# Statistical aspects of algorithmic fairness

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10/18/2019

# Outline

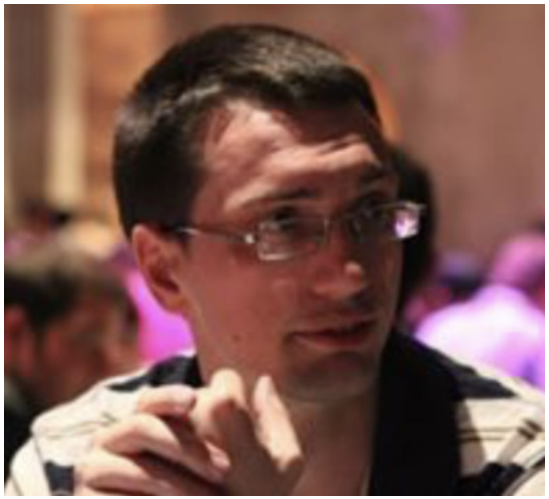
- Long intro with many high level **examples**
- **Counterfactual fairness** and causality
- Other fairness definitions and "**impossibility**"
- **Causality** as a path forward

The (technical) material here can be found in

- *Counterfactual Fairness* (Kusner et al, NeurIPS 2017)
- *When Worlds Collide: Integrating Different Counterfactual Assumptions in Fairness* (Russell et al, NeurIPS 2017)
- *Causal Reasoning for Algorithmic Fairness* (Loftus et al, preprint 2018)
- *Making Decisions that Reduce Discriminatory Impacts* (Kusner et al, ICML 2019)

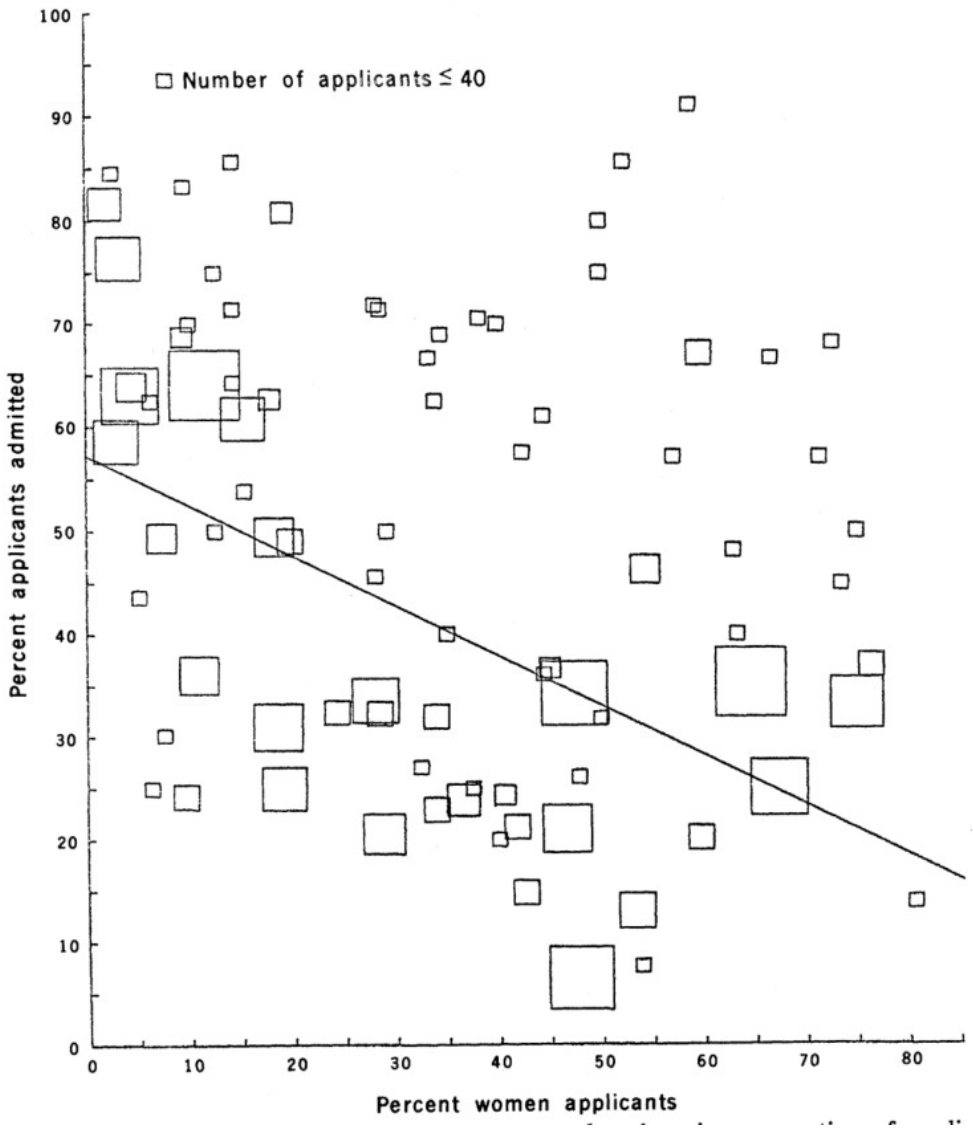
# Joint work with

Matt Kusner[1→3,4] Chris Russell[2,4] Ricardo Silva[3,4]


[1]Oxford, NYU, [2]Surrey, [3]UCL, [4]Alan Turing Institute

# Question: when can data tell us about discrimination?



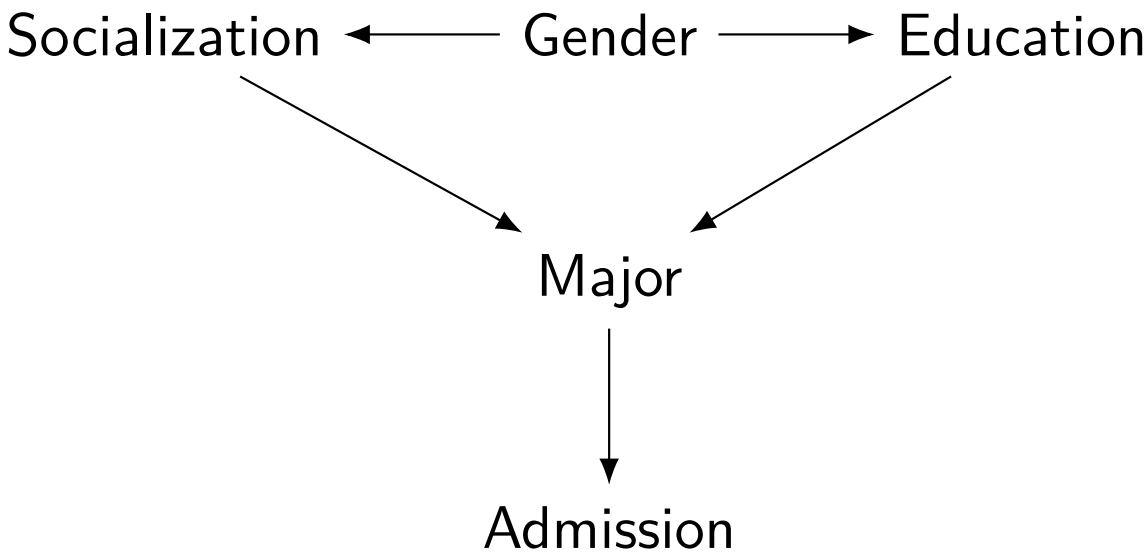

*Sex Bias in Graduate Admissions: Data from Berkeley* (P. J. Bickel, E. A. Hammel, J. W. O'Connell, 1975)

# One answer: when we focus on causes

*The bias in the aggregated data stems not from any pattern of discrimination on the part of admissions committees, which seem quite fair on the whole, but apparently from prior screening at earlier levels of the educational system. Women are shunted by their socialization and education toward fields of graduate study that are generally more crowded, less productive of completed degrees, and less well funded, and that frequently offer poorer professional employment prospects.*

- from the final paragraph of Bickel et al (1975)

# Causal diagram

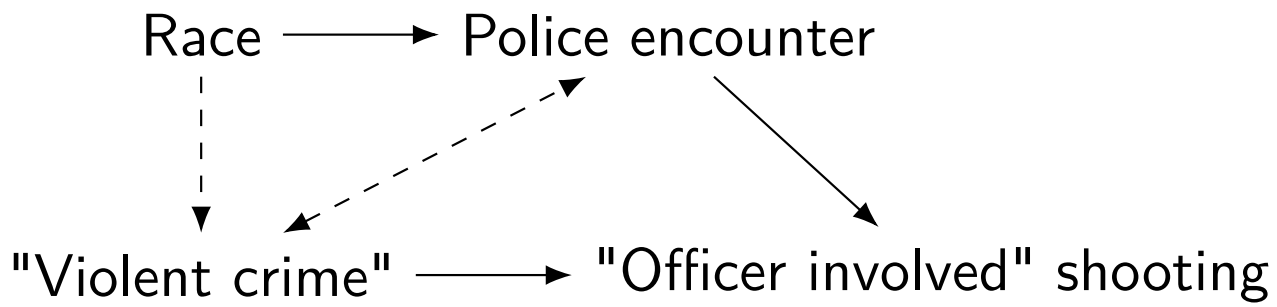



Imagine the counterfactual: when I showed enjoyment of math as a young student, what if my teachers, family, etc, all reacted to that by encouraging me to aim for a career in nursing or elementary school teaching?

*Officer characteristics and racial disparities in fatal officer-involved shootings* (David J. Johnson, Trevor Tress, Nicole Burkel, Carley Taylor, and Joseph Cesario, PNAS 2019)

> *A persistent point of debate in studying police use of force concerns how to calculate racial disparities. Racial disparities in fatal shootings have traditionally been tested by asking whether officers fatally shoot a racial group more than some benchmark, such as that group's population proportion in the United States. [. . . ]*
>
> *However, using population as a benchmark makes the strong assumption that White and Black civilians have equal exposure to situations that result in FOIS. [. . . ] When violent crime is used as a benchmark, anti-Black disparities in FOIS* ***disappear or even reverse****.*

# Police encounters

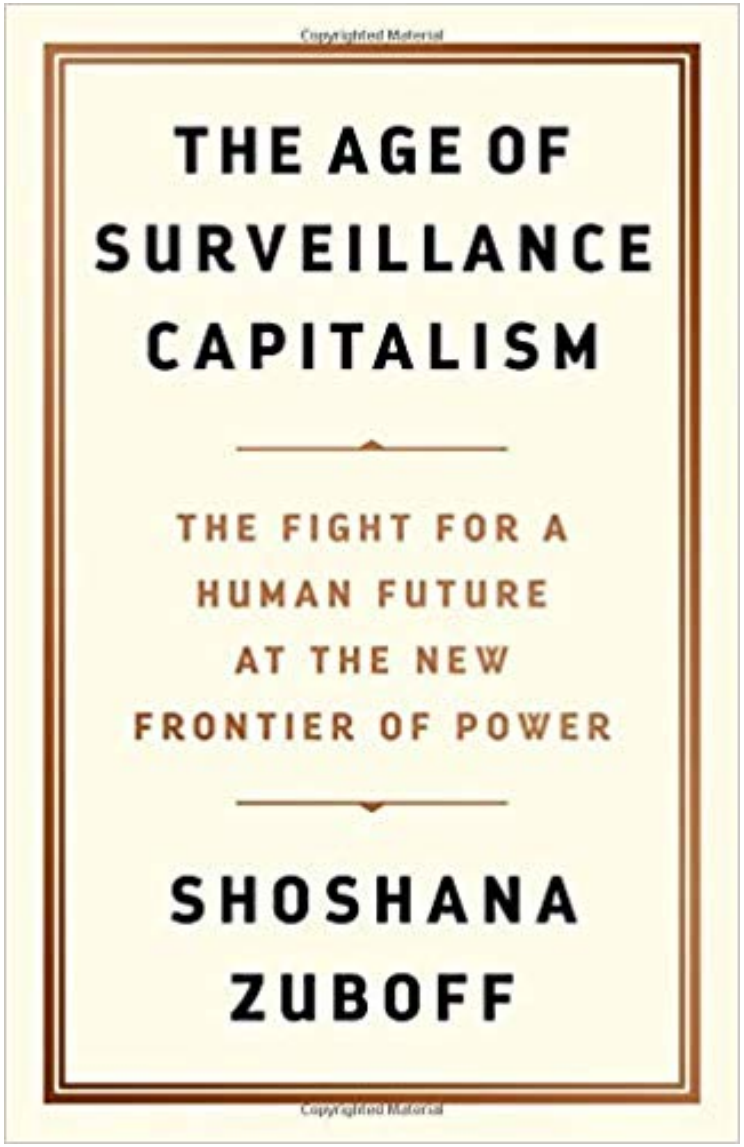


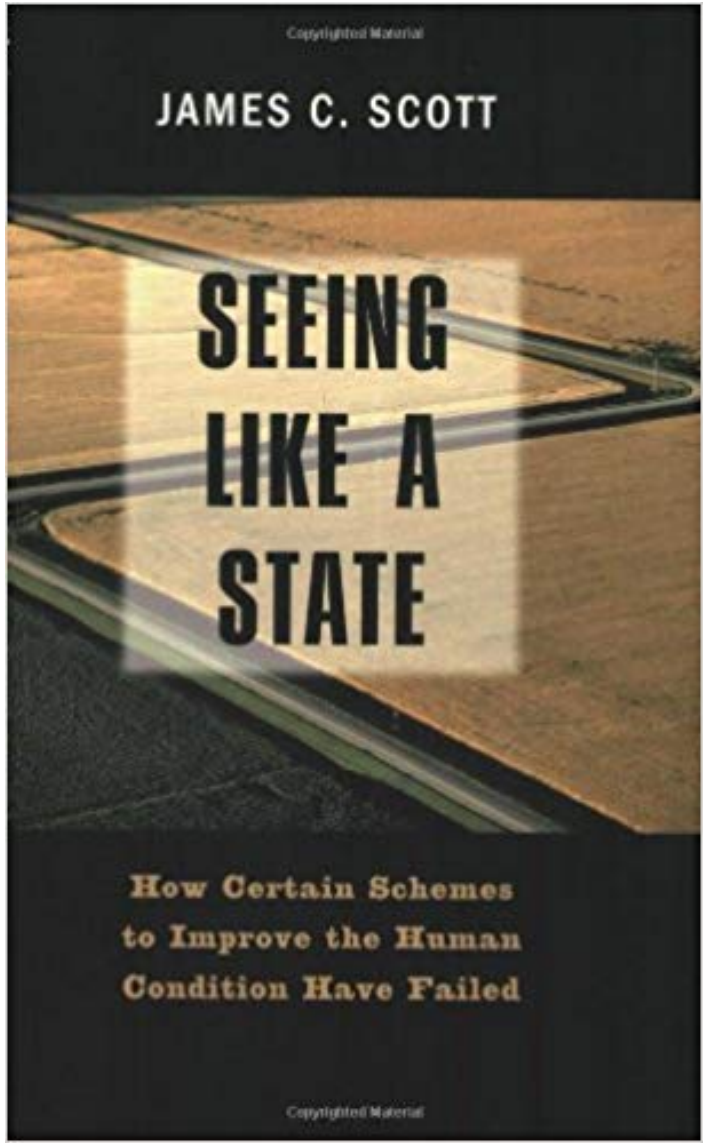

Does it make sense to condition on violent crime (use it as a benchmark)? Not so clear, the processes causing such encounters and/or the data records for them are known to also be racially biased.

# Data and data-driven decisions are not, by default, ethical or fair

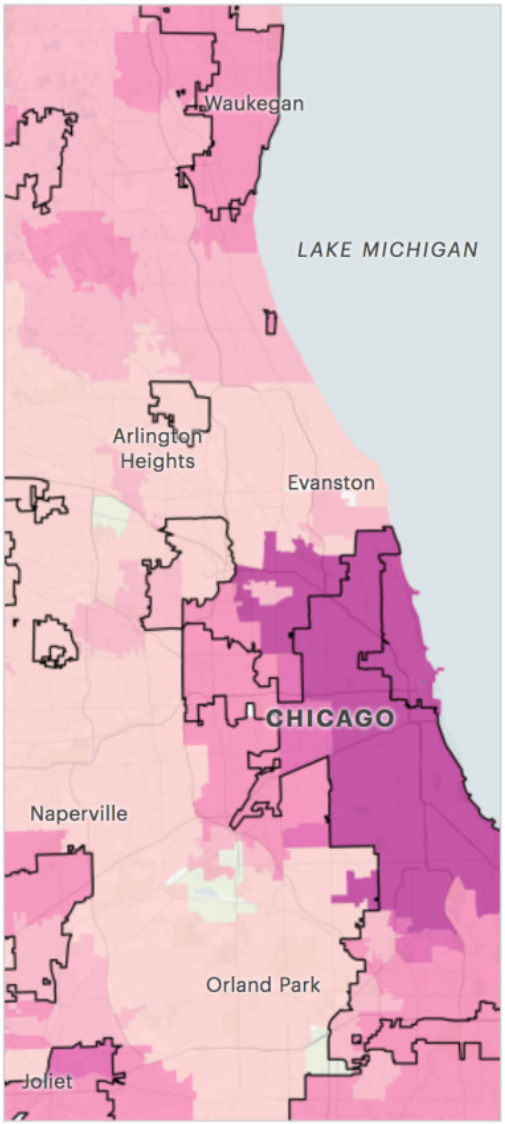

Source: flir.com "SkyWatch"

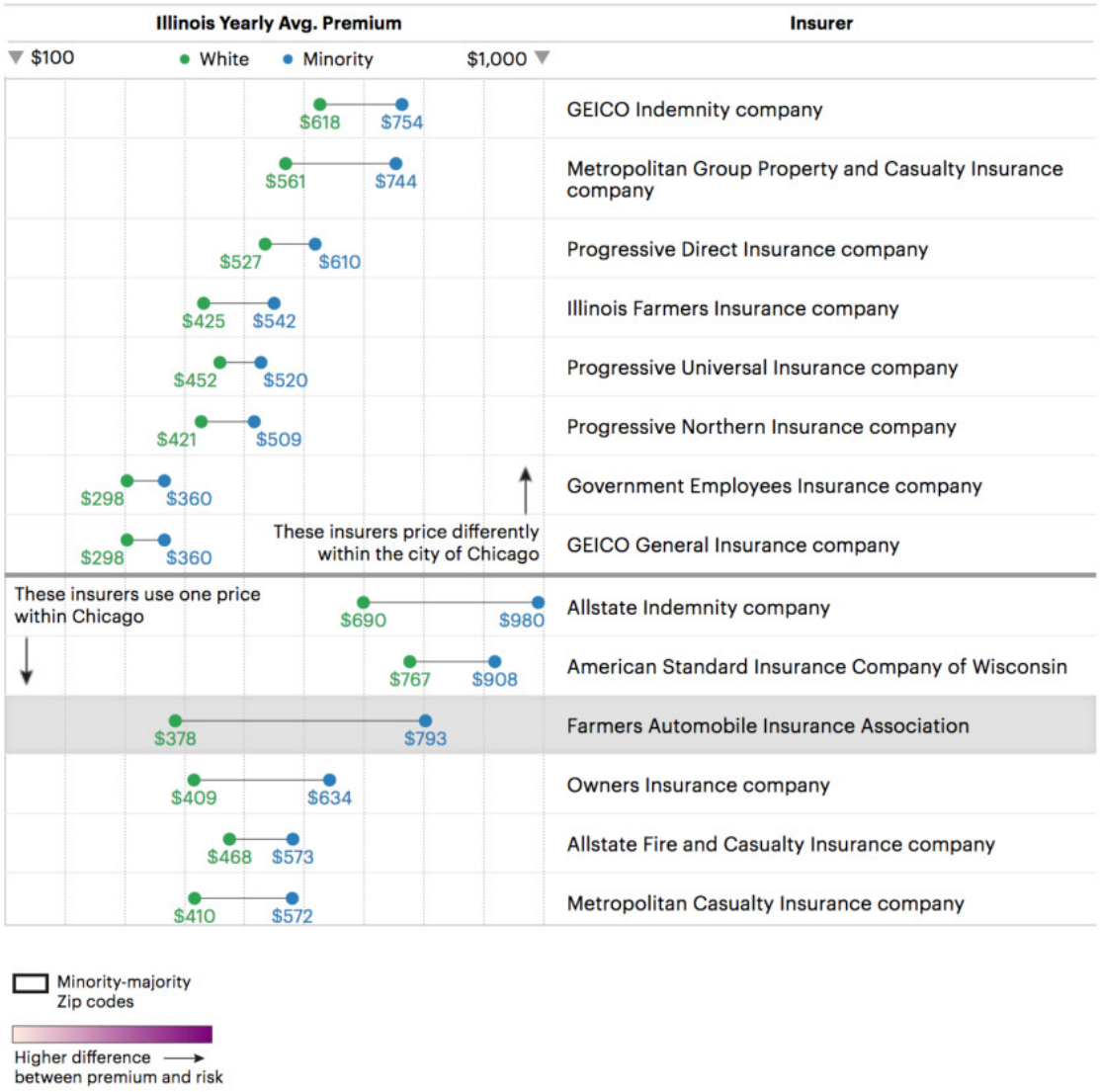
# Maybe closer to the opposite of fair by default...



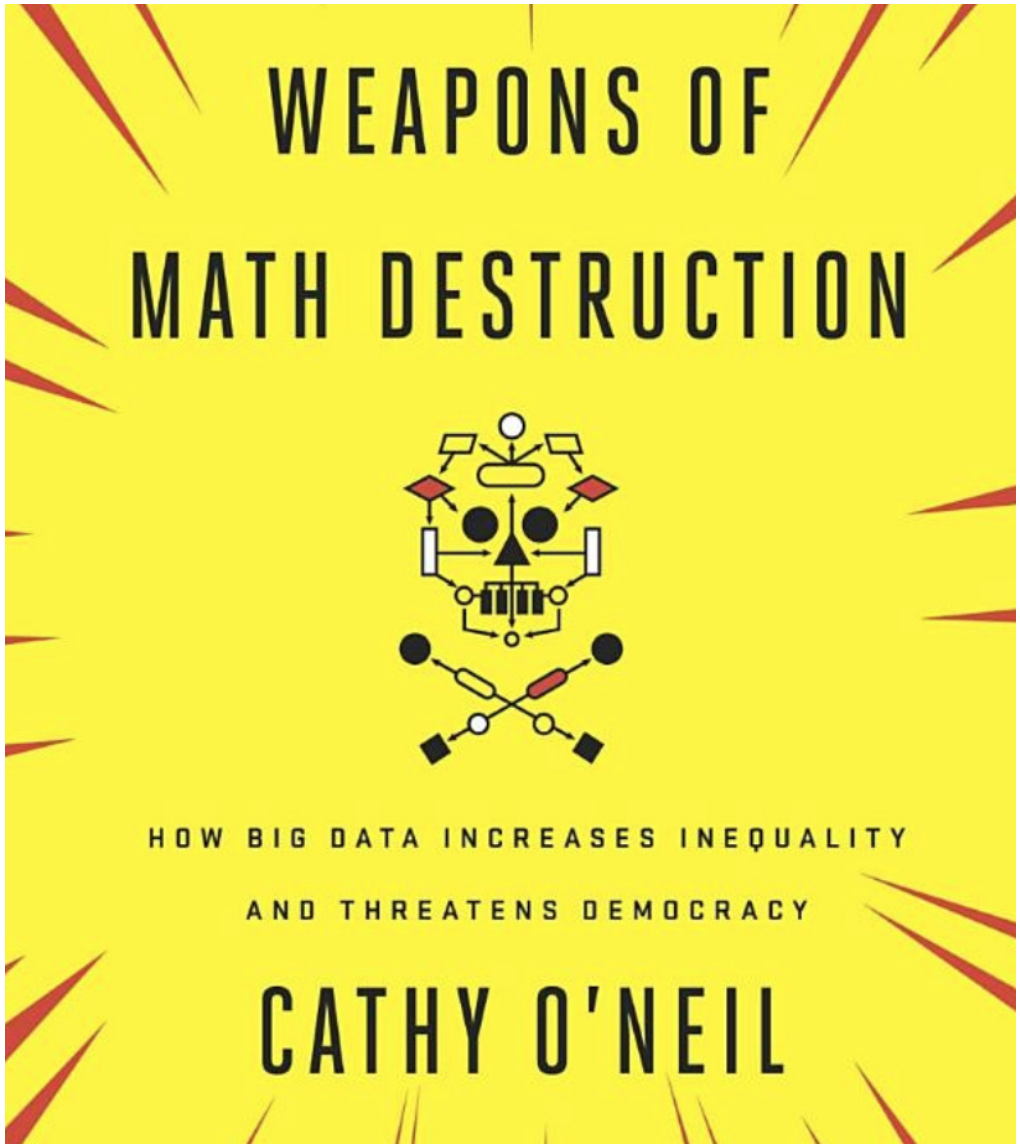
# “Indirect” discrimination based on non-sensitive variables




Correlations with sensitive variables: location, high-dimensional issues (Source)

# Important decisions automated or influenced by algorithms/data




- Admissions
- Credit
- Employment
- Insurance
- Healthcare

Unique dangers: scale, opacity, biased data, faux objectivity

"New products and services, including those that incorporate or utilize artificial intelligence and machine learning, can raise new or exacerbate existing ethical, technological, legal, and other challenges, which may negatively affect our brands and demand for our products and services and adversely affect our revenues and operating results"

TOM SIMONITE BUSINESS 02.11.19 07:00 AM

# GOOGLE AND MICROSOFT WARN THAT AI MAY DO DUMB THINGS

ALYSSA FOOTE

Source: WIRED article, Feb. 2019

## Overt discrimination

- Failure to apply relevant laws/regulations
- Poor design/incentives
- Rationalized "statistical discrimination"

## "Unintentional" disparate impact

- Non-diverse workplaces
- Bias introduced by data collection/use
- Unfair world: many predictor variables correlated with both outcome and protected attributes (race, sex, etc)

(Not an exhaustive list)

# A narrow, "internal" focus

Here are some questions I won't address today:

- What about privacy or other (ethical) objectives?
- Which attributes should be protected?
- How are such attributes (race, gender) defined or measured?
- What if the premise of the system is fundamentally unfair?
- Will market dynamics or Goodhart's/Campbell's law invalidate all this (eventually)?

Focus on an oversimplified model for a tiny part of the process/system in which these questions are embedded

# Also off-topic: unsupervised fairness

Here is a poem written by Google Translate on the topic of gender. It is the result of translating Turkish sentences using the gender-neutral "o" to English (and inspired by this Facebook post).

**Gender**

*by Google Translate*

he is a soldier
she's a teacher
he is a doctor
she is a nurse

he is a writer
he is a dog
she is a nanny
it is a cat

Source

## Selective history of fairness in machine learning

- Pre-history: non-automated decisions (50 Years of Test (Un)fairness, Hutchinson & Mitchell)
- Fairness, Accountability, and Transparency (FAT) workshop in ML conferences (2014: 2 organizers)
- 2016: ProPublica series on Machine bias (COMPAS). Weapons of Math Destruction by Cathy O'Neil, ...
- 2017: more fairness papers in NeurIPS (causal approach takes off) and Kate Crawford's invited talk, more books, ...
- 2018: FAT* conference (and others) growing exponentially, even more books, NYT vs FB takes off, Google walkout, ...
- 2019: Google AI ethics board, Algorithmic Accountability Act (impact assessments), presidential candidates with AI policies, ...

# The notation slide

Supervised learning

- Outcome variable $\mathbf{Y}$ - consider as a score for decisions, or $\mathbf{Y} = 1$ as the desirable decision
- Sensitive/protected attribute(s) $\mathbf{A}$ - race, gender, ...
- Other predictors $\mathbf{X}$ - not sensitive (*prima facie*)

Machine learning task: learn a function $f(\mathbf{X}, \mathbf{A})$ from (labeled) training data to predict values of $\widehat{\mathbf{Y}} = f(\mathbf{X}, \mathbf{A})$ on (unlabeled/future) test data (by minimizing some loss function that measures closeness of $\widehat{\mathbf{Y}}$ to $\mathbf{Y}$ on the training data)

What would it mean for such function to be fair with respect to $\mathbf{A}$?

# A causal perspective on fairness

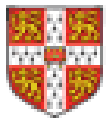
Ethicists and social choice theorists have various notions about

- the role of agency in justice
- responsibility-sensitive egalitarianism
- luck egalitarianism

which rely on causal reasoning. Roughly, it is unfair for individuals to experience different outcomes due to factors outside of their control.

# Counterfactual fairness (*NeurIPS 2017*)

The Alan Turing Institute



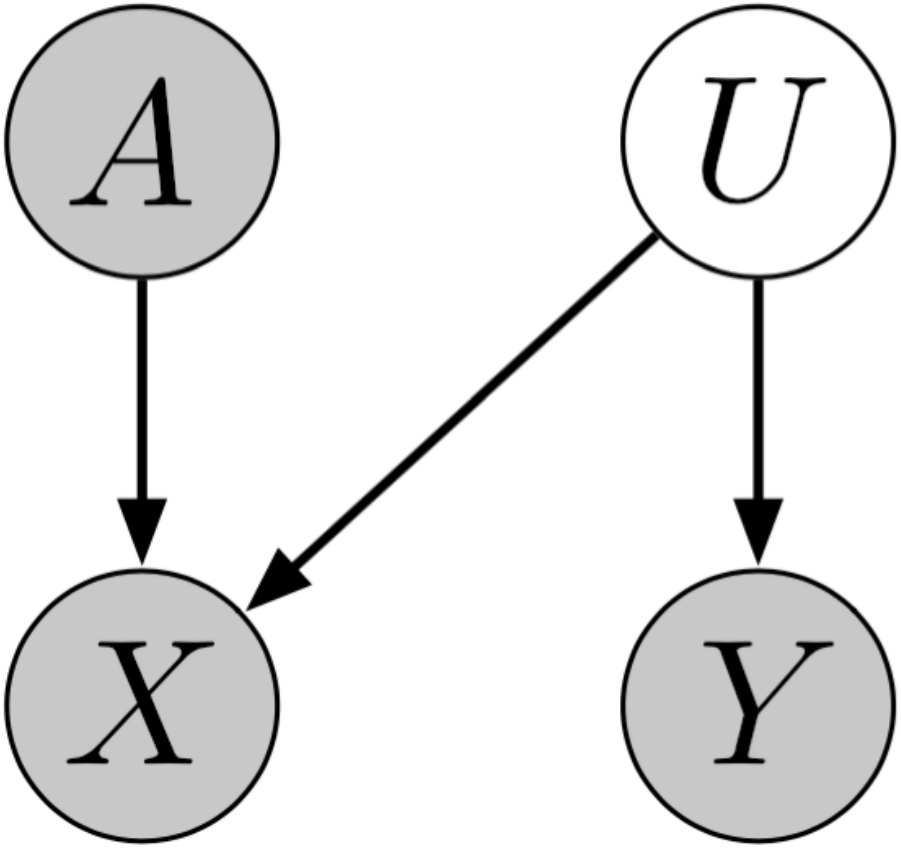

Statistical Laboratory

## Basic idea

Model the relevant real-world causal relationships to separate discrimination on the basis of protected attributes from other, potentially correlated observables (and unobserved confounders)

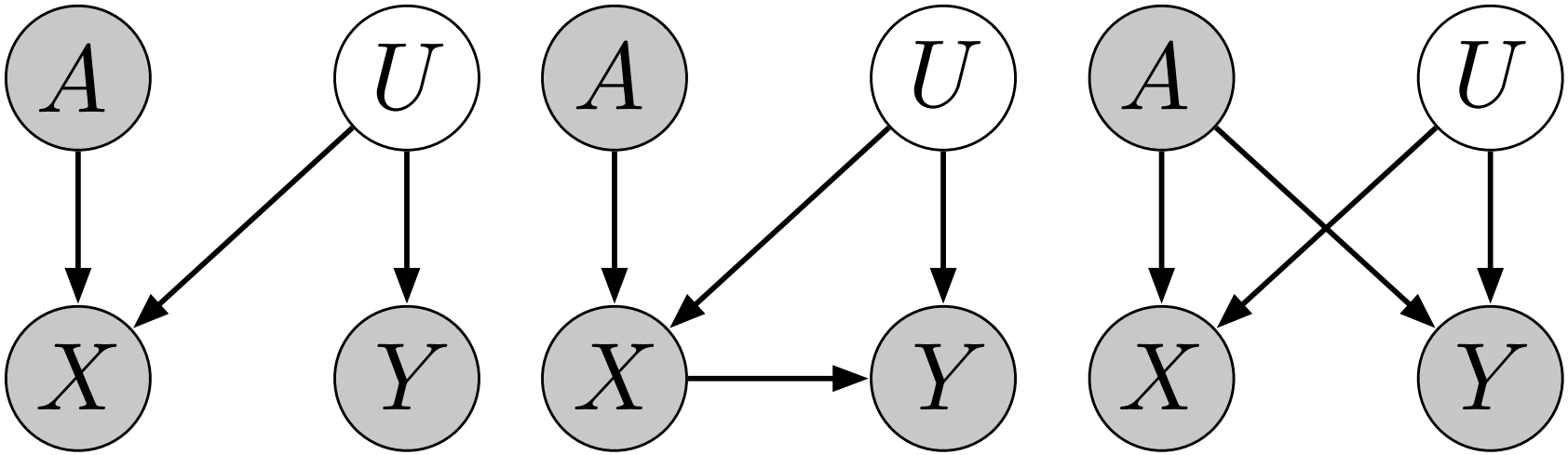
(Similar works: Pearl et al (2016) (textbook), DeDeo (2014), Kilbertus et al (2017), Johnson et al (2016), Nabi and Shpitser (2018), Zhang and Bareinboim (2017), Chiappa and Gillam (2018), and others)

# DAG/SEM causal model framework




- Nodes: variables (**U** unobserved)
- Arrows: causal relationships / conditional (in)dependence
- Structural equations: functional forms of (arrow) relationships

# Computing counterfactuals: follow the paths




1. Assume a probabilistic model for **U**, estimate parameters using observed data
2. For a given individual, change $a$ to $a'$ and propagate that change through the structural equations to all their covariates which are descendents of **A**

### Counterfactual fairness

An estimator $\widehat{\mathbf{Y}}$ is **counterfactually fair** if

$$\mathbb{P}(\widehat{\mathbf{Y}}_{a}|\mathbf{X} = x, \mathbf{A} = a) = \mathbb{P}(\widehat{\mathbf{Y}}_{a'}|\mathbf{X} = x, \mathbf{A} = a)$$

for all $a'$.

### Proposition: structural counterfactual fairness

Any estimator $\widehat{\mathbf{Y}}$ which is a function of only non-descendents of $\mathbf{A}$ is counterfactually fair (sufficient condition, not necessary)

## Intuitive appeal

- This definition captures the intuition that the outcome should not depend in a causal way on an individual's sensitive attributes *or* other causal consequences thereof.
- With correct model of the world* it addresses root sources of unfairness.
- Next: A few *observational* definitions of fairness, a simple example, and then back to causality...

*Big assumption, but also **transparent** because the model is explicit.

(Likely violates "no causation without manipulation" unless we restrict to *perception* of the sensitive attribute)

Perhaps the most straightforward definition (and my favorite due to its elegant simplicity), often described as **equality of outcomes**

**Demographic parity**

Predictions (or decisions) are independent of $\mathbf{A}$:

$$\mathbb{P}(\widehat{\mathbf{Y}}|\mathbf{A}=0) = \mathbb{P}(\widehat{\mathbf{Y}}|\mathbf{A}=1)$$

**Equality of opportunity (Hardt et al, 2016)**

The accuracy of the algorithm does not depend on $\mathbf{A}$:

$$\mathbb{P}(\widehat{\mathbf{Y}} = 1 | \mathbf{A} = 0, \mathbf{Y} = 1) = \mathbb{P}(\widehat{\mathbf{Y}} = 1 | \mathbf{A} = 1, \mathbf{Y} = 1)$$

Demographic parity but only among individuals "qualified" for the desirable outcome

"Equal treatment," people tend to believe such treatment is fair.

**Grgic-Hlaca et al. (2016)**

Prediction does not *explicitly* use $\mathbf{A}$, i.e.

$$\widehat{\mathbf{Y}} = f(\mathbf{X})$$

Unfortunately encoded in US law (despite contradicting other laws)

**Dwork et al. (2012)**

Similar predictions for individuals who are similar (in their unprotected attributes). If $\mathbf{X}_i \approx \mathbf{X}_{i'}$ then

$$\widehat{\mathbf{Y}}(\mathbf{X}_i, \mathbf{A}_i) \approx \widehat{\mathbf{Y}}(\mathbf{X}_{i'}, \mathbf{A}_{i'})$$

Continuity condition in $\mathbf{X}$ but not $\mathbf{A}$. Can be related to matching approaches to causal inference

Various works showing impossibility of simultaneously satisfying several of the different fairness definitions at once: Kleinberg et al (2016), Chouldechova (2016)

**(Simplified) impossibility theorem**

Unless the world is already fair, the only solutions satisfying both equal treatment (or opportunity) and equal outcomes (demographic parity) are trivial ones (e.g. jail everyone)

Many versions of this can be proven with different sets of assumptions but basically the same conclusion: some fairness definitions are contradictory

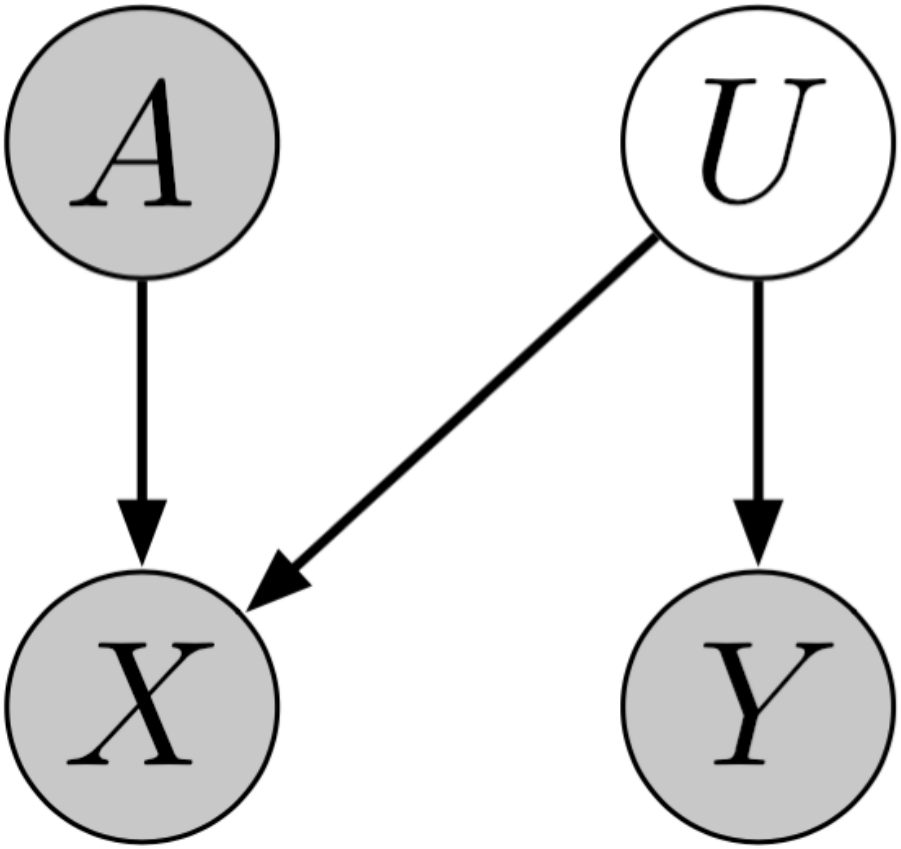
I do not advocate everyone use the counterfactual definition of fairness. Maybe there is no one "right" answer. This approach is useful for probing/understanding limitations.

Chief Justice Roberts: "The way to stop discrimination on the basis of race is to stop discriminating on the basis of race" (PICS, 2007).

Equal treatment or fairness through unawareness

Is it actually any good?

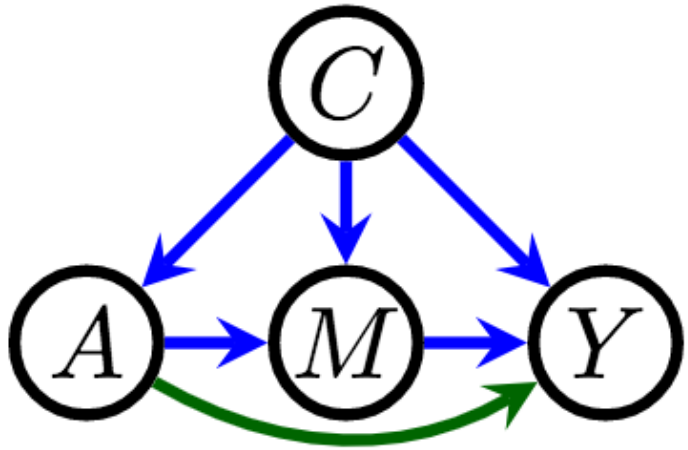
# Chief Justice Roberts is *mathematically* wrong




- Auto insurance risk **Y**
- Car color **X**
- Policyholder's gender **A**
- "Aggressiveness" **U**

"Equal treatment" actually *introduces* unfairness where there was none

- Kusner et al (2017): path-dependent counterfactual fairness (supplement)
- Kilbertus et al (2017): proxies and resolving variables
- Nabi and Shpitser (2018): path specific effects, mediators, constrain parameters
- Chiappa and Gillam (2018): more flexible modeling, modify features
- Zhang and Bareinboim (2017): (counterfactual) direct, indirect, and spurious




Model for crime data where the mediator can be, e.g., prior convictions

## Pathways and proxies

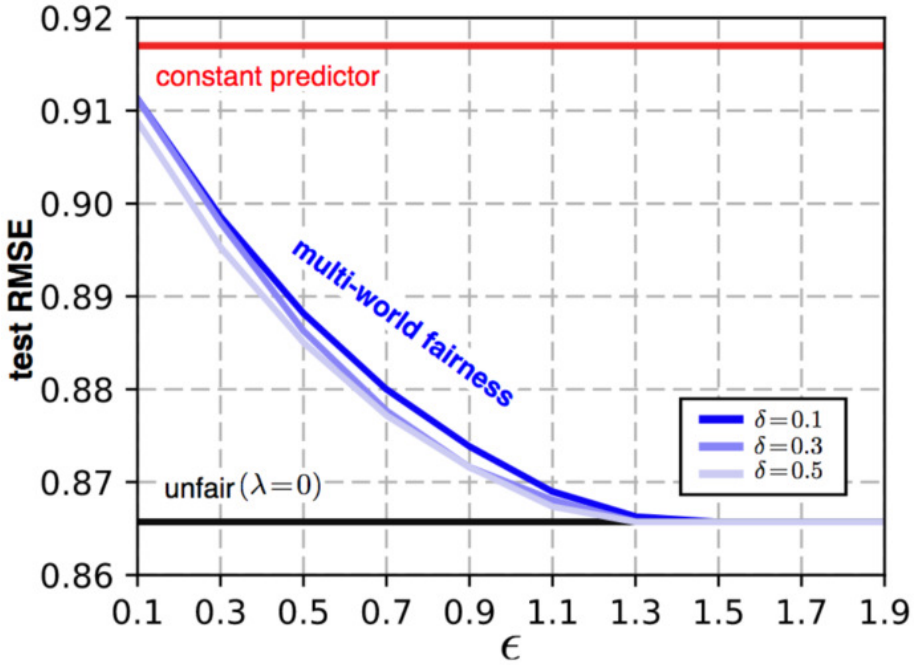
- Enhanced capability of causal modeling to address fairness questions
- Capture *some aspects* of equal treatment, equal outcomes, equal opportunity
- Does this resolve the Fundamental Contradiction of Fairness?

In my opinion: no. People will disagree about pathways

# Problem: consensus on a causal model / pathways

When Worlds Collide: Integrating Different Counterfactual Assumptions in Fairness (Russell et al, *NeurIPS 2017*)

- Competing causal models
- Approximate counterfactual fairness (relax equality constraint)
- Predictions approximately satisfy fairness across both (all) models
- Limitation: the more contradictory are the competing models, the more trivial the predictions (constant)
- Causal framing of fundamental contradiction




At least $1 - \delta$ probability of satisfying $\epsilon$-relaxation of counterfactual fairness, $\lambda$ is an optimization tuning parameter which weights the multi-world fairness penalty

## Resolving the contradiction

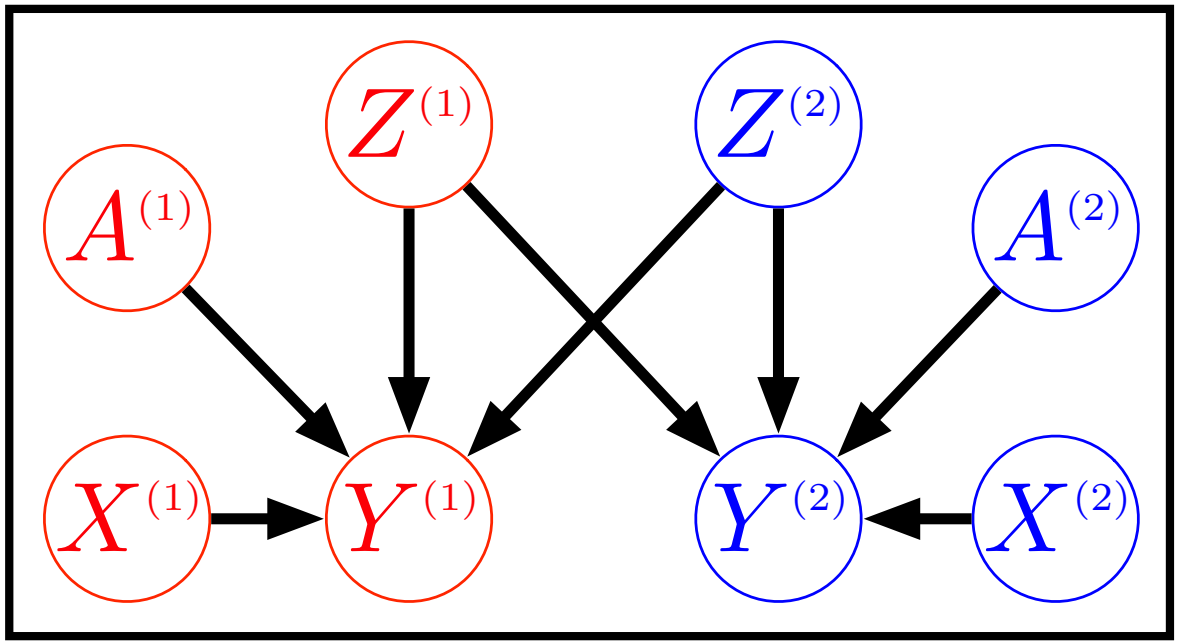
I think this is the right *path*. It's now about understanding the causes of unfairness well enough to reach consensus.

## Recognizing separate design elements of predictive ML

- Model the **intervention** (that predictions will be used for) as its own separate variable **Z**
- Causal model including **Z**, explicitly model changes in the world due to use of ML
- Potentially multiple objectives to represent interests of different stakeholders

Recent work: Making Decisions that Reduce Discriminatory Impacts (Kusner et al, *ICML 2019*)

# Example: fair intervention under interference



When designing an optimal, fair intervention $\mathbf{Z}$, instead of enforcing the equality in the definition of counterfactual fairness, we can also use an asymmetric bound on **counterfactual privilege**, for $\tau \geq 0$

$$\mathbb{E}[\widehat{\mathbf{Y}}(a, \mathbf{Z})] - \mathbb{E}[\widehat{\mathbf{Y}}(a', \mathbf{Z})] \leq \tau$$

- In practice these *asymmetric constraints* will only be active for privileged values of $a$ (actual, left term), and inactive otherwise
- Intervention should not allocate resources in a way that helps people (in expectation) become more than $\tau$ (in terms of the outcome) units better than they would be if they were not privileged

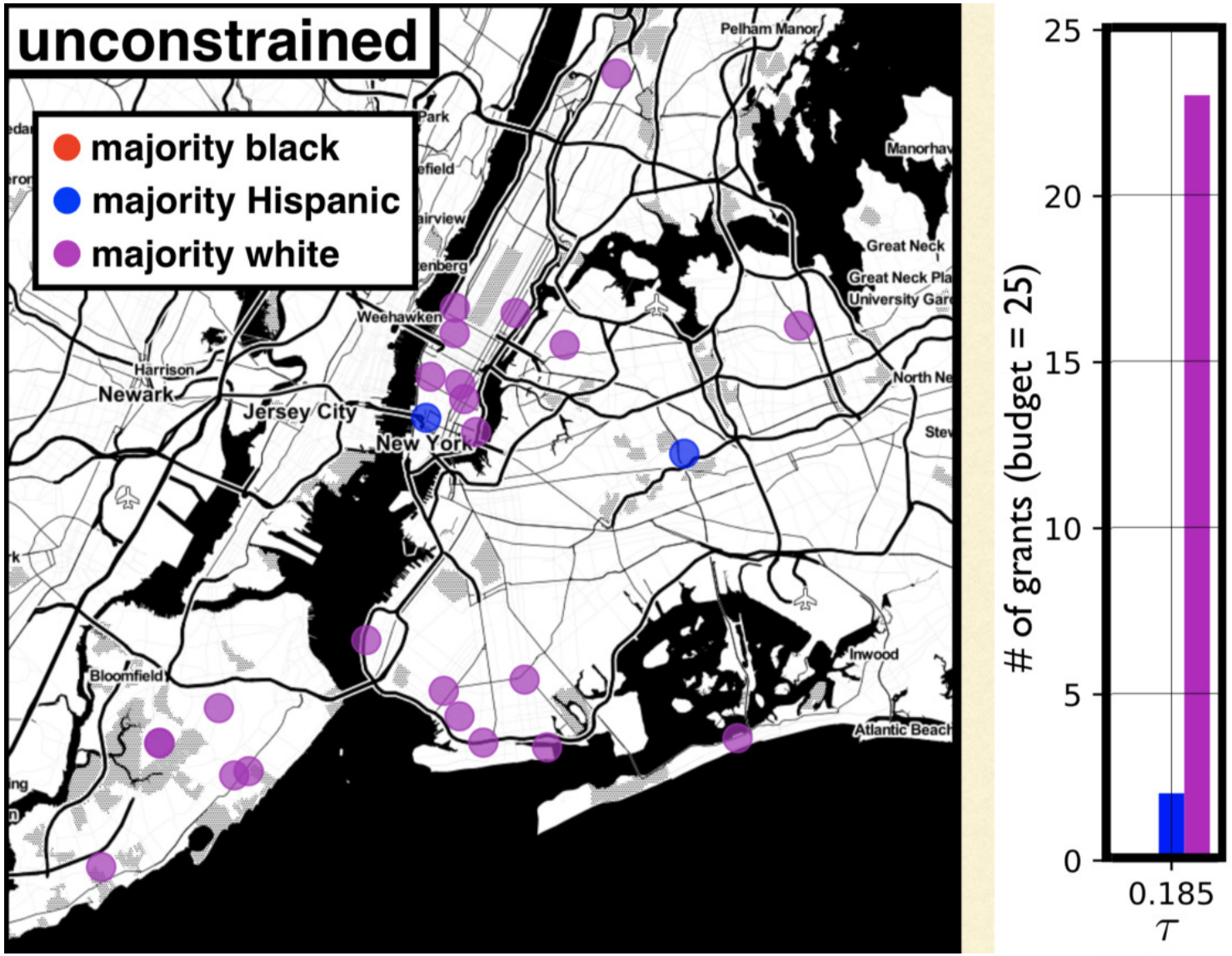
# Optimal intervention under interference

- Our goal is to design optimal interventions or policies $\mathbf{Z}$ subject to a budget constraint, e.g.

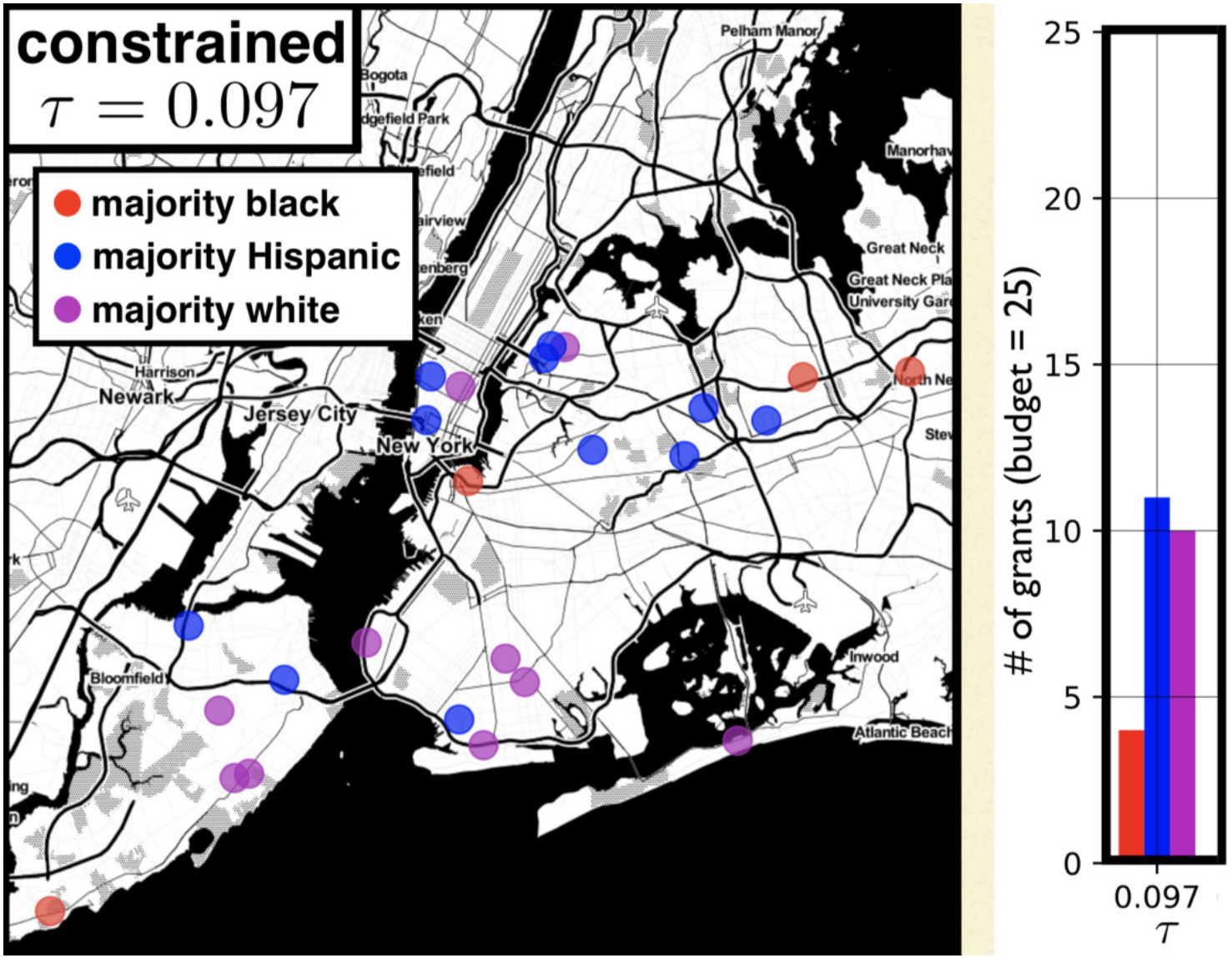
$$\mathbf{Z} = \arg\max \sum_i \mathbb{E}\left[\widehat{\mathbf{Y}}^{(i)}(a^{(i)}, \mathbf{Z}) | \mathbf{A}^{(i)}, \mathbf{X}^{(i)}\right] \quad s.t. \quad \sum_i \mathbf{Z}^{(i)} \leq b$$

- Interference means $\mathbf{Y}^{(i)}$ is potentially a function of all of $\mathbf{Z}$ and not just $\mathbf{Z}^{(i)}$
- Next two slides: optimal interventions with and without counterfactual privilege constraint

# School resource allocation without fairness constraint



# School resource allocation bounded counterfactual privilege



# Other directions

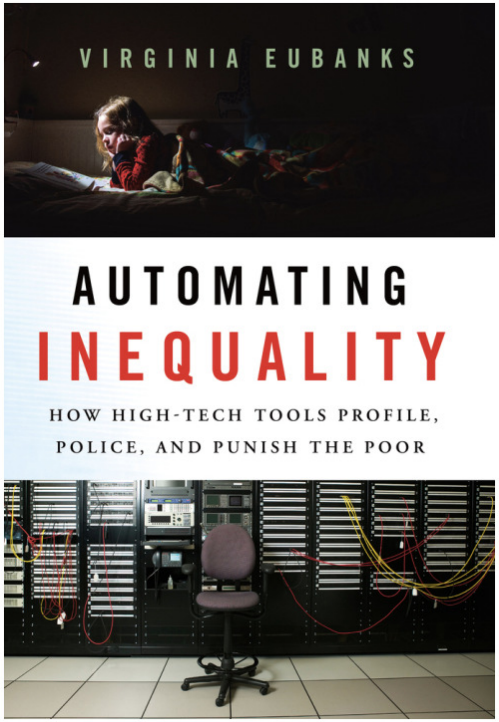
Things it would be cool if more people worked on, in general

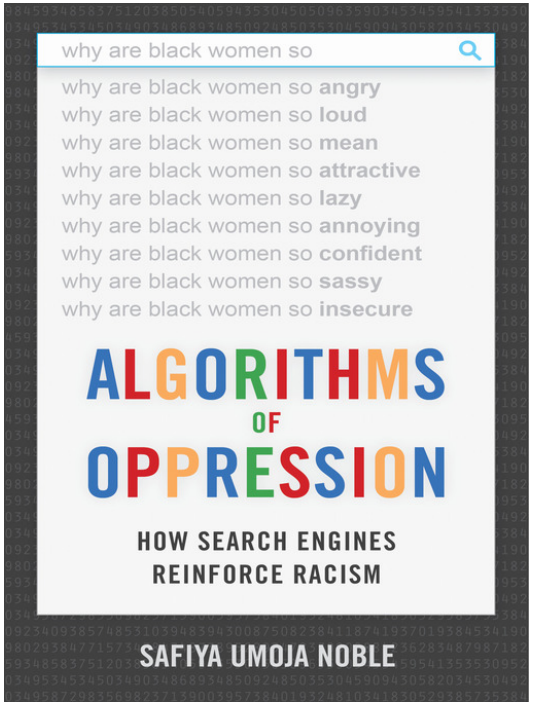
- Interdisciplinary/STS-informed tech/quantitative research
- Empirical ethics, "big data"/ML-informed social research
- Political/economy of whether any of this is actually headed in a good direction

# Questions?

Thank you for listening!

More books full of examples: Eubanks, Noble, Wachter-Boettcher





*The rise of big data policing: Surveillance, Race, and the Future of Law Enforcement* by A. Ferguson