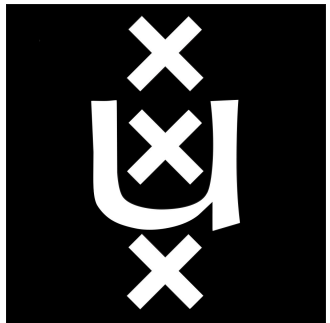
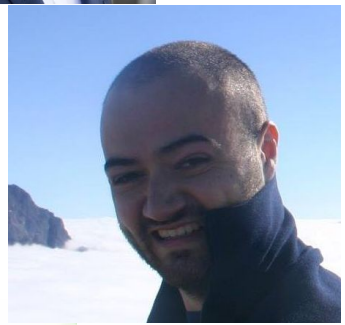
AI for Society

BSc AI 2020/21



Who we are

Tobias Blanke, university professor AI & Humanities



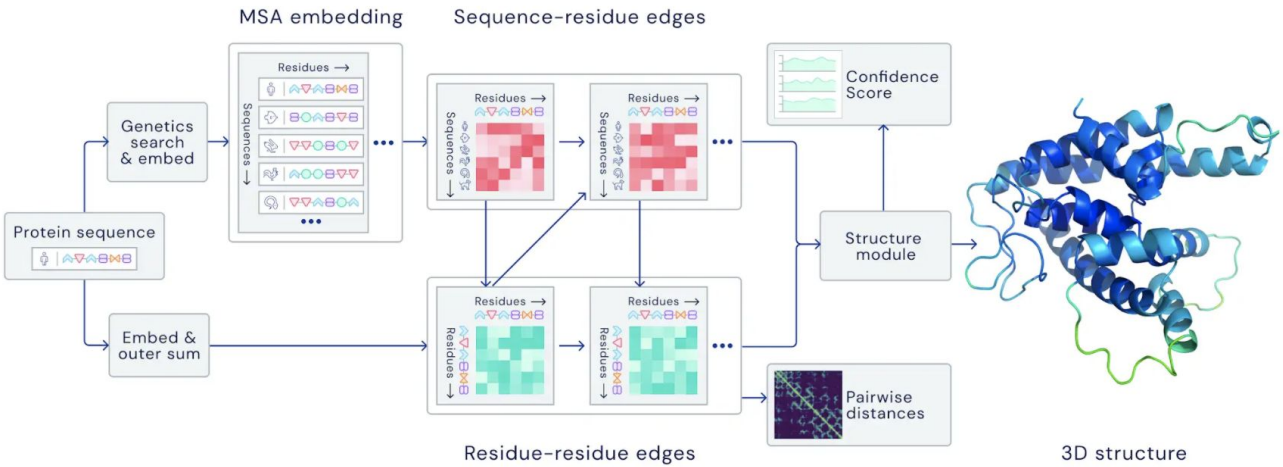
Giovanni Colavizza*, assist. prof. Digital Humanities

Zarah van Hout, research assistant

* Main point of contact, via Canvas (preferably) or g.colavizza@uva.nl

What is AI for Society about?

AI is increasingly being used to great benefit; notorious examples include **DeepMind's Alpha Fold**, which recently solved protein folding..



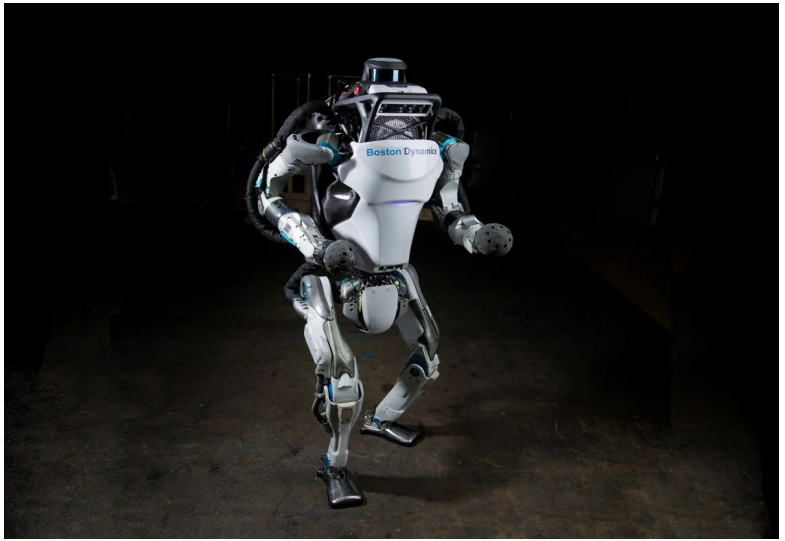
AN OVERVIEW OF THE MAIN NEURAL NETWORK MODEL ARCHITECTURE. THE MODEL OPERATES OVER EVOLUTIONARILY RELATED PROTEIN SEQUENCES AS WELL AS AMINO ACID RESIDUE PAIRS, ITERATIVELY PASSING INFORMATION BETWEEN BOTH REPRESENTATIONS TO GENERATE A STRUCTURE.

What is AI for Society about?

AI is increasingly being used to great benefit;

SpaceX's landing rockets..

Boston Dynamics' robots..

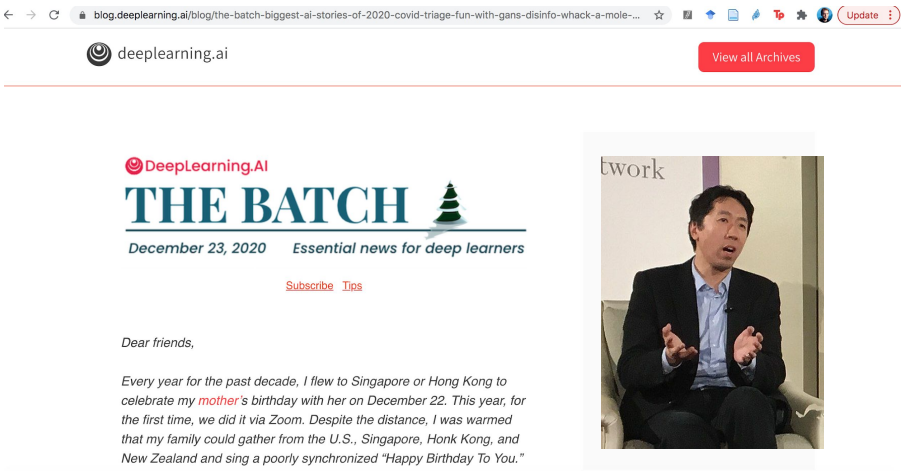


What is AI for Society about?

Many states are seeing AI as of strategic value..

https://www.holoniq.com/notes/50-national-ai-strategies-the-2020-ai-strategy-landscape

What is AI for Society about - AI in 2020?



Coping with Covid

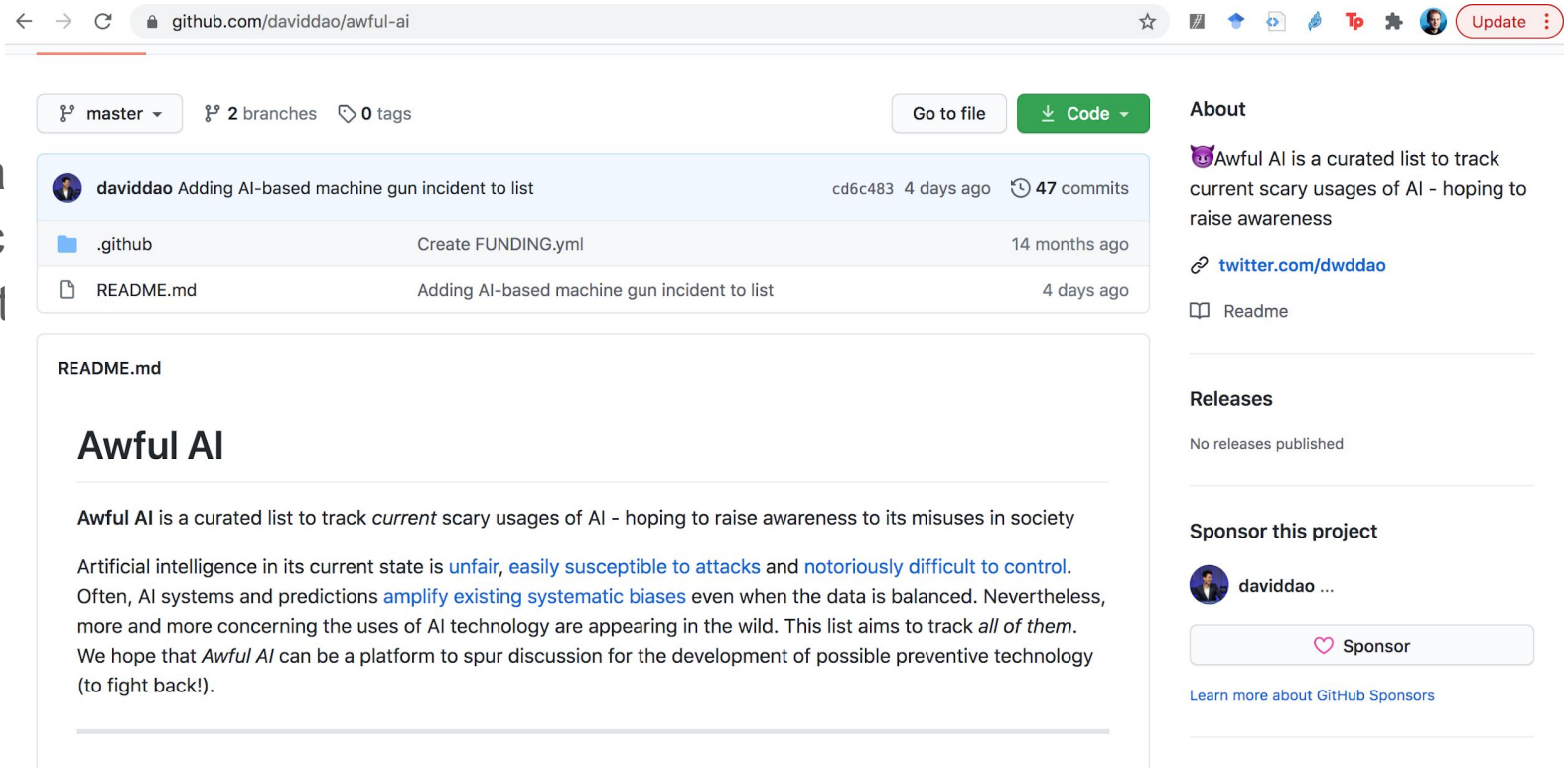
This Snowman Does Not Exist

Representing the Underrepresented

Algorithms Against Disinformation

What is AI for Society about?

We face ma
transparenc
advertising t



Technology

Algorithms are deciding who gets the first vaccines. Should we trust them?

Clashes over who gets vaccinated first could ramp up as supplies roll out nationwide. Transparency over how these mathematical formulas work is critical, their designers say.

RESEARCH ARTICLE

Dissecting racial bias in an algorithm used to manage the health of populations

Ziad Obermeyer[1,2,*], Brian Powers[3], Christine Vogeli[4], Sendhil Mullainathan[5,*,†]

+ See all authors and affiliations

Science 25 Oct 2019:
Vol. 366, Issue 6464, pp. 447-453
DOI: 10.1126/science.aax2342

Racial bias in health algorithms

The U.S. health care system uses commercial algorithms to guide health decisions. Obermeyer *et al.* find evidence of racial bias in one widely used algorithm, such that Black patients assigned the same level of risk by the algorithm are sicker than White patients (see the Perspective by Benjamin). The authors estimated that this racial bias reduces the number of Black patients identified for extra care by more than half. Bias occurs because the algorithm uses health costs as a proxy for health needs. Less money is spent on Black patients who have the same level of need, and the algorithm thus falsely concludes that Black patients are healthier than equally sick White patients. Reformulating the algorithm so that it no longer uses costs as a proxy for needs eliminates the racial bias in predicting who needs extra care.

‘(...) the algorithm uses health costs as a proxy for health needs.’

What could be the problem with this assumption?

Why would algorithm designers do this?

What alternative proxies might there be?

Type into the chatbox ...

Weekly topics

1. Introduction + Fairness and Bias (**TODAY**)
2. Explainable and Interpretable AI
3. AI to Study Society and Culture
4. The Economics of AI

Course logistics

Each week we meet for a **lecture (Mondays, 11:00-13:00)** and a **laboratory (Wednesdays, 11:00-15:00)**. Yes, we will do a lunch break for labs.

Lectures are lectures on the topic at hand. We will pre-record each one and leave time for Q&A. At the end of each lecture, we will hand-out a **group assignment**.

Laboratories give you time to work on your group assignments, plus there will be some reporting back and discussion.

Assessment

60% for 4 group assignments (weekly deadlines)

40% for a final individual essay (take-home, after the course ends)

For more details, see Canvas

How to communicate and code of conduct

Please use Canvas to email Giovanni for any question on the course. Try to use the Discussion section first, to get support among your peers.

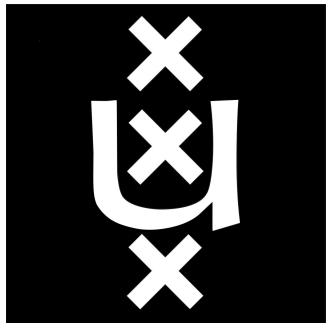
We will mainly use Announcements and class time to communicate with you.

Please take close note of the applicable **code of conduct** regarding group and individual work, including plagiarism. We will use anti-plagiarism software to check your submissions. We trust you will do your own work.

Q&A

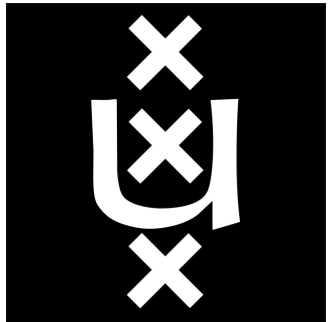
AI for Society

BSc AI 2020/21



Week 1: Fairness and Bias

Giovanni Colavizza

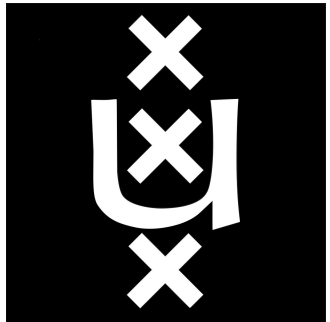


Topics

1. Fairness
2. Bias
3. Countermeasures
4. Assignment

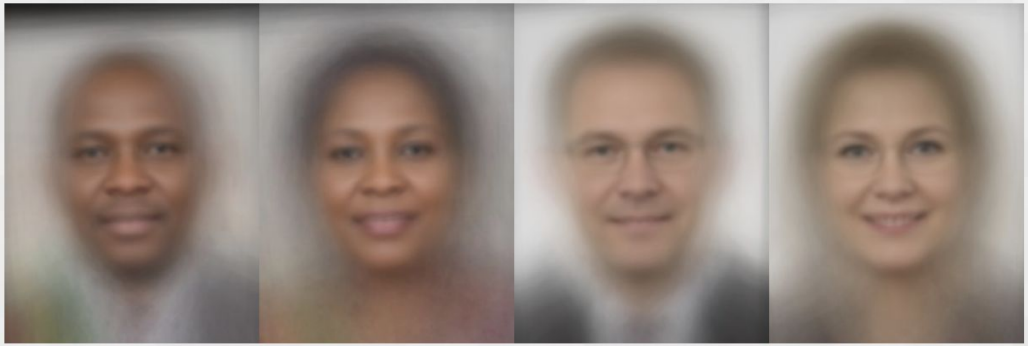
PART 1: Fairness

Giovanni Colavizza



Facial recognition

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%



Bouwlaimi and Gebru. 2018. *Gender Shades* http://gendershades.org/index.html

Recidivism detection

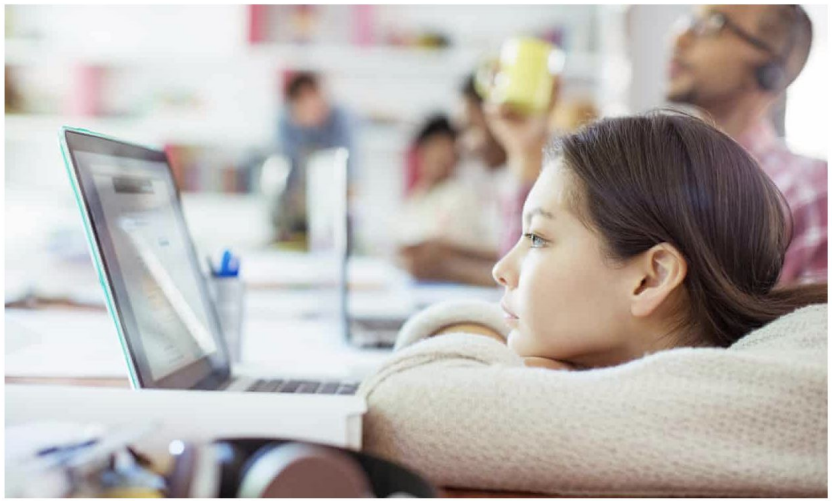
https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Targeted ads

This article is more than **5 years old**

Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



▲ One experiment showed that Google displayed adverts for a career coaching service for executive jobs 1,852 times to the male group and only 318 times to the female group. Photograph: Alamy

https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study

Questions

- If a classifier works with 100% accuracy, who is affected by it?
- What if it works 90% uniformly?
- What if it works 90% non-uniformly, e.g., 95% for one non-protected group and 60% for a protected group?

- Ethical questions:
  - What should be done?
    - Which requirements should this classifier abide to?
    - Should it be forbidden or regulated? If so, how?
  - Who is responsible?

By the way.. Advertising

Algorithmic Bias? An Empirical Study into Apparent Gender-Based Discrimination in the Display of STEM Career Ads

40 Pages • Posted: 15 Oct 2016 • Last revised: 12 Mar 2018

Anja Lambrecht
London Business School

Catherine E. Tucker
Massachusetts Institute of Technology (MIT) - Management Science (MS)

Date Written: March 9, 2018

Abstract

We explore data from a field test of how an algorithm delivered ads promoting job opportunities in the Science, Technology, Engineering and Math (STEM) fields. This ad was explicitly intended to be gender-neutral in its delivery. Empirically, however, fewer women saw the ad than men. This happened because younger women are a prized demographic and are more expensive to show ads to. An algorithm which simply optimizes cost-effectiveness in ad delivery will deliver ads that were intended to be gender-neutral in an apparently discriminatory way, due to crowding out. We show that this empirical regularity extends to other major digital platforms.

Lambrecht and Tucker. 2016. *Algorithmic Bias?* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2852260

What do we mean by ‘fairness’?

Fairness is an elusive concept.

Oftentimes, it refers to lack of bias in decisions. In a related way, fairness might entail the balanced treatment of sub-populations and individuals.

Fairness is elusive also because some people mainly care about **equality** of opportunity, while others emphasize **equity** in the outcomes.

> Learn 21 definitions of ‘fairness’ by Arvind Narayanan: https://www.youtube.com/watch?v=jIXIuYdnyyk.

What do we mean by ‘ethics’?

“Ethics is based on well-founded standards of right and wrong that prescribe what humans ought to do, usually in terms of rights, obligations, benefits to society, **fairness**, or specific virtues.”*

Any ethical framework is contingent to time, place, culture. Some components are so widely shared that might have deep roots into our evolutionary history too (e.g., reciprocity).

The first question to ask when you hear ‘Ethical AI’ is: ***whose ethics?*** Often, that goes unstated. Please always ask yourself the question during this course (and afterwards).

* Velasquez et al. 2010. *What is Ethics?* https://www.scu.edu/ethics/ethics-resources/ethical-decision-making/what-is-ethics.

What do we mean by ‘fairness’?

Many **formal definitions of fairness** have been proposed.

Their goal is to formalize what it means for an AI (e.g., a classifier) to be ‘fair’, according to some notion of fairness. It is then up to someone (Governments? Individuals? Companies?) to decide which notion of fairness is appropriate.

Note that definitions of fairness are often (mathematically and morally) mutually exclusive.

We mainly use (you will find more in there):

- Suresh and Guttag. 2020. *A Framework* https://arxiv.org/abs/1901.10002
- Mitchell et al. 2021. *Algoritmic Fairness* https://www.annualreviews.org/doi/abs/10.1146/annurev-statistics-042720-125902
- Mehrabi et al. 2019. *A Survey* https://arxiv.org/abs/1908.09635

Families of definitions of fairness

- **Group-Independent Predictions** require that the decisions that are made are independent (or conditionally independent) of group membership. For example, the *demographic parity criterion* states that the proportion of each segment of a protected class (e.g., gender) should receive the positive outcome at equal rates.
- **Equal Metrics Across Groups** require equal prediction metrics of some sort (this could be accuracy, true positive rates, false positive rates, and so on) across groups. For example, the *equality of opportunity criterion* requires equal true positive/negative rates across groups.
- **Individual Fairness** requires that individuals who are similar with respect to the prediction task are treated similarly. There is an assumption that an ideal feature space exists in which to compute similarity, and that those features are recoverable in the available data. For example, *fairness through (un)awareness* tries to identify a task-specific similarity metric in which individuals who are close according to this metric are also close in outcome space.
- **Causal Fairness** definitions place some requirement on the causal graph that generated the data and outcome. For example, *counterfactual fairness* requires that there is not a causal pathway from a sensitive attribute to the outcome decision

Suresh and Guttag 2020. *A Framework* https://arxiv.org/abs/1901.10002

How to formalize a definition

Notation (assume, w/o loss of generality, a binary classifier 1/0):

- D is your decision {0,1}
- Y is the ground truth {0,1}
- X are non-protected covariates (e.g., income and age)
- A are protected covariates (e.g., race or sex)

How to formalize a definition

- *Demographic parity* (also called statistical parity or group fairness) entails that outcomes need to be balanced across groups, irrespective of ground truth and covariates.
    - $P(D = 1|\mathbf{A = 1}) = P(D = 1|\mathbf{A = 0})$ and possibly the same for $D = 0$.

How to formalize a definition

- *Demographic parity* (also called statistical parity or group fairness) entails that outcomes need to be balanced across groups, irrespective of ground truth and covariates.
  - P(D = 1|**A = 1**) = P(D = 1|**A = 0**) and possibly the same for D = 0.

- *Equality of opportunity* entails that the TP and/or TN rates are balanced.
  - TP: P(D = 1|**Y = 1**,A = 1) = P(D = 1|**Y = 1**,A = 0)
  - TN: P(D = 0|**Y = 0**,A = 1) = P(D = 0|**Y = 0**,A = 0)

How to formalize a definition

- *Demographic parity* (also called statistical parity or group fairness) entails that outcomes need to be balanced across groups, irrespective of ground truth and covariates.
  - P(D = 1|**A = 1**) = P(D = 1|**A = 0**) and possibly the same for D = 0.

- *Equality of opportunity* entails that the TP and/or TN rates are balanced.
  - TP: P(D = 1|**Y = 1**,A = 1) = P(D = 1|**Y = 1**,A = 0)
  - TN: P(D = 0|**Y = 0**,A = 1) = P(D = 0|**Y = 0**,A = 0)

- *Fairness through (un)awareness* entails that similar individuals will get similar results.
  - Unawareness: P(D = 1|**X_i**) = P(D = 1|**X_j**) where X_i is very similar to X_j
  - Awareness: P(D = 1|**X_i**,**A = 1**) = P(D = 1|**X_j**,**A = 0**) where X_i is very similar to X_j

How to formalize a definition

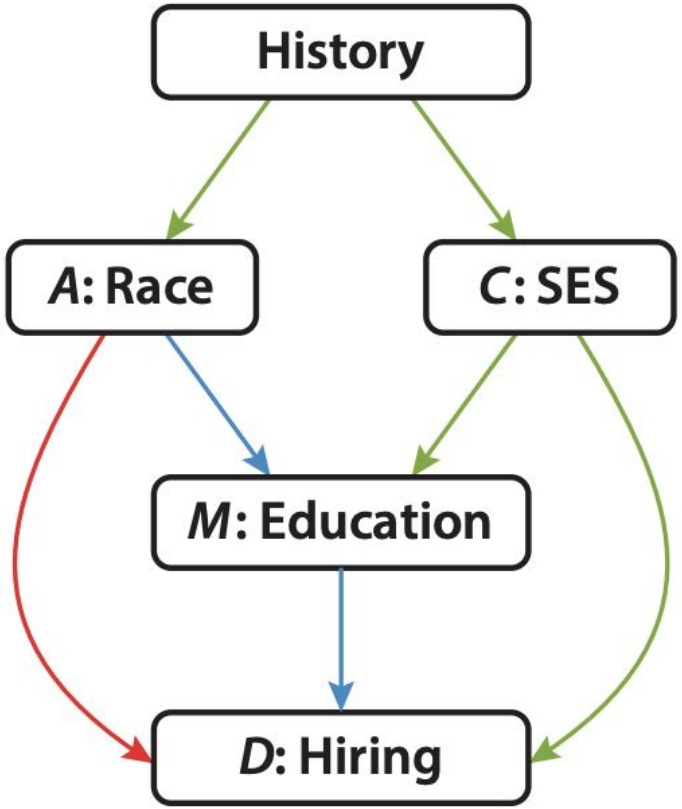
	$Y=1$	$Y=0$	$P(Y=1\|D)$	$P(Y=0\|D)$
$D=1$	True positive	False positive	$P(Y=1\|D=1)$: Positive predictive value	$P(Y=0\|D=0)$: False discovery rate
$D=0$	False negative	True negative	$P(Y=1\|D=0)$: False omission rate	$P(Y=0\|D=0)$: Negative predictive value
$P(D=1\|Y)$	$P(D=1\|Y=1)$: True positive rate	$P(D=1\|Y=0)$: False positive rate		
$P(D=0\|Y)$	$P(D=0\|Y=1)$: False negative rate	$P(D=0\|Y=0)$: True negative rate		$P(D=Y)$: Accuracy

Mitchell et al. 2021. *Algoritmic Fairness* https://www.annualreviews.org/doi/abs/10.1146/annurev-statistics-042720-125902

Counterfactual fairness

Red and (usually) blue would be forbidden; green would be (usually) allowed, yet this is also questionable.

Green (back-door) paths bring back the discussion on “correlation vs causation” and the burden of proof.

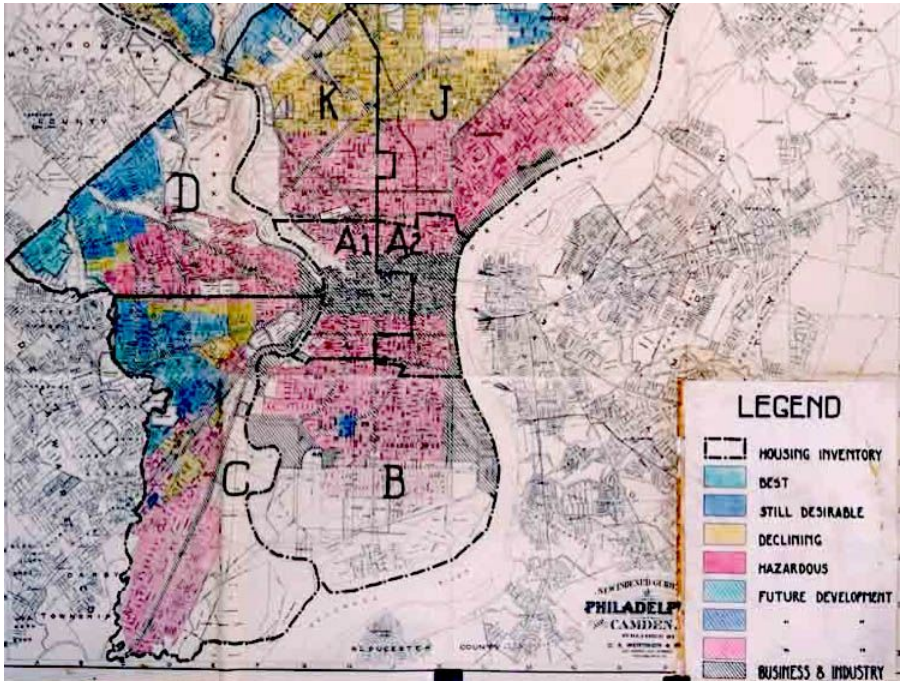


Mitchell et al. 2021. *Algoritmic Fairness* https://www.annualreviews.org/doi/abs/10.1146/annurev-statistics-042720-125902

An example: Redlining

“**Redlining** is the systematic denial of various services or goods by US federal government agencies, local governments, or the private sector either directly or through the selective raising of prices.”

https://en.wikipedia.org/wiki/Redlining



An example: Redlining

Notation:

- D is your decision {0,1}, e.g., to give credit or not.
- Y is the ground truth {0,1}
- X are non-protected covariates (e.g., zip code)
- A are protected covariates (e.g., race)

An example: Redlining

- *Demographic parity*.
  - P(D = 1|**A = 1**) = P(D = 1|**A = 0**) and possibly the same for D = 0.
  - Would be fair (in the equity sense) to groups, but unfair (in the equality sense) to individuals. It would also be economically inefficient. Can you think why?

An example: Redlining

- *Demographic parity*.
  - P(D = 1|**A = 1**) = P(D = 1|**A = 0**) and possibly the same for D = 0.
  - Would be fair (in the equity sense) to groups, but unfair (in the equality sense) to individuals. It would also be economically inefficient. Can you think why?
- *Equality of opportunity*.
  - TP: P(D = 1|**Y = 1**,A = 1) = P(D = 1|**Y = 1**,A = 0)
  - TN: P(D = 0|**Y = 0**,A = 1) = P(D = 0|**Y = 0**,A = 0)
  - Would be fair (in the equality sense) but *to work it would require to drop non-protected covariates which are highly correlated with protected ones*. Can you think why?

An example: Redlining

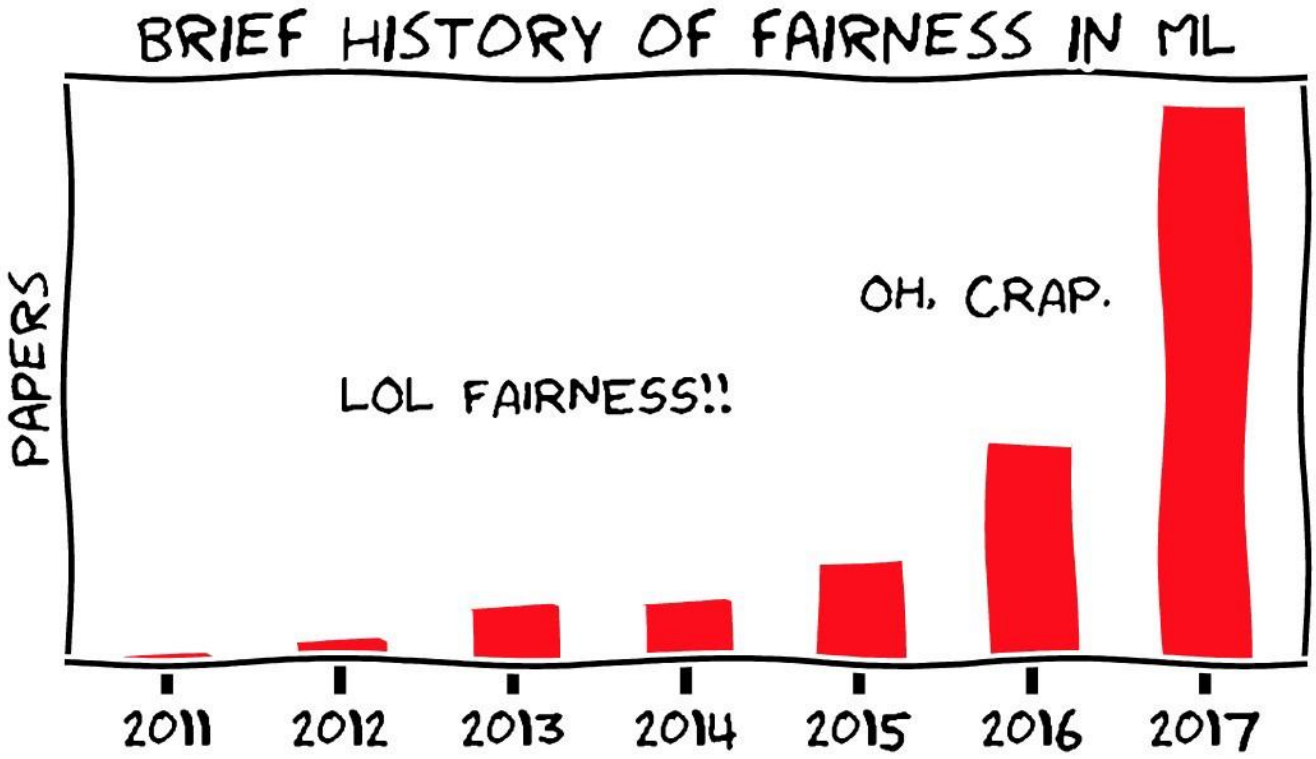
- *Demographic parity*.
  - P(D = 1|**A = 1**) = P(D = 1|**A = 0**) and possibly the same for D = 0.
  - Would be fair (in the equity sense) to groups, but unfair (in the equality sense) to individuals. It would also be economically inefficient. Can you think why?
- *Equality of opportunity*.
  - TP: P(D = 1|**Y = 1**,A = 1) = P(D = 1|**Y = 1**,A = 0)
  - TN: P(D = 0|**Y = 0**,A = 1) = P(D = 0|**Y = 0**,A = 0)
  - Would be fair (in the equality sense) but *to work it would require to drop non-protected covariates which are highly correlated with protected ones*. Can you think why?
- *Fairness through (un)awareness* entails that similar individuals will get similar results.
  - Unawareness: P(D = 1|**X_i**) = P(D = 1|**X_j**) where X_i is very similar to X_j
    - It would be unfair in both equity and equality senses. Can you think why?
    - *This is the argument that was used to justify redlining.*
  - Awareness: P(D = 1|**X_i**,**A = 1**) = P(D = 1|**X_j**,**A = 0**) where X_i is very similar to X_j
    - Likely similar to equality of opportunity. Can you think why?
- What about *counterfactual fairness*? Would zip-codes be allowed there?

Why care about ‘fairness’?

Disparate impact: errors do not affect everyone in the same way. For example, being flagged at high-risk of recidivism by error (FP) usually has worse consequences than being flagged at low-risk by error (FN).

Allocative vs representational harm: allocative harm refers to unfair allocation of resources (e.g., hiring or mortgage decisions), representational refers to the unfair depiction of individuals or groups (e.g., stereotyping).

> Watch Kate Crawford’s lecture ‘The trouble with bias’: https://www.youtube.com/watch?v=fMym_BKWQzk.



Credit: Moritz Hardt

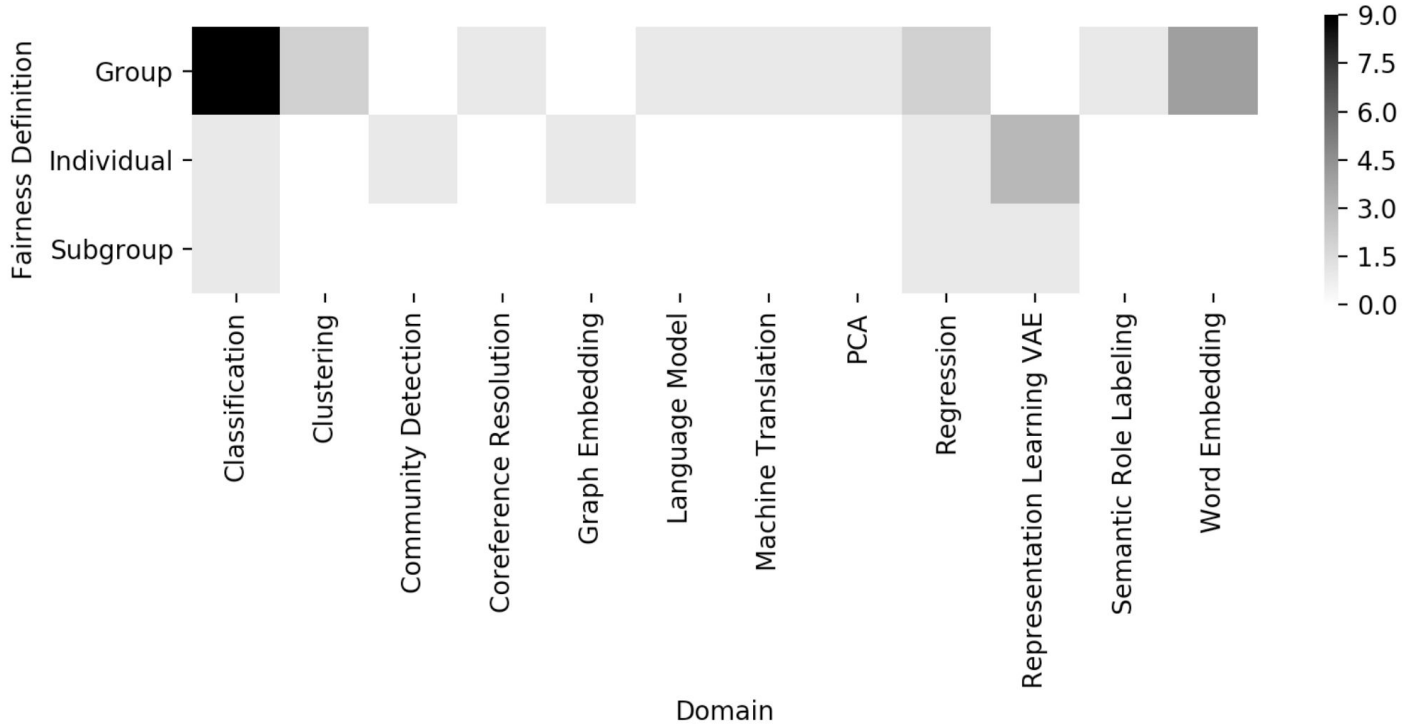


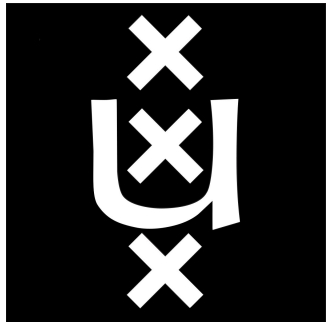
Fig. 7. Heatmap depicting distribution of previous work in fairness, grouped by domain and fairness definition.

Mehrabi et al. 2019. *A Survey* https://arxiv.org/pdf/1908.09635.pdf

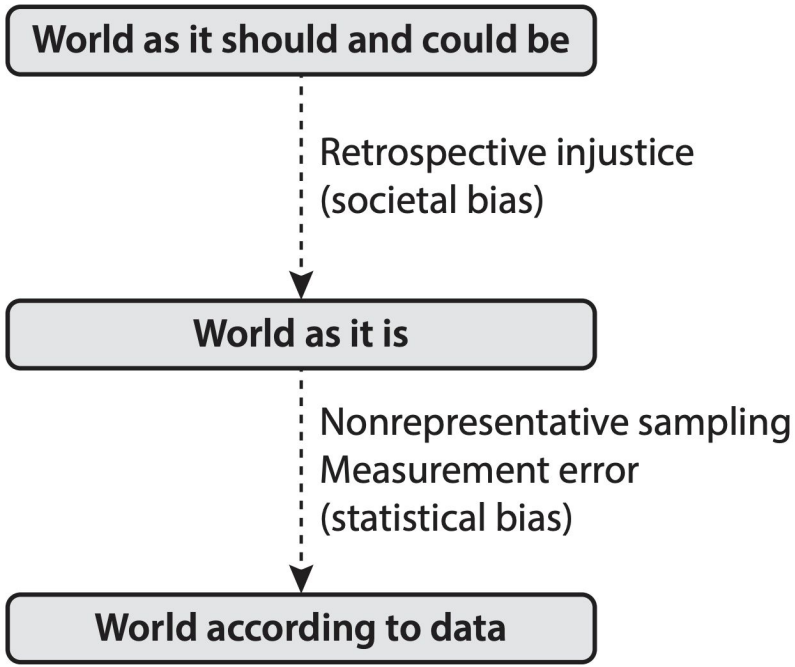
Q&A

PART 2: Bias

Giovanni Colavizza



What do we mean by ‘bias’?



Mitchell et al. 2021. *Algorithmic Fairness* https://www.annualreviews.org/doi/abs/10.1146/annurev-statistics-042720-125902

Statistical bias

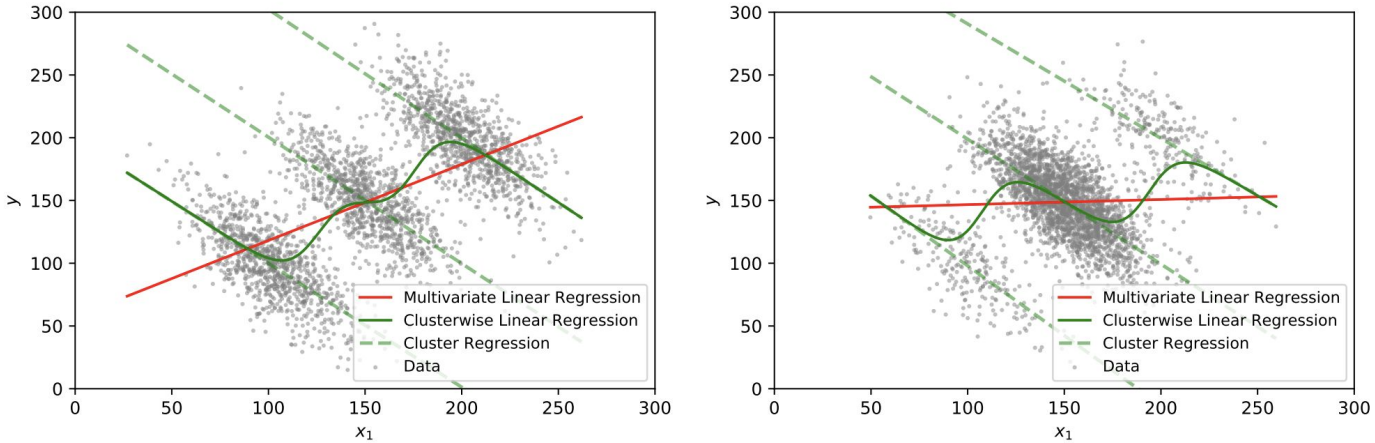
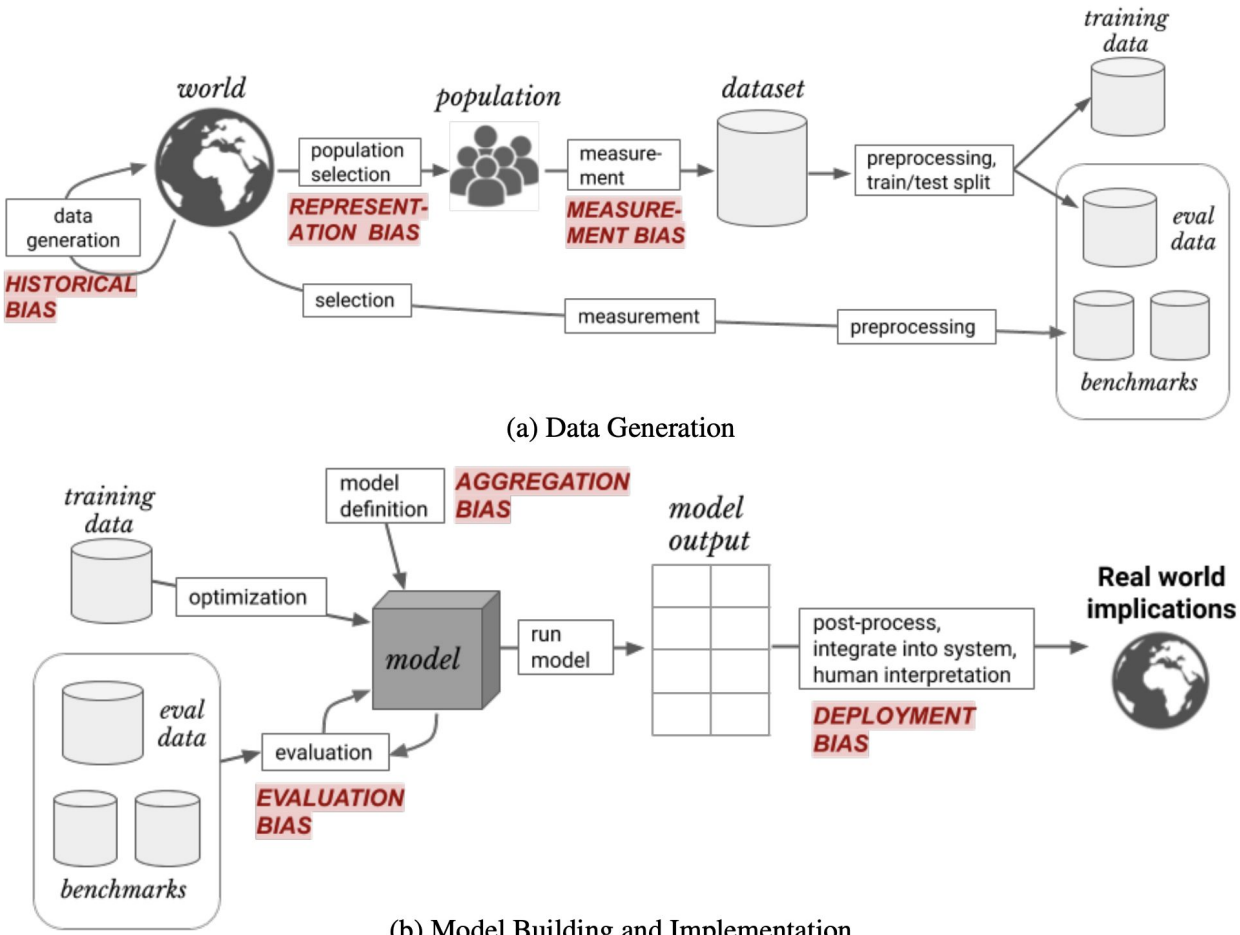


Fig. 1. Illustration of biases in data. Red line shows the regression (MLR) for the entire population, while dashed green lines are regressions for each subgroup, and the solid green line is the unbiased regression. (a) When all subgroups are of equal size, then MLR shows a positive relationship between the outcome and the independent variable. (b) Regression shows almost no relationship in less balanced data. The relationships between variables within each subgroup, however, remain the same. (Credit: Nazanin Alipourfard)

Meherabi et al. 2019. *A Survey* https://arxiv.org/pdf/1908.09635.pdf

Bias in AI



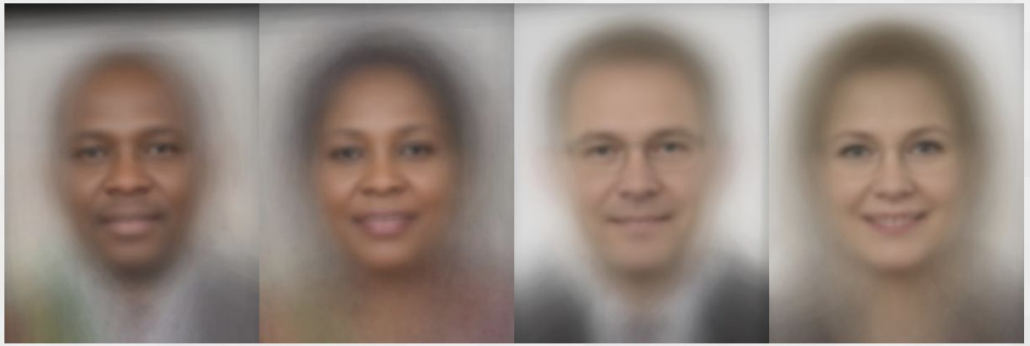
Suresh and Guttag. 2020. *A Framework* https://arxiv.org/pdf/1901.10002.pdf

Examples of bias in AI

- Historical bias
- Representation bias
- Measurement bias
- Evaluation bias
- Aggregation bias
- Deployment bias

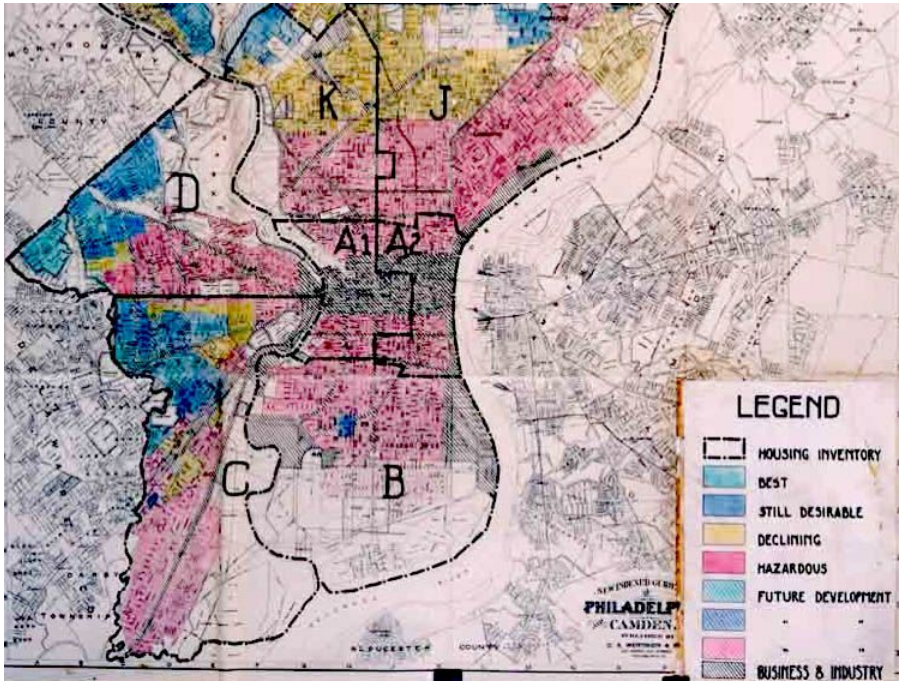
Probably yes
Maybe
Probably not

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%



Examples of bias in AI

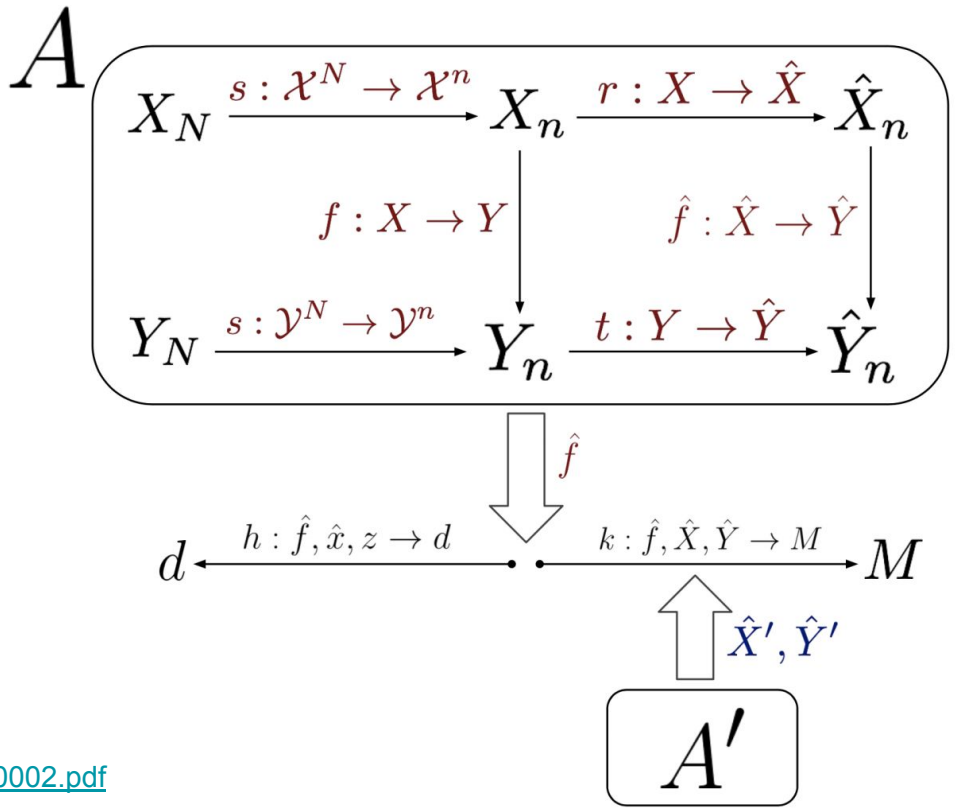
- Historical bias
- Representation bias
- Measurement bias
- Evaluation bias
- Aggregation bias
- Deployment bias



Probably yes
Maybe
Probably not

How to reason about AI bias formally?

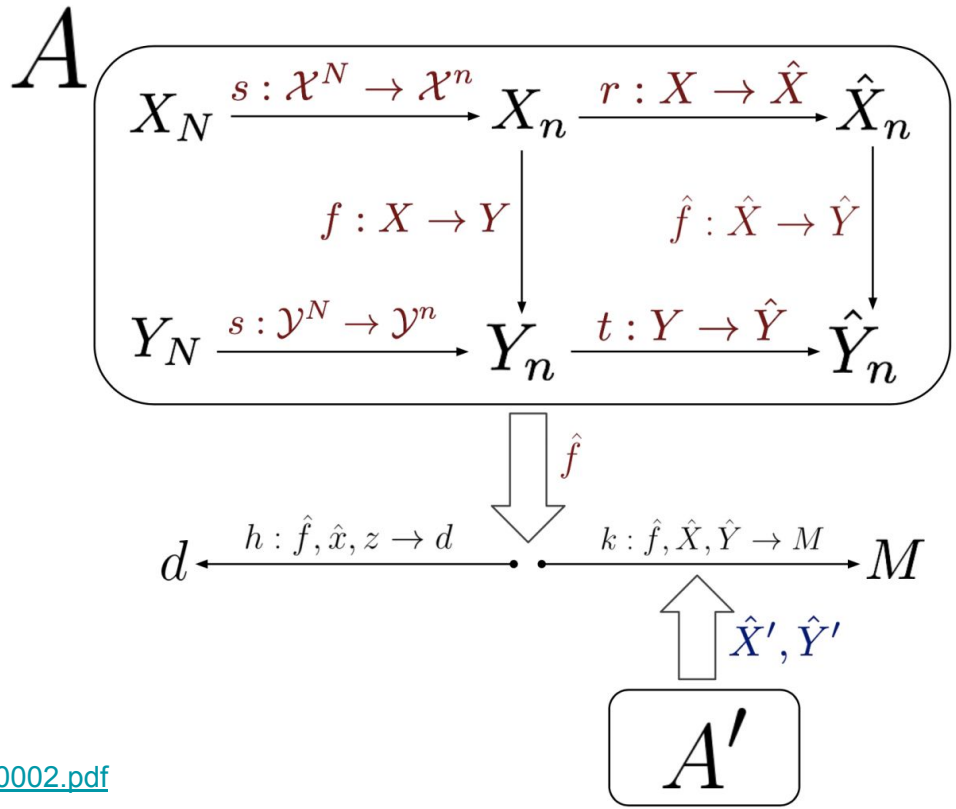
Using **data transformations** is one possible way



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

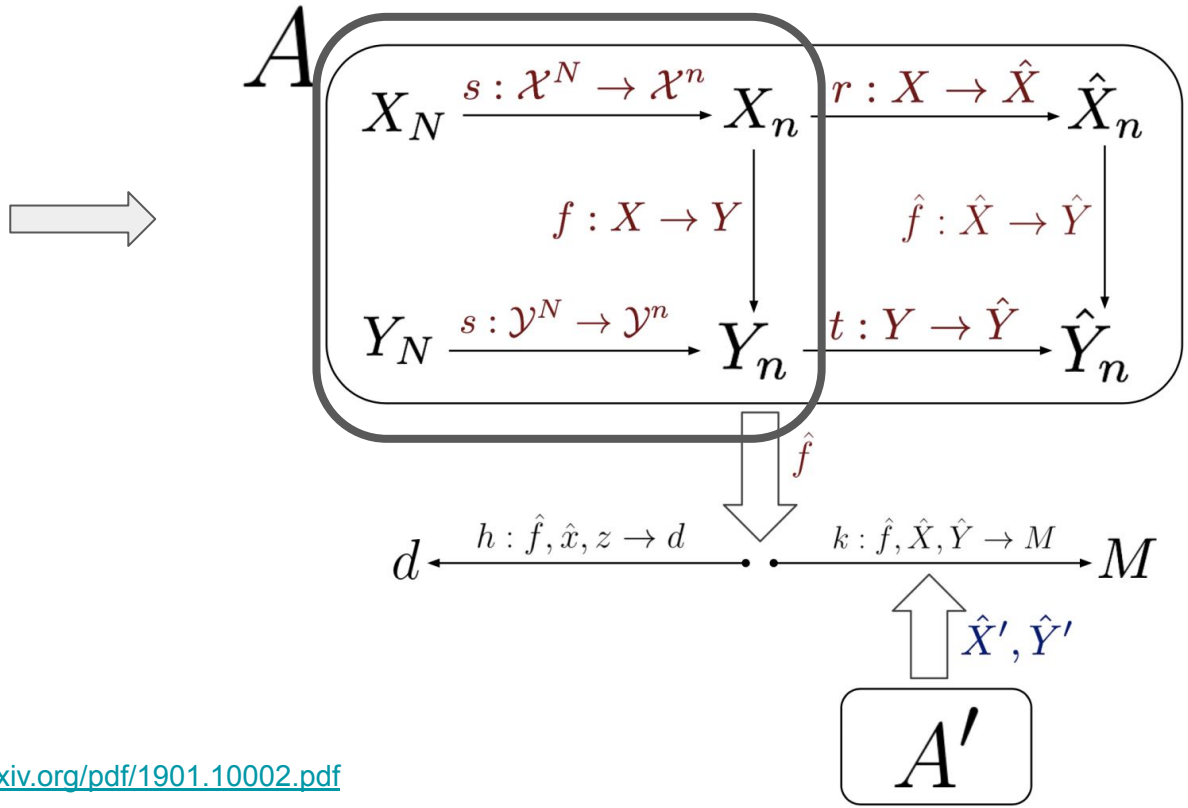
X are real features, **Y** are outcomes. For example, X might be the skills of candidates, Y might be the hiring decisions.



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

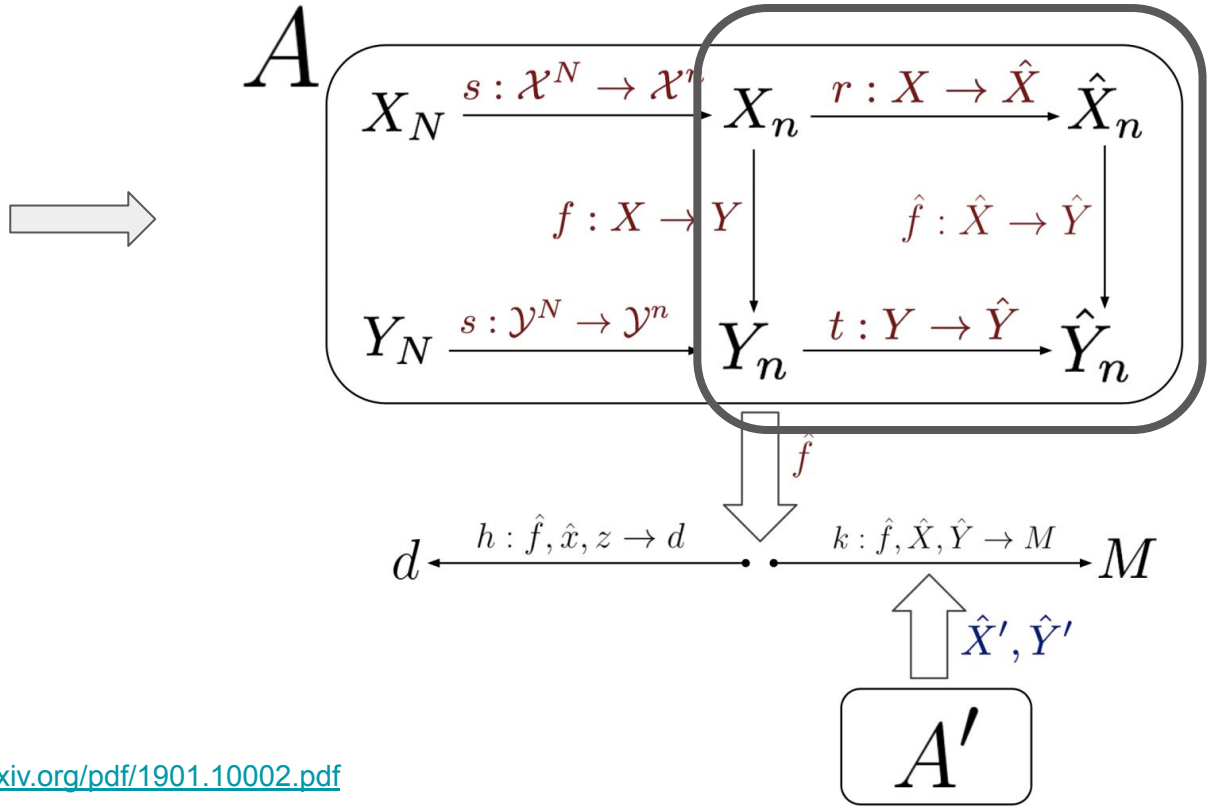
First, we map from the full population ***N*** to a sample ***n*** via the function ***s***. This might introduce **representation (sampling) bias**.



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

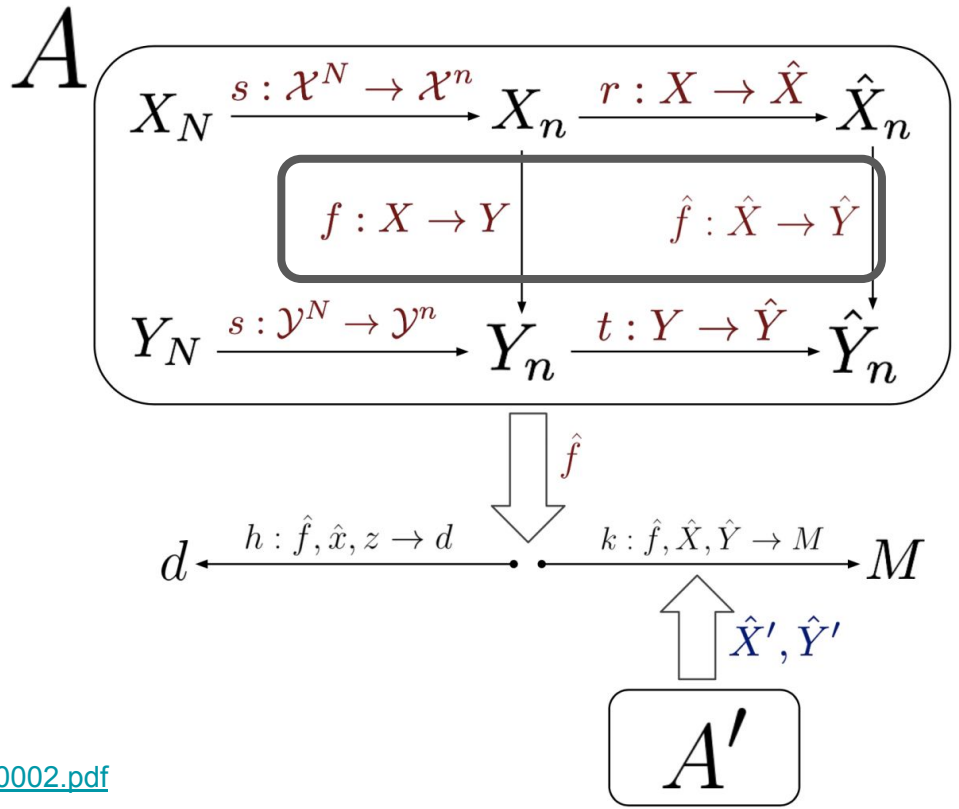
Then, we measure real-world features (e.g., skill) into machine-readable features (e.g., years of experience), via functions ***r*** and ***t***. This might introduce **measurement (and possibly historical) bias**.



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

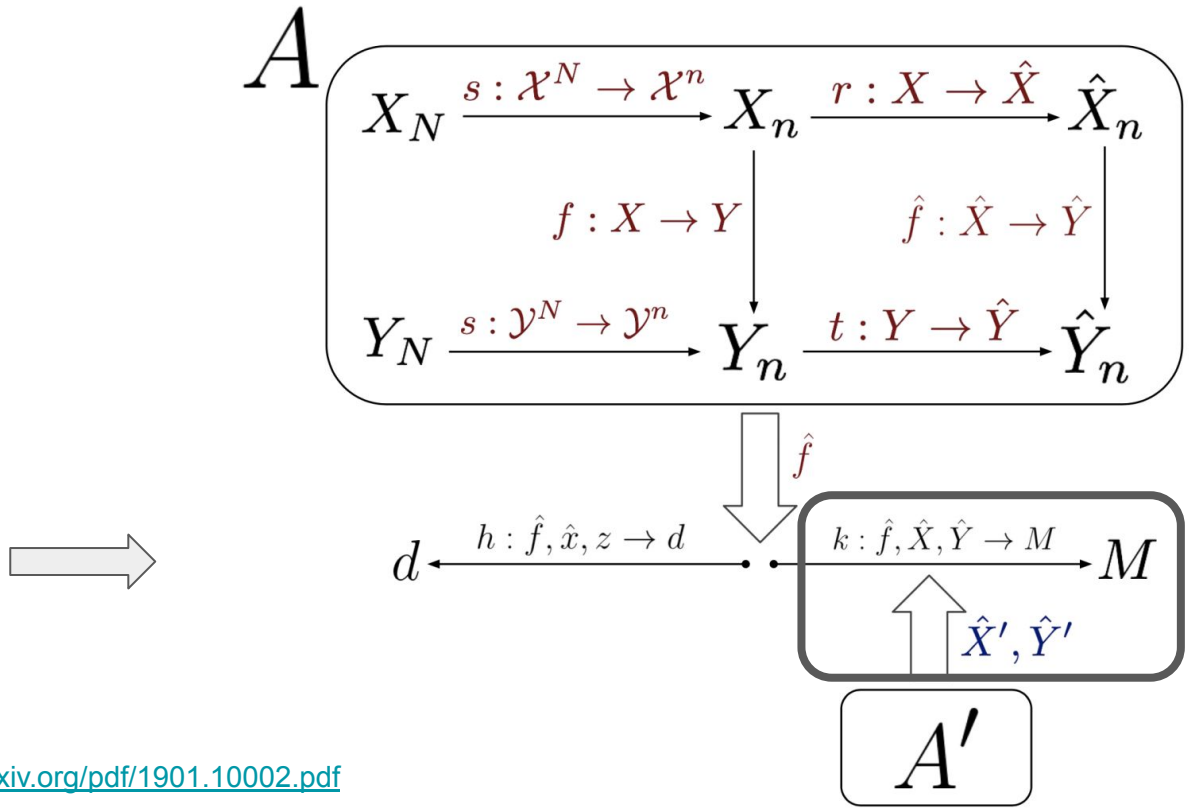
What we want to learn is ***f***, a function from real-world features to outcomes. What we can learn is **\hat{f}**.



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

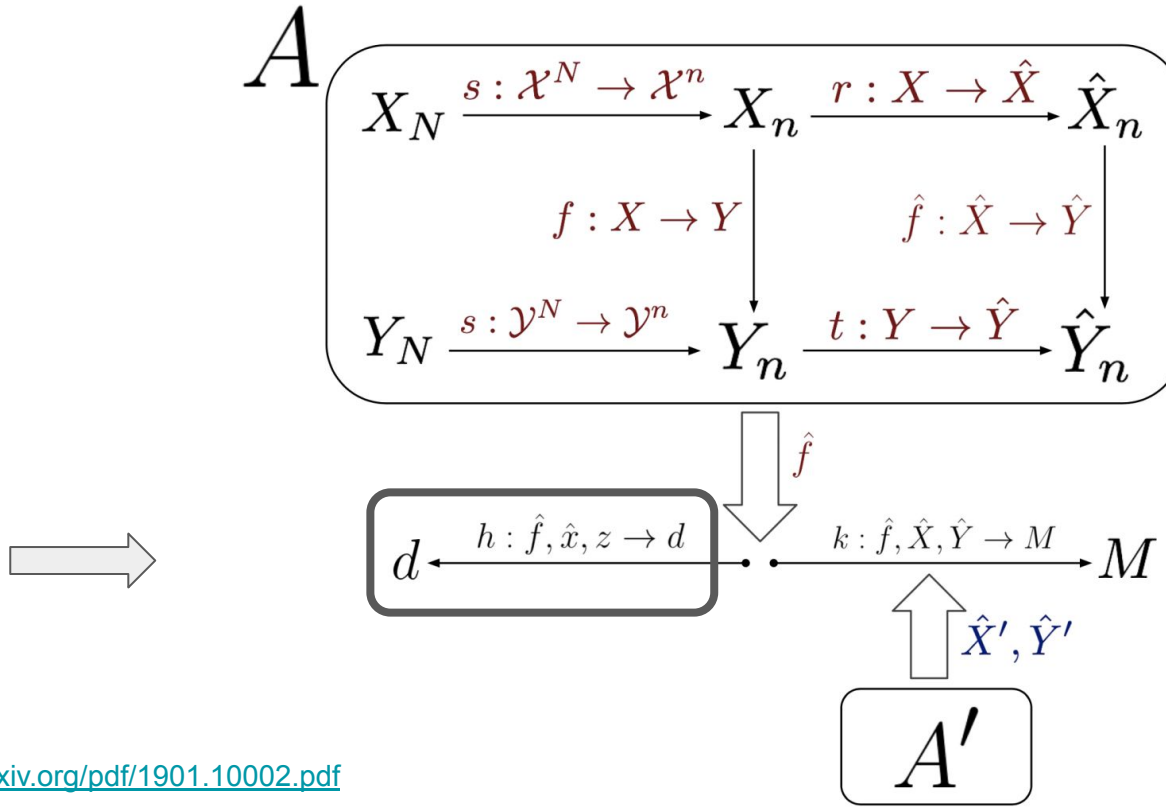
We evaluate \hat{f} using ***k***, on held-out data. This might introduce **evaluation bias**.



Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How to reason about AI bias formally?

Finally, we use \hat{f} to make a decision ***d*** on new data points. This might introduce **aggregation and deployment bias**.

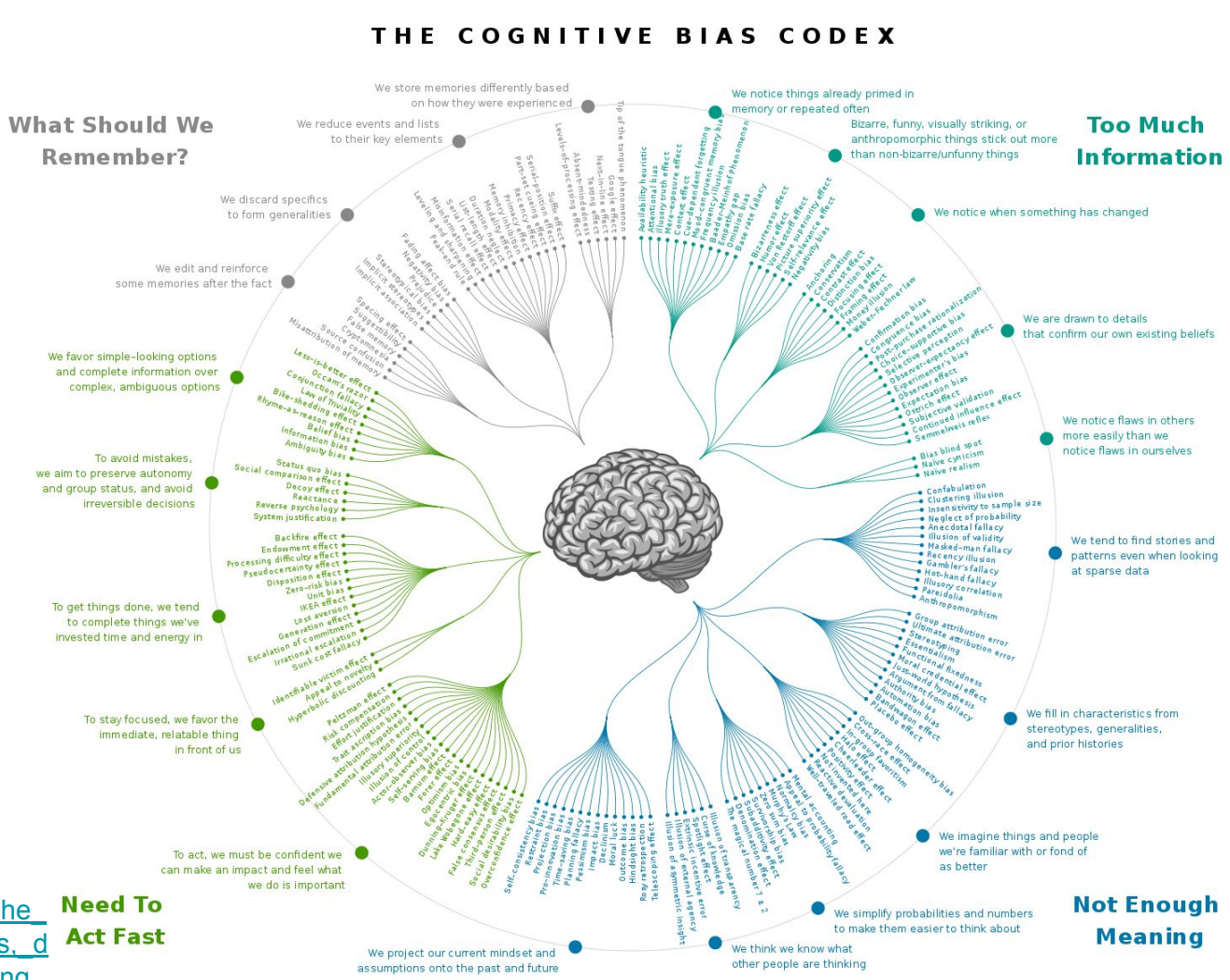


Suresh and Guttag. 2020. *A framework* https://arxiv.org/pdf/1901.10002.pdf

How are fairness and bias related?

As we mention at the beginning, fairness could be defined as lack of bias. Which forms of bias to focus on, and thus what form of fairness to implement, is sometimes a technical choice (e.g., statistical bias), sometimes an ethical choice.

Beware! Cognitive bias

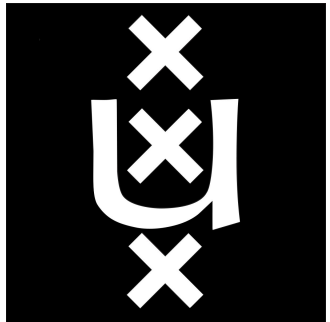


https://commons.wikimedia.org/wiki/File:The_Cognitive_Bias_Codex_-_180%2B_biases,_designed_by_John_Manoogian_III_(jm3).png

Q&A

PART 3: Countermeasures

Giovanni Colavizza



How to ‘deal with’ bias?

Start by **defining what you mean by bias**, this should be tightly related with your **problem formulation** (what is it that you are trying to solve or understand?). If your models or insights will become operational (go ‘in production’), also consider which **definition of fairness** you want them to live up to, if any.

How to ‘deal with’ bias?

Start by **defining what you mean by bias**, this should be tightly related with your **problem formulation** (what is it that you are trying to solve or understand?). If your models or insights will become operational (go ‘in production’), also consider which **definition of fairness** you want them to live up to, if any.

If you have **data**, explore/profile your data *before* doing any modelling. Look for skewness, missing values, outliers, unbalance across protected groups, etc. Perform data selection or correction accordingly. If you don’t have data, design a **data acquisition** process which avoids possible bias (as you previously defined).

Data

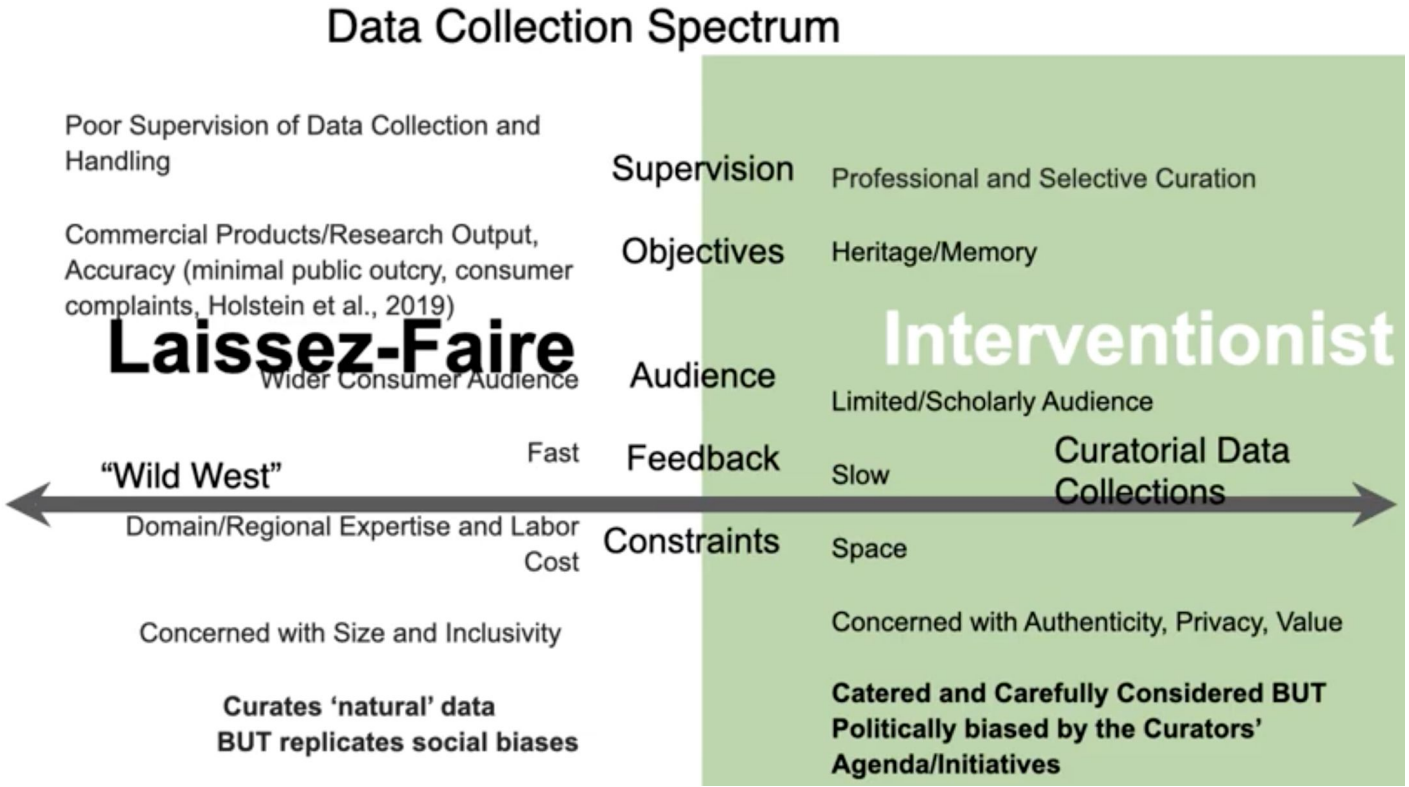
Collecting and using data is a big deal, and goes a long way in explaining biases.

Issues to consider when thinking data include: **consent, power, inclusion, representation (e.g., of protected groups), privacy, transparency, provenance, quality**, and more.

Useful references are:

- Jo and Gebru. 2020. *Lessons from archives* https://dl.acm.org/doi/abs/10.1145/3351095.3372829
  - Introduces useful concepts and ideas from archives are applied to AI data. An example is **'appraisal'**, or the task of selecting data according to a predefined set of objectives and criteria.
- Gebru et al. 2018. *Datasheets for datasets* https://arxiv.org/abs/1803.09010
  - Proposes a simple and effective way to **attach useful documentation to datasets** (e.g., goals and criteria, evaluation, funding, etc.)

Data



From https://www.youtube.com/watch?v=v_XBJd1Fxqc (minute 23:42)

Cf. Jo and Gebru. 2020. *Lessons from archives* https://dl.acm.org/doi/abs/10.1145/3351095.3372829

How to ‘deal with’ bias?

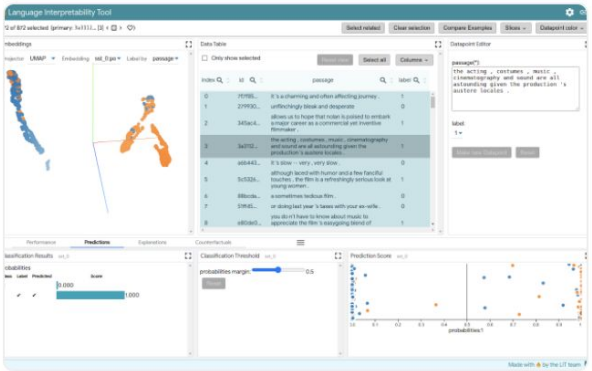
Start by **defining what you mean by bias**, this should be tightly related with your **problem formulation** (what is it that you are trying to solve or understand?). If your models or insights will become operational (go ‘in production’), also consider which **definition of fairness** you want them to live up to, if any.

If you have **data**, explore/profile your data *before* doing any modelling. Look for skewness, missing values, outliers, unbalance across protected groups, etc. Perform data selection or correction accordingly. If you don’t have data, design a **data acquisition** process which avoids possible bias (as you previously defined).

Make sure you put extra care to consider underrepresented and protected groups when doing **model evaluation**, and to consider possibly unintended consequences when **deploying**. Evaluation is never over, don’t sleep on your models.

Above all, keeping an open mind and ask for diverse feedback!

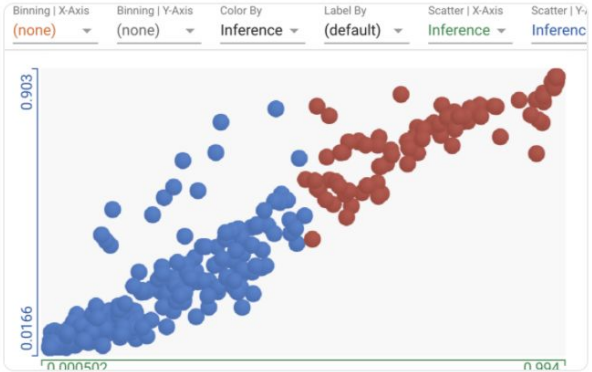
Useful tools: PAIR



LIT

Interactively analyze natural language models in an extensible and framework-agnostic interface.

↗ Explore LIT



What-If Tool

Visually probe the behavior of trained models, with minimal coding.

↗ Explore What-If Tool

Facets

Visualization libraries to explore, understand, and analyze large machine learning datasets.

↗ Explore Facets

https://pair.withgoogle.com/tools

A word of caution

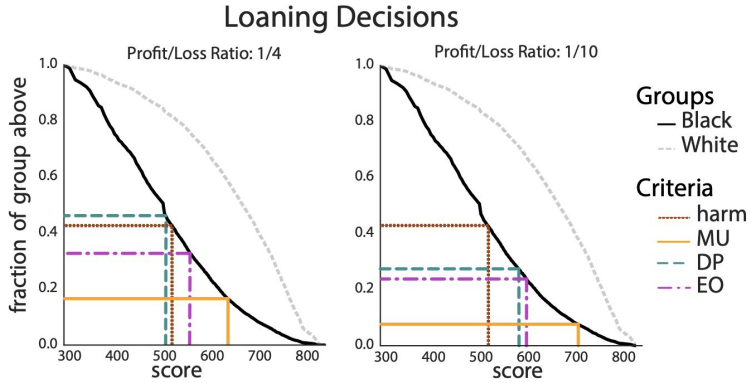


Figure 5: The empirical CDFs of both groups are plotted along with the decision thresholds resulting from `MaxUtil`, `DemParity`, and `EqOpt` for a model with bank utilities set to (a) $\frac{u_-}{u_+} = -4$ and (b) $\frac{u_-}{u_+} = -10$. The threshold for active harm is displayed; in (a) `DemParity` causes active harm while in (b) it does not. `EqOpt` and `MaxUtil` never cause active harm.

Liu et al. 2018. *Delayed impact* https://arxiv.org/abs/1803.04383

A word of caution

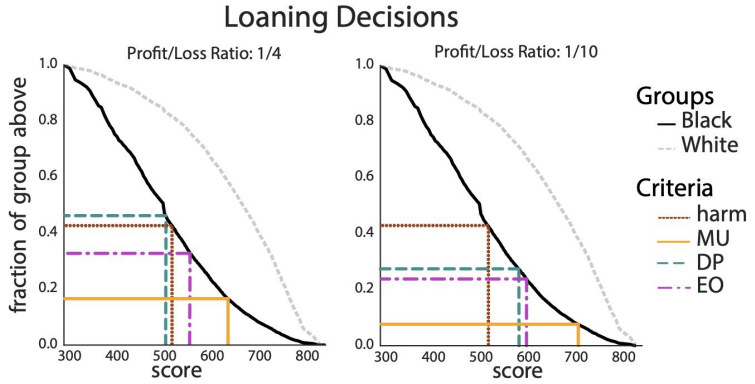


Figure 5: The empirical CDFs of both groups are plotted along with the decision thresholds resulting from `MaxUtil`, `DemParity`, and `EqOpt` for a model with bank utilities set to (a) $\frac{u_-}{u_+} = -4$ and (b) $\frac{u_-}{u_+} = -10$. The threshold for active harm is displayed; in (a) `DemParity` causes active harm while in (b) it does not. `EqOpt` and `MaxUtil` never cause active harm.

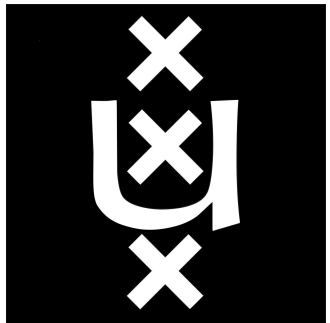
Socio-technical issues cannot be solved by technology alone. Sometimes, the urge to 'do the right thing' can lead to even worse outcomes.

Liu et al. 2018. *Delayed impact* https://arxiv.org/abs/1803.04383

Q&A

PART 4: Assignment

Giovanni Colavizza



ProPublica's 'Machine Bias'

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

ProPublica’s ‘Machine Bias’

ProPublica (a US newsroom) investigated a commercial system to predict recidivism risk called COMPAS. The **COMPAS system** is a black-box (i.e., its inner workings are proprietary), assigning a score from 1 (low-risk) to 10 (high-risk) to people, which might be used for decision making (e.g., bail or preventive incarceration).

ProPublica performed an analysis (releasing data and code), attempting to replicate COMPAS’ predictions using some variables and **claiming that the COMPAS system is biased against African-Americans**.

ProPublica’s ‘Machine Bias’

ProPublica (a US newsroom) investigated a commercial system to predict recidivism risk called COMPAS. The **COMPAS system** is a black-box (i.e., its inner workings are proprietary), assigning a score from 1 (low-risk) to 10 (high-risk) to people, which might be used for decision making (e.g., bail or preventive incarceration).

ProPublica performed an analysis (releasing data and code), attempting to replicate COMPAS’ predictions using some variables and **claiming that the COMPAS system is biased against African-Americans**.

Your task will be, in groups, to a) get to know the dataset ProPublica used; b) replicate their analysis and understand their claims in terms of ‘bias’ and ‘fairness’; c) engage with critical reviews on ProPublica’s analysis and convey your own informed opinion on it.

Set-up

Please organise yourselves into groups of 4 students (exceptionally, 3 or 5). You will keep the same group for all assignments. Motivated requests to change group can be made.

Let’s check the course repository for more info (assignment 1):
https://github.com/Giovanni1085/UvA_AIforSociety_2021

Note: we will assume you can clone a GitHub repository, set-up a working Python environment (ideally virtual, e.g., via Conda) and work with Jupyter notebooks. If you need some pointers/help, we have included a guide to setting up your working environment in the repo.

Q&A