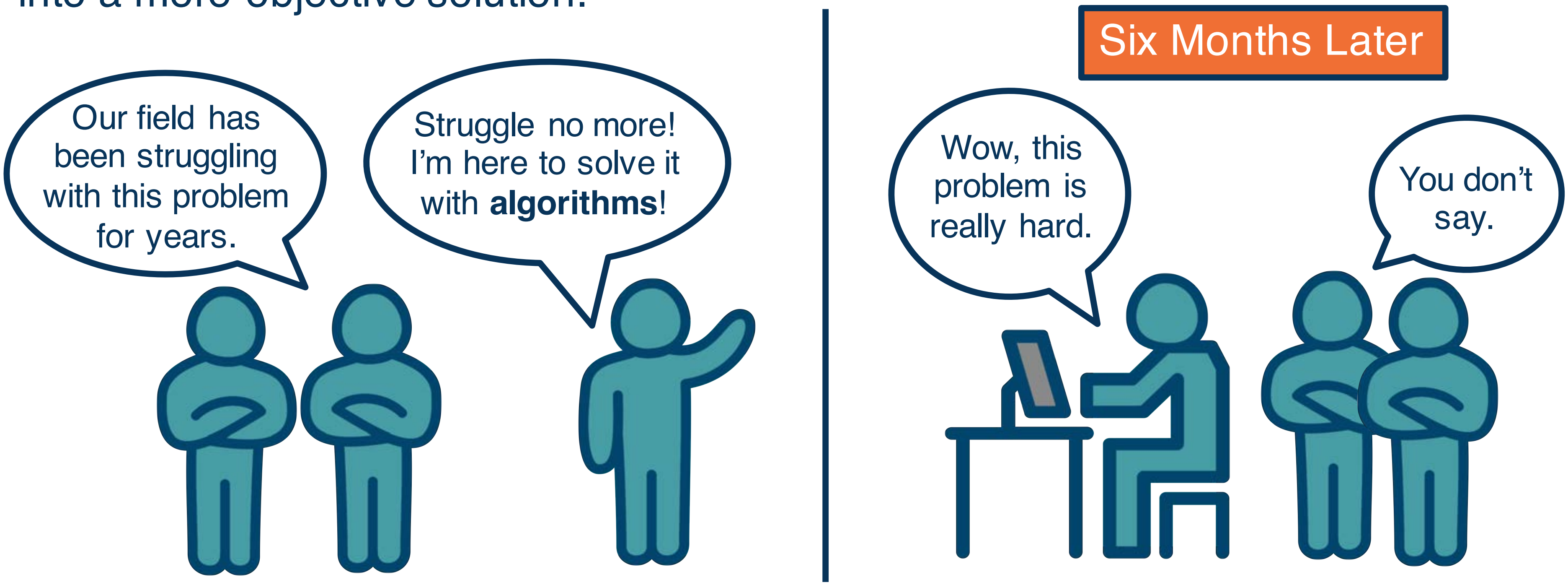
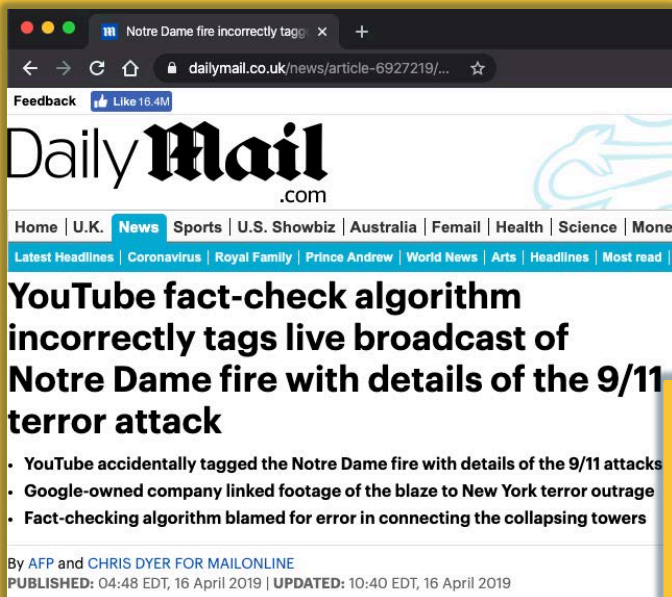
Fairness and Bias

Applications and Future Opportunities: Understand tools and methods to quantify bias and examine ways to use algorithmic fairness to mitigate this bias. Apply your knowledge of analytics and AI/ML to transform a current biased data-set into a more objective solution.



Learning Objective



Notre Dame fire incorrectly tagg

dailymail.co.uk/news/article-6927219/...

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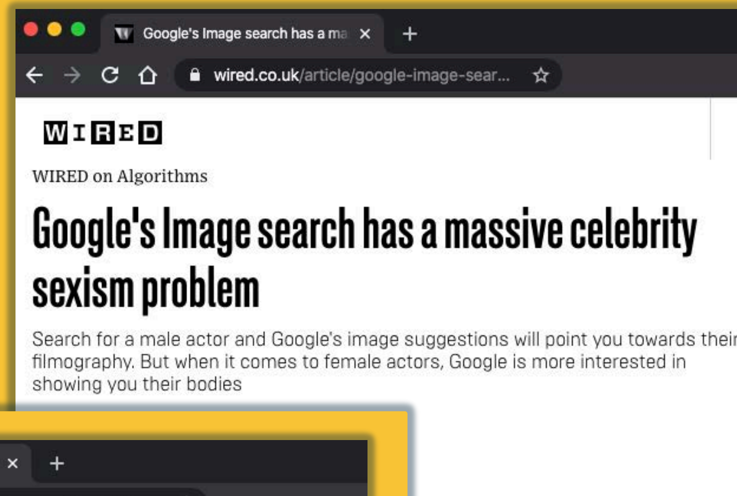
YouTube fact-check algorithm incorrectly tags live broadcast of Notre Dame fire with details of the 9/11 terror attack

- YouTube accidentally tagged the Notre Dame fire with details of the 9/11 attacks
- Google-owned company linked footage of the blaze to New York terror outrage
- Fact-checking algorithm blamed for error in connecting the collapsing towers

By AFP and CHRIS DYER FOR MAILONLINE
PUBLISHED: 04:48 EDT, 16 April 2019 | UPDATED: 10:40 EDT, 16 April 2019



Google's Image search has a ma

wired.co.uk/article/google-image-sear...

WIRED

WIRED on Algorithms

Google's Image search has a massive celebrity sexism problem

Search for a male actor and Google's image suggestions will point you towards their filmography. But when it comes to female actors, Google is more interested in showing you their bodies

Government 'deported 7,000 for

independent.co.uk/news/uk/politics/ho...

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Theresa May introduced the 'hostile environment' policy when she was home secretary

Government 'deported 7,000 foreign students after falsely accusing them of cheating in English language tests'

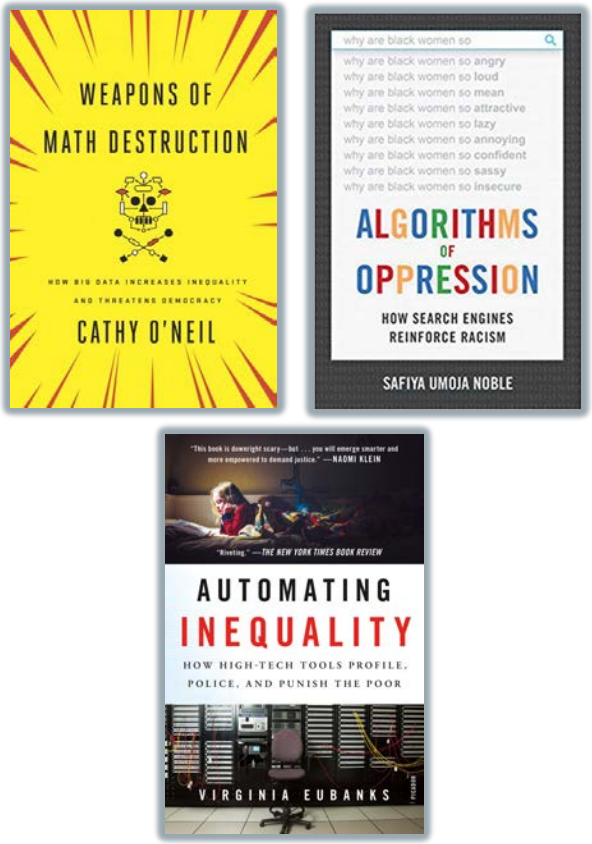
Judges found 'multiple frailties and shortcomings' in evidence used to justify deportations

Chris Baynes | Wednesday 2 May 2018 00:57 | 176 comments

As we've learned, the impact of AI on society is not all good. AI can encode and amplify human biases, leading to unfair outcomes at scale.

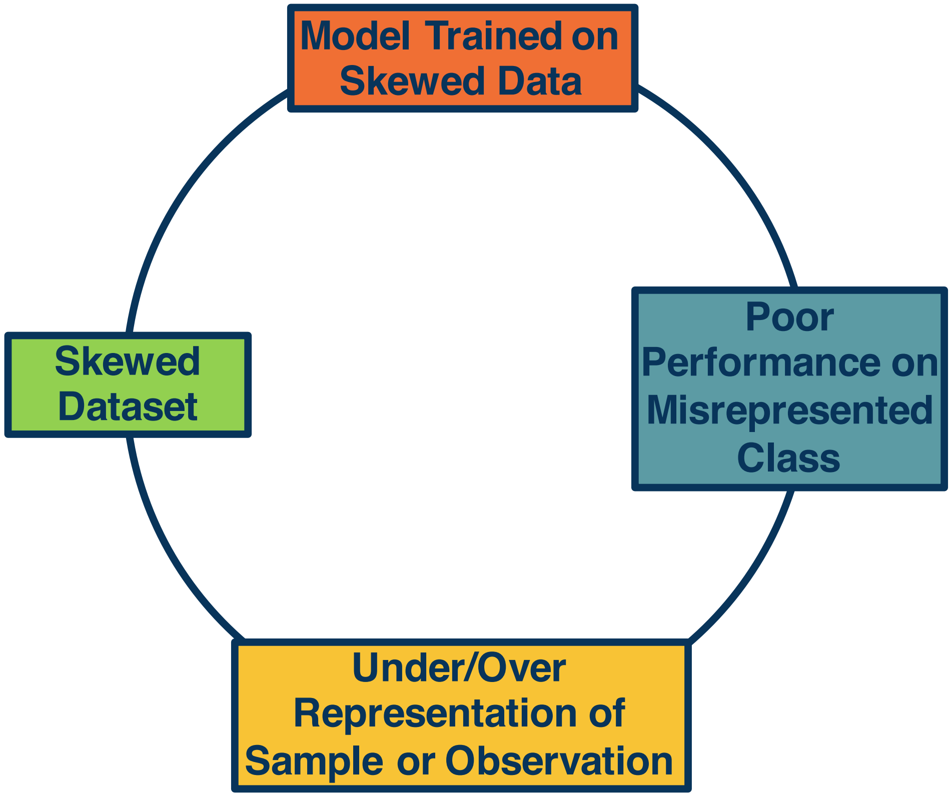
Talk of AI and Ethics Is On the Rise

Georgia Tech



- **Algorithmic Fairness** is a growing field of research that **aims to mitigate the effects of unwarranted bias/discrimination** on people propagated by **AI/ML algorithms.**
- The primary focus is **on mathematical formalisms** and **algorithm approaches of fairness** to help develop solutions.

Bias and Fairness



Representational Harm

- When an AI/ML system amplifies or reflects negative stereotypes about particular groups.

Opportunity Denial

- When an AI/ML system negative impacts individuals' access to opportunities, resources, and overall quality of life

Disproportionate Failure

- When the experience of interacting with an AI/ML system is disproportionately failing for particular groups.

Which is then exacerbated by a **feedback loop**

Some Examples of Algorithmic Bias

54% of Americans think automated finance scores would be effective – but just 32% think they would be fair

% of U.S. adults who say the following types of computer programs would be very/somewhat ...

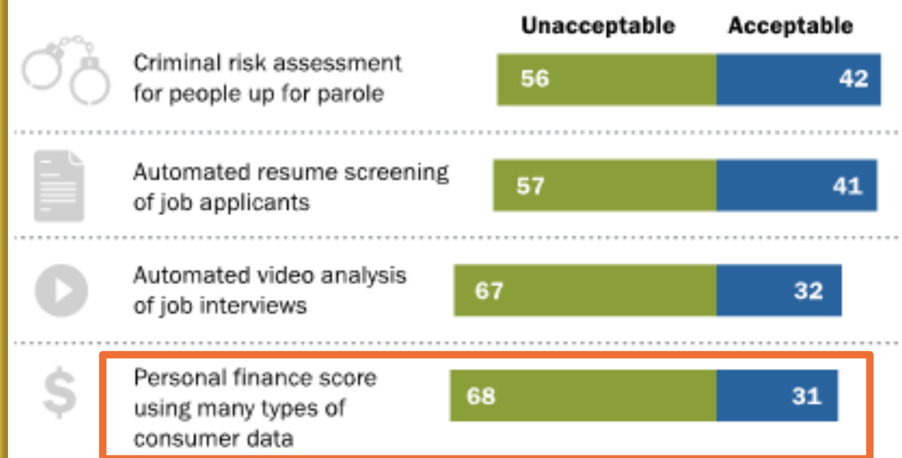
	Effective	Fair	Effective-fair difference
Automated personal finance score	54%	32%	+22
Automated video analysis of job interviews	39	33	+6
Automated resume screening of job applicants	47	43	+4
Automated scoring of people up for parole	49	50	-1

Note: Respondents who did not give an answer or gave other answers are not shown.
Source: Survey of U.S. adults conducted May 29-June 11, 2018.
"Public Attitudes Toward Computer Algorithms"

PEW RESEARCH CENTER

Majorities of Americans find it unacceptable to use algorithms to make decisions with real-world consequences for humans

% of U.S. adults who say the following examples of algorithmic decision-making are ...



Note: Respondents who did not give an answer are not shown.
Source: Survey of U.S. adults conducted May 29-June 11, 2018.
"Public Attitudes Toward Computer Algorithms"

PEW RESEARCH CENTER

Public Sentiments About Algorithmic Fairness

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Addressing: Source of Bias

	Previous Views/Strategies	New Views/Strategies
Source of Bias	None	Human Biases – Garbage in, Garbage out
Protected Features	Unawareness	Redundant Encodings
Fairness Measures	None	Blindness, Disparate Impact (many)
Solution	None	Fair Classifiers

Solutions Have Been Proposed

Georgia Tech

Problem:
Biased Data Stored in Protected Attributes

Solution:
Blind the model to Protected Features

Protected Attributes:

- Age
- Disability
- National Origin
- Race/color
- Religion
- Sex

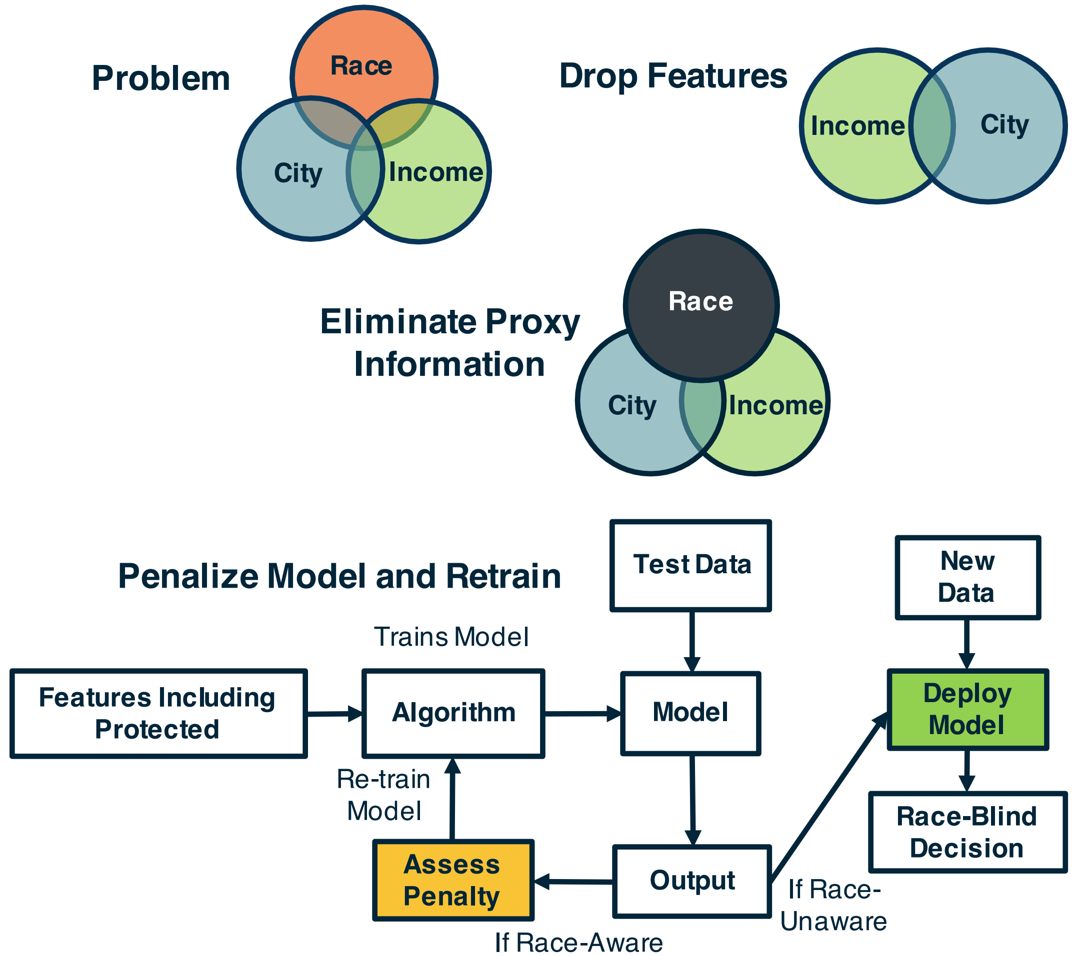
Garbage In, Garbage Out

Problem: Discriminatory Decisions

Goal: Race-Blindness

Issue:

- Redundant Encodings or Proxies
- By “removing” protected features, we ignore the underlying processes that affect different demographics.



Examples of How This Would Work

Addressing: Fairness Measures

	Previous Views/Strategies	New Views/Strategies
Source of Bias	None	Human Biases – Garbage in, Garbage out
Protected Features	Unawareness	Redundant Encodings
Fairness Measures	None	Blindness, Disparate Impact (many)
Solution	None	Fair Classifiers

Solutions Have Been Proposed

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	Definition	Paper	Citation #	Result
3.1.1	Group fairness or statistical parity	[12]	208	×
3.1.2	Conditional statistical parity	[11]	29	✓
3.2.1	Predictive parity	[10]	57	✓
3.2.2	False positive error rate balance	[10]	57	×
3.2.3	False negative error rate balance	[10]	57	✓
3.2.4	Equalised odds	[14]	106	×
3.2.5	Conditional use accuracy equality	[8]	18	×
3.2.6	Overall accuracy equality	[8]	18	✓
3.2.7	Treatment equality	[8]	18	×
3.3.1	Test-fairness or calibration	[10]	57	✓×
3.3.2	Well calibration	[16]	81	✓×
3.3.3	Balance for positive class	[16]	81	✓
3.3.4	Balance for negative class	[16]	81	×
4.1	Causal discrimination	[13]	1	×
4.2	Fairness through unawareness	[17]	14	✓
4.3	Fairness through awareness	[12]	208	×
5.1	Counterfactual fairness	[17]	14	–
5.2	No unresolved discrimination	[15]	14	–
5.3	No proxy discrimination	[15]	14	–
5.4	Fair inference	[19]	6	–

http://www.ece.ubc.ca/~mjulia/publications/Fairness_Definitions_Explained_2018.pdf

Problem: There are issues with Error-Rate Imbalances such that different groups have different outcomes

Solution: Only Outcomes Matter. Make sure groups are in line with predetermined "fairness metrics"

Issue:

- There are many (30+) definitions for fairness
- Many of the definitions conflict
- The way you define fairness impacts bias

Principles for Quantifying Fairness

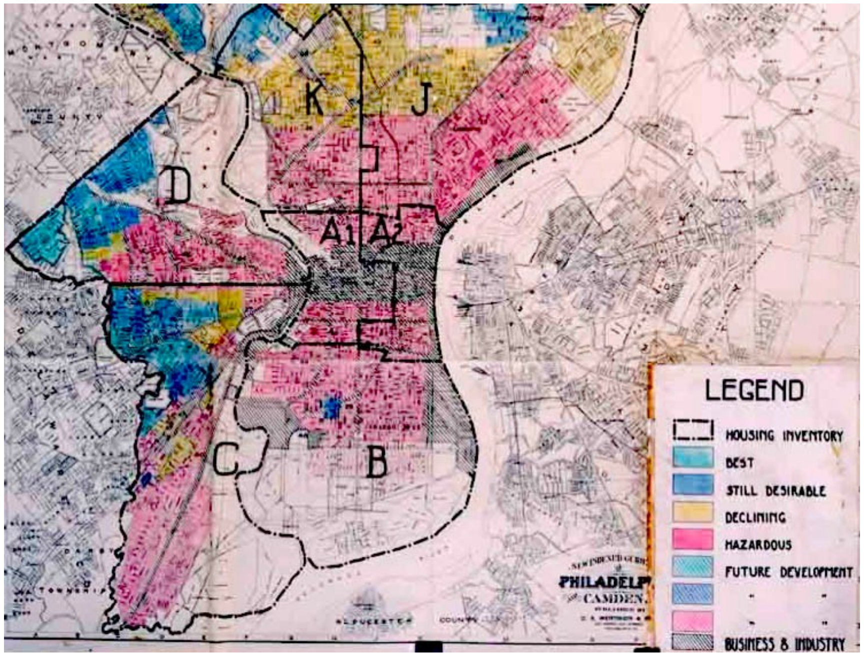
In the context of an algorithm generating a prediction:

- Predictions for people with similar non-protected attributes should be similar
- Differences should be mostly explainable by non-protected attributes

Two basic frameworks for measuring fairness:

- Fairness at the individual level: consistency or individual fairness
- Fairness at the group level: statistical parity

I. Žliobaitė (2015): A survey on measuring indirect discrimination in machine learning. arXiv pre-print.



Supposedly 'Fair' Algorithms Can Perpetuate Discrimination, WIRED, 2019-02-05, https://www.wired.com/story/ideas-joi-ito-insurance-algorithms/

Case: Redlining, USA, 1968

- "redlining, an insurance-company term for drawing a red line on a map around parts of a city deemed too risky to insure"
- "once a minority community had been redlined, the red line established a feedback cycle that continued to drive inequity and deprive poor neighborhoods of financing and insurance coverage—redlining had contributed to creating poor economic conditions, which already affected these areas in the first place."

Negative feedback cycle:

- The insurance companies didn't sell insurances
- Banks didn't offer loans as there was no insurances
- The areas got even more poor

Insurers' arguments ("actuarial fairness"):

- "…their job was purely technical and that it didn't involve moral judgments."
- "Second-order effects on society were really not their problem or their business."

Impact Analysis Case: Redlining

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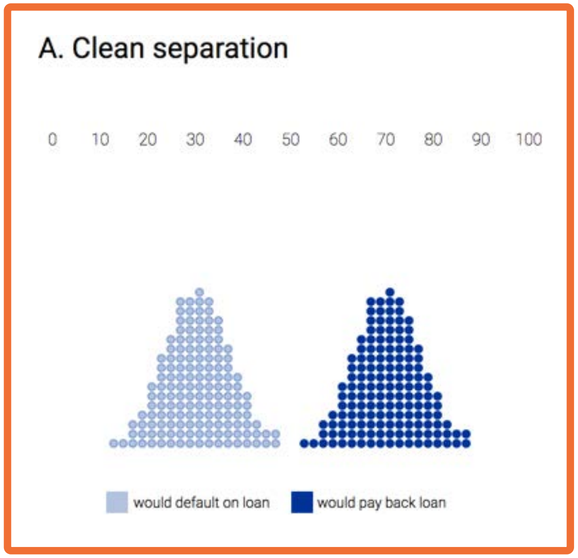
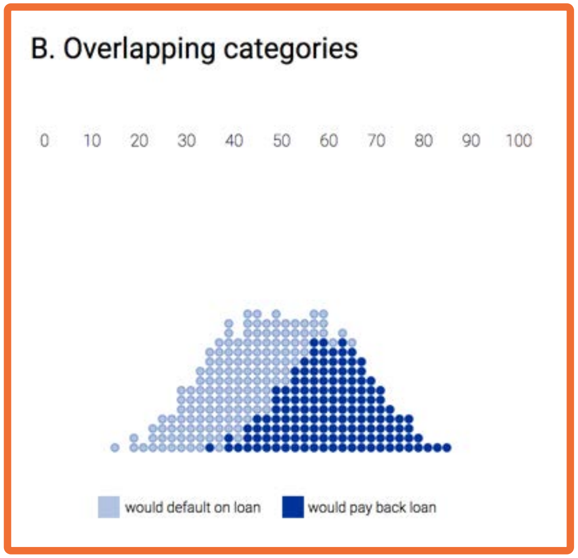
Question: How can scoring models become unfair?

Example: Loan applicants

- Score each customer with probability to pay back the loan (0-100)
- Define a threshold, under which lender does not grant loans

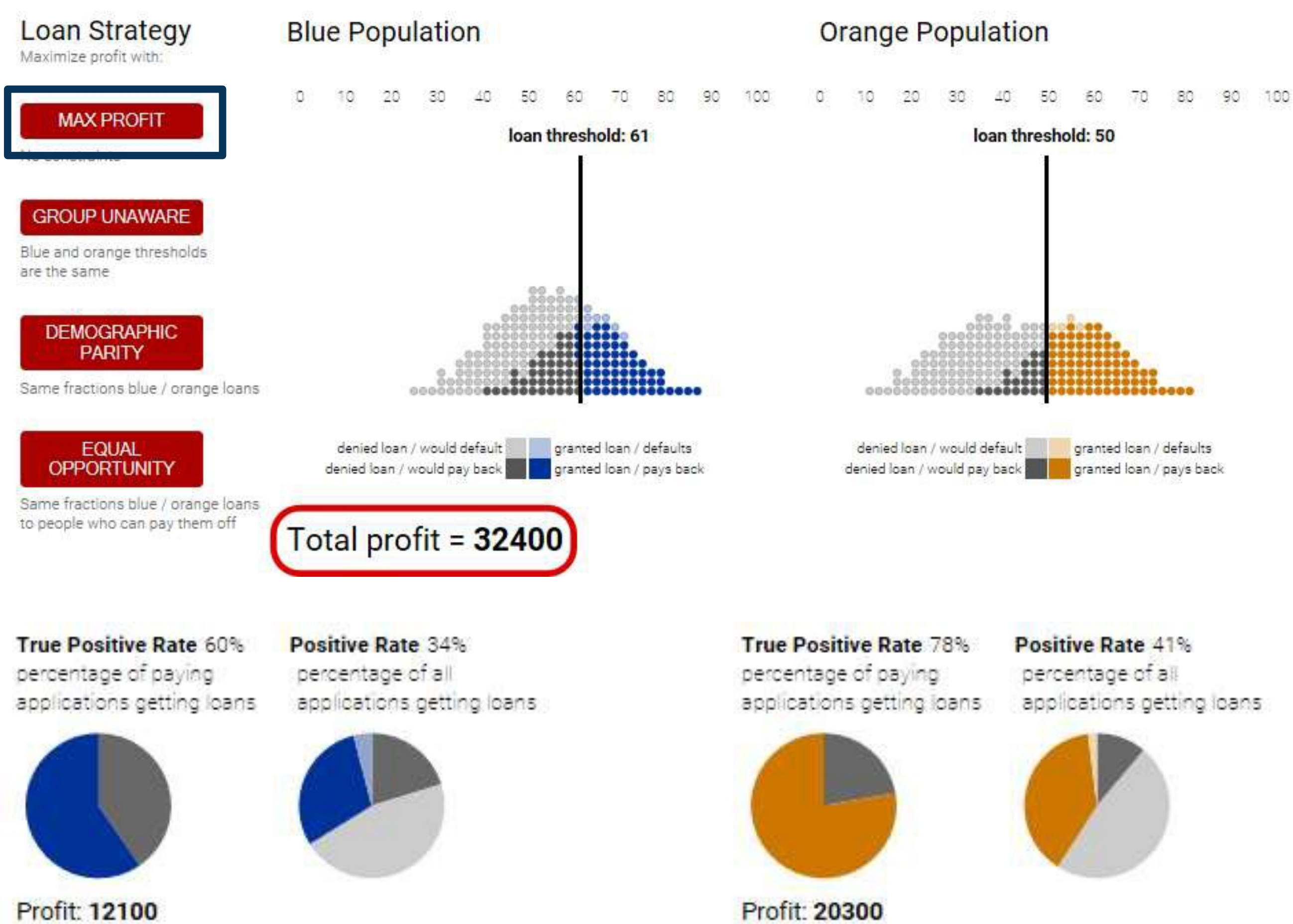


Reality is more difficult:



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

Getting a predictive model is easy. But is it fair?



Max Profit

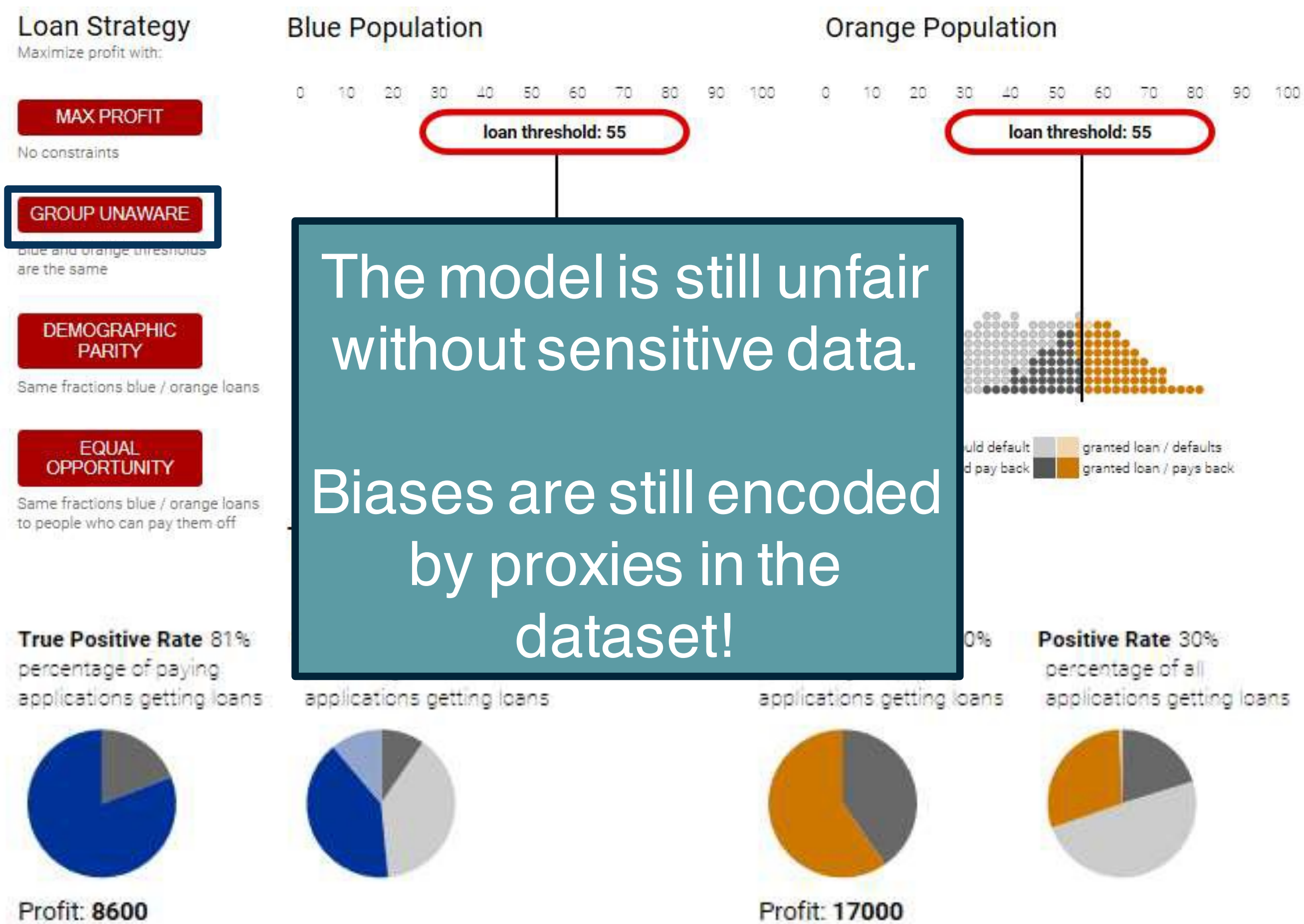
Maximize profits: Obvious

Total Profit: 32,400

Decision Rules: Different

True Positive Rate: Unequal

Percent Approved: Unequal



The model is still unfair without sensitive data.

Biases are still encoded by proxies in the dataset!

Blinding Model

Group Unaware: Class features and all "proxy" information removed

Total Profit: 25,600

Decision Rules: Same

True Positive Rate: Unequal

Percent Approved: Unequal

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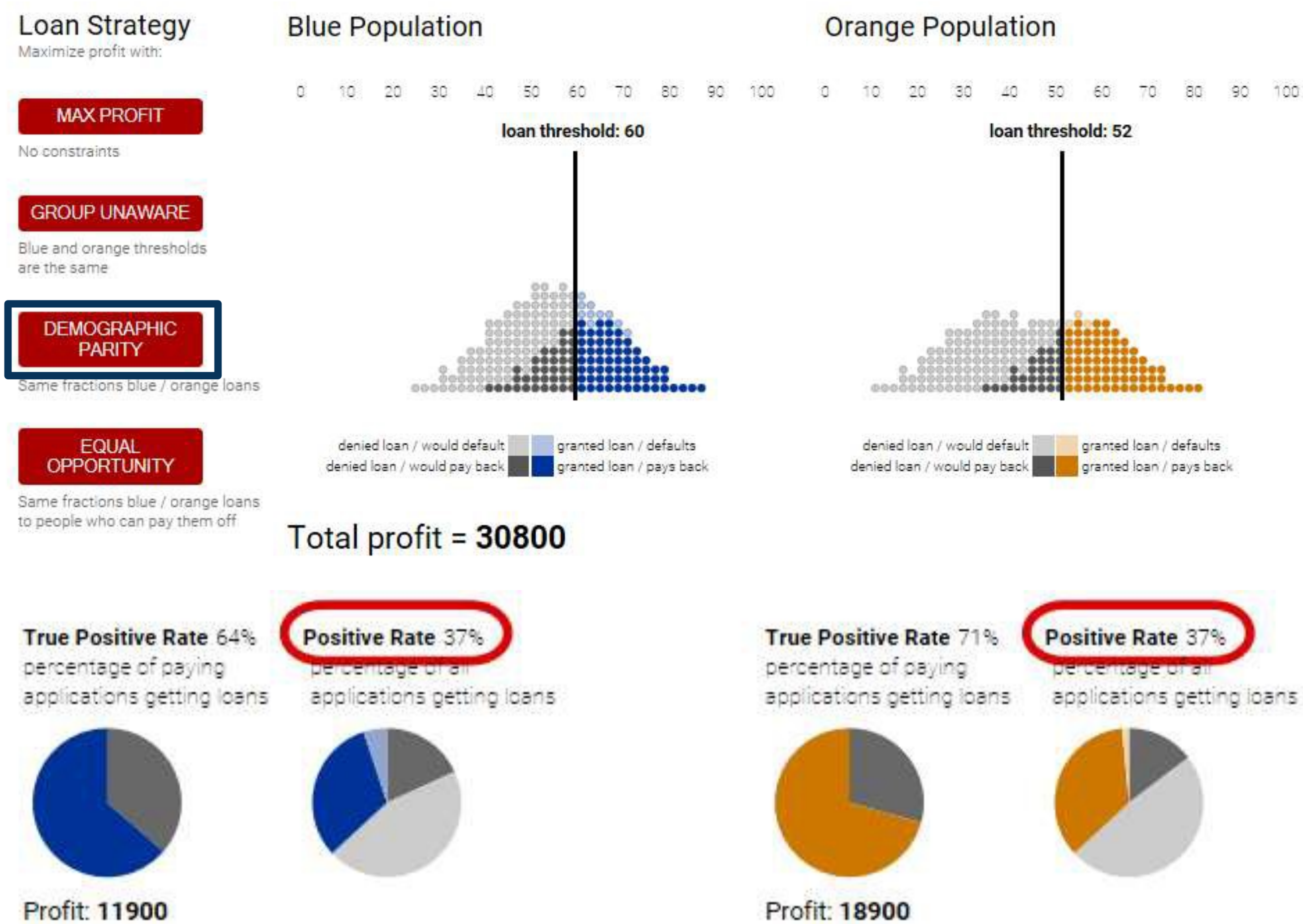

Demographic Parity

Parity:
All groups have same percentage approved

Total Profit: 30,800

Decision Rules:
Different

True Positive Rate:
Unequal

Percent Approved:
Equal

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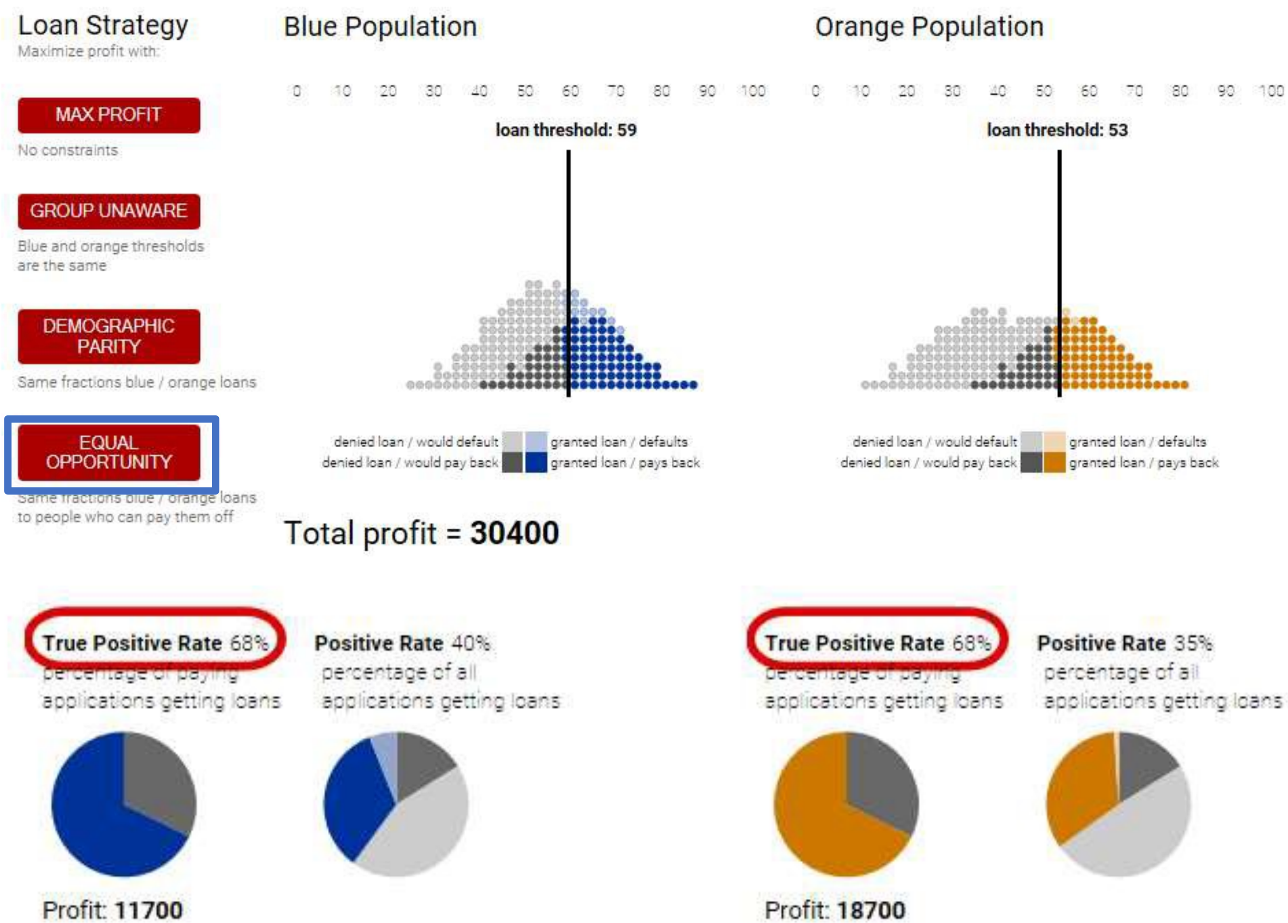


Equal Opportunity

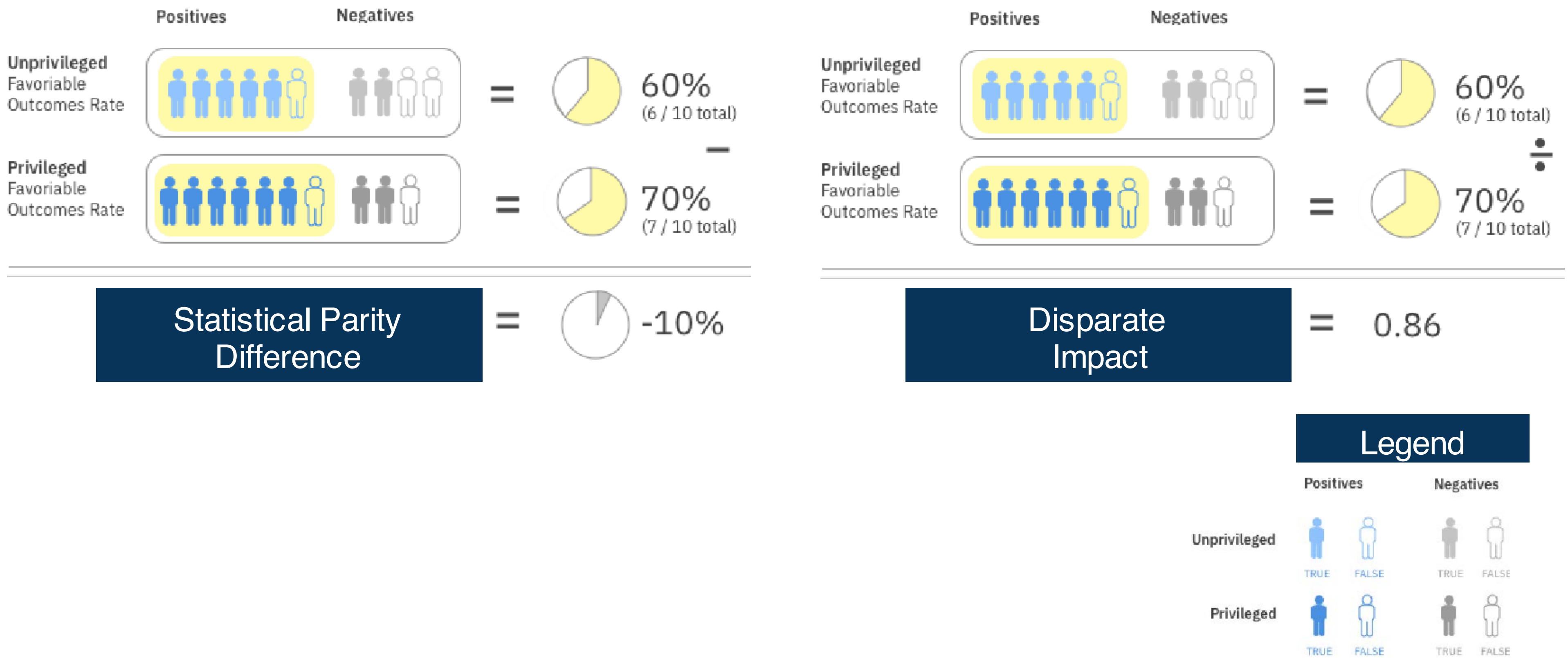
Opportunity: Same percentage of "credit-worthy" candidates

Total Profit: 30,400

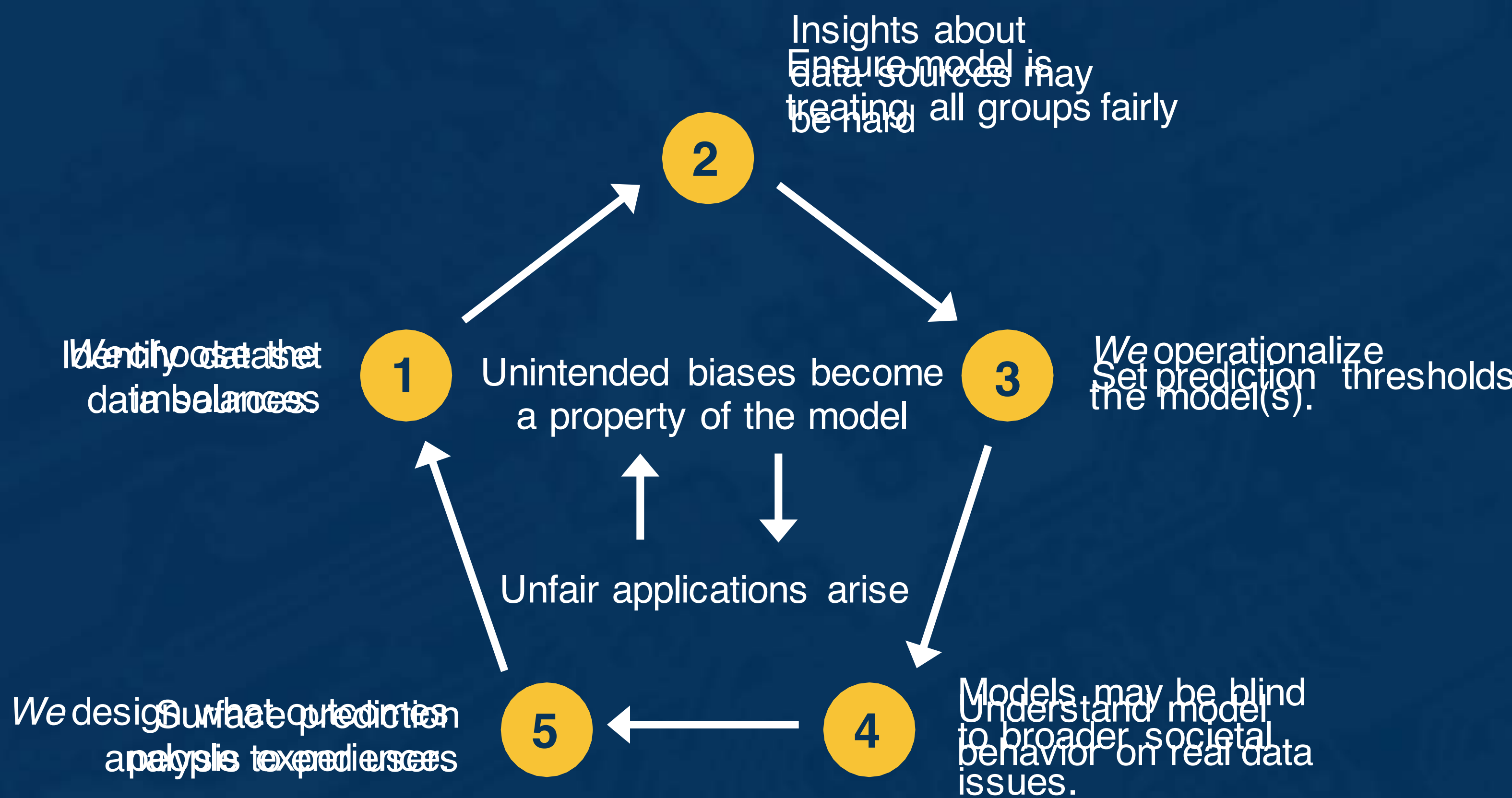
Decision Rules: Different

True Positive Rate: Equal

Percent Approved: Unequal



Some Other Group Fairness Metrics



Other Ways Bias Is Introduced into the Algorithm Process

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Other Bias Mitigation Approaches at the Three Phases

Pre-processing Algorithms
- Reweighing
- Optimized Preprocessing
- Learning Fair Representations
- Disparate Impact Remover

In-processing Algorithms
- Adversarial Debiasing
- Prejudice Remover

Post-processing Algorithms
- Equalized Odds Postprocessing
- Calibrated Equalized Odds Postprocessing
- Reject Option Classification

Bias Mitigation Strategies for ML Models

https://dzone.com/articles/machine-learning-models-bias-mitigation-strategies

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AI Fairness 360

https://aif360.mybluemix.net/

Open Source Toolbox to Mitigate Bias

- Demos & Tutorials on Industry Use Cases
- Fairness Guidance
- **Comprehensive Toolbox**
  - 75+ Fairness metrics
  - 10+ Bias Mitigation Algorithms
  - Fairness Metric Explanations

Extensible Toolkit for Detecting, Understanding, & Mitigating Unwanted **Algorithmic Bias**

Leading Fairness Metrics and Algorithms from **Industry & Academia**

Designed to **translate new research from the lab to industry practitioners** (using Scikit Learn's fit/predict paradigm)

AI Fairness 360

Pre-Processing Algorithms Mitigates Bias in **Training Data**

Reweighing
Modifies the weights of different training examples

Disparate Impact Remover
Edits feature values to improve group fairness

Optimized Preprocessing
Modifies training data features & labels

Learning Fair Representations
Learns fair representations by obfuscating information about protected attributes

In-Processing Algorithms Mitigates Bias in **Classifiers**

Adversarial Debiasing
Uses adversarial techniques to maximize accuracy & reduce evidence of protected attributes in predictions

Prejudice Remover
Adds a discrimination-aware regularization term to the learning objective

Meta Fair Classifier
Takes the fairness metric as part of the input & returns a classifier optimized for the metric

Post-Processing Algorithms Mitigates Bias in **Predictions**

Reject Option Classification
Changes predictions from a classifier to make them fairer

Calibrated Equalized Odds Postprocessing
Optimizes over calibrated classifier score outputs that lead to fair output labels

Equalized Odds
Modifies the predicted label using an optimization scheme to make predictions fairer

Bias Mitigation Algorithms For Each Phase of the Pipeline

Pre-Processing Algorithms Mitigates Bias in **Training Data**

Reweighing
Modifies the weights of different training examples

Reweighing only changes **Weights** applied to training samples (no changes to feature/labels). Ideal if you cannot change values

Disparate Impact Remover
Edits feature values to improve group fairness

Optimized Preprocessing
Modifies training data features & labels

Disparate Impact Remover and **Optimized Preprocessing** yield modified datasets in the same space as the input training data (provides transparency)

Learning Fair Representations
Learns fair representations by obfuscating information about protected attributes

Learning Fair Representations yields modified datasets in the latent space

Pre-Processing to Mitigate Bias

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What-if Tool

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What if...

you could inspect machine learning models, with **minimal coding** required?

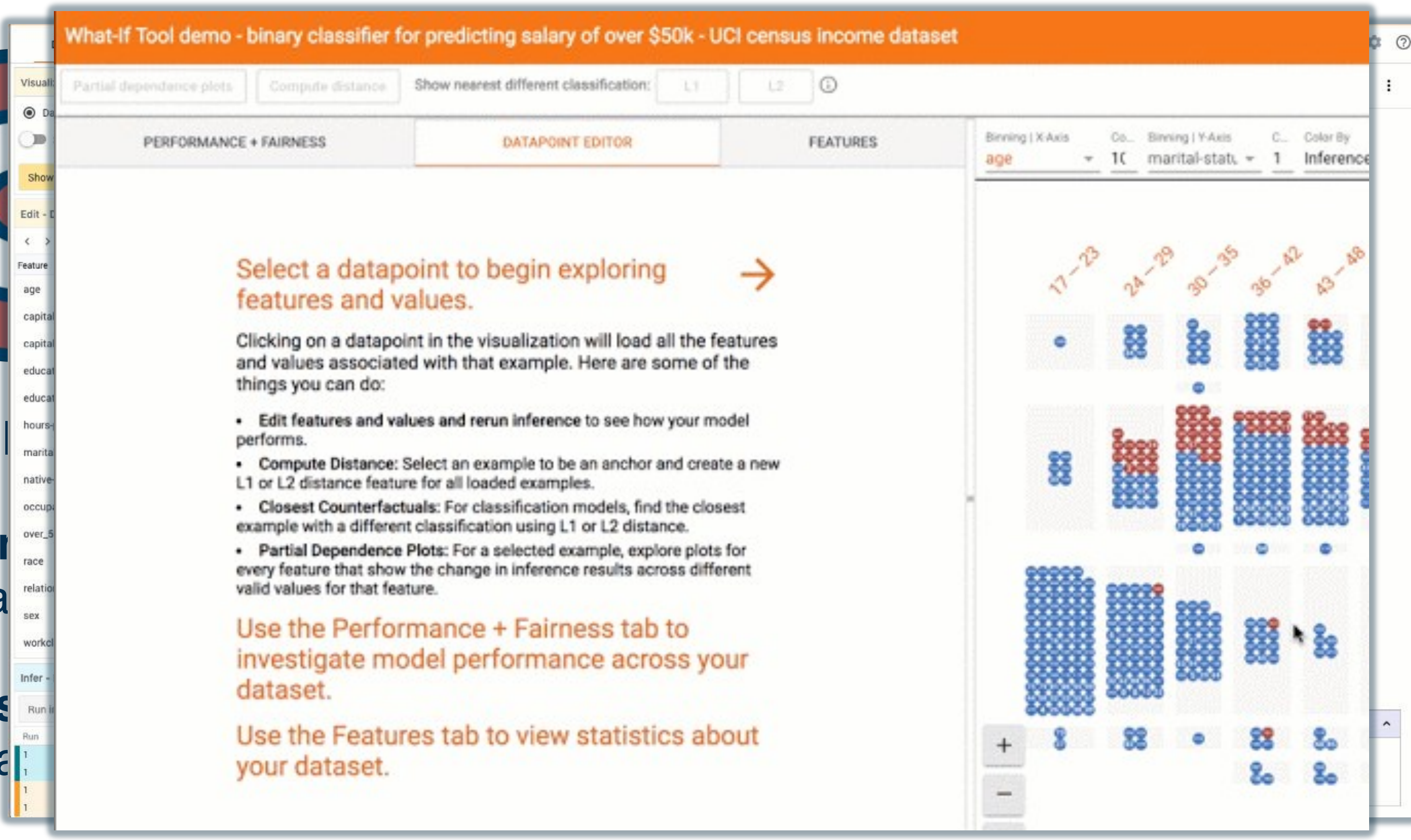
How **does** my model perform...

classification accuracy / precision-recall curve / <insert metric here>

How **might** my model perform...

on subgroups in test data / on cross-slices in test data / <insert question here>

- **Easi** ... change
- **Cou** ... or me to ha ...
- **[Clas** ... taking into a ...



What If Tool

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Fairness Measures	Framework to test given algorithm on variety of datasets and fairness metrics	https://github.com/megantosh/fairness_m e_asures_code
Fairness Comparison	Extensible test-bed to facilitate direct comparisons of algorithms with respect to fairness measures. Includes raw & preprocessed datasets	https://github.com/algofairness/fairness - comparison
Themis-ML	Python library built on scikit-learn that implements fairness-aware machine learning algorithms	https://github.com/cosmicBboy/themis-ml
FairML	Looks at significance of model inputs to quantify prediction dependence on inputs	https://github.com/adebayoj/fairml
Aequitas	Web audit tool as well as python lib. Generates bias report for given model and dataset	https://github.com/dssg/aequitas
Fairtest	Tests for associations between algorithm outputs and protected populations	https://github.com/columbia/fairtest
Themis	Takes a black-box decision-making procedure and designs test cases automatically to explore where the procedure might be exhibiting group-based or causal discrimination	https://github.com/LASER-UMASS/Themis
Audit-AI	Python library built on top of scikit-learn with various statistical tests for classification and regression tasks	https://github.com/pymetrics/audit-ai

Other Tools

Solutions to Mitigate Bias

	Previous Views/Strategies	New Views/Strategies
Source of Bias	None	Human Biases – Garbage in, Garbage out
Protected Features	Unawareness	Redundant Encodings
Fairness Measures	None	Blindness, Disparate Impact (many)
Solution	None	Fair Classifiers

Solutions Have Been Proposed

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It isn’t 100% possible to mitigate bias and create fair algorithms, but are we really surprised?

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Evaluating Fairness-Aware Algorithms

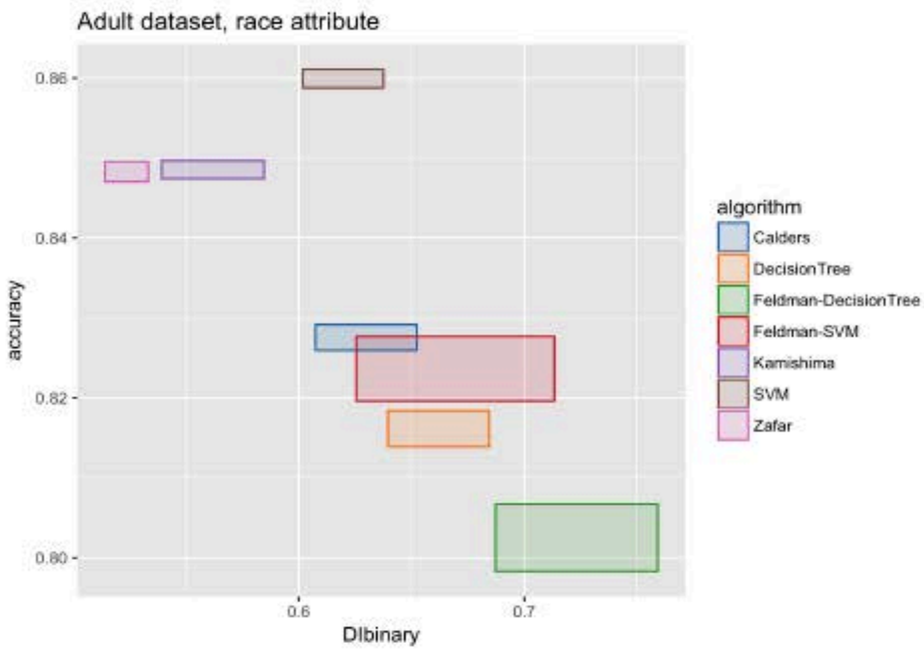
Which algorithm is the best?

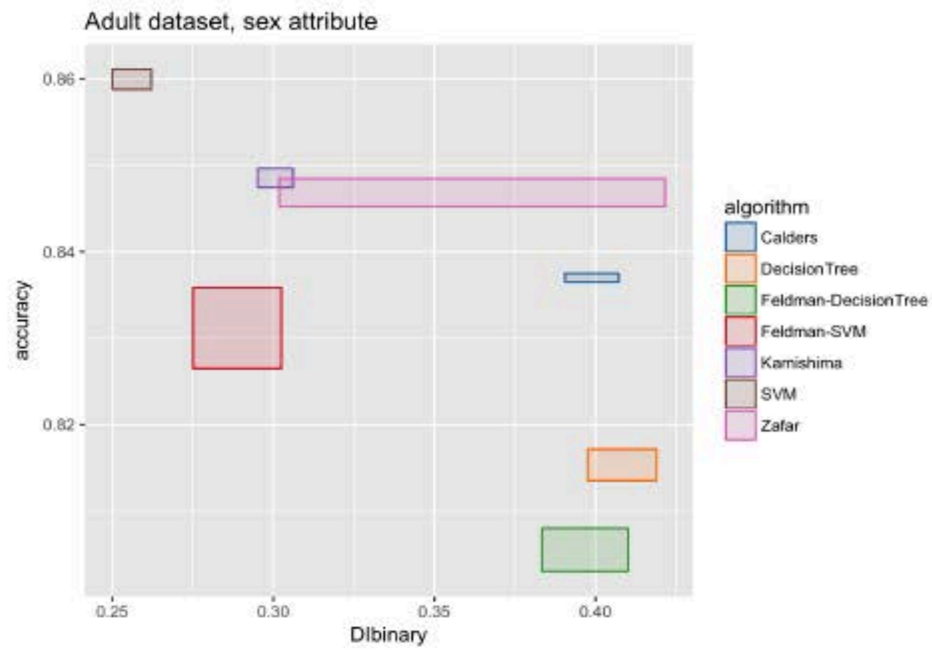
- ...on which dataset?
- …how was it preprocessed?
- …under which measure?
- …with which training / test split?
- …what if there are multiple sensitive attributes?

Fairness/Bias Mitigation Is Not Easy

Cannot simply drop protected attributes because other features are correlated with them

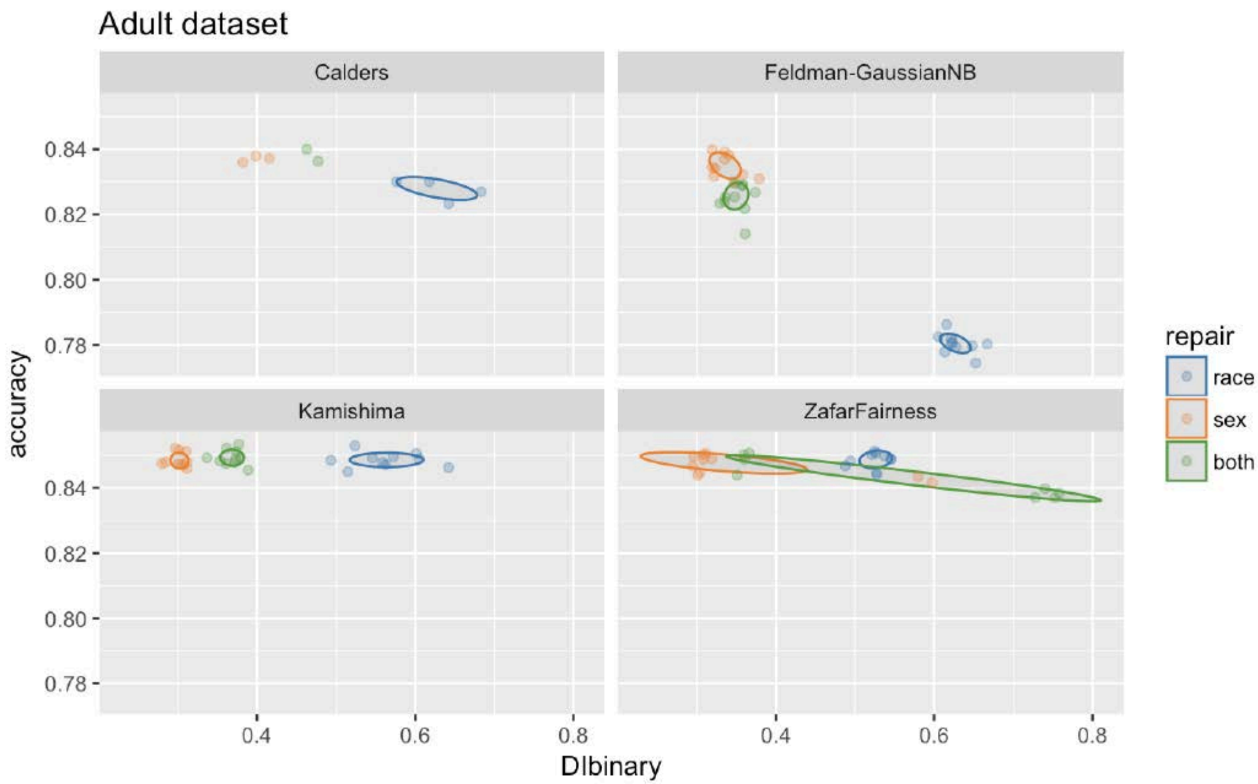
Performance can depend on **which attribute you focus on** and **what algorithm you choose**





https://arxiv.org/pdf/1802.04422.pdf

Performance can depend on **which attribute you focus on** and **what algorithm you choose**



https://arxiv.org/pdf/1802.04422.pdf

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Fairness-Aware Algorithms Trade-Offs

Is the model doing **good things or bad things** to people?

- If your model is sending people to jail, may be better to have more false positives than false negatives

- If your model is handing out loans, may be better to have more False Negatives than False Positives

Determining **thresholds for accuracy vs. fairness** must take into **considerations legal, ethical and trust guidelines**

Doing what is legal is top priority (Penalties)

What's your company's Ethics (Amazon Echo)

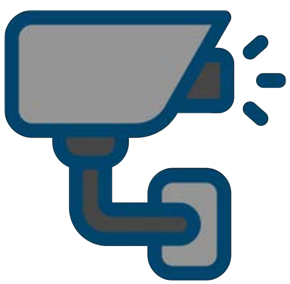
Losing customer's Trust costly (Facebook)

Tradeoffs - Bias vs. Accuracy

False Positives Might be Better than False Negatives

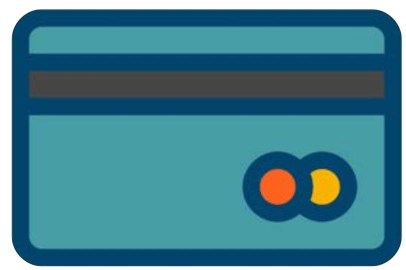
False Positive: Something that doesn't need to be gets blurred.

Can be a bummer for surveillance applications.



False Negative: Something that needs to be blurred is not blurred.

Can be a bummer for protecting against identity theft.



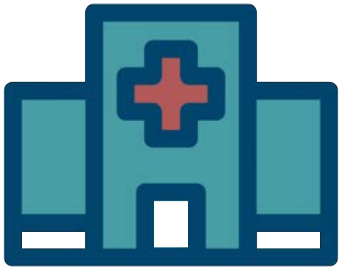
False Negatives Might Be Better than False Positives

False Negative: SPAM email that is not caught, so gets delivered to your inbox.

Annoying at the minimum

False Positive: Email flagged as SPAM is removed from your inbox.

If it's a highly-sensitive/time-critical email, could be disastrous



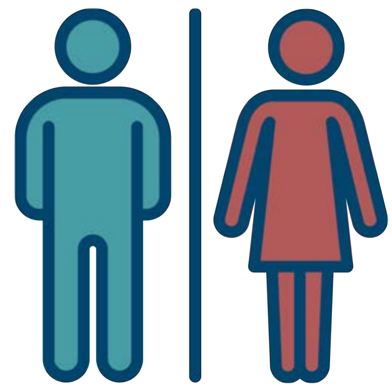
Spam Filtering

Bias Must be Considered Relative to Task

Gender in loan application

Gender discrimination is illegal

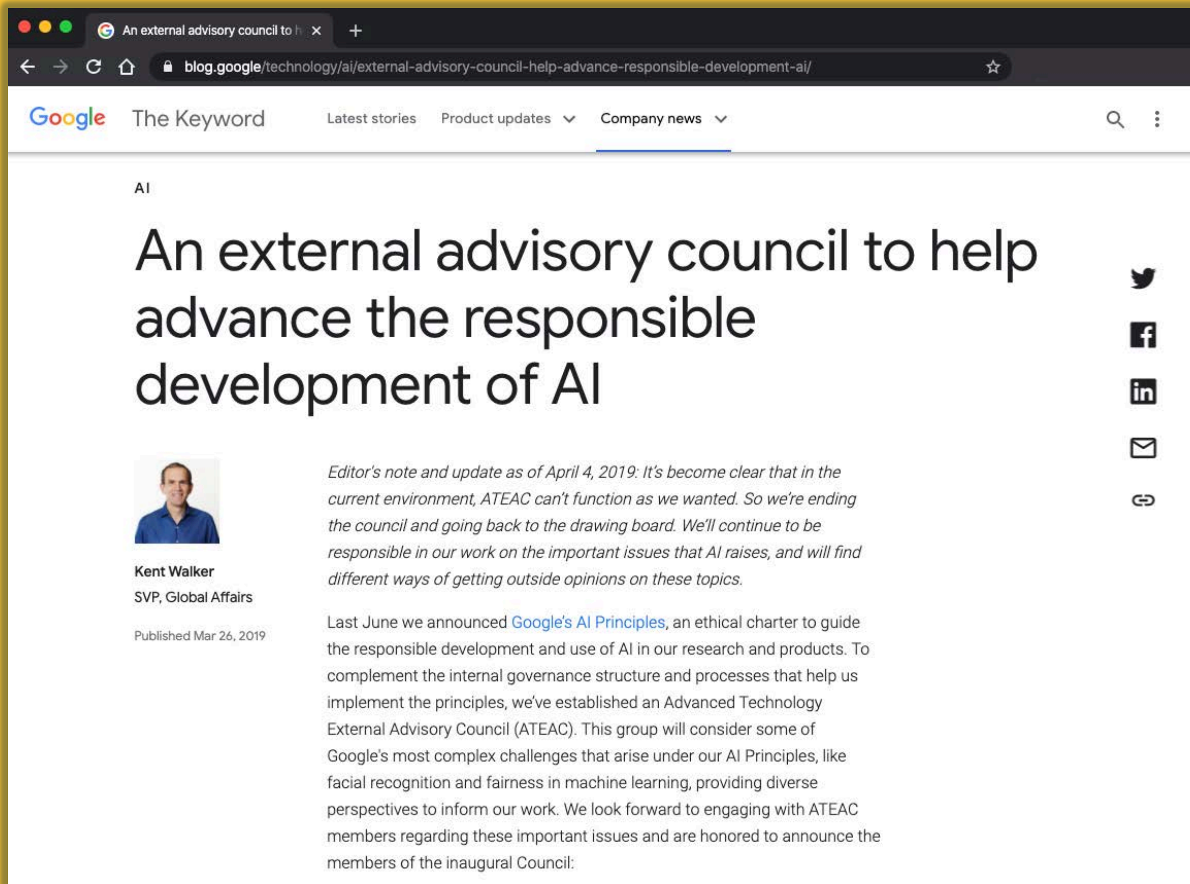
Gender in medical diagnosis



Gender-specific medical diagnosis is desirable

Note

It’s Not Easy



An external advisory council to h

blog.google/technology/ai/external-advisory-council-help-advance-responsible-development-ai/

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An external advisory council to help advance the responsible development of AI

Kent Walker
SVP, Global Affairs

Published Mar 26, 2019

Editor's note and update as of April 4, 2019: It's become clear that in the current environment, ATEAC can't function as we wanted. So we're ending the council and going back to the drawing board. We'll continue to be responsible in our work on the important issues that AI raises, and will find different ways of getting outside opinions on these topics.

Last June we announced Google's AI Principles, an ethical charter to guide the responsible development and use of AI in our research and products. To complement the internal governance structure and processes that help us implement the principles, we've established an Advanced Technology External Advisory Council (ATEAC). This group will consider some of Google's most complex challenges that arise under our AI Principles, like facial recognition and fairness in machine learning, providing diverse perspectives to inform our work. We look forward to engaging with ATEAC members regarding these important issues and are honored to announce the members of the inaugural Council:

https://www.blog.google/technology/ai/external-advisory-council-help-advance-responsible-development-ai/

Exclusive: Google cancels AI eth ×

vox.com/future-perfect/2019/4/4/18295933/google-cancels-ai-ethics-board

Vox

CORONAVIRUS OPEN SOURCED RECODE THE GOODS FUTURE PERFECT THE HIGHLIGHT MORE

Exclusive: Google cancels AI ethics board in response to outcry

The controversial panel lasted just a little over a week.

By Kelsey Piper | Apr 4, 2019, 7:00pm EDT

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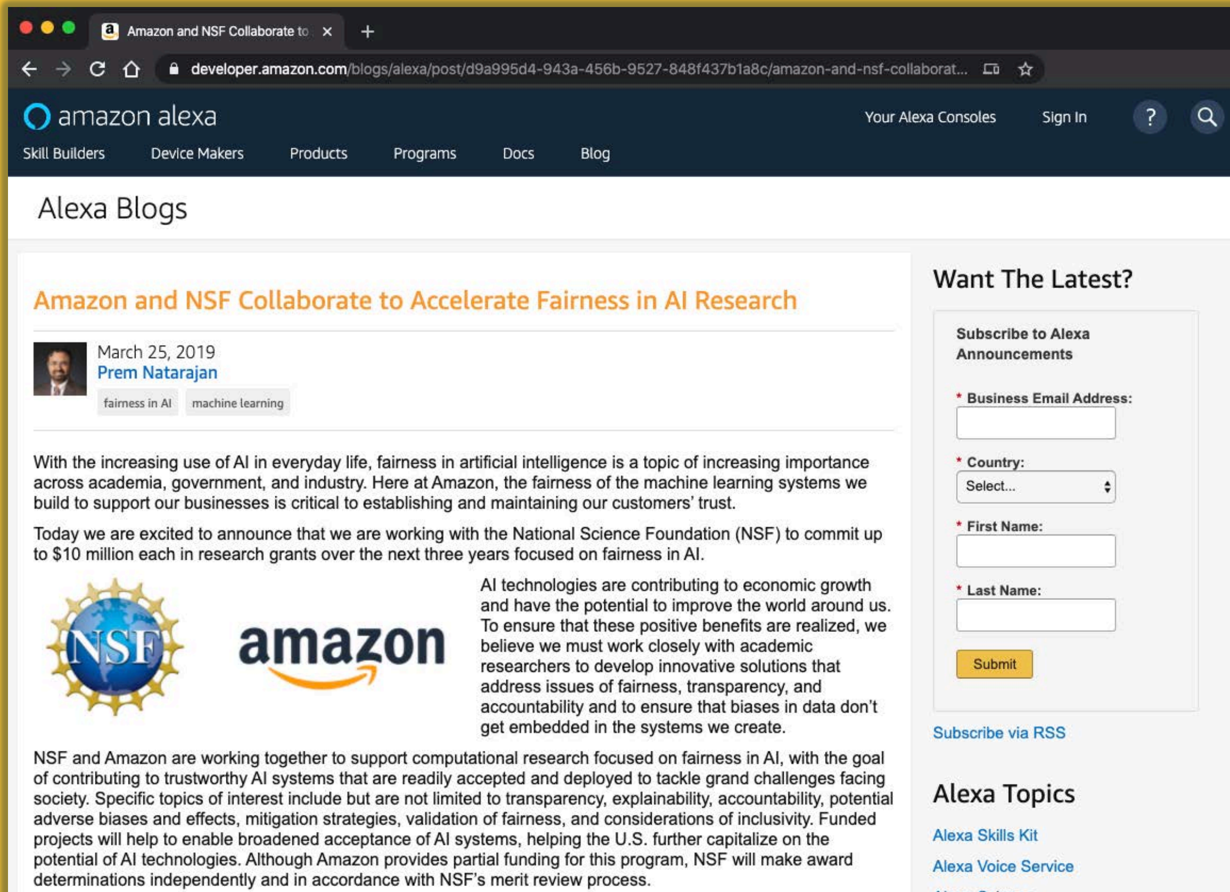
https://www.vox.com/future-perfect/2019/4/4/18295933/google-cancels-ai-ethics-board



Amazon and NSF Collaborate to

developer.amazon.com/blogs/alexa/post/d9a995d4-943a-456b-9527-848f437b1a8c/amazon-and-nsf-collaborat...

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Alexa Blogs

Amazon and NSF Collaborate to Accelerate Fairness in AI Research

March 25, 2019
Prem Natarajan
fairness in AI | machine learning

With the increasing use of AI in everyday life, fairness in artificial intelligence is a topic of increasing importance across academia, government, and industry. Here at Amazon, the fairness of the machine learning systems we build to support our businesses is critical to establishing and maintaining our customers' trust.

Today we are excited to announce that we are working with the National Science Foundation (NSF) to commit up to $10 million each in research grants over the next three years focused on fairness in AI.

AI technologies are contributing to economic growth and have the potential to improve the world around us. To ensure that these positive benefits are realized, we believe we must work closely with academic researchers to develop innovative solutions that address issues of fairness, transparency, and accountability and to ensure that biases in data don't get embedded in the systems we create.

NSF and Amazon are working together to support computational research focused on fairness in AI, with the goal of contributing to trustworthy AI systems that are readily accepted and deployed to tackle grand challenges facing society. Specific topics of interest include but are not limited to transparency, explainability, accountability, potential adverse biases and effects, mitigation strategies, validation of fairness, and considerations of inclusivity. Funded projects will help to enable broadened acceptance of AI systems, helping the U.S. further capitalize on the potential of AI technologies. Although Amazon provides partial funding for this program, NSF will make award determinations independently and in accordance with NSF's merit review process.

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Amazon's role in co-sponsoring research on fairness in AI draws mixed reaction

March 31, 2019 at 5:00 pm | *Updated April 1, 2019 at 6:25 pm*

By Benjamin Romano

Seattle Times business reporter

Amazon has partnered with the taxpayer-funded National Science Foundation on a three-year, $20 million program to fund basic research into fairness in artificial intelligence systems, which are under increasing scrutiny as they spread in society and sometimes amplify existing biases.

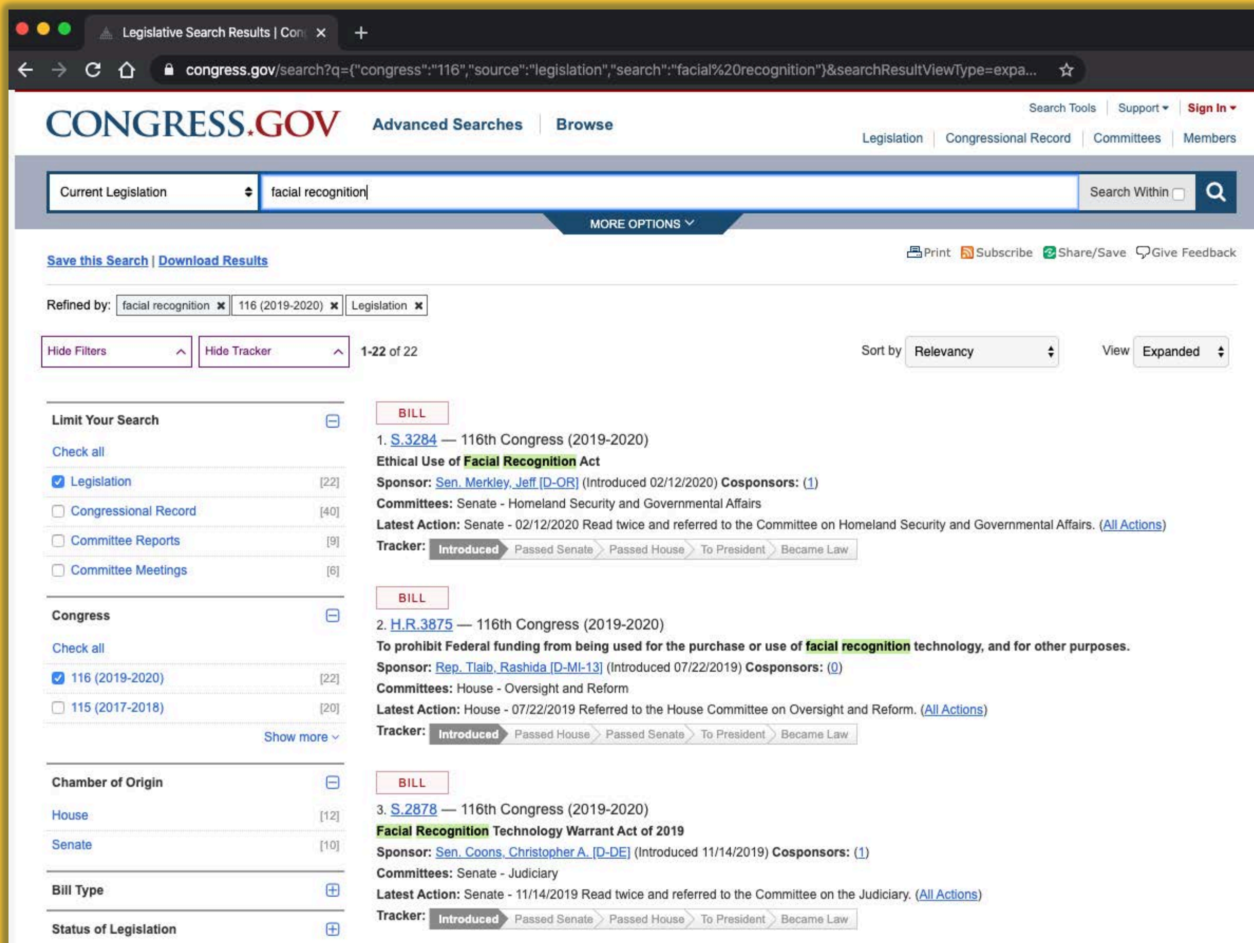
Some researchers welcomed the move, suggesting it signals a growing awareness of the importance of this area of inquiry. Others raised concerns about Amazon's participation, pointing to potential conflicts of interest for researchers who would scrutinize artificial intelligence technologies at both the company and its competitors.

https://www.seattletimes.com/business/amazon/amazons-role-in-co-sponsoring-research-on-fairness-in-a-i-draws-mixed-reaction/

Georgia Tech

https://www.theguardian.com/technology/2019/mar/28/big-tech-ai-ethics-boards-prejudice

https://www.bbc.com/news/technology-48276660



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Facial recognition

This article is more than **1 year old**

Police face legal action over use of facial recognition cameras

Campaigners say technology risks turning UK citizens into 'walking ID cards'

Owen Bowcott
Legal affairs correspondent

@owenbowcott

Thu 14 Jun 2018
16.45 EDT

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▲ It has been claimed that Met police carried out biometric checks at last year's Remembrance Sunday service.

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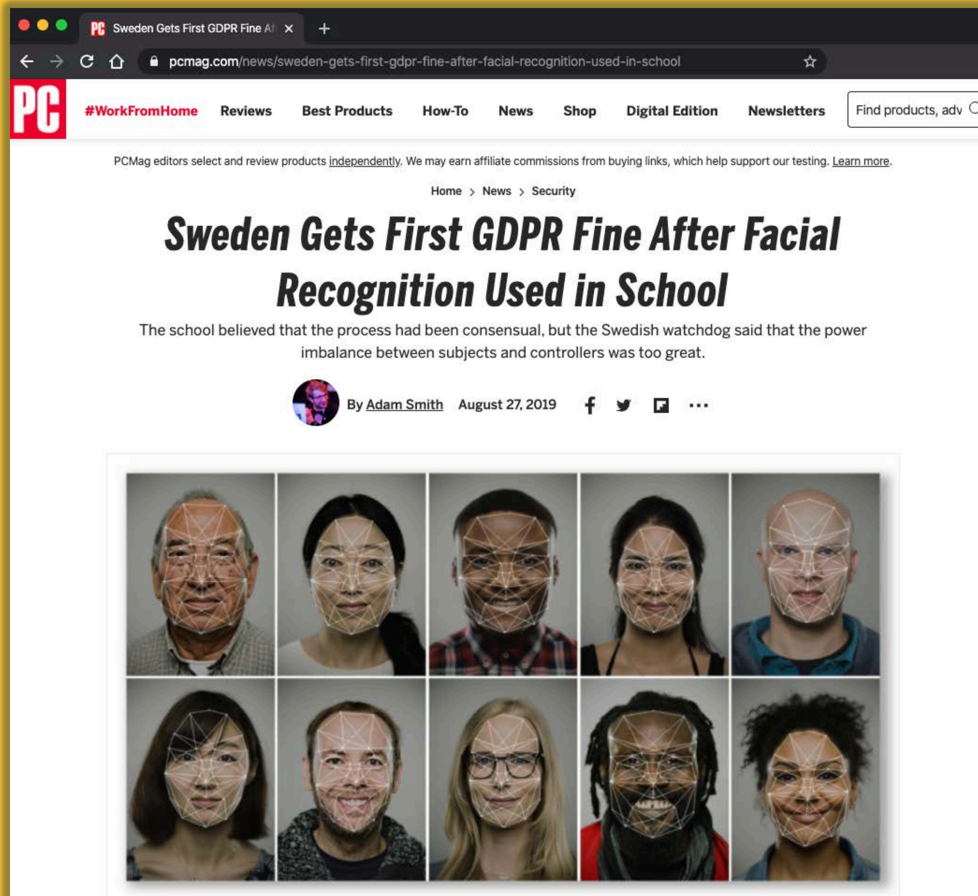
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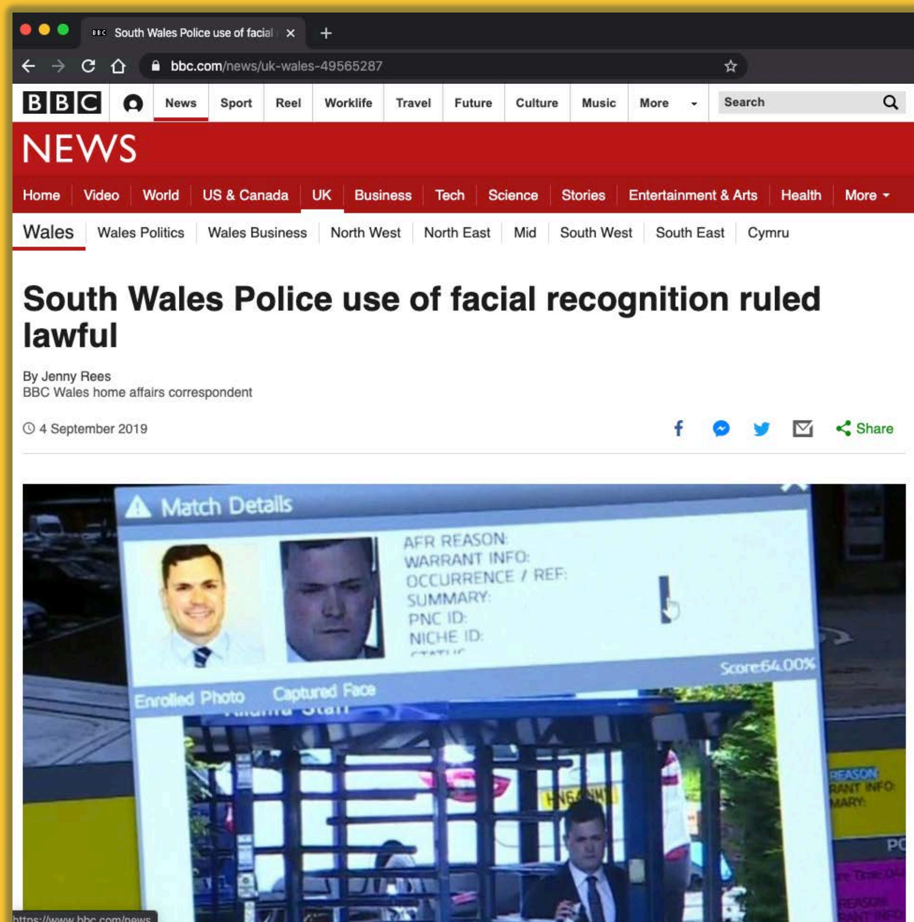
Sweden Gets First GDPR Fine After Facial Recognition Used in School

The school believed that the process had been consensual, but the Swedish watchdog said that the power imbalance between subjects and controllers was too great.

By Adam Smith August 27, 2019

https://www.pcmag.com/news/sweden-gets-first-gdpr-fine-after-facial-recognition-used-in-school



South Wales Police use of facial

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South Wales Police use of facial recognition ruled lawful

By Jenny Rees
BBC Wales home affairs correspondent

4 September 2019

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Georgia Tech

Last Thoughts

Georgia Tech

Intended use of AI/ML can provide great value

- Increased productivity
- Overcome human biases

The stakes are high, with potential long term negative social impact

- Injustice
- Significant public embarrassments

AI/ML models may boost bias even further

- Pros & cons of benchmark datasets
- Facebook feed – elections/polarization and Twitter bots - Brexit

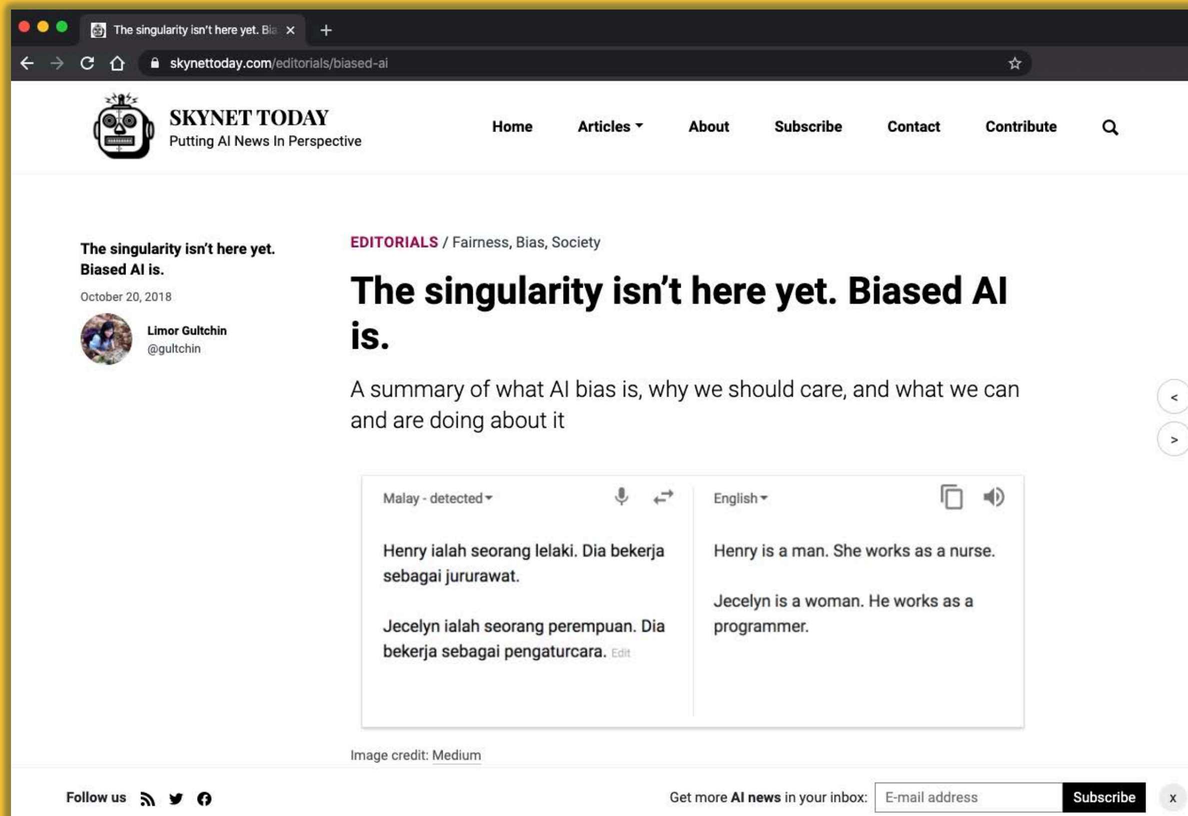
We don't know the ground truth that machine learning relies on

- What does "fairness" or "unbiased" really mean?
- How to translate that definition to math and supervise our models

Last Thoughts

Georgia Tech

- Ethical responsibility
- Selfish Reasons
- **Both**



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