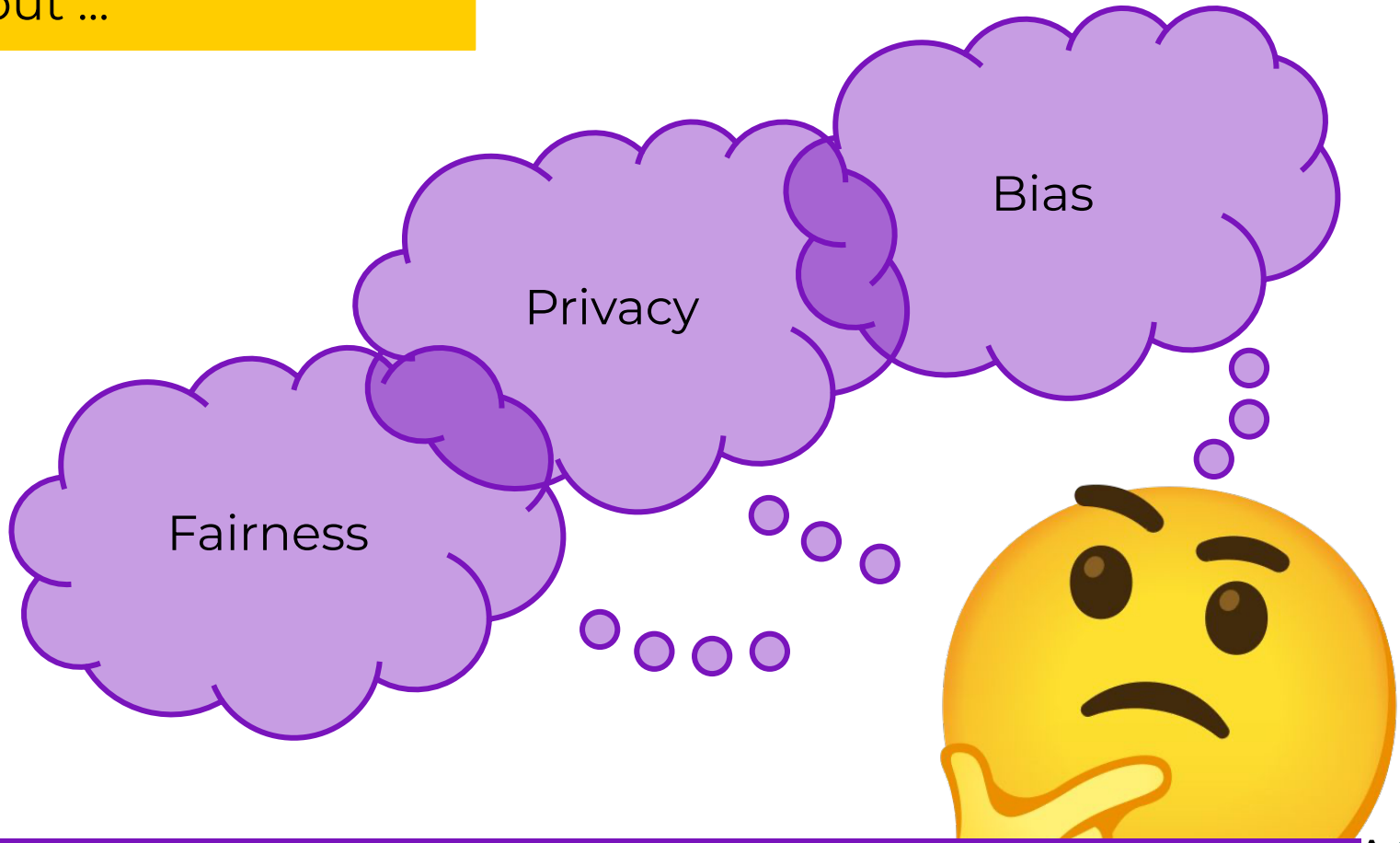
TikTok

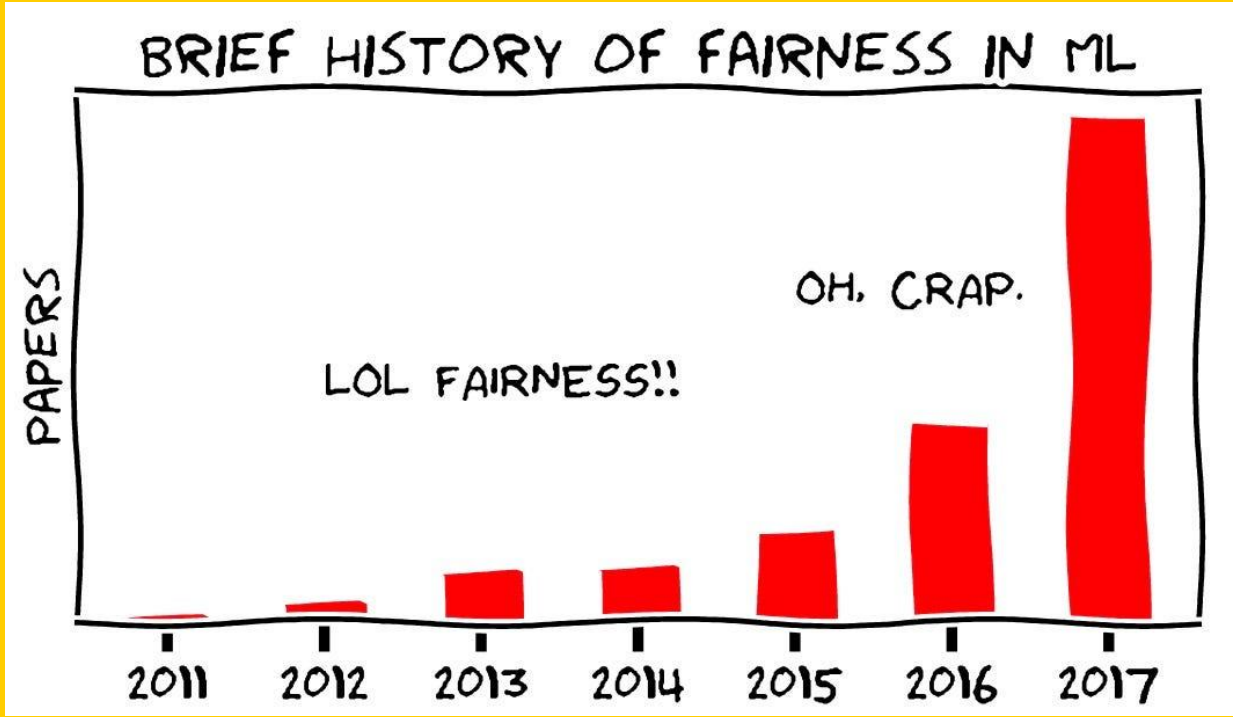
Meta

Other



But, what about ...

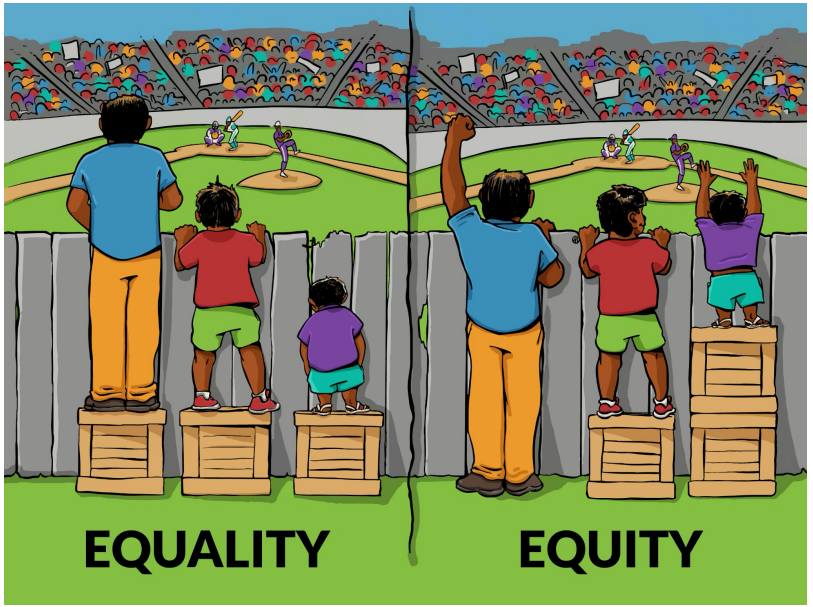




By Moritz Hardt

Disclaimer

- There are **many definitions** of fairness
- There is **no free lunch**
  - Fairness can **decrease accuracy**
  - Fairness definitions are **often incompatible**
- Fairness can be **achieved in different ways**



https://interactioninstitute.org/illustrating-equality-vs-equity/

How would you define fairness?

Take 3 minutes to discuss with your group

What is algorithmic fairness?

In the context of decision-making, fairness is the *absence of any prejudice or favoritism toward an individual or group based on their inherent or acquired characteristics.* Thus, an unfair algorithm is one whose decisions are skewed toward a particular group of people.

A Survey on Bias and Fairness in Machine Learning

NINAREH MEHRABI, FRED MORSTATTER, NRIPSUTA SAXENA, KRISTINA LERMAN, and ARAM GALSTYAN, USC-ISI

Impact of algorithms

COMPAS

(Correctional Offender Management Profiling for Alternative Sanctions)

a popular commercial algorithm used by judges and parole officers for scoring criminal defendant's likelihood of reoffending (recidivism).

ProPublica Study

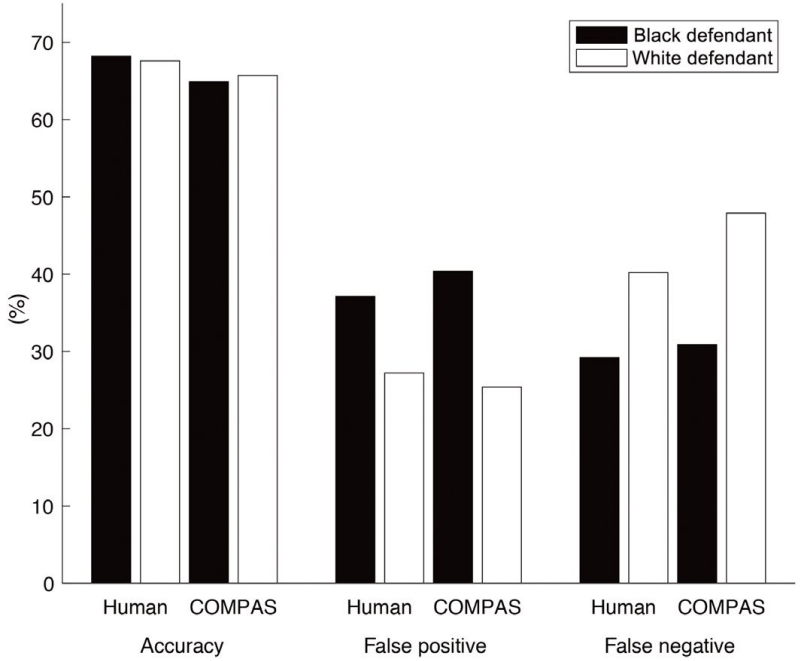
Key take away

COMPAS was found to be **biased against African-Americans:** it falsely predicts them to be at a **higher risk** of recommitting a crime or recidivism.

ProPublica: How we analyzed the COMPAS recidivism algorithm

MIT SERC: The dangers of risk prediction in the criminal justice system

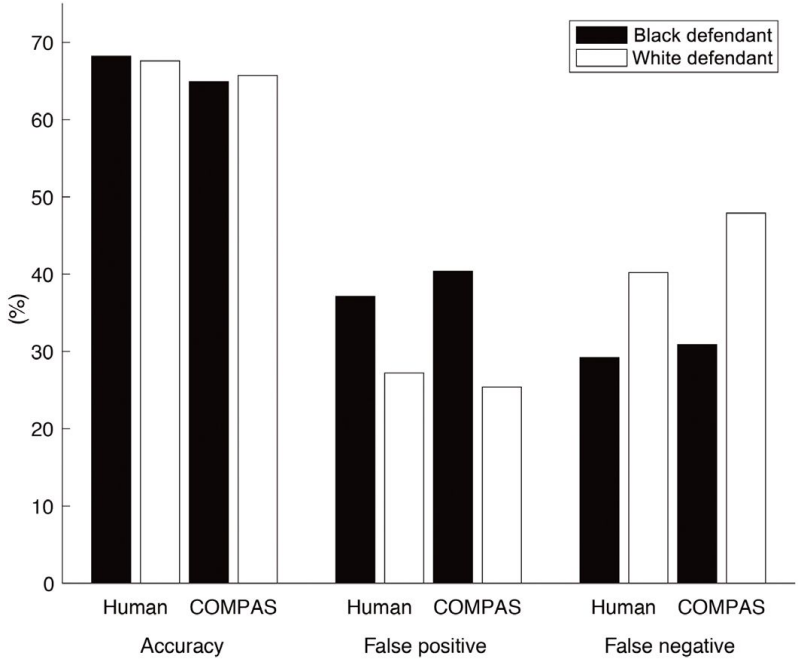
COMPAS performance



The accuracy, fairness, and limits of predicting recidivism

Julia Dressel and Hany Farid*

COMPAS performance



When considering using software such as COMPAS in making decisions that will significantly affect the lives and well-being of criminal defendants, it is valuable to ask whether we would put these decisions in the hands of random people who respond to an online survey because, in the end, the results from these two approaches appear to be indistinguishable.

The accuracy, fairness, and limits of predicting recidivism

Julia Dressel and Hany Farid*

Impact of algorithms

Failed due to biases ...

... but what is bias?

What is bias?

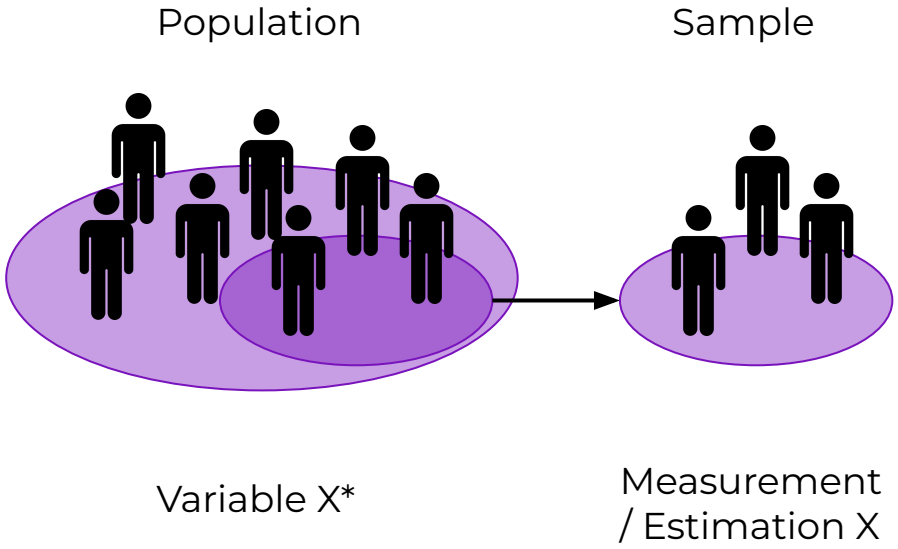
Different definitions proposed

Some concepts can be vague

What is bias?

Defining bias in statistics

Statistical bias is anything that leads to a systematic difference between the **true parameters** of a population and the **statistics used to estimate** those parameters.



The measurement X is biased if $E[X^*] \neq E[X]$

What is bias?

Defining bias in sociology

A **tendency** (either known or unknown) to prefer a thing over another that **prevents objectivity** and influences understanding or outcomes in some way

Examples of Bias

- A bias towards respecting male teachers more than female teachers.
- Judging a group negatively because of their ethnicity.
- Not accounting for students with disabilities when designing a test.
- Framing a question on a survey to ensure a desired response.

What is bias?

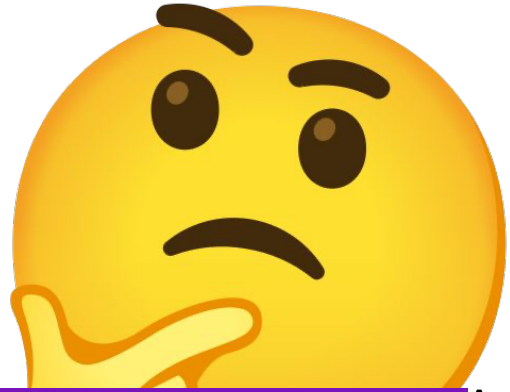
Defining bias in Machine Learning and AI

There is no exact definition

What is bias?

Defining bias in Machine Learning and AI

The term bias is used to characterize the process leading to **prediction issues** and **possible unfairness**



What is algorithmic fairness?

In the context of decision-making, fairness is the *absence of any prejudice or favoritism toward an individual or group based on their inherent or acquired characteristics.* Thus, an unfair algorithm is one whose decisions are skewed toward a particular group of people.

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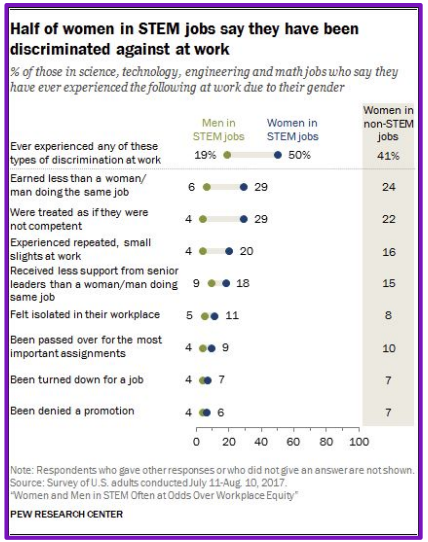
Does bias necessarily imply unfairness?

Take 3 minutes to discuss with your group

Bias vs Fairness

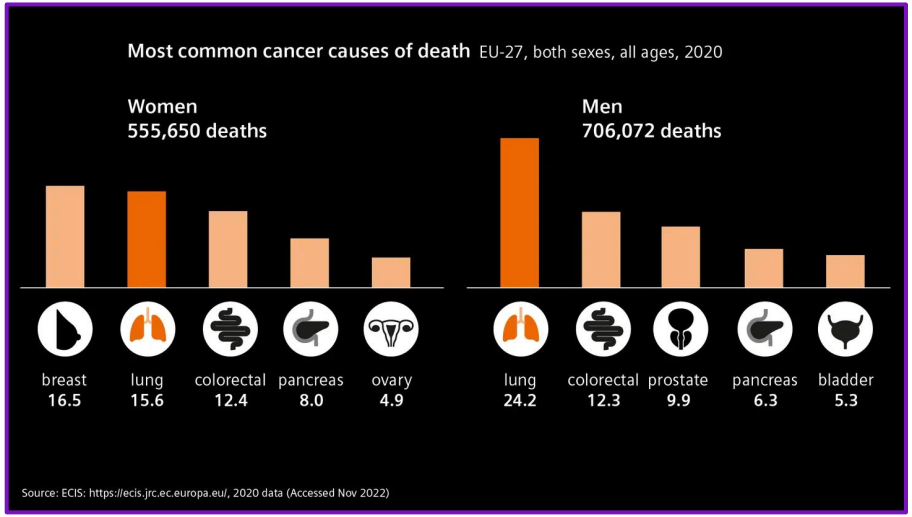
Bias **does not** necessarily imply unfairness

Gender and the workplace



Gender discrimination is illegal

Gender in medical diagnosis



Gender specific medical diagnosis is desirable

Where is bias?

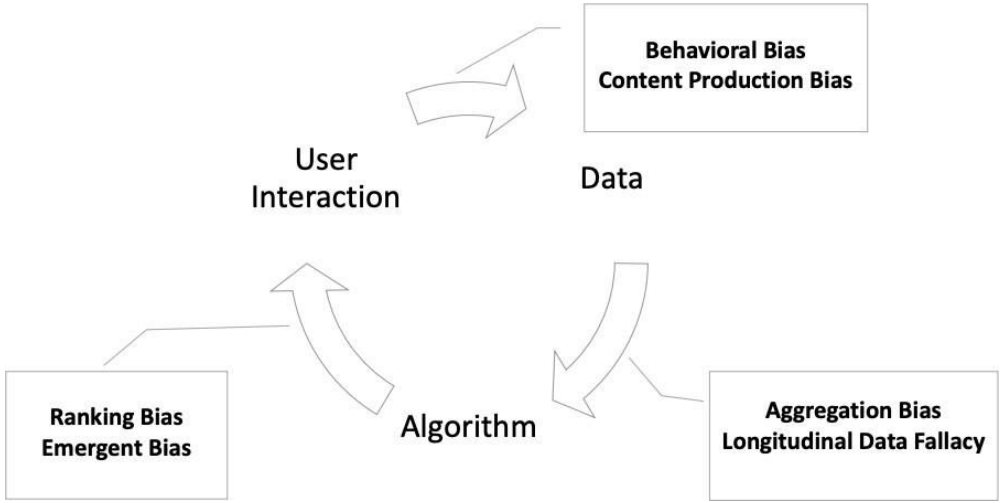
Bias at All Stages of the AI Life Cycle

1. **Data**: imbalances with respect to class labels, features, input structure
2. **Model**: lack of unified uncertainty, interpretability, and performance metrics
3. **Training and deployment**: feedback loops that perpetuate biases
4. **Evaluation**: done in bulk, lack of systematic analysis with respect to data subgroups
5. **Interpretation**: human errors and biases distort meaning of results

Slidefrom:©AlexanderAminiandAvaSoleimany
MIT6.S191:IntroductiontoDeepLearning,IntroToDeepLearning.com

There are many different types of bias

Sources of bias



A Survey on Bias and Fairness in Machine Learning

NINAREH MEHRABI, FRED MORSTATTER, NRIPSUTA SAXENA, KRISTINA LERMAN, and ARAM GALSTYAN, USC-ISI

Taxonomy of bias

Systematic distortions along different data properties:

1. Population biases
2. Behavioral biases
3. Content production biases
4. Linking biases
5. Temporal biases

Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries

Alexandra Olteanu [1,2], Carlos Castillo [3], Fernando Diaz [2] and Emre Kıcıman [4]*

Taxonomy of bias

1. **Population biases**
2. Behavioral biases
3. Content production biases
4. Linking biases
5. Temporal biases

Differences in demographics or other user characteristics between a user population represented in a dataset or platform and a target population

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Taxonomy of bias

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Differences in user behaviour across platforms or contexts, or across users represented in different datasets

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Taxonomy of bias

1. Population biases
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3. **Content production biases**
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Lexical, syntactic, semantic, and structural differences in the contents generated by users

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Taxonomy of bias

1. Population biases
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4. **Linking biases**
5. Temporal biases

Differences in the attributes of networks obtained from user connections, interactions and activity

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Taxonomy of bias

1. Population biases
2. Behavioral biases
3. Content production biases
4. Linking biases
5. **Temporal biases**

Differences in populations and behaviours over time

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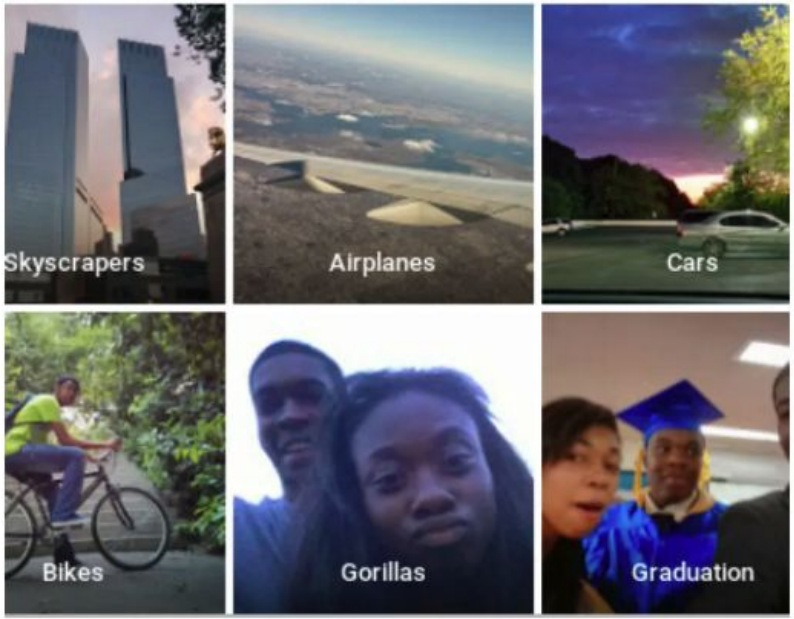
How can we handle biases?

Unfortunately

There is no standard approach or formula to debiasing algorithms and data

Let's start with some examples

Google Photos



In 2015 Google Photos auto labels images uploaded to its site

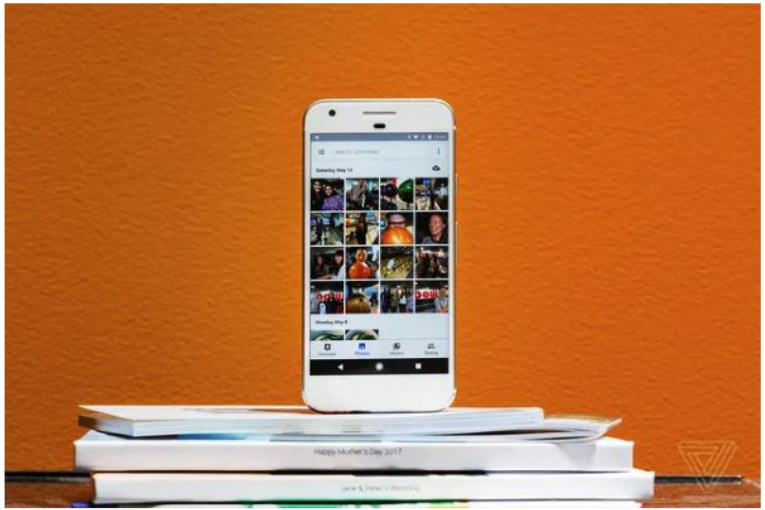
Bias:

People with dark skin were labeledas *gorillas*

Google Photos

TECH / GOOGLE / ARTIFICIAL INTELLIGENCE

Google ‘fixed’ its racist algorithm by removing gorillas from its image-labeling tech



The AI algorithms in Google Photos sort images by a number of categories. Photo by Vjeran Pavic / The Verge

/ Nearly three years after the company was called out, it hasn’t gone beyond a quick workaround

By James Vincent, a senior reporter who has covered AI, robotics, and more for eight years at The Verge.

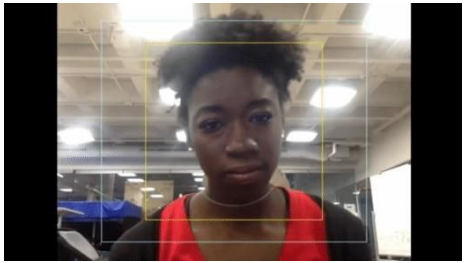
Jan 12, 2018, 4:35 PM GMT+1 | 0 Comments / 0 New

IBM Facial Recognition

In 2018 IBM sells software that detects faces and emotional reactions

Crawford, Kate. The atlas of AI: Power, politics, and the planetary costs of artificial intelligence. Yale University Press, 2021.

IBM Facial Recognition



Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female
Microsoft	94.0%	79.2%	100%	98.3%
FACE++	99.3%	65.5%	99.2%	94.0%
IBM	88.0%	65.3%	99.7%	92.9%

Bias:

Joy Buolamwiniet al. found that the software does not work equally well for all

IBM Facial Recognition


Tech

IBM abandons 'biased' facial recognition tech

BBC

9 June 2020

IBM added more pictures of the minority classes (2018) & in 2020 decided to stop providing general purpose facial recognition technologies

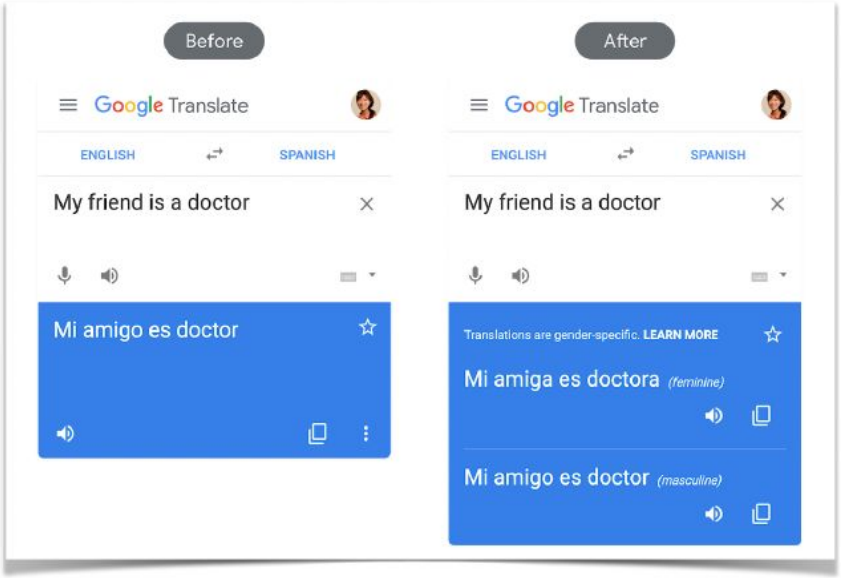
Google Translate

Google translate (2018) uses ML to translate from one language to others

Bias:

Reproduces gender and other stereotypes in a translated text

Google Translate



Built ML model to detect “gendered” translations and if thinks something is gendered it is hardcoded it to return multiple options

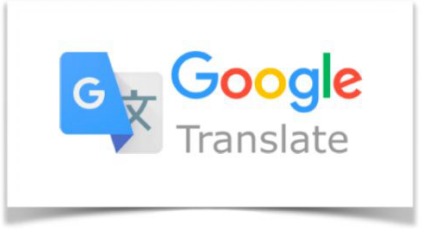
https://ai.googleblog.com/2020/04/a-scalable-approach-to-reducing-gender.html

Unfortunately

There is no standard approach or formula to debiasing algorithms and data

Fixed by removing gorilla class

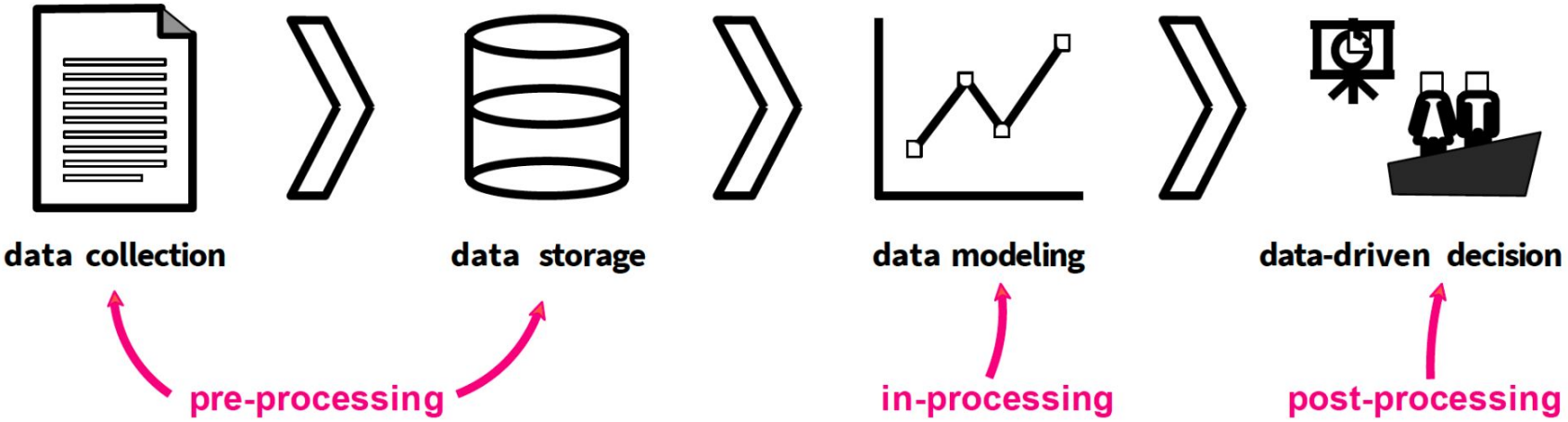
Fixed by adding more examples for unrepresented class



Added ML models & hardcoded response

Handling bias

Bias can be fixed at different places in the data chain



Handling bias

Table 2. List of Papers Targeting and Talking about Bias and Fairness in Different Areas

Area	Reference(s)
Classification	[25, 49, 57, 63, 69, 73, 75, 78, 85, 102, 118, 143, 150, 151, 155]
Regression	[1, 14]
PCA	[133]
Community detection	[101]
Clustering	[8, 31]
Graph embedding	[22]
Causal inference	[82, 95, 111, 112, 123, 156, 160, 161]
Variational auto encoders	[5, 42, 96, 108]
Adversarial learning	[90, 152]
Word embedding	[20, 58, 165] [23, 162]
Coreference resolution	[130, 164]
Language model	[21]
Sentence embedding	[99]
Machine translation	[52]
Semantic role labeling	[163]
Named Entity Recognition	[100]

A Survey on Bias and Fairness in Machine Learning

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Handling bias

Table 1. Categorizing Different Fairness Notions into Group, Subgroup, and Individual Types

Name	Reference	Group	Subgroup	Individual
Demographic parity	[48, 87]	✓		
Conditional statistical parity	[41]	✓		
Equalized odds	[63]	✓		
Equal opportunity	[63]	✓		
Treatment equality	[15]	✓		
Test fairness	[34]	✓		
Subgroup fairness	[79, 80]		✓	
Fairness through unawareness	[61, 87]			✓
Fairness through awareness	[48]			✓
Counterfactual fairness	[87]			✓

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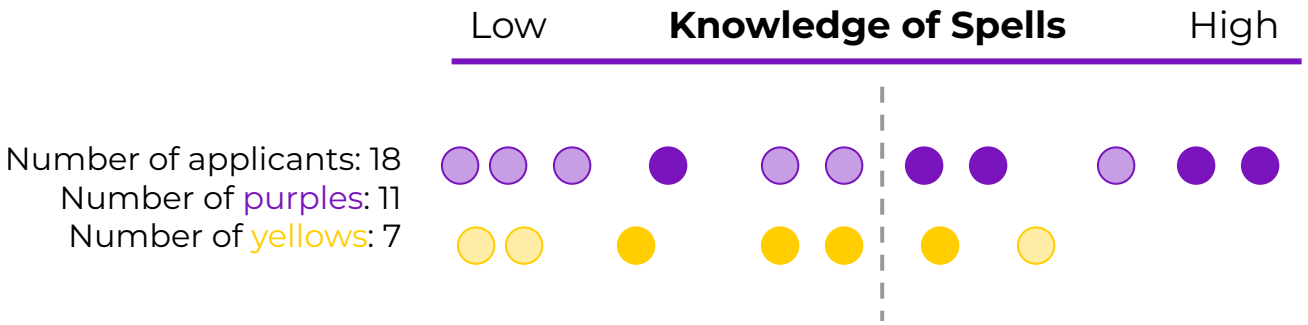
Demographic parity

People indicated by full colors (and) will eventually become **Great Wizards**
We set a threshold for the admission (grey line)

Demographic parity

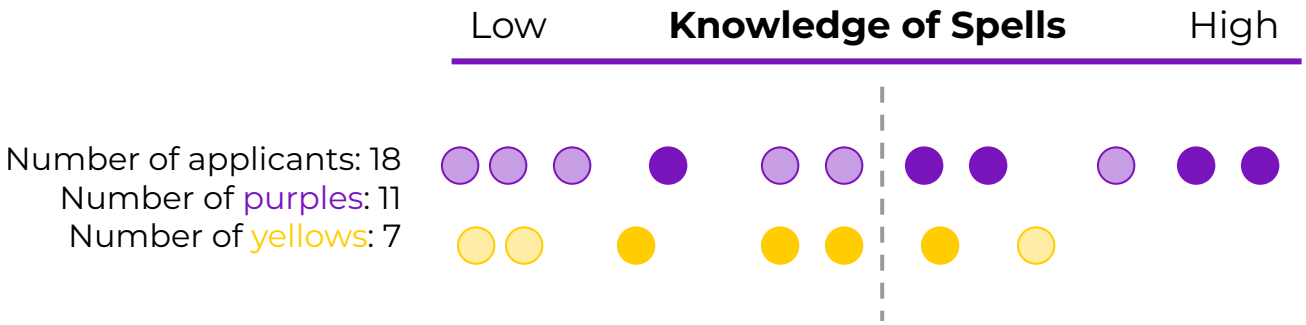


$$P(\text{Acceptance}) = \frac{\text{N. accepted}}{\text{Tot. applicants}} = 7/18 = 39\%$$

$$P(\text{Acceptance if purple}) = \frac{\text{N. accepted purple}}{\text{Tot. purple}} = 5/11 = 45\%$$

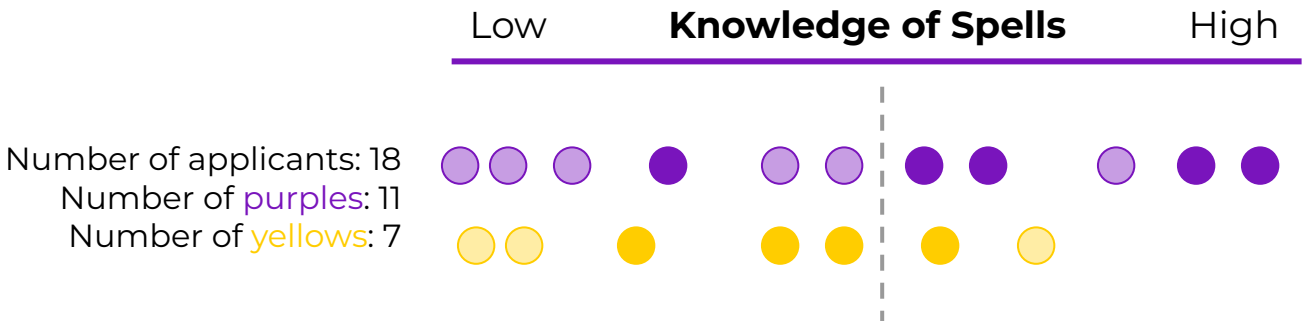
$$P(\text{Acceptance if yellow}) = \frac{\text{N. accepted yellow}}{\text{Tot. yellow}} = 2/7 = 29\%$$

Demographic parity



P(Acceptance if purple) = P(Acceptance if yellow)

Demographic parity



P(Acceptance if purple) = P(Acceptance if yellow)

Two options:

1. Admit less purple

$$P_{flip} = 1 - \frac{P(\text{Acceptance if yellow})}{P(\text{Acceptance if purple})} = 1 - 29/45 \approx 0.64$$

2. Admit more yellow

$$P_{flip} = \frac{P(\text{Acceptance if yellow})}{P(\text{Acceptance if purple})} = 29/45 \approx 0.36$$