

# **Responsible Data Science**

## **Algorithmic Fairness**

*February 1 & 8, 2022*

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Center for Data Science &  
Computer Science and Engineering  
New York University

# RDS course overview

# So what is RDS?

**As advertised:** ethics, legal compliance, personal responsibility.  
But also: **data quality!**

A technical course, with content drawn from:

1. fairness, accountability and transparency
2. data engineering
3. privacy & data protection



We will learn **algorithmic techniques** for data analysis.

We will also learn about recent **laws / regulatory frameworks**.

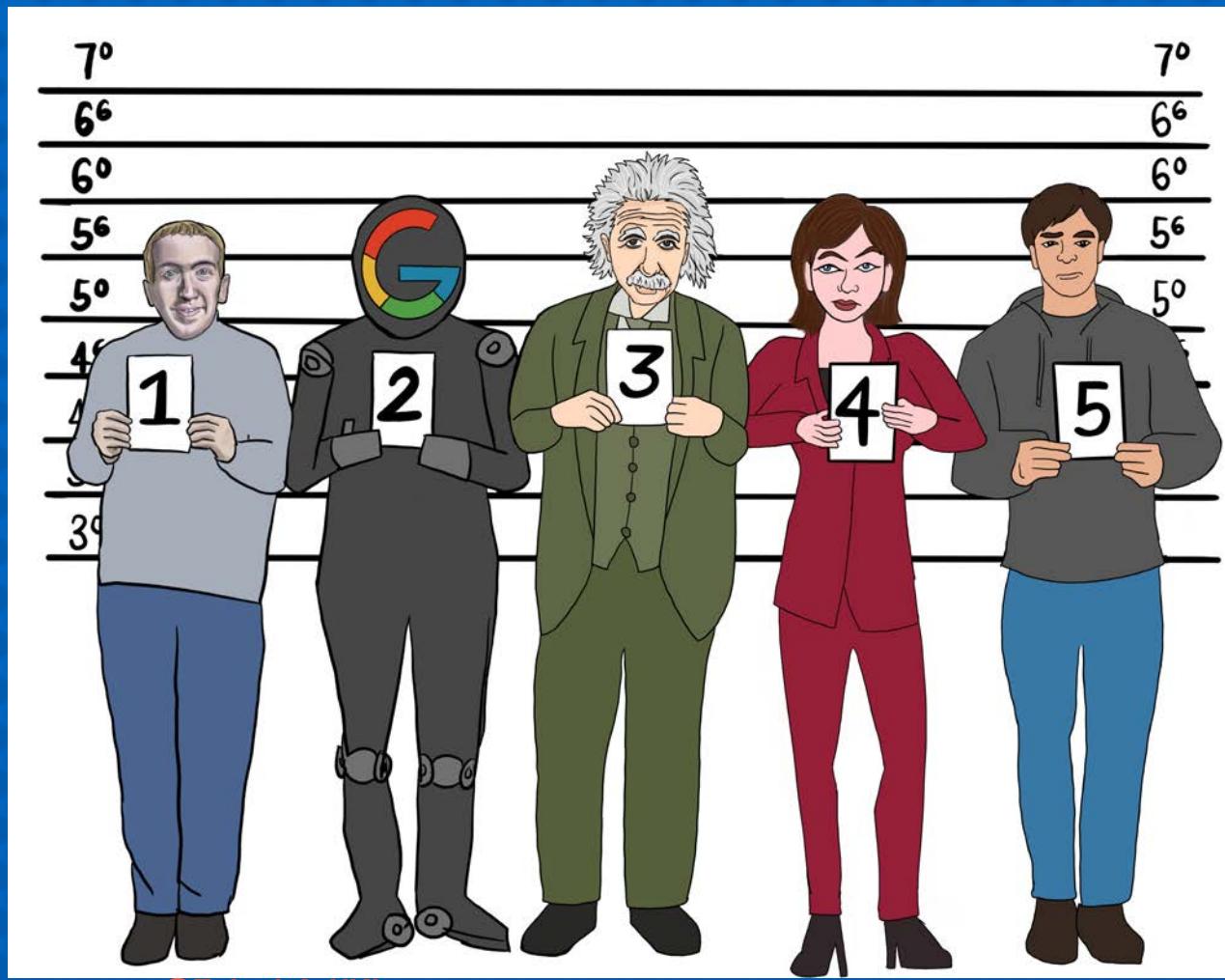
Bottom line: we will learn that many of the problems are **socio-technical**, and so cannot be “solved” with technology alone.

My perspective: a pragmatic engineer, **not** a technology skeptic.

# Nuance, please!



# We all are responsible



@FalaahArifKhan

# Reading: Algorithmic bias

## Bias in Computer Systems

BATYA FRIEDMAN

Colby College and The Mina Institute

and

HELEN NISSENBAUM

Princeton University

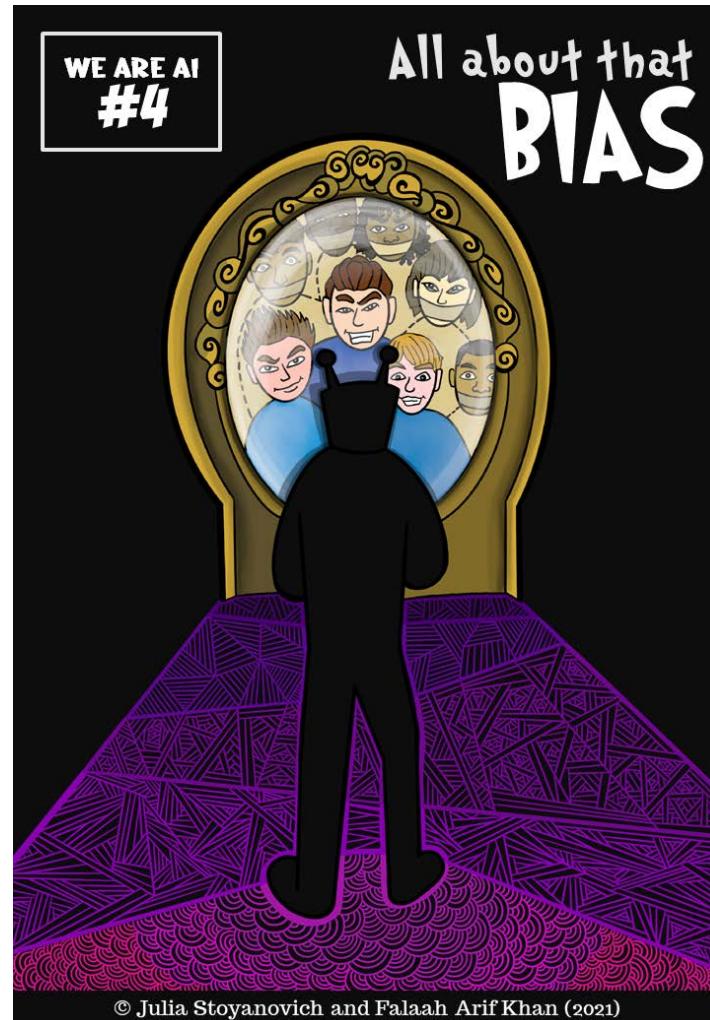
From an analysis of actual cases, three categories of bias in computer systems have been developed: preexisting, technical, and emergent. Preexisting bias has its roots in social institutions, practices, and attitudes. Technical bias arises from technical constraints or considerations. Emergent bias arises in a context of use. Although others have pointed to bias in particular computer systems and have noted the general problem, we know of no comparable work that examines this phenomenon comprehensively and which offers a framework for understanding and remedying it. We conclude by suggesting that freedom from bias should be counted among the select set of criteria—including reliability, accuracy, and efficiency—according to which the quality of systems in use in society should be judged.

Categories and Subject Descriptors: D.2.0 [**Software**]: Software Engineering; H.1.2 [**Information Systems**]: User/Machine Systems; K.4.0 [**Computers and Society**]: General

General Terms: Design, Human Factors

Additional Key Words and Phrases: Bias, computer ethics, computers and society, design methods, ethics, human values, standards, social computing, social impact, system design, universal design, values

[Friedman & Nissenbaum, Comm ACM (1996)]



# Reading: Algorithmic fairness

DOI:10.1145/3376898

**A group of industry, academic, and government experts convene in Philadelphia to explore the roots of algorithmic bias.**

BY ALEXANDRA CHOULDECHOVA AND AARON ROTH

## A Snapshot of the Frontiers of Fairness in Machine Learning

[Chouldechova & Roth, Comm ACM (2020)]

### Fairness Through Awareness

Cynthia Dwork\*    Moritz Hardt†    Toniann Pitassi‡    Omer Reingold§  
Richard Zemel¶

November 30, 2011

optional

#### Abstract

We study *fairness in classification*, where individuals are classified, e.g., admitted to a university, and the goal is to prevent discrimination against individuals based on their membership in some group, while maintaining utility for the classifier (the university). The main conceptual contribution of this paper is a framework for fair classification comprising (1) a (hypothetical) task-specific metric for determining the degree to which individuals are similar with respect to the classification task at hand; (2) an algorithm for maximizing utility subject to the *fairness constraint*, that similar individuals are treated similarly. We also present an adaptation of our approach to achieve the complementary goal of “fair affirmative action,” which guarantees *statistical parity* (i.e., the demographics of the set of individuals receiving any classification are the same as the demographics of the underlying population), while treating similar individuals as similarly as possible. Finally, we discuss the relationship of fairness to privacy: when fairness implies privacy, and how tools developed in the context of differential privacy may be applied to fairness.

### On the (im)possibility of fairness\*

Sorelle A. Friedler    Carlos Scheidegger    Suresh Venkatasubramanian  
Haverford College†    University of Arizona‡    University of Utah§

optional

#### Abstract

What does it mean for an algorithm to be fair? Different papers use different notions of algorithmic fairness, and although these appear internally consistent, they also seem mutually incompatible. We present a mathematical setting in which the distinctions in previous papers can be made formal. In addition to characterizing the spaces of inputs (the “observed” space) and outputs (the “decision” space), we introduce the notion of a *construct space*: a space that captures unobservable, but meaningful variables for the prediction. We show that in order to prove desirable properties of the entire decision-making process, different mechanisms for fairness require different assumptions about the nature of the mapping from construct space to decision space. The results in this paper imply that future treatments of algorithmic fairness should more explicitly state assumptions about the relationship between constructs and observations.

# Reading: Fairness in risk assessment

## 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



Fair prediction with disparate impact:  
A study of bias in recidivism prediction instruments

Alexandra Chouldechova \*

Last revised: February 8, 2017

### Abstract

Recidivism prediction instruments (RPI's) provide decision makers with an assessment of the likelihood that a criminal defendant will reoffend at a future point in time. While such instruments are gaining increasing popularity across the country, their use is attracting tremendous controversy. Much of the controversy concerns potential discriminatory bias in the risk assessments that are produced. This paper discusses several fairness criteria that have recently been applied to assess the fairness of recidivism prediction instruments. We demonstrate that the criteria cannot all be simultaneously satisfied when recidivism prevalence differs across groups. We then show how disparate impact can arise when a recidivism prediction instrument fails to satisfy the criterion of error rate balance.

**Keywords:** disparate impact; bias; recidivism prediction; risk assessment; fair machine learning

[Chouldechova, BigData (2017)]

## Inherent Trade-Offs in the Fair Determination of Risk Scores

Jon Kleinberg<sup>1</sup>, Sendhil Mullainathan<sup>2</sup>, and Manish Raghavan<sup>3</sup>

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[kleinber@cs.cornell.edu](mailto:kleinber@cs.cornell.edu)

<sup>2</sup> Harvard University, Cambridge, USA  
[mullain@fas.harvard.edu](mailto:mullain@fas.harvard.edu)

<sup>3</sup> Cornell University, Ithaca, USA  
[manish@cs.cornell.edu](mailto:manish@cs.cornell.edu)

### Abstract

Recent discussion in the public sphere about algorithmic classification has involved tension between competing notions of what it means for a probabilistic classification to be fair to different groups. We formalize three fairness conditions that lie at the heart of these debates, and we prove that except in highly constrained special cases, there is no method that can satisfy these three conditions simultaneously. Moreover, even satisfying all three conditions approximately requires that the data lie in an approximate version of one of the constrained special cases identified by our theorem. These results suggest some of the ways in which key notions of fairness are incompatible with each other, and hence provide a framework for thinking about the trade-offs between them.

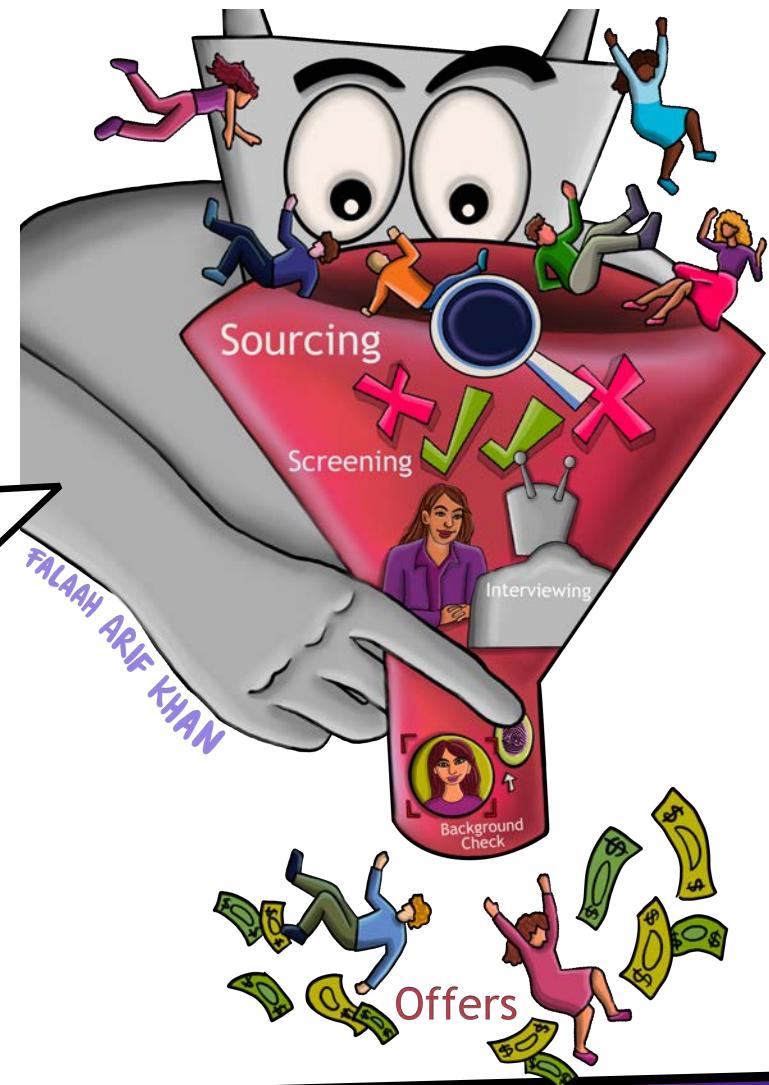
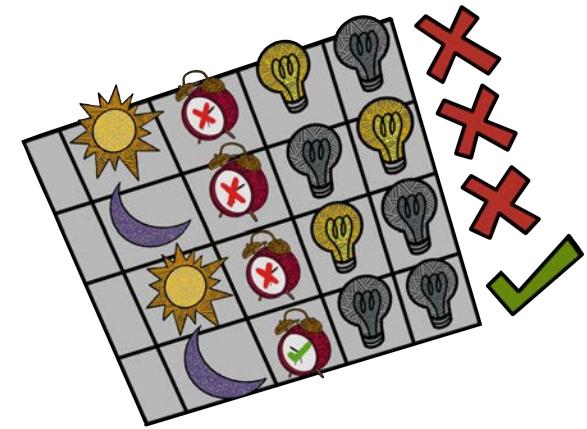
1998 ACM Subject Classification H.2.8 Database Applications, J.1 Administrative Data Processing

Keywords and phrases algorithmic fairness, risk tools, calibration

Digital Object Identifier 10.4230/LIPIcs.ITCS.2017.43

[Kleinberg, Mullainathan & Raghavan, ITCS (2017)]

# Recall: Individual & cumulative harms



## Questions to keep in mind:

what are the **goals** of the AI system?

what are the **benefits** and to **whom**?

what are the **harms** and to **whom**?



technical teaser c. 2015:  
fairness in classification

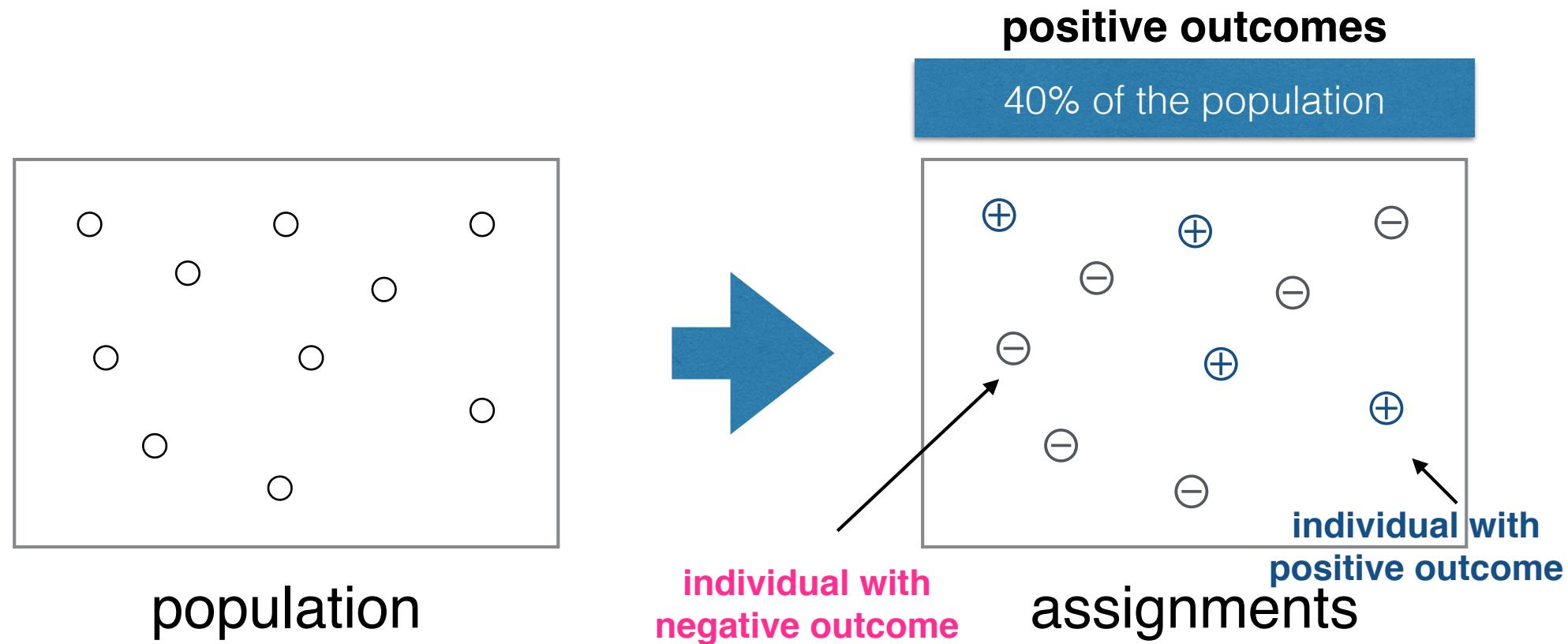
# Vendors and outcomes

Consider a **vendor** assigning positive or negative **outcomes** to individuals.

Positive Outcomes	Negative Outcomes
offered employment	not offered employment
accepted to school	not accepted to school
offered a loan	denied a loan
shown relevant ad for choc	shown irrelevant ad for choc

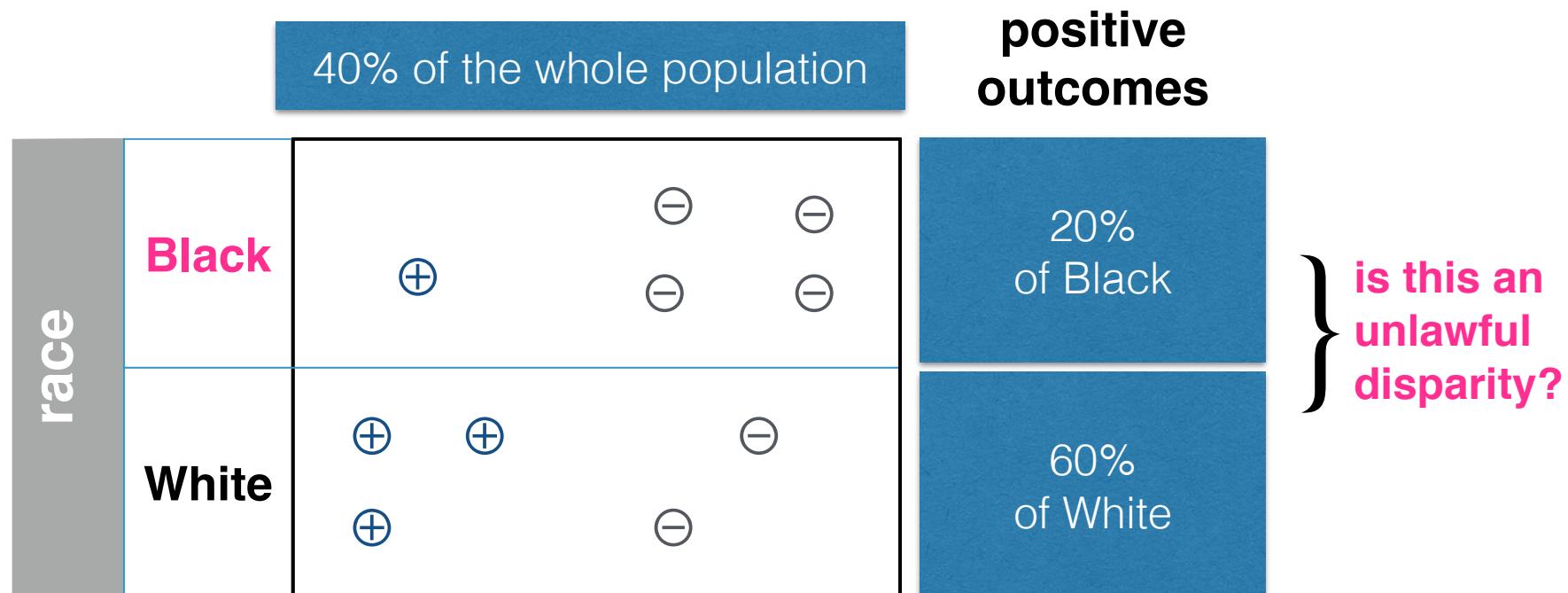
# Fairness in classification

**Fairness** in classification is concerned with how outcomes are assigned to a population



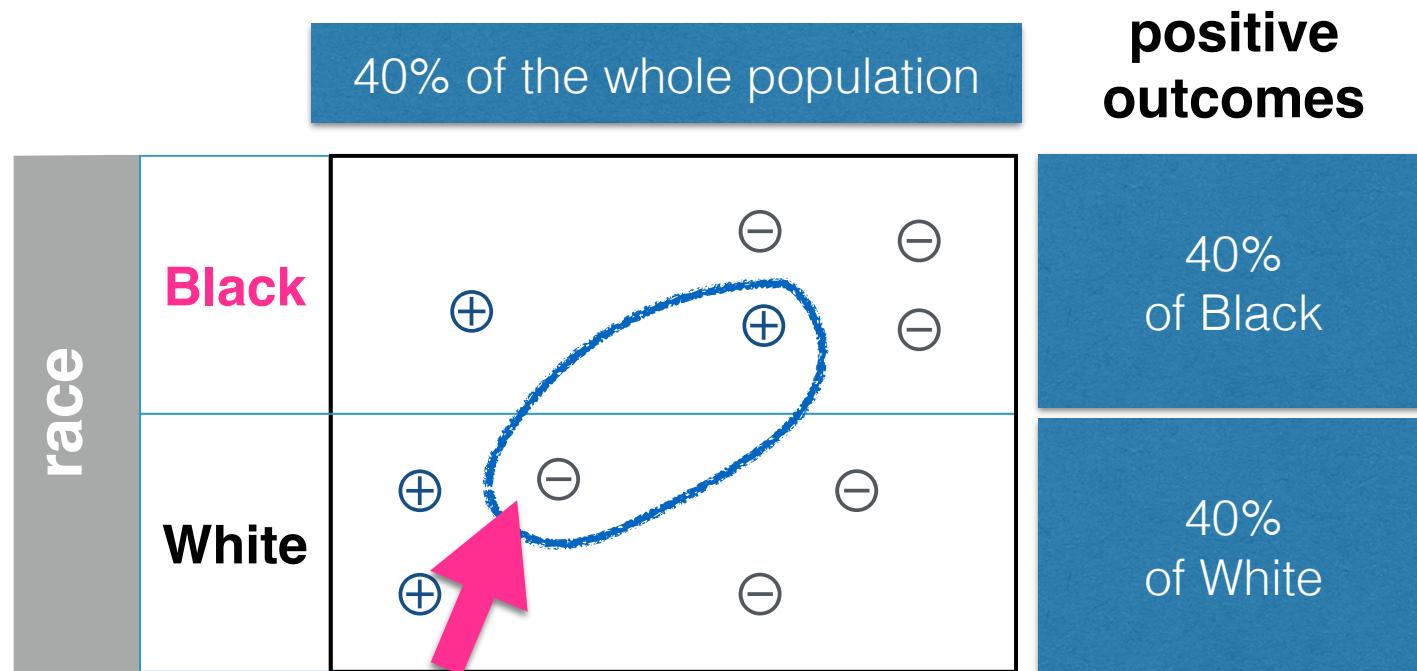
# Fairness in classification

**Sub-populations** may be treated differently



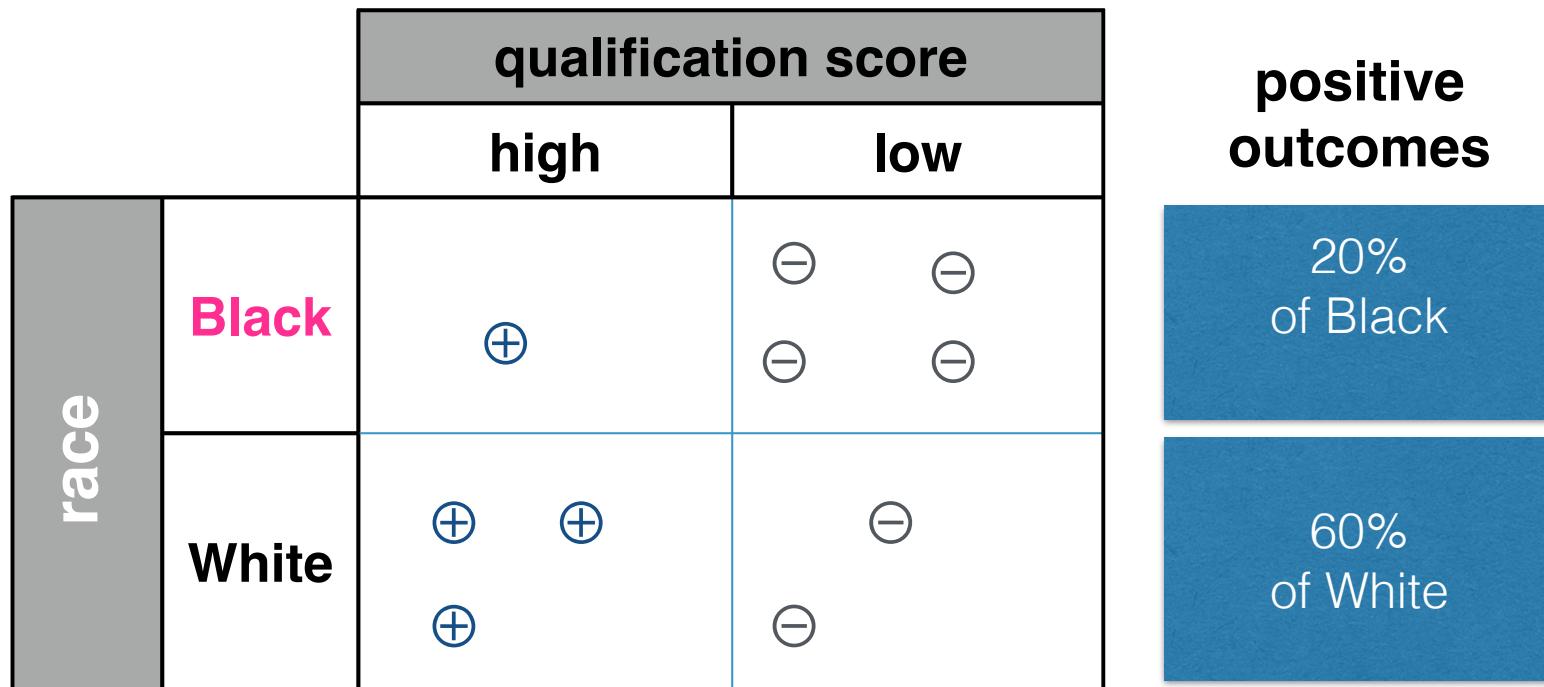
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# Fairness in classification

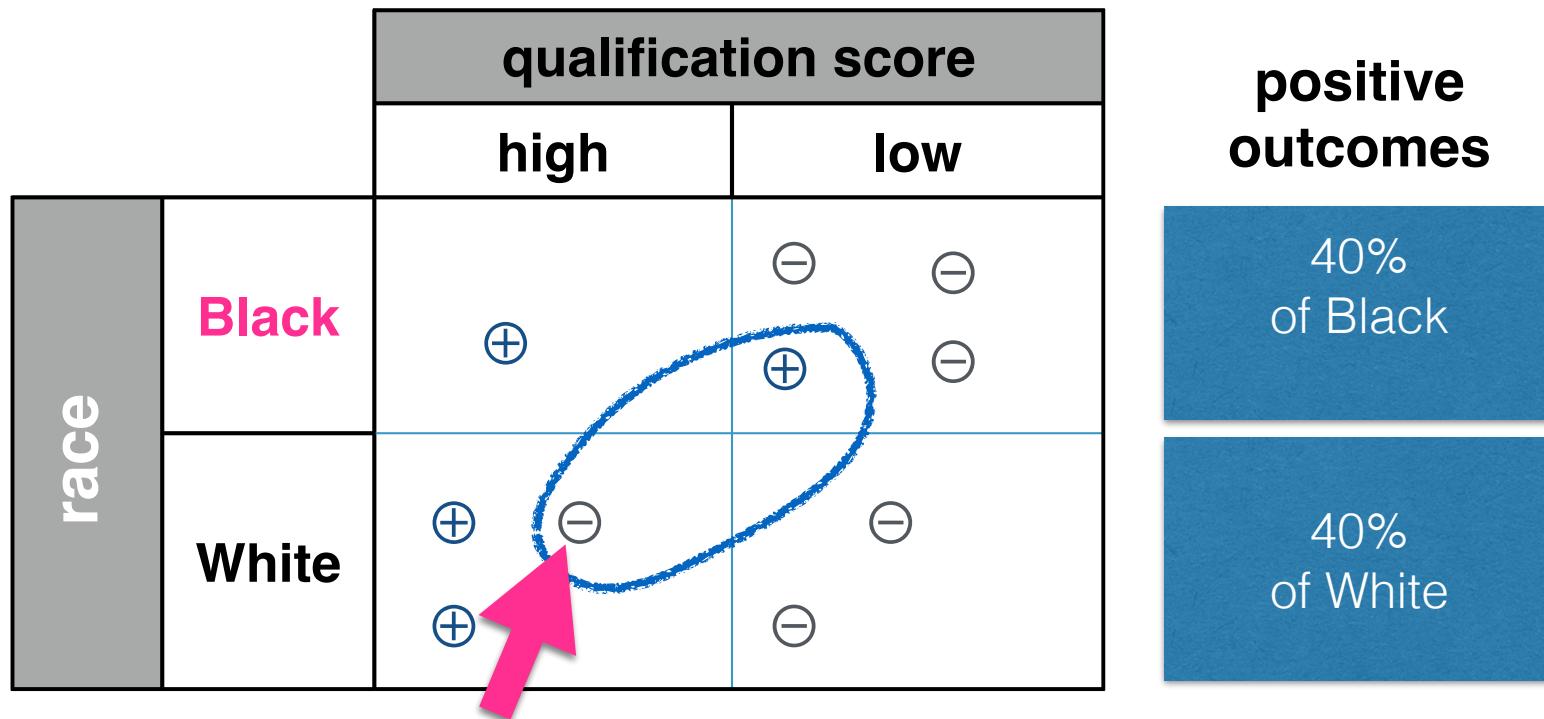
Explaining the disparity with proxy variables





quick discussion

# Swapping outcomes



# Two families of fairness measures

## Group fairness (here, **statistical parity**)

demographics of the individuals receiving any outcome - positive or negative - should be the same as demographics of the underlying population

## Individual fairness

any two individuals who are similar **with respect to a task** should receive similar outcomes

# Bias in computer systems

**Pre-existing** is independent of an algorithm and has origins in society

**Technical** is introduced or exacerbated by the technical properties of an ADS

**Emergent** arises due to context of use



[Friedman & Nissenbaum (1996)]



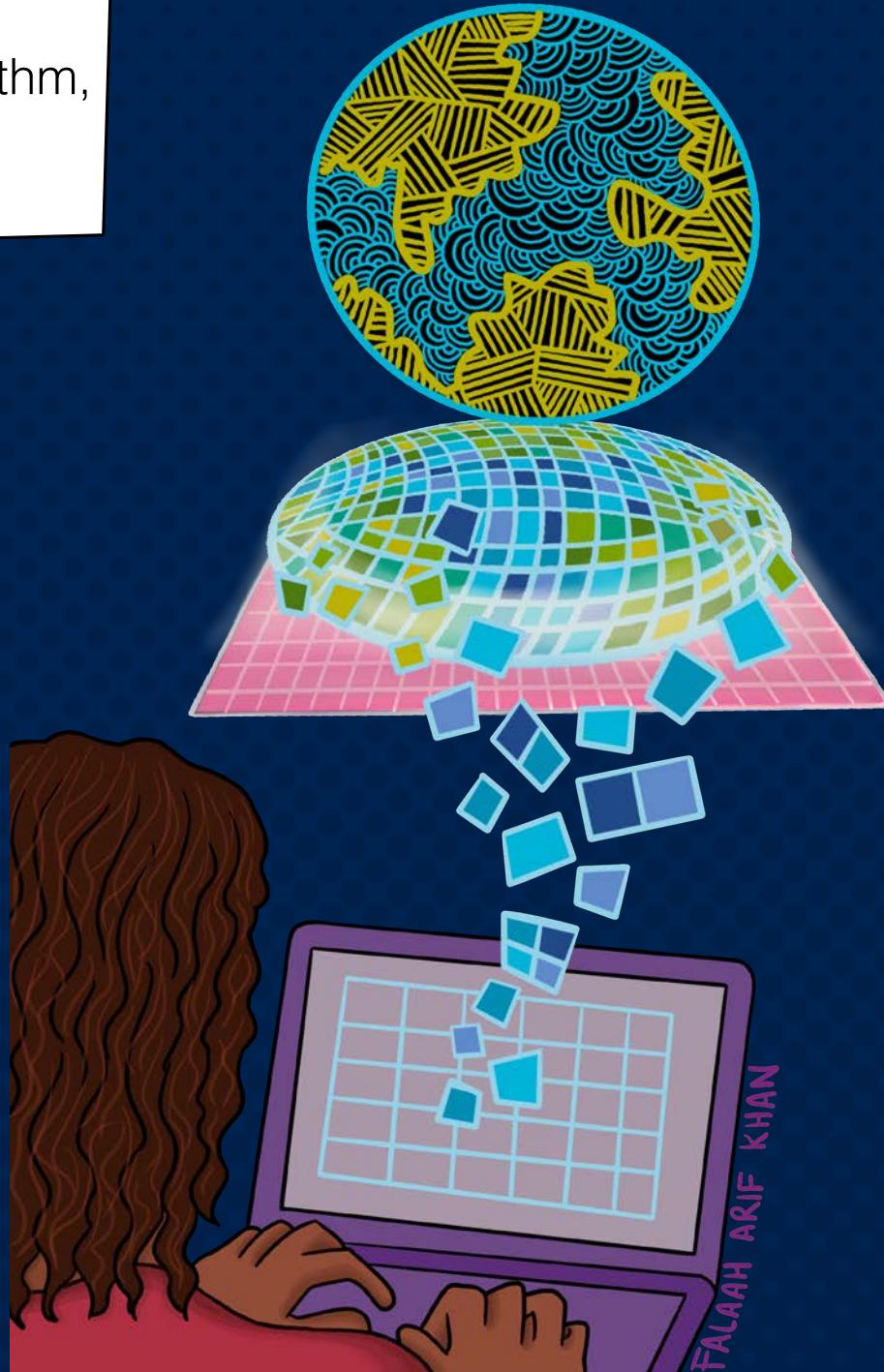
## Pre-existing bias:

independent of an algorithm,  
has its origins in society



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FALAAH ARIF KHAN

r/ai

## Pre-existing bias:

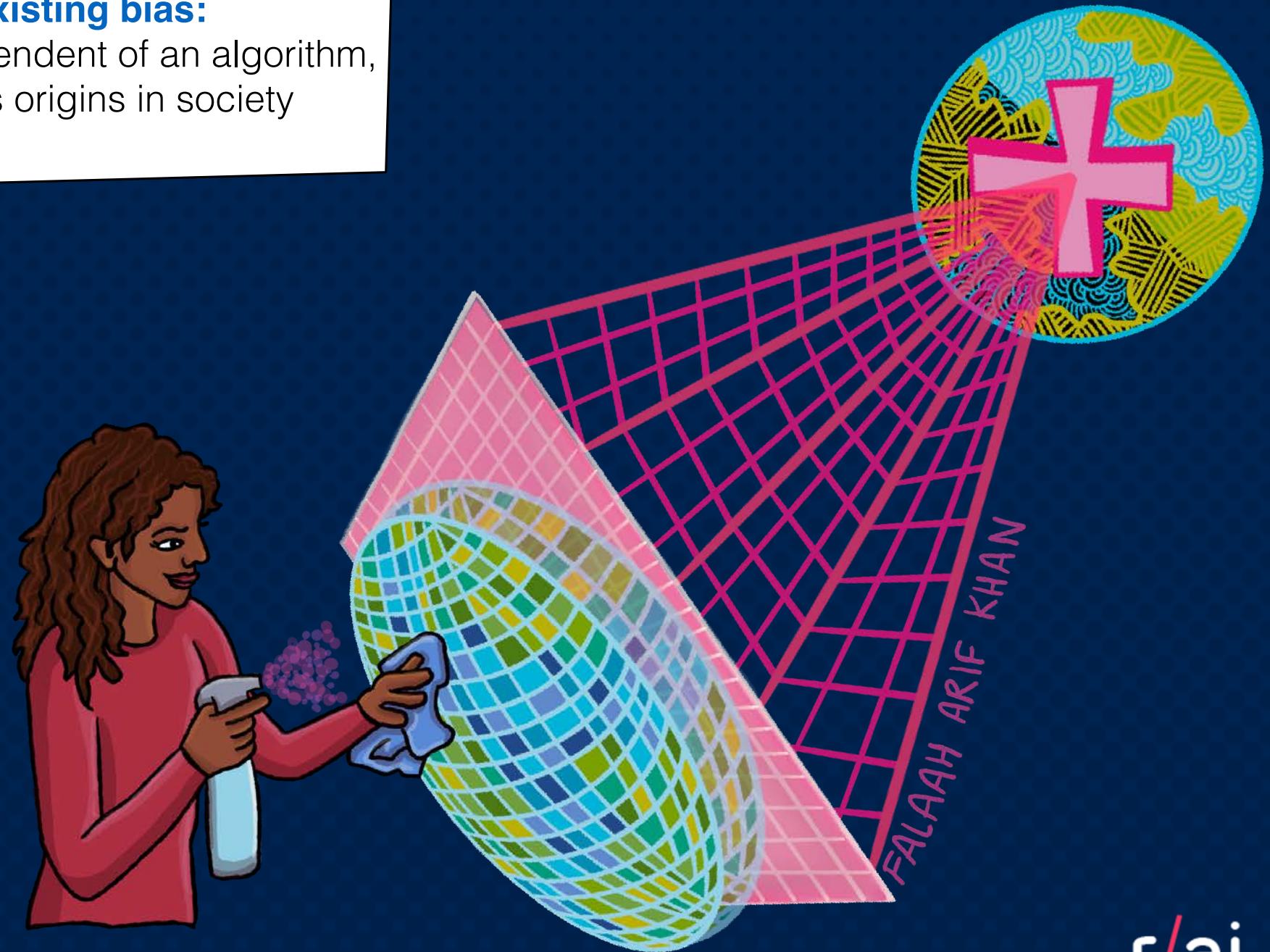
independent of an algorithm,  
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FALAAH ARIF KHAN

## Pre-existing bias:

independent of an algorithm,  
has its origins in society





**bias can lead to  
discrimination**

# The evils of discrimination

## Disparate treatment

is the illegal practice of treating an entity, such as a job applicant or an employee, differently based on a **protected characteristic** such as race, gender, age, disability status, religion, sexual orientation, or national origin.

## Disparate impact

is the result of systematic disparate treatment, where disproportionate **adverse impact** is observed on members of a **protected class**.

# Ricci v. DeStefano (2009)

## *Supreme Court Finds Bias Against White Firefighters*

By ADAM LIPTAK JUNE 29, 2009



Karen Lee Torre, left, a lawyer who represented the New Haven firefighters in their lawsuit, with her clients Monday at the federal courthouse in New Haven. Christopher Capozziello for The New York Times

### Case opinions

**Majority** Kennedy, joined by Roberts, Scalia, Thomas, Alito

**Concurrence** Scalia

**Concurrence** Alito, joined by Scalia, Thomas

**Dissent** Ginsburg, joined by Stevens, Souter, Breyer

### Laws applied

Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000e<sup>et seq.</sup>

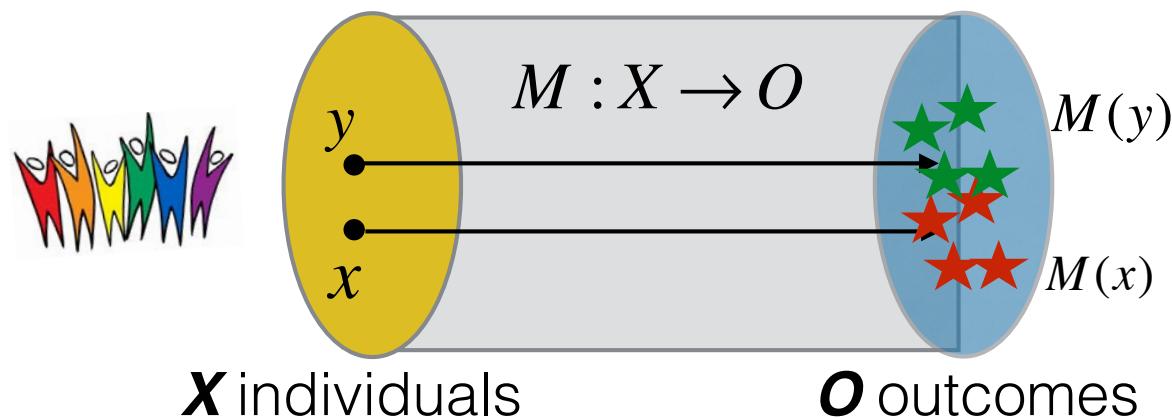


**fairness through  
awareness**

# Fairness through awareness

[C. Dwork, M. Hardt, T. Pitassi, O. Reingold, R. S. Zemel; *ITCS 2012*]

**Fairness:** Individuals who are **similar** for the purpose of classification task should be **treated similarly**.



A task-specific similarity metric is given  $d(x, y)$

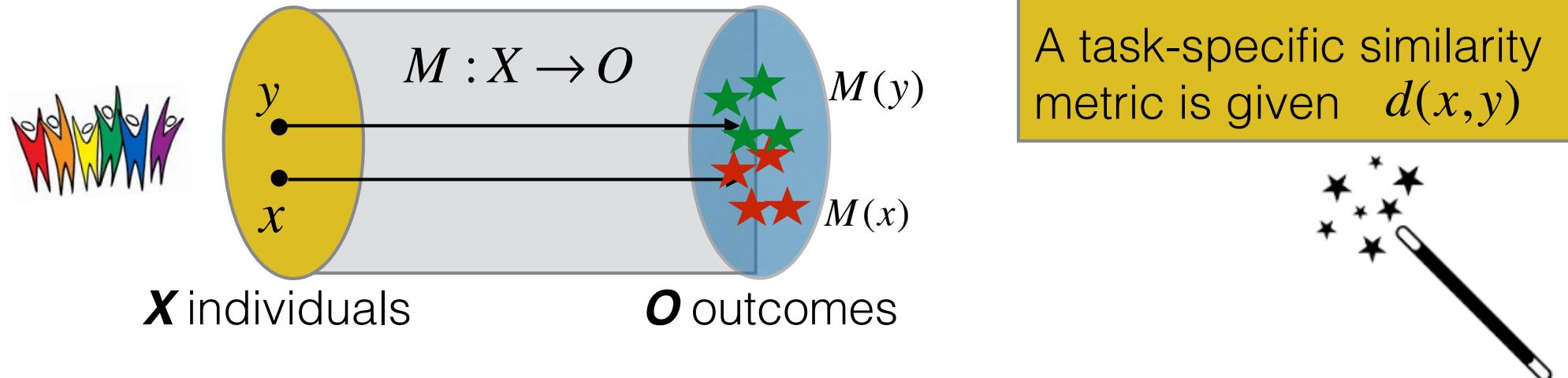


$M : X \rightarrow O$  is a **randomized mapping**: an individual is mapped to a distribution over outcomes

# Fairness through a Lipschitz mapping

[C. Dwork, M. Hardt, T. Pitassi, O. Reingold, R. S. Zemel; *ITCS 2012*]

**Fairness:** Individuals who are **similar** for the purpose of classification task should be **treated similarly**.

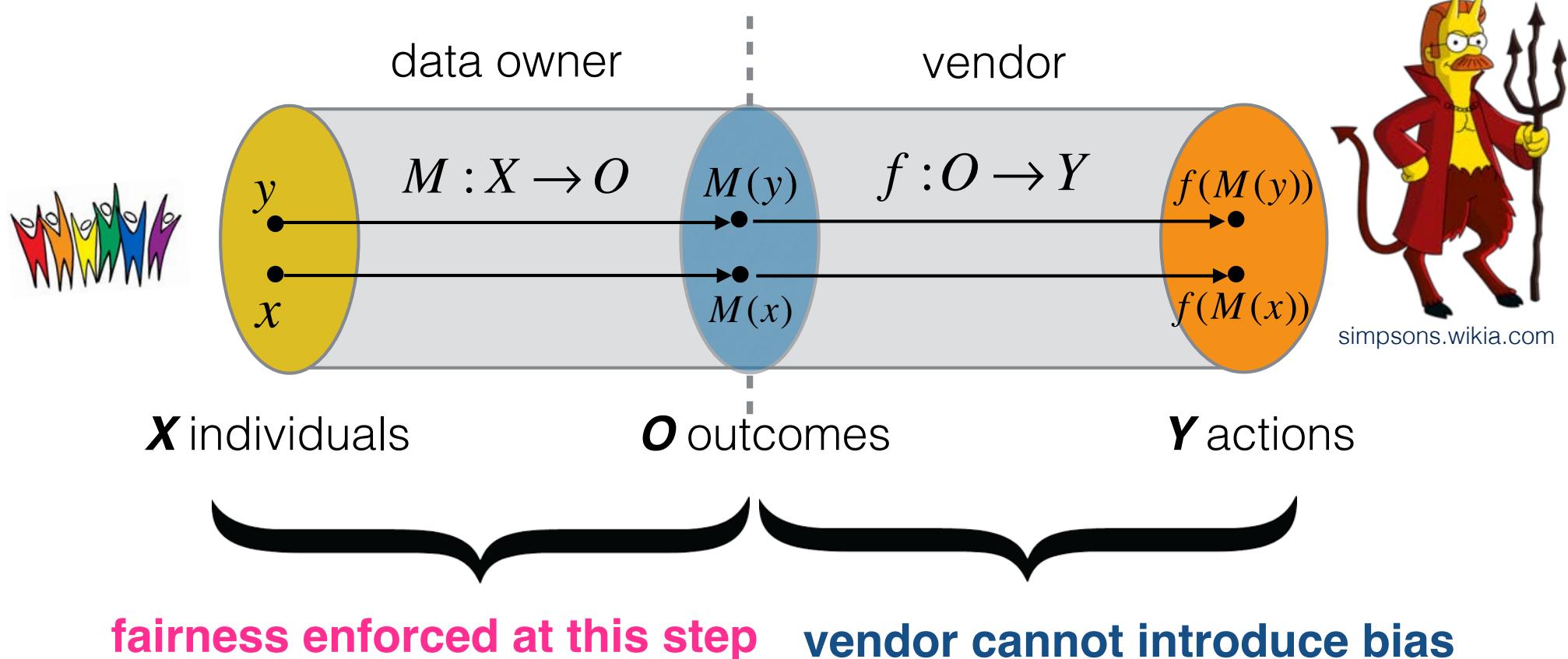


$M$  is a Lipschitz mapping if  $\forall x, y \in X \quad \|M(x), M(y)\| \leq d(x, y)$

**close individuals map to close distributions**  
**there always exists a Lipschitz mapping - which?**

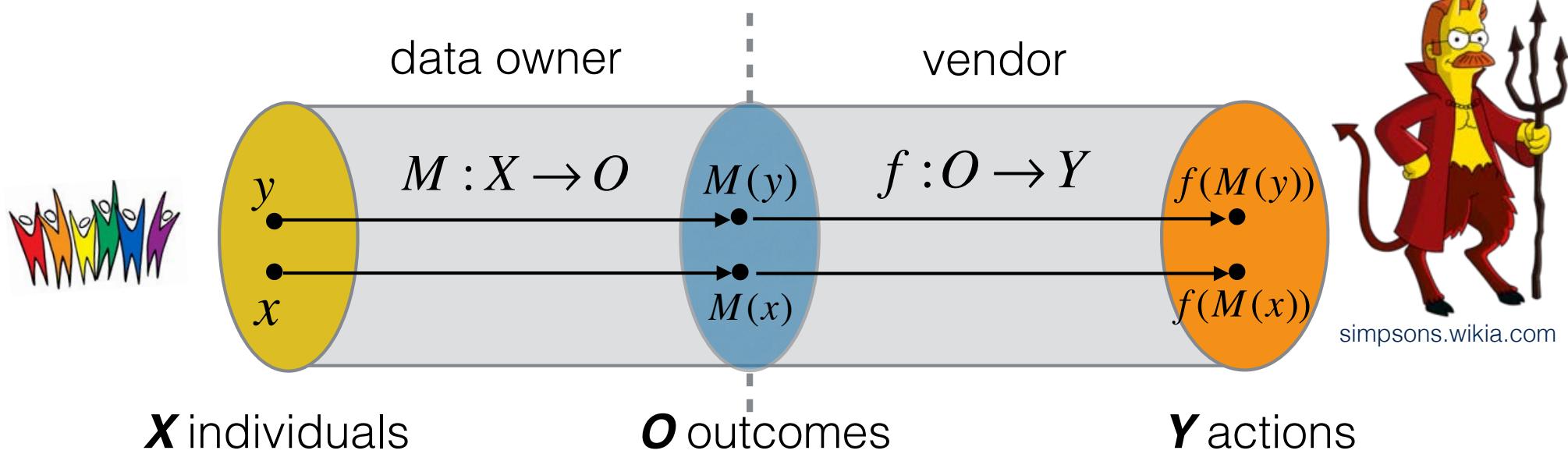
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# Fairness through a Lipschitz mapping

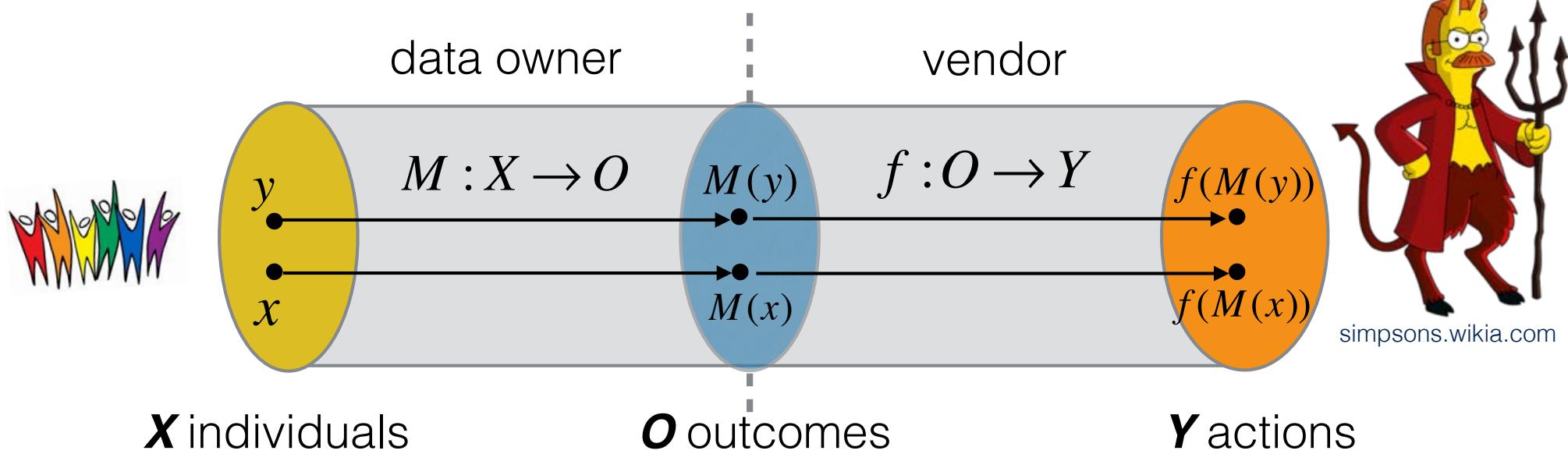
[C. Dwork, M. Hardt, T. Pitassi, O. Reingold, R. S. Zemel; *ITCS 2012*]



Find a mapping from individuals to distributions over outcomes that minimizes expected loss, **subject to the Lipschitz condition**. Optimization problem: minimize an arbitrary loss function.

# Fairness through a Lipschitz mapping

[C. Dwork, M. Hardt, T. Pitassi, O. Reingold, R. S. Zemel; *ITCS 2012*]



Computed with a linear program of size  $\text{poly}(|X|, |Y|)$

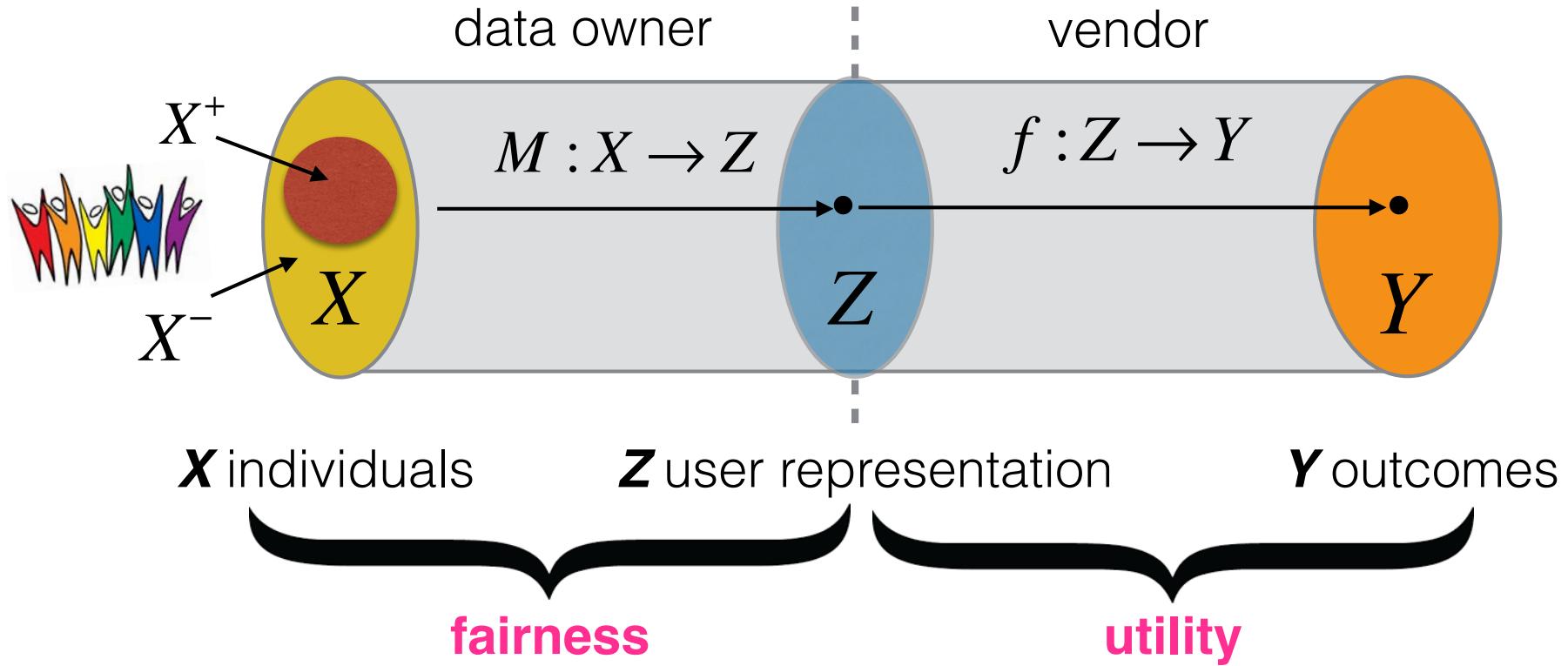
**the same mapping can be used by multiple vendors**



learning fair  
representations

# Learning fair representations

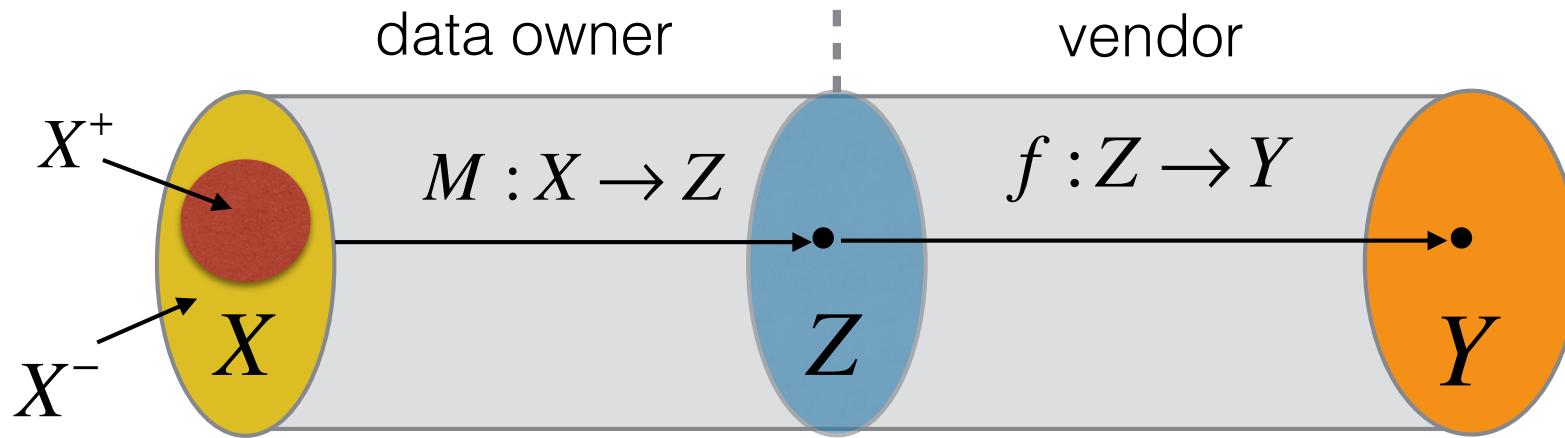
[R. S. Zemel, Y. Wu, K. Swersky, T. Pitassi, C. Dwork; ICML 2013]



**Idea:** remove reliance on a “fair” similarity measure, instead **learn** representations of individuals, distances

# Fairness and utility

[R. S. Zemel, Y. Wu, K. Swersky, T. Pitassi, C. Dwork; ICML 2013]



Learn a **randomized mapping**  $M(X)$  to a set of  $K$  prototypes  $Z$

$M(X)$  should lose information about membership in  $S$      $P(Z | S = 0) = P(Z | S = 1)$

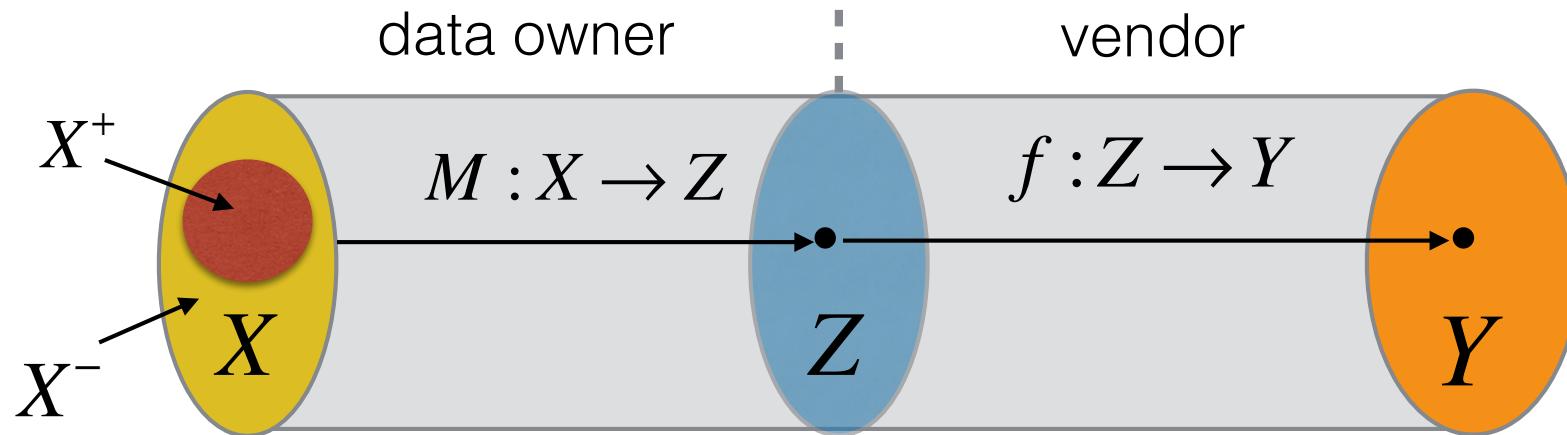
$M(X)$  should preserve other information so that vendor can maximize utility

$$L = A_z \cdot L_z + A_x \cdot L_x + A_y \cdot L_y$$

**group fairness**      **individual fairness**      **utility**

# Fairness and utility

[R. S. Zemel, Y. Wu, K. Swersky, T. Pitassi, C. Dwork; ICML 2013]



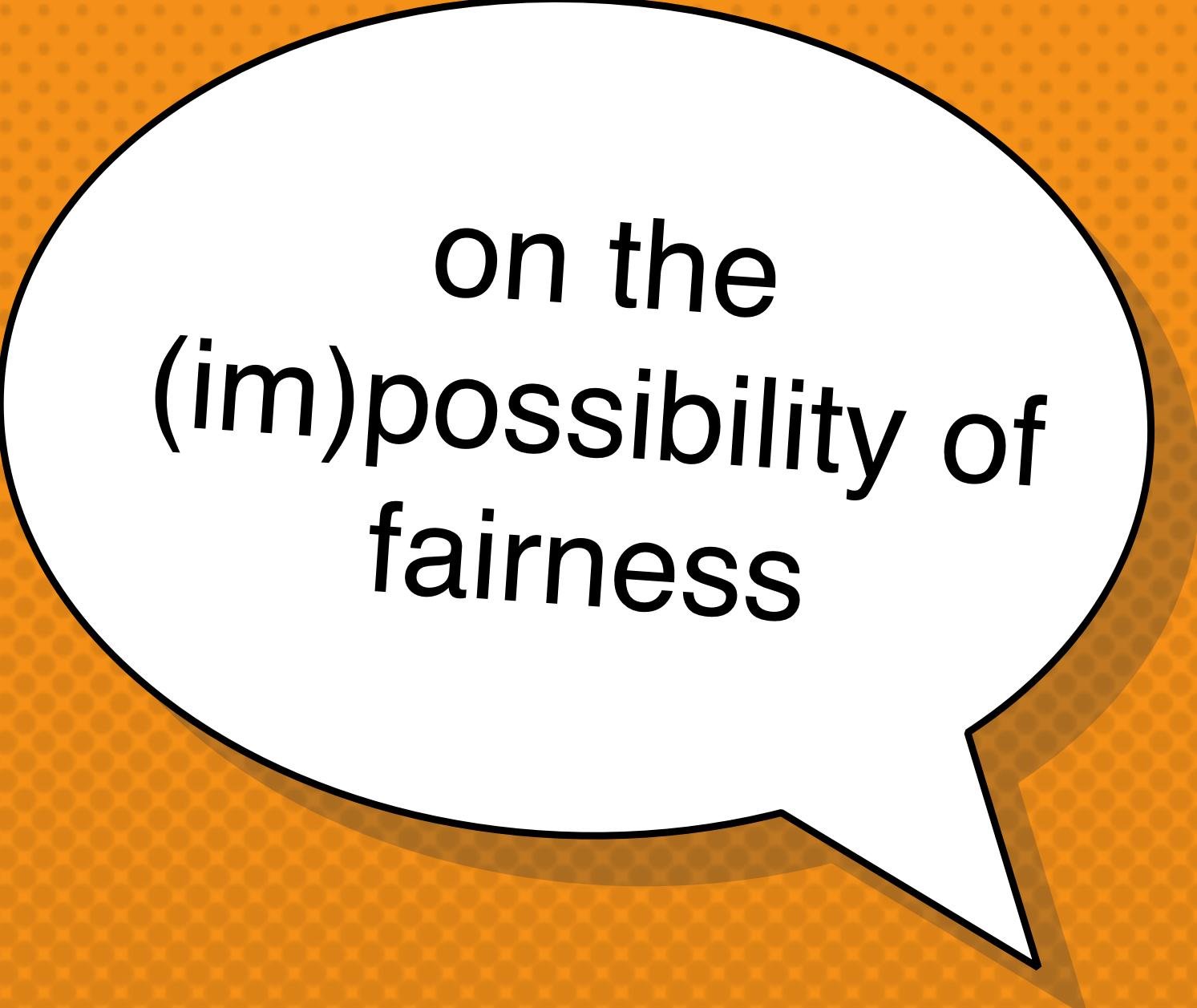
$$P_k^+ = P(Z = k \mid x \in X^+)$$

$$L_z = \sum_k |P_k^+ - P_k^-| \quad L_x = \sum_n (x_n - \hat{x}_n)^2$$

$$P_k^- = P(Z = k \mid x \in X^-)$$

$$L_y = \sum_n -y_n \log \hat{y}_n - (1-y_n) \log(1-\hat{y}_n)$$

**does this make sense?**



on the  
(im)possibility of  
fairness

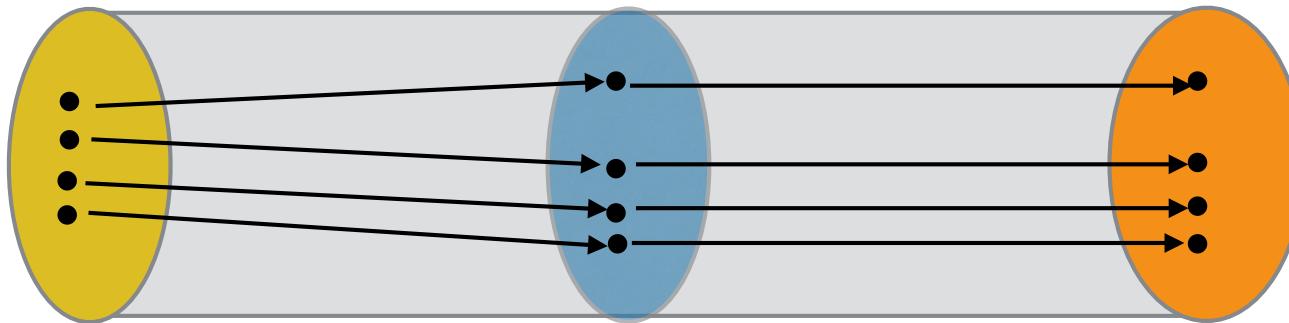
# On the (im)possibility of fairness

[S. Friedler, C. Scheidegger and S. Venkatasubramanian, arXiv:1609.07236v1 (2016)]

**Goal:** tease out the difference between *beliefs* and *mechanisms* that logically follow from those beliefs.

**Main insight:** To study algorithmic fairness is to study the interactions between different spaces that make up the decision pipeline for a task

Construct Space (**CS**)    Observed Space (**OS**)    Decision Space (**DS**)



# On the (im)possibility of fairness

[S. Friedler, C. Scheidegger and S. Venkatasubramanian, arXiv:1609.07236v1 (2016)]

Construct Space	Observed Space	Decision Space
intelligence	SAT score	performance in college
grit	high-school GPA	
propensity to commit crime	family history	recidivism
risk-averseness	age	

**define fairness through properties of mappings**

# Fairness through mappings

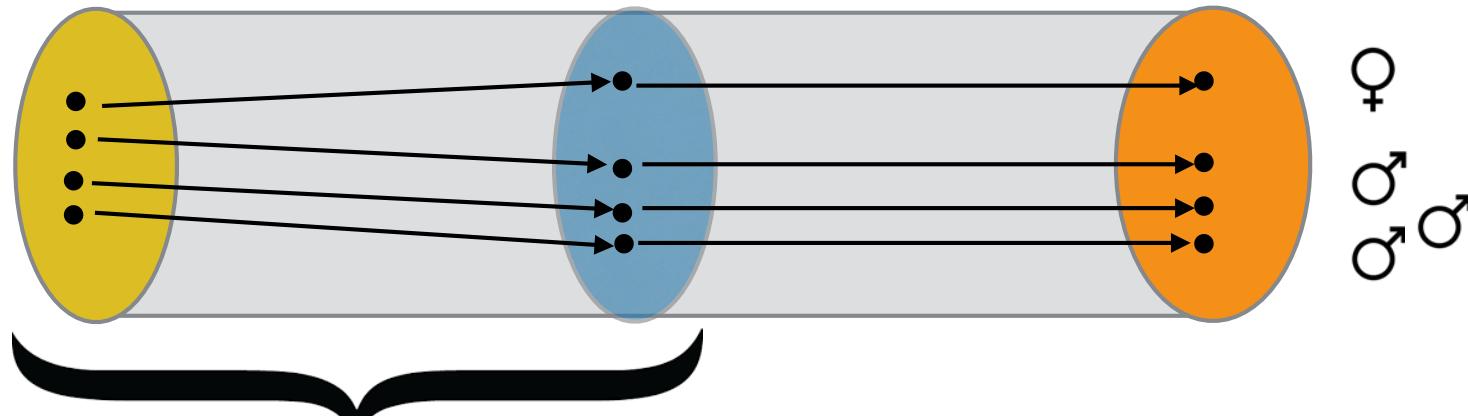
[S. Friedler, C. Scheidegger and S. Venkatasubramanian, arXiv:1609.07236v1 (2016)]

**Fairness**: a mapping from **CS** to **DS** is  $(\epsilon, \epsilon')$ -fair if two objects that are no further than  $\epsilon$  in **CS** map to objects that are no further than  $\epsilon'$  in **DS**.

$$f : CS \rightarrow DS$$

$$d_{CS}(x, y) < \epsilon \Rightarrow d_{DS}(f(x), f(y)) < \epsilon'$$

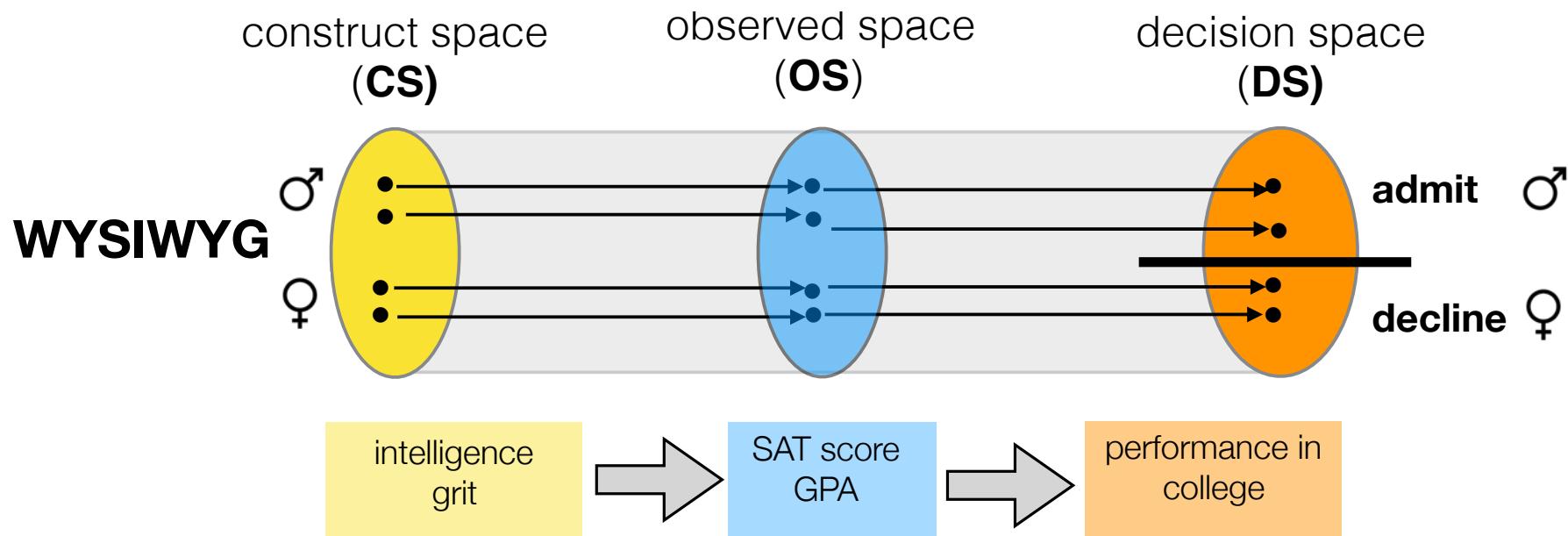
Construct Space (**CS**)    Observed Space (**OS**)    Decision Space (**DS**)



let's focus on this portion

# WYSWYG

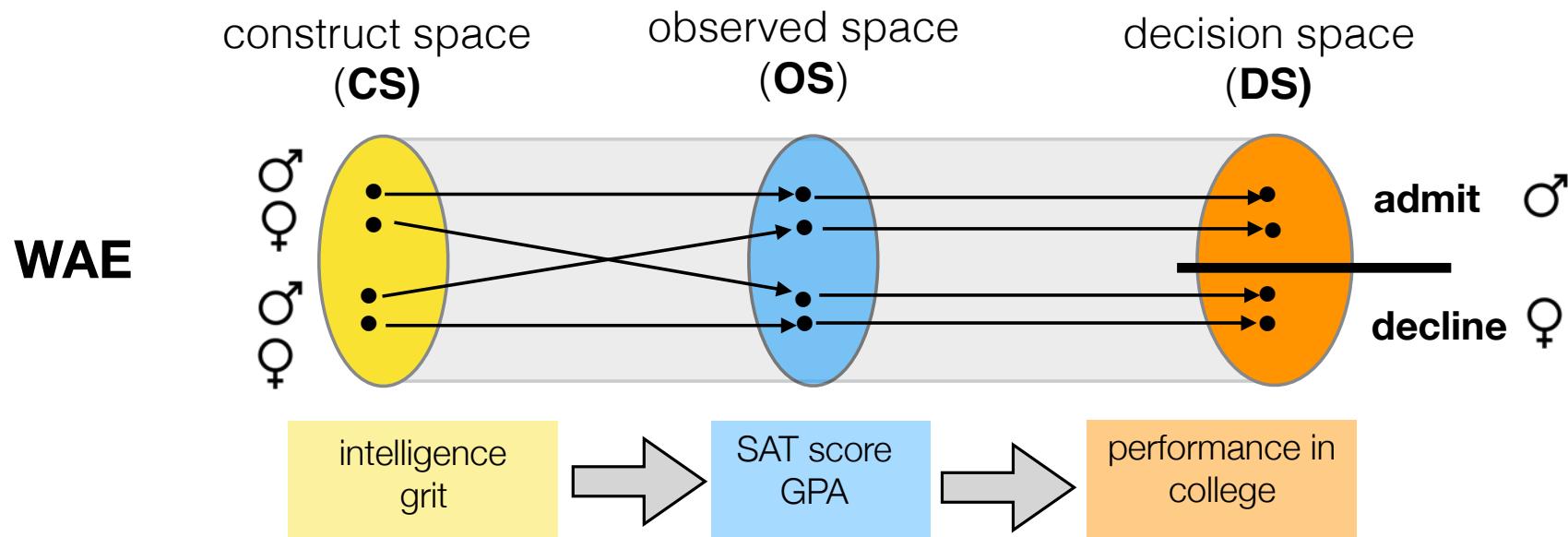
[S. Friedler, C. Scheidegger and S. Venkatasubramanian, arXiv:1609.07236v1 (2016)]



What you see is what you get (**WYSIWYG**): there exists a mapping from CS to OS that has low distortion. That is, we believe that OS faithfully represents CS. **This is the individual fairness world view.**

# WAE

[S. Friedler, C. Scheidegger and S. Venkatasubramanian, arXiv:1609.07236v1 (2016)]



We are all equal (**WAE**): the mapping from CS to OS introduces **structural bias** - there is a distortion that aligns with the group structure of CS. **This is the group fairness world view.**

**Structural bias examples:** SAT verbal questions function differently in the African-American and in the Caucasian subgroups in the US. Other examples?

# Fairness and worldviews



individual  
fairness

equality of  
treatment

group  
fairness

equality of  
outcome



# What's the right answer?

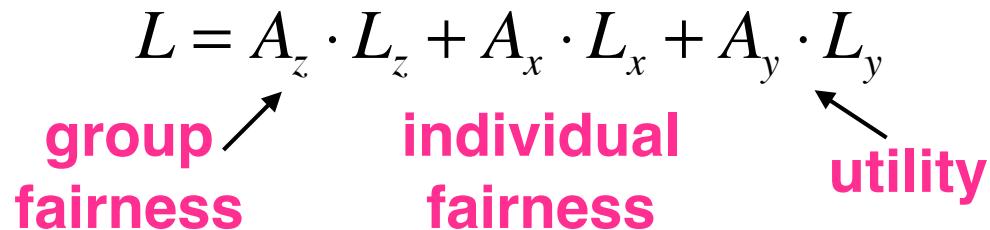
**There is no single answer!**

**Need transparency and public debate**

- Consider harms and benefits to different stakeholders
- Being transparent about which fairness criteria we use, how we trade them off
- Recall “Learning Fair Representations”: a typical ML approach

$$L = A_z \cdot L_z + A_x \cdot L_x + A_y \cdot L_y$$

group fairness      individual fairness      utility



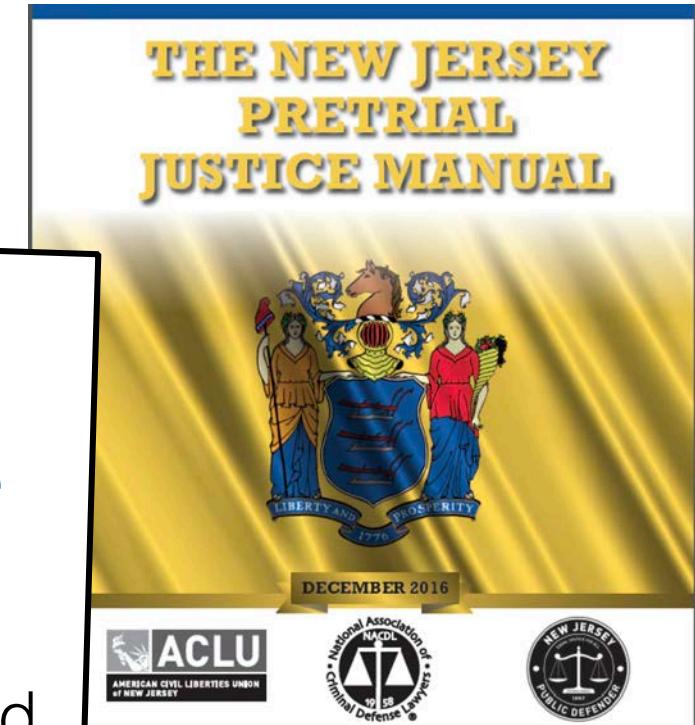
**apples + oranges + fairness = ?**



**fairness in risk  
assessment**

# New Jersey bail reform

Switching from a system based solely on instinct and experience [...] to one in which judges have access to **scientific, objective risk assessment** tools could further the criminal justice system's central goals of increasing public safety, reducing crime, and making the most effective, fair, and efficient use of public resources.



# ProPublica's COMPAS study

## 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



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

A commercial tool **COMPAS May 2016** automatically predicts some categories of future crime to assist in bail and sentencing decisions. It is used in courts in the US.

The tool correctly predicts recidivism **61% of the time.**

**Blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend.**

The tool 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.

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A commercial tool **COMPAS** **May 2016** automatically predicts some categories of future crime to assist in bail and sentencing decisions. It is used in courts in the US.

### 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.)*

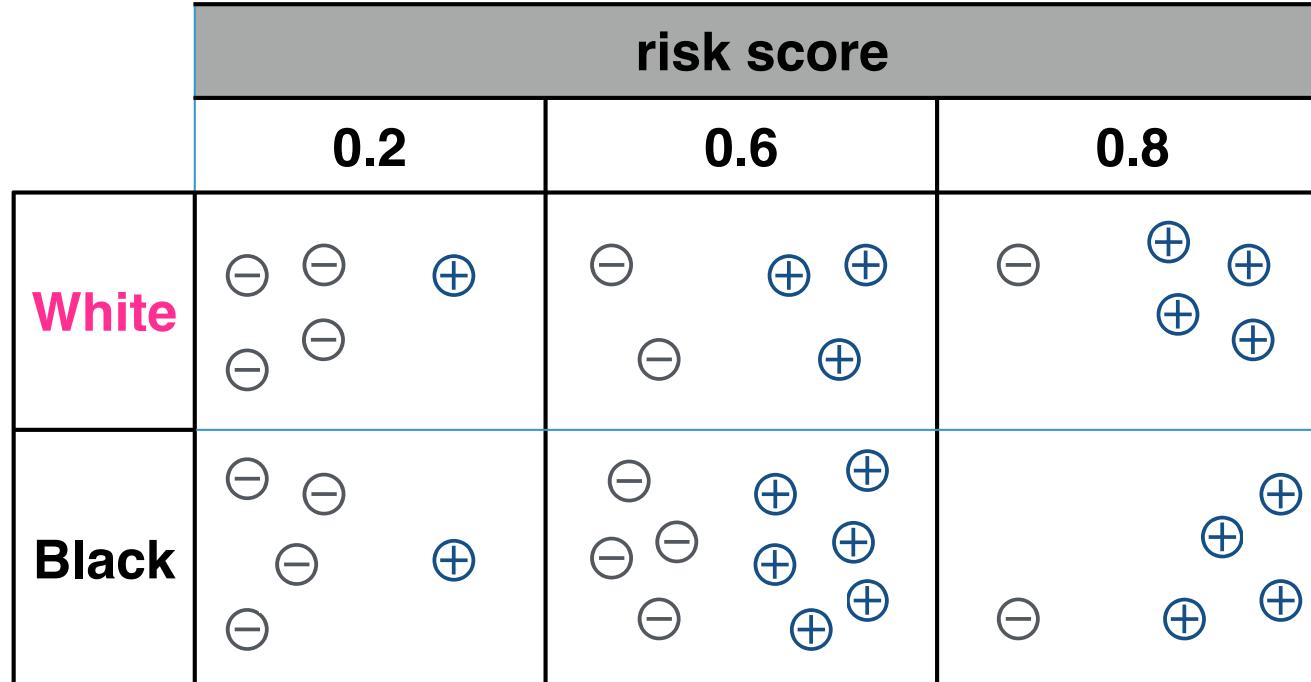
<https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>

# Fairness in risk assessment

- A risk assessment tool **gives a probability estimate of a future outcome**
- Used in many domains:
  - insurance, criminal sentencing, medical testing, hiring, banking
  - also in less-obvious set-ups, like online advertising
- **Fairness** in risk assessment is concerned with **how different kinds of error are distributed among sub-populations**

# Calibration

positive  
outcomes:  
do recidivate



given the output of a risk tool, likelihood of belonging to the positive class is independent of group membership

0.6 means 0.6 for any defendant - likelihood of recidivism

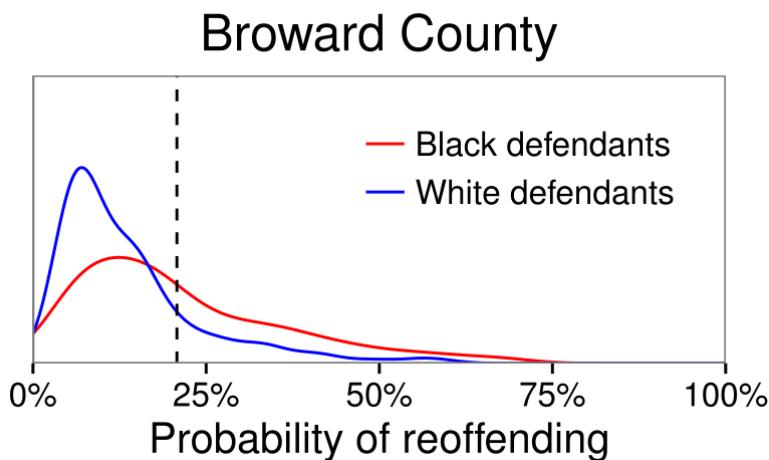
why do we want calibration?

# COMPAS as a predictive instrument

## Predictive parity (also called **calibration**)

an instrument identifies a set of instances as having probability  $x$  of constituting positive instances, then approximately an  $x$  fraction of this set are indeed positive instances, over-all and in sub-populations

COMPAS is well-calibrated: in the window around 40%, the fraction of defendants who were re-arrested is ~40%, both over-all and per group.



[plot from Corbett-Davies et al.; KDD 2017]

# An impossibility result

If a predictive instrument **satisfies predictive parity**, but the **prevalence** of the phenomenon **differs between groups**, then the instrument **cannot achieve** equal false positive rates and equal false negative rates across these groups.

Recidivism rates in the ProPublica dataset are higher for the Black group than for the White group

Defendants	WHITE	AFRICAN AMERICAN
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[A. Chouldechova; arXiv:1610.07524v1 (2017)]

# A more general statement: Balance

- **Balance for the positive class:** Positive instances are those who go on to re-offend. The average score of positive instances should be the same across groups.
- **Balance for the negative class:** Negative instances are those who do not go on to re-offend. The average score of negative instances should be the same across groups.
- Generalization of: Both groups should have equal false positive rates and equal false negative rates.
- Different from statistical parity!

**the chance of making a mistake does not depend on race**

[J. Kleinberg, S. Mullainathan, M. Raghavan; *ITCS 2017*]

# Desiderata, re-stated

- For each group, a  $v_b$  fraction in each bin  $b$  is positive
- Average score of positive class same across groups
- Average score of negative class same across groups

**can we have all these properties?**

[J. Kleinberg, S. Mullainathan, M. Raghavan; *ITCS 2017*]

# Achievable only in trivial cases

- **Perfect information:** the tool knows who recidivates (score 1) and who does not (score 0)
- **Equal base rates:** the fraction of positive-class people is the same for both groups

**a negative result, need tradeoffs**

**proof sketched out in (starts 12 min in)**

<https://www.youtube.com/watch?v=UUC8tMNxwV8>

[J. Kleinberg, S. Mullainathan, M. Raghavan; *ITCS 2017*]

# Fairness for whom?

**Decision-maker:** of those labeled low-risk, how many will recidivate?

**Defendant:** how likely will I be incorrectly labeled high-risk?

	labeled low-risk	labeled high-risk
did not recidivate	TN	FP
recidivated	FN	TP

based on a slide by Arvind Narayanan

# What's the right answer?

# There is no single answer!

## **Need transparency and public debate**

- Consider harms and benefits to different stakeholders
  - Being transparent about which fairness criteria we use, how we trade them off
  - Recall “Learning Fair Representations”: a typical ML approach

$$L = A_z \cdot L_z + A_x \cdot L_x + A_y \cdot L_y$$

group fairness      individual fairness      utility

# apples + oranges + fairness = ?

# Responsible Data Science

Algorithmic Fairness

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# Thank you!



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