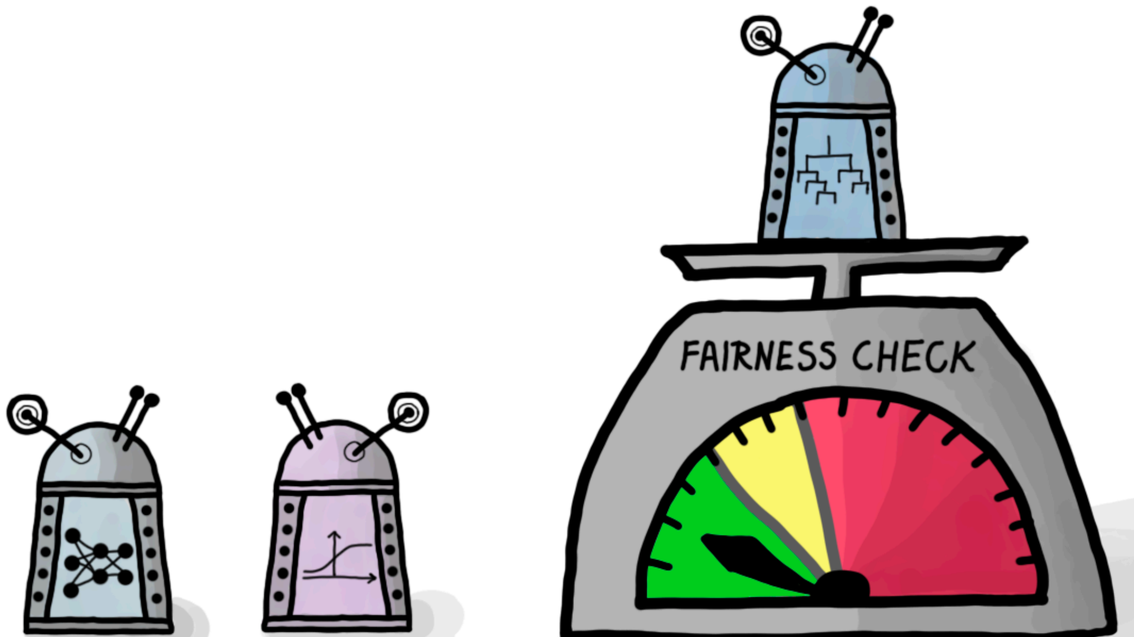
Explaining and Checking Fairness for Predictive Models

Przemysław Biecek

3rd Workshop
eXplaining Knowledge Discovery in Data Mining
2021

https://github.com/ModelOriented/fairmodels



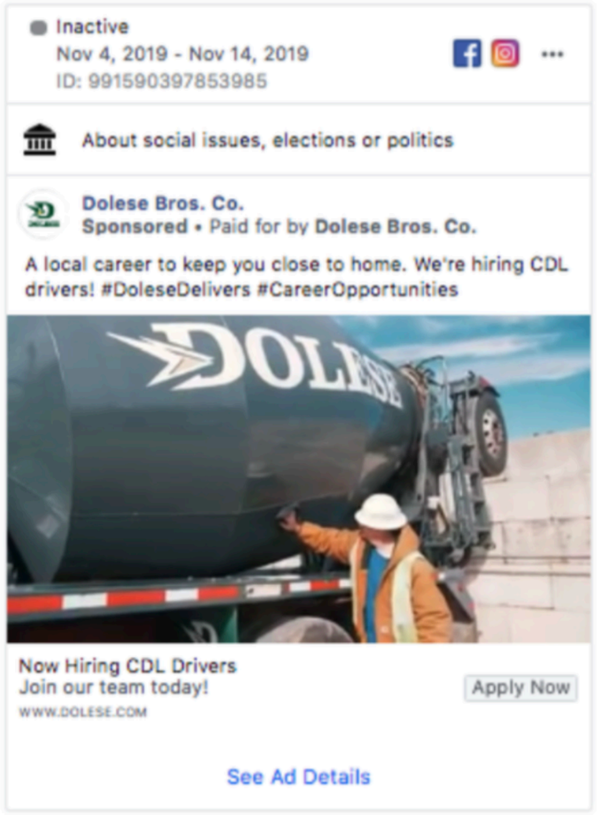
Do algorithms discriminate?

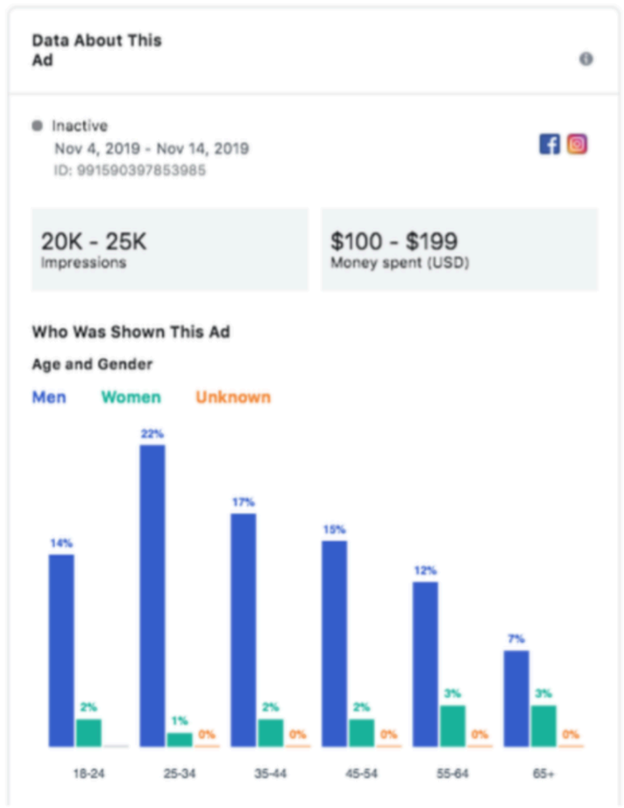
MACHINE BIAS

Facebook Ads Can Still Discriminate Against Women and Older Workers, Despite a Civil Rights Settlement

New research and Facebook's own ad archive show that the company's new system to ensure diverse audiences for housing and employment ads has many of the same problems as its predecessor.

by Ava Kofman and Ariana Tobin, Dec. 13, 2019, 5 a.m. EST





Left: A Facebook ad for Dolese Bros. Co. Right: Facebook's chart shows that 87 percent of the people who saw the ad were men.

https://www.propublica.org/article/facebook-ads-can-still-discriminate-against-women-and-older-workers-despite-a-civil-rights-settlement

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BUSINESS NEWS OCTOBER 10, 2018 / 5:12 AM / A MONTH AGO

Amazon scraps secret AI recruiting t showed bias against women

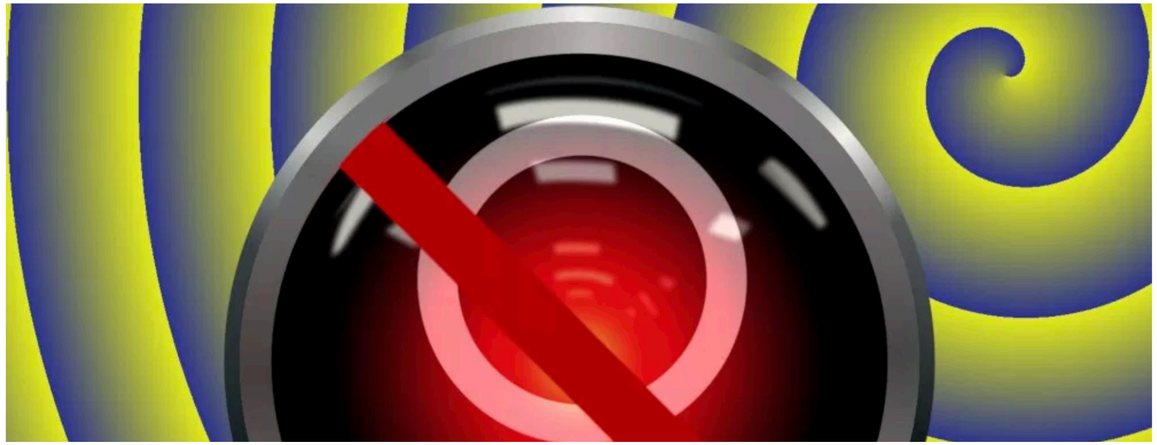
Jeffrey Dastin 8 MIN

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-specialists uncovered a big problem: their new recruiting engine did no

The group created 500 computer models focused on specific job functions and locations. They taught each to recognize some 50,000 terms that showed up on past candidates' resumes. The algorithms learned to assign little significance to skills that were common across IT applicants, such as the ability to write various computer codes, the people said.

Instead, the technology favored candidates who described themselves using verbs more commonly found on male engineers' resumes, such as "executed" and "captured," one person said.

Amazon trained a sexism-fighting, resume-screening AI with sexist hiring data, so the bot became sexist



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21

Amazon reportedly scraps internal AI recruiting tool that was biased against women

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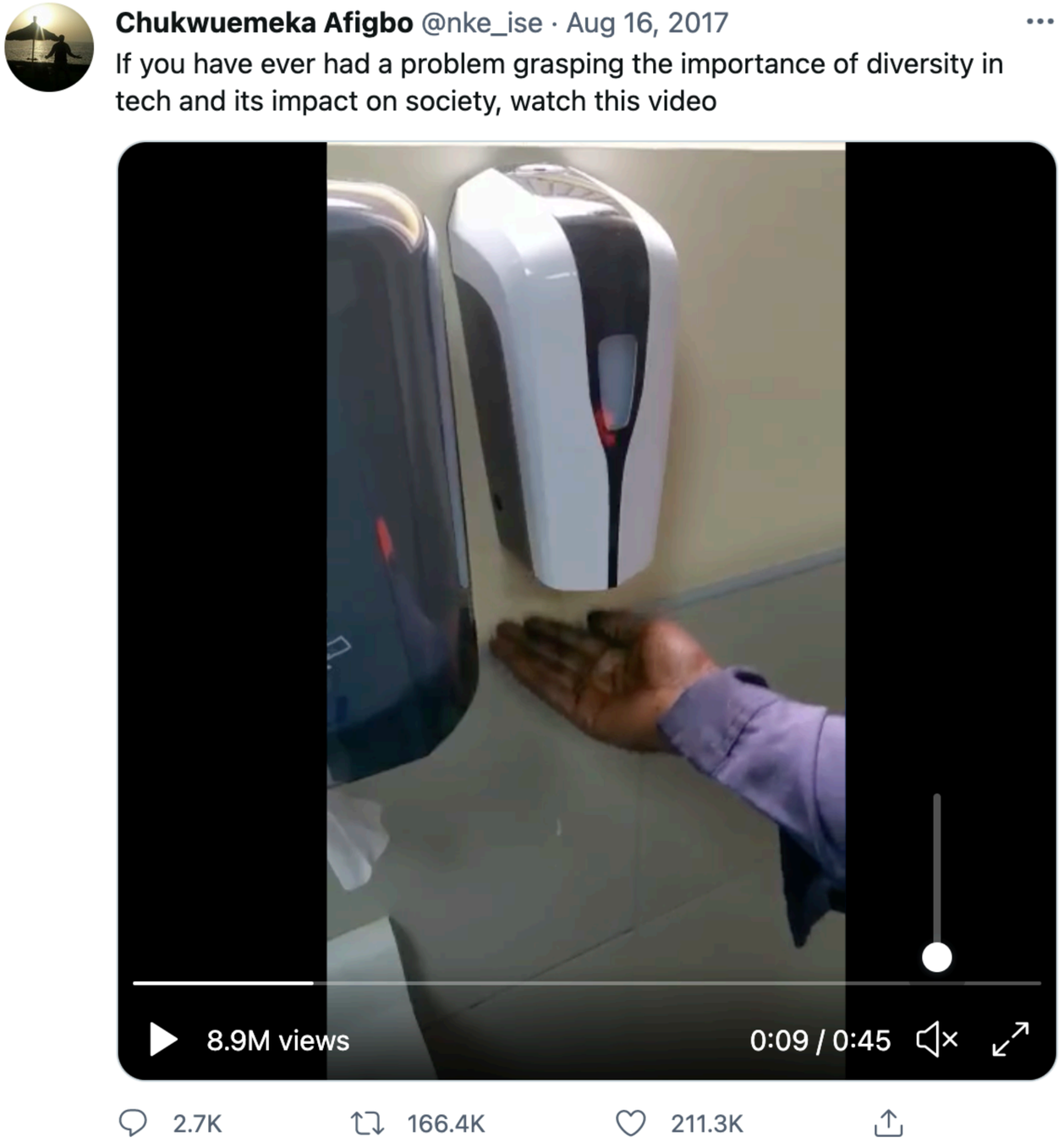
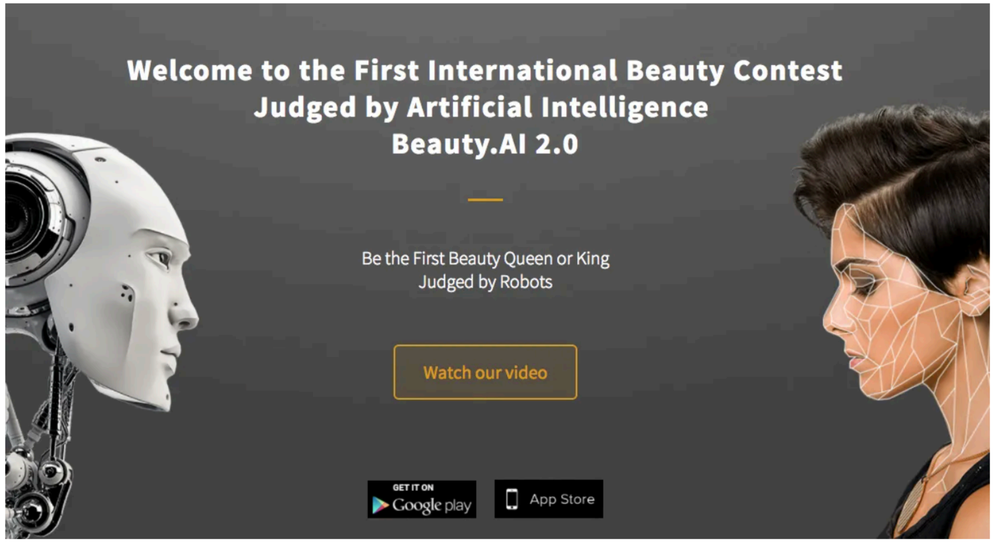
Racist Soap Dispenser



https://twitter.com/nke_ise/status/897756900753891328

Beauty.AI's 'robot beauty contest' is back — and this time it promises not to be racist

The Beauty.AI robot beauty contest discriminated against dark skin. Now it's being relaunched - along with a 'Diversity AI think tank'



BEAUTY.AI

Update 02.03.2017 12:19: Since this article was published, the material on the Diversity.AI website has been taken down and replaced with a single message: "The initiative has not yet been launched." To see what it used to be like take a look at the cached version.

Launched in 2016 by "deep learning" group Youth Laboratories, Beauty.AI used age and facial recognition algorithms to choose what its creators declared would be "the First Beauty Queen or King Judged by Robots." But the 44 winners – selected from among more than 7,000 entrants who had submitted selfies through the app – included only one with dark skin, although numerous people of colour had sent in photographs. The resulting media coverage saw the contest labelled as racist.

Most Popular

Māori are trying to save their language from Big Tech

BY DONAVYN COFFEY

Why a James Bond film will never premiere on Netflix

BY WILL BEDINGFIELD

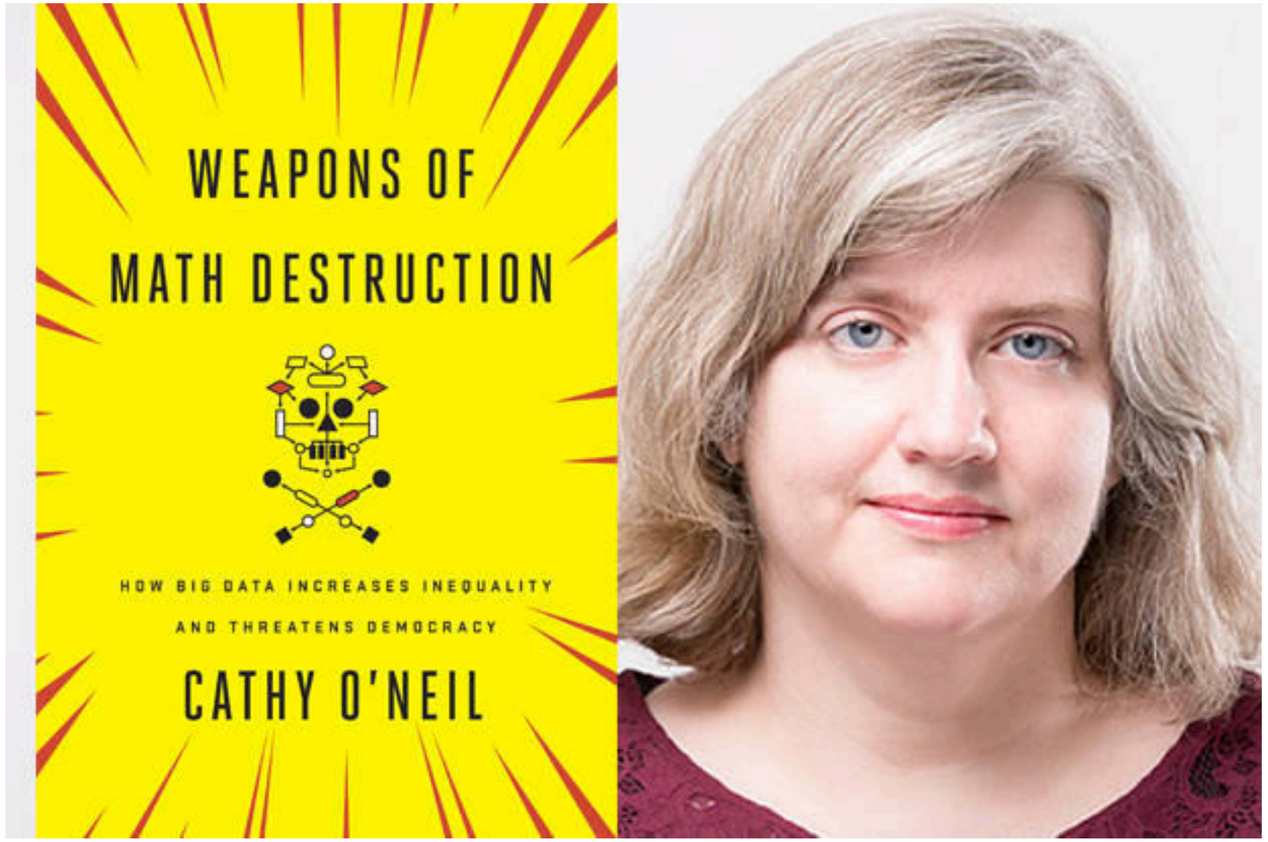
Here comes a new wave of green watches

BY JEREMY WHITE

The future of social media is sharing less, not more

BY HUSSEIN KESVANI

Cathy O'Neil:
The era of blind faith in ~~big data~~ black boxes must end



- “You don’t see a lot of skepticism,” she says. “The algorithms are like shiny new toys that we can’t resist using. We trust them so much that we project meaning on to them.”
- Ultimately algorithms, according to O’Neil, reinforce discrimination and widen inequality, “using people’s fear and trust of mathematics to prevent them from asking questions”.

https://www.theguardian.com/books/2016/oct/27/cathy-oneil-weapons-of-math-destruction-algorithms-big-data

What does it mean to discriminate?

Key point

- Discrimination defines a situation where an individual is disadvantaged in some way on the basis of ‘one or multiple protected grounds’.

https://fra.europa.eu/sites/default/files/fra_uploads/fra-2018-handbook-non-discrimination-law-2018_en.pdf

https://fra.europa.eu/en/publication/2018/handbook-european-non-discrimination-law-2018-edition

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PROTECTED GROUNDS

- Sex
- Gender identity
- Sexual orientation
- Disability
- Age
- Race, ethnicity, colour and membership of a national minority
- Nationality or national origin
- Religion or belief
- Social origin, birth and property
- Language
- Political or other opinion

https://fra.europa.eu/sites/default/files/fra_uploads/fra-2018-handbook-non-discrimination-law-2018_en.pdf

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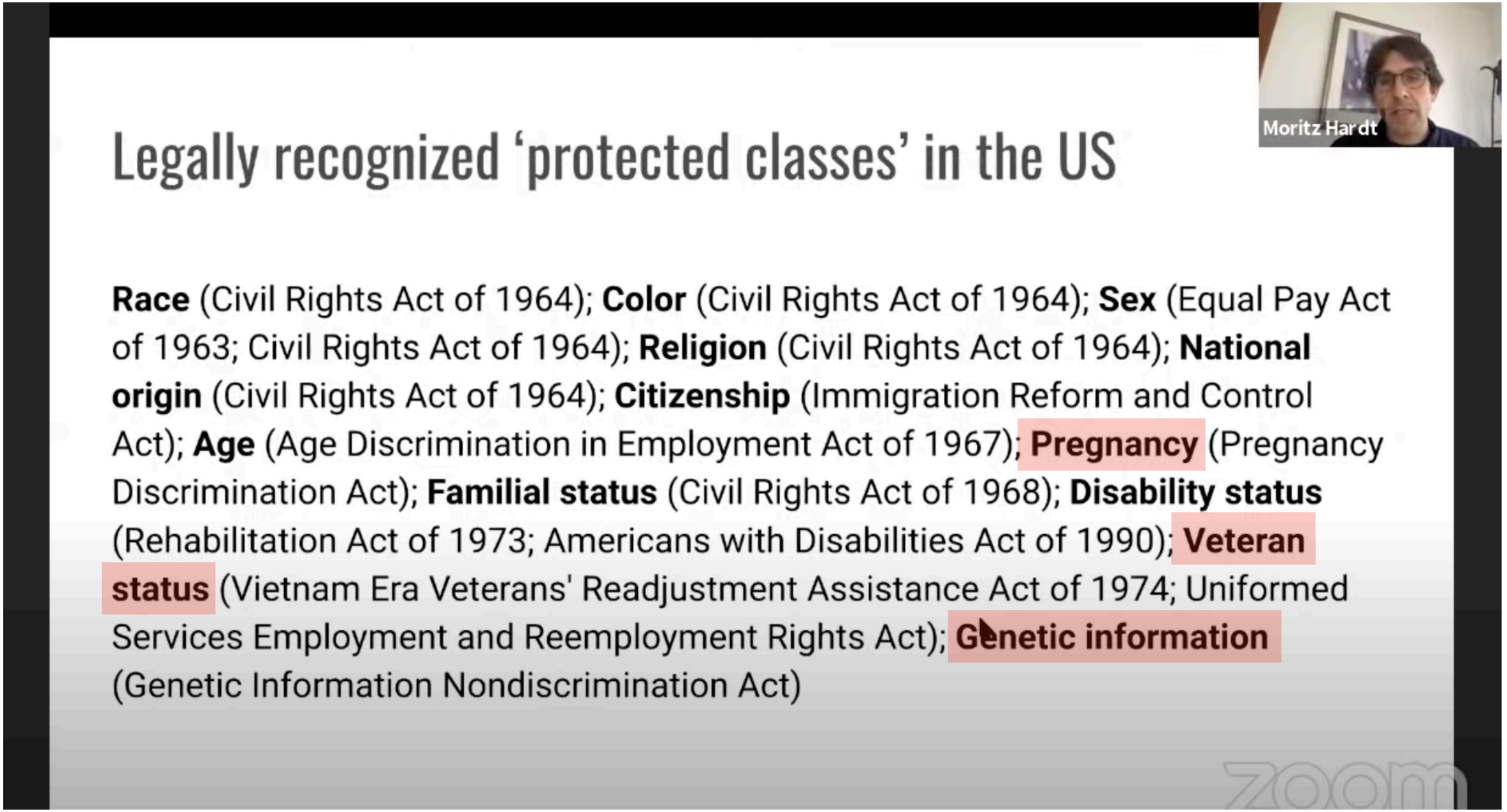

Moritz Hardt 2020, Fairness and Machine Learning (MLSS)
https://www.youtube.com/watch?v=Igq_S_7IfOU

Principles for AI Ethics

1. Fairness

The company will strive to apply the values of **equality and diversity** in AI system throughout its entire lifecycle.
The company will strive not to **reinforce nor propagate negative or unfair bias.**
The company will strive to provide **easy access** to all users.

2. Transparency

Users will be aware that they are **interacting with AI.**
AI will be explainable for users to understand its decision or recommendation to the extent technologically feasible.
The process of collecting or utilizing personal data will be **transparent.**

3. Accountability

The company will strive to apply the principles of **social and ethical responsibility**
AI system will be **adequately protected** and have **security measures** to prevent da
The company will strive to **benefit the society and promote the corporate citizen**

h2o.ai/responsible-ai/

Learn how H2O.ai is responding to COVID-19 with AI. >

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Overview

What is Responsible AI?

Explainable AI and the pursuit of using technology and statistical methods to explain Machine Learning models, quickly became a much larger question. Best practices in applying AI is not just a statistical question, but a people and process question as well, which forms the key elements of Responsible AI. In order to achieve maximum transparency and understanding of AI, it is imperative to address and understand the full view of models and their impact.

Trusted AI Lifecycle through Open Source

Pillars of trust, woven into the lifecycle of an AI application

Did anyone tamper with it?	Is it fair?	Is it easy to understand?	Is it accountable?
ROBUSTNESS	FAIRNESS	EXPLAINABILITY	LINEAGE
Adversarial Robustness 360 ↳ (ART)	AI Fairness 360 ↳ (AIF360)	AI Explainability 360 ↳ (AIX360)	In the works!
github.com/IBM/adversarial-robustness-toolbox	github.com/IBM/AIF360	github.com/IBM/AIX360	
art-demo.mybluemix.net	aif360.mybluemix.net	aix360.mybluemix.net	

tensorflow.org/resources/responsible-ai

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What is Responsible AI?

The development of AI is creating new opportunities to solve challenging, r problems. It is also raising new questions about the best way to build AI system everyone.

Recommended best practices for AI
Designing AI systems should follow software development best practices while taking a human-centered approach to ML

Fairness
As the impact of AI increases across sectors and societies, it is critical to work towards systems that are fair and inclusive to everyone

Interpretability
Understanding and trusting AI systems is important to ensuring they are working as intended

Privacy
Training models off of sensitive data needs privacy preserving safeguards

Security
Identifying potential threats can help keep AI systems safe and secure

Learn more about Google's Responsible AI Practices ↗

A practical guide to Responsible Artificial Intelligence (AI)

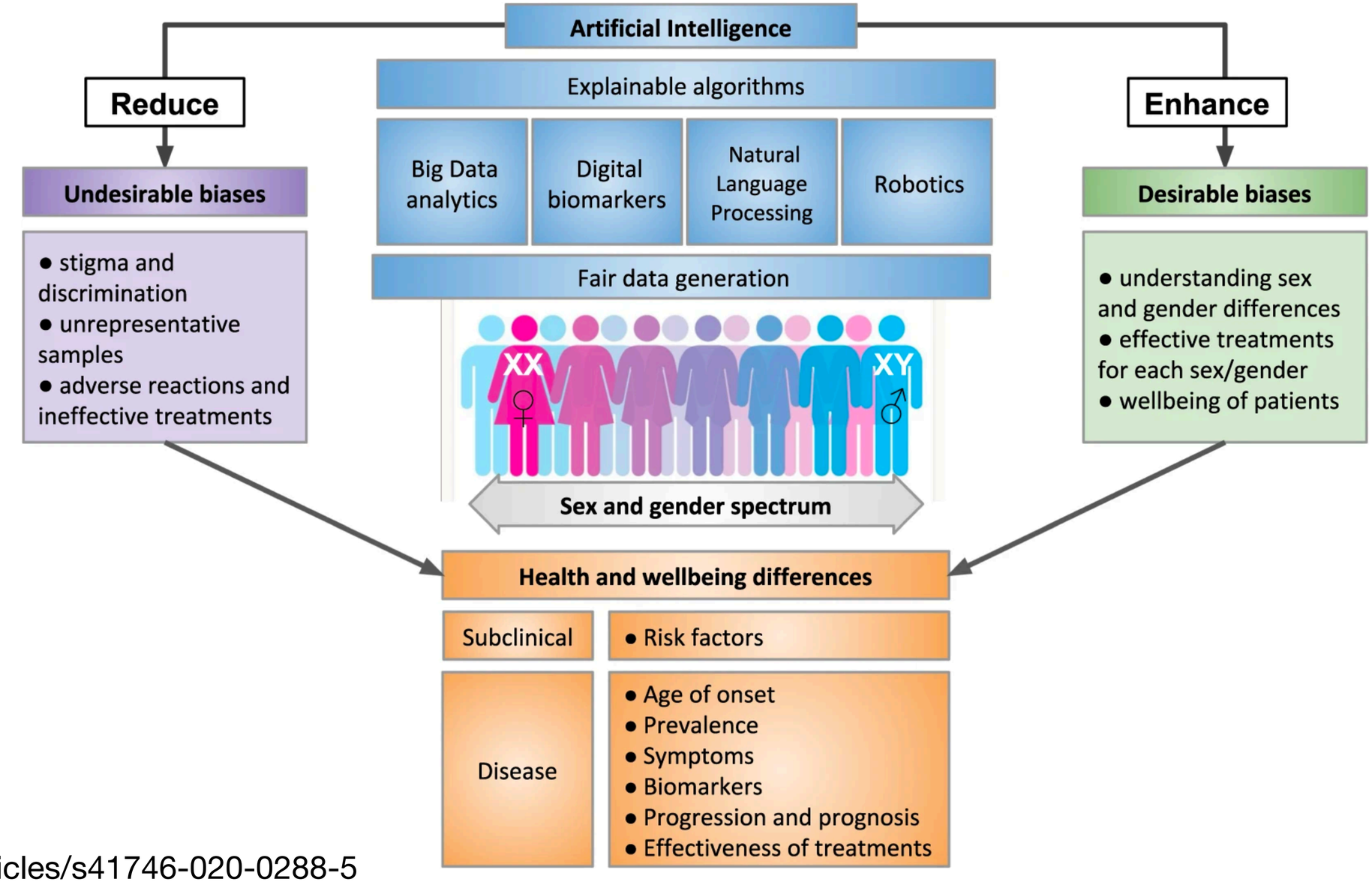
pwc

pwc.com/rai

Is different treatment always a discrimination?

Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare

Cirillo et al 2020



https://www.nature.com/articles/s41746-020-0288-5

Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare

Cirillo et al 2020

Clinical conditions and studies	Current status without the desirable bias	Utility of the desirable bias
Autistic spectrum disorder	There is a current lack of consideration of the demonstrated age-dependent sex differences in the symptomatology related with impairments in social communication and interaction, expressive behaviour, reciprocal conversation, non-verbal gestures for diagnostic purposes[123].	Differential diagnostic criteria for males and females could facilitate the identification of the clinical diagnosis leading to appropriate treatment.
Cardiovascular disorders	Although it has been documented that men and women respond differently to many cardiovascular medications such as statins, angiotensin-converting enzyme inhibitors and β-Blockers among others, adopted treatments do not consider sex differences[124].	Making prescriptions according to the sex of the patient could lead to improved health benefits.
	Despite the fact that Coronary heart disease (CHD) is the leading cause of death among women[125], the majority (67%) of patients enroled in clinical trials for cardiovascular devices are male[126].	The application of a desirable bias towards women would lead to a more accurate representation of sex differences in clinical research.
Genome-wide association studies (GWAS)	Most of genome-wide association studies (GWAS) focus on white male subjects[127] and those that explore sex differences in complex traits are scarce[128].	The introduction of desirable biases to deliberately include female subjects and other ethnicities in GWAS could lead to better account for potential sex differences in disease that are currently unknown because of being overlooked.
Human immunodeficiency virus (HIV)	The observed lower female representation in HIV clinical trials depends, among other factors, from the disadvantaged awareness about treatment and enrolment options compared with men[129–131].	Promoting empowerment initiatives in those patients with disadvantages will increase their exposure to treatment options and clinical trial enrolment.

https://www.nature.com/articles/s41746-020-0288-5

Think about the whole process

bias may be everywhere

Some sources of bias

- **Historical bias.** The data are correctly sampled and correspond well to the observed relationships, but due to different treatment in the past some prejudices are encoded in the data. Think about gender and occupation stereotypes.

partially based on Cirillo et al, 2020. https://www.nature.com/articles/s41746-020-0288-5

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- **Representation bias.** The available data is not a representative sample of the population of interest. Think about the available facial images of actors, often white men. Or genetic sequences of covid variants, mostly collected in developed European countries. Or crime statistics in the regions to which the police are directed.

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- **Measurement bias.** The variable of interest is not directly observable or is difficult to measure and the way it is measured may be distorted by other factors. Think of the results of the mathematics skills assessment (e.g. PISA) measured by tasks on computers not that widely available in some countries.

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- **Evaluation bias.** The evaluation of the algorithm is performed on a population that does not represent all groups. Think of a lung screening algorithm tested primarily on a population of smokers (older men).

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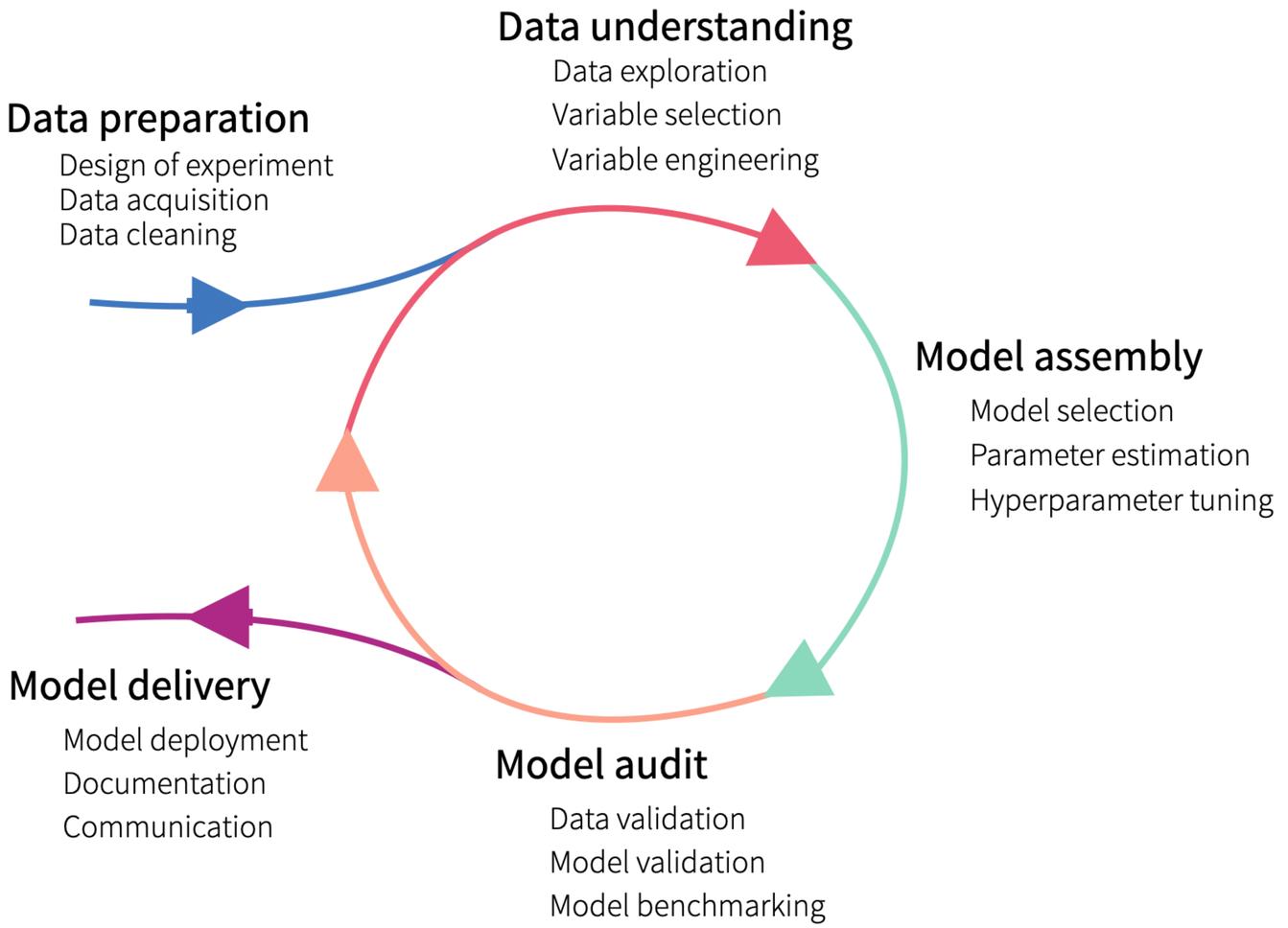
- **Proxy bias.** The algorithm uses variables that are proxies for protected attributes. Think of male/female only schools where the gender effect can be hidden under the school effect.

partially based on Cirillo et al, 2020. https://www.nature.com/articles/s41746-020-0288-5



Explanatory Model Analysis
https://ema.drwhy.ai/

possible source of bias

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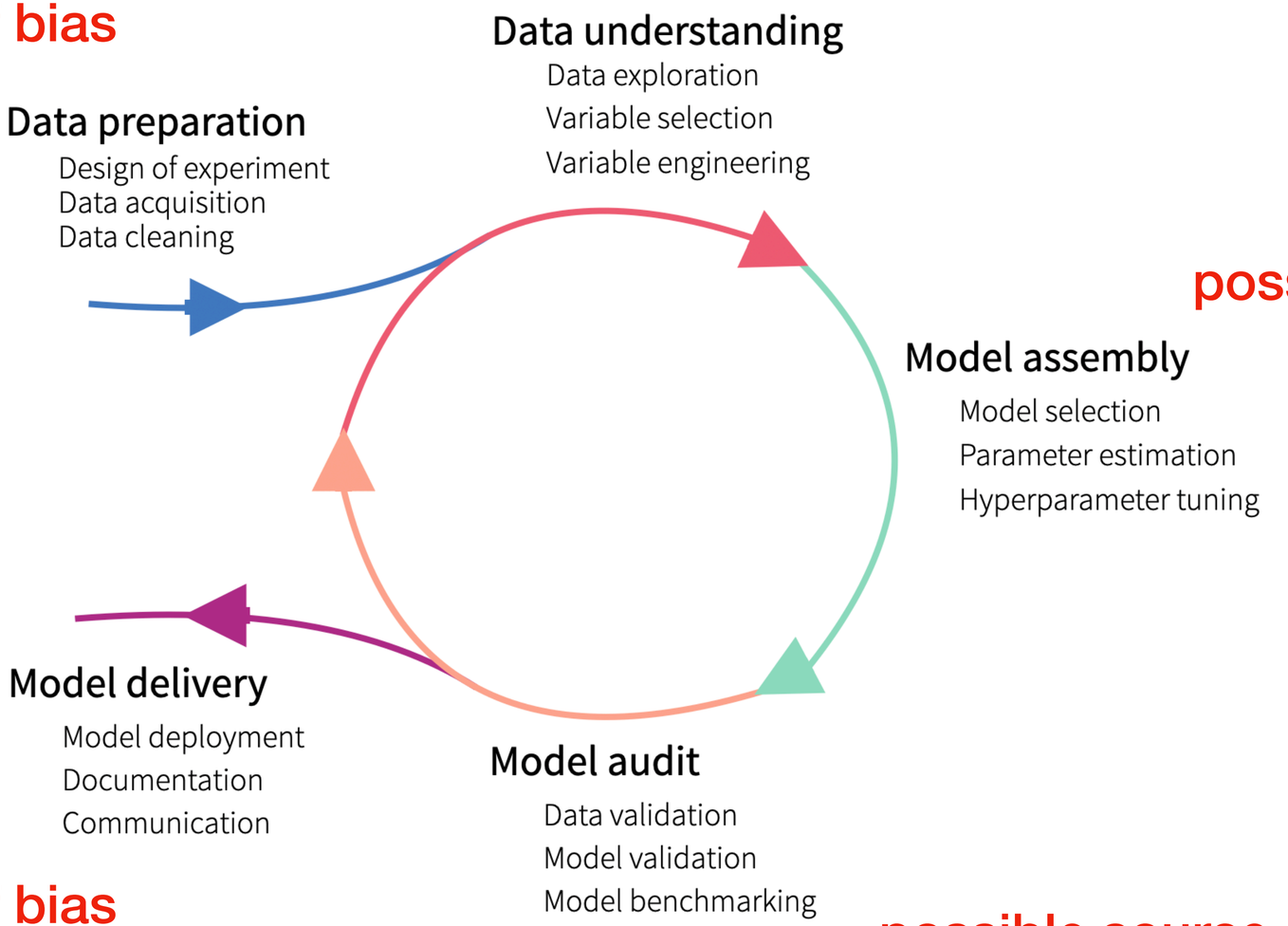

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An interesting example is the StreetBumps project.
The city of Boston released an application for mobile phones that allows to identify potholes based on vibrations measured by accelerometer.
It is a very innovative idea, but when analyzing such data one has to take into account the representativeness of the collected data.
Much more information about potholes will come from the neighborhoods where wealthier and younger people live, who use mobile phone more often.

https://hbr.org/2013/04/the-hidden-biases-in-big-data

Technology

The Hidden Biases in Big Data

by Kate Crawford

April 01, 2013

This looks to be the year that we reach peak big data hype. From wildly popular big data conferences to columns in major newspapers, the business and science worlds are focused on how large datasets can give insight on previously intractable challenges. The hype becomes problematic when it leads to what I call "data fundamentalism," the notion that correlation always indicates causation, and that massive data sets and predictive analytics always reflect objective truth. Former *Wired* editor-in-chief Chris Anderson embraced this idea in his comment, "with enough data, the numbers speak for themselves." But can big data really deliver on that promise? Can numbers actually speak for themselves?

Sadly, they can't. Data and data sets are not objective; they are creations of human design. We give numbers their voice, draw inferences from them, and define their meaning through our interpretations. Hidden biases in both the collection and analysis stages present considerable risks, and are as important to the big-data equation as the numbers themselves.

Bias encoded in data embeddings

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Bolukbasi et al, 2016

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}.$$

https://arxiv.org/pdf/1607.06520.pdf

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

Figure 1: The most extreme occupations as projected on to the *she*−*he* gender direction on g2vNEWS. Occupations such as *businesswoman*, where gender is suggested by the orthography, were excluded.

Gender stereotype *she-he* analogies.

sewing-carpentry	register-nurse-physician	housewife-shopkeeper
nurse-surgeon	interior designer-architect	softball-baseball
blond-burly	feminism-conservatism	cosmetics-pharmaceuticals
giggle-chuckle	vocalist-guitarist	petite-lanky
sassy-snappy	diva-superstar	charming-affable
volleyball-football	cupcakes-pizzas	hairdresser-barber

Gender appropriate *she-he* analogies.

queen-king	sister-brother	mother-father
waitress-waiter	ovarian cancer-prostate cancer	convent-monastery

Figure 2: **Analogy examples**. Examples of automatically generated analogies for the pair *she-he* using the procedure described in text. For example, the first analogy is interpreted as *she*:*sewing* :: *he*:*carpentry* in the original w2vNEWS embedding. Each automatically generated analogy is evaluated by 10 crowd-workers are to whether or not it reflects gender stereotype. Top: illustrative gender stereotypic analogies automatically generated from w2vNEWS, as rated by at least 5 of the 10 crowd-workers. Bottom: illustrative generated gender-appropriate analogies.

Measuring Bias in Contextualized Word Representations
Bolukbasi et al 2016, https://arxiv.org/pdf/1607.06520.pdf

Examining Gender and Race Bias in Two Hundred Sentiment Analysis Systems
Kiritchenko et al 2018, https://arxiv.org/pdf/1805.04508.pdf

Learning Gender-Neutral Word Embeddings
Zhao et al 2018, https://aclanthology.org/D18-1521/

Mitigating Gender Bias in Natural Language Processing: Literature Review
Sun et al 2019, https://arxiv.org/pdf/1906.08976.pdf

Reducing Gender Bias in Word-Level Language Models with a Gender-Equalizing Loss Function
Qian et al 2019, https://arxiv.org/pdf/1905.12801.pdf

Identifying and Reducing Gender Bias in Word-Level Language Models
Bordia et al 2019, https://aclanthology.org/N19-3002.pdf

Investigating Gender Bias in Language Models Using Causal Mediation Analysis
Vig et al 2020, https://proceedings.neurips.cc/paper/2020/file/92650b2e92217715fe312e6fa7b90d82-Paper.pdf

Stereotype and Skew: Quantifying Gender Bias in Pre-trained and Fine-tuned Language Models
de Vassimon Manela et al 2021, https://arxiv.org/pdf/2101.09688.pdf

Is it always about higher scores?

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Midterm Elections | Imprisoned In Myanmar | Sectors Up Close | Breakingviews | Investing | Future of Money | Charged: The Future of Aut

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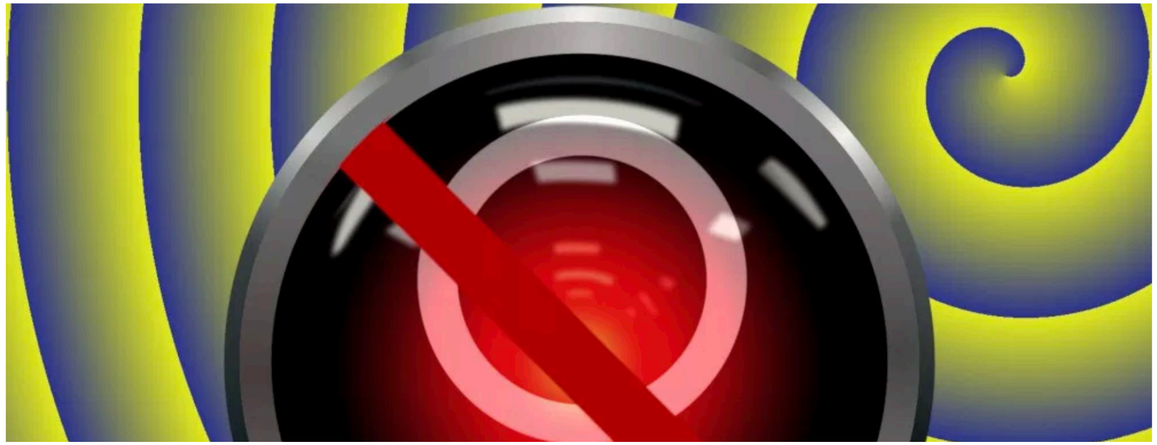

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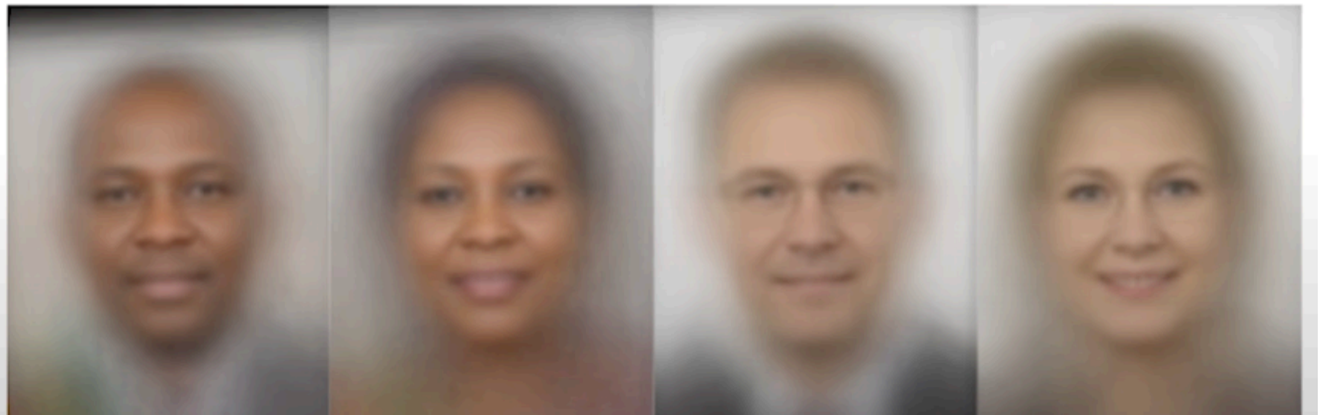
Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification

Buolamwini and Gebru, 2018

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%

Metric	All	F	M	Darker	Lighter	DF	DM	LF	LM
PPV(%)	93.7	89.3	97.4	87.1	99.3	79.2	94.0	98.3	**100**
Error Rate(%)	6.3	10.7	2.6	12.9	0.7	**20.8**	6.0	1.7	0.0
TPR (%)	93.7	96.5	91.7	87.1	99.3	92.1	83.7	**100**	98.7
FPR (%)	6.3	8.3	3.5	12.9	0.7	**16.3**	7.9	1.3	0.0
PPV(%)	90.0	78.7	99.3	83.5	95.3	65.5	**99.3**	94.0	99.2
Error Rate(%)	10.0	21.3	0.7	16.5	4.7	**34.5**	0.7	6.0	0.8
TPR (%)	90.0	98.9	85.1	83.5	95.3	98.8	76.6	**98.9**	92.9
FPR (%)	10.0	14.9	1.1	16.5	4.7	**23.4**	1.2	7.1	1.1
PPV(%)	87.9	79.7	94.4	77.6	96.8	65.3	88.0	92.9	**99.7**
Error Rate(%)	12.1	20.3	5.6	22.4	3.2	**34.7**	12.0	7.1	0.3
TPR (%)	87.9	92.1	85.2	77.6	96.8	82.3	74.8	**99.6**	94.8
FPR (%)	12.1	14.8	7.9	22.4	3.2	**25.2**	17.7	5.20	0.4



https://proceedings.mlr.press/v81/buolamwini18a/buolamwini18a.pdf

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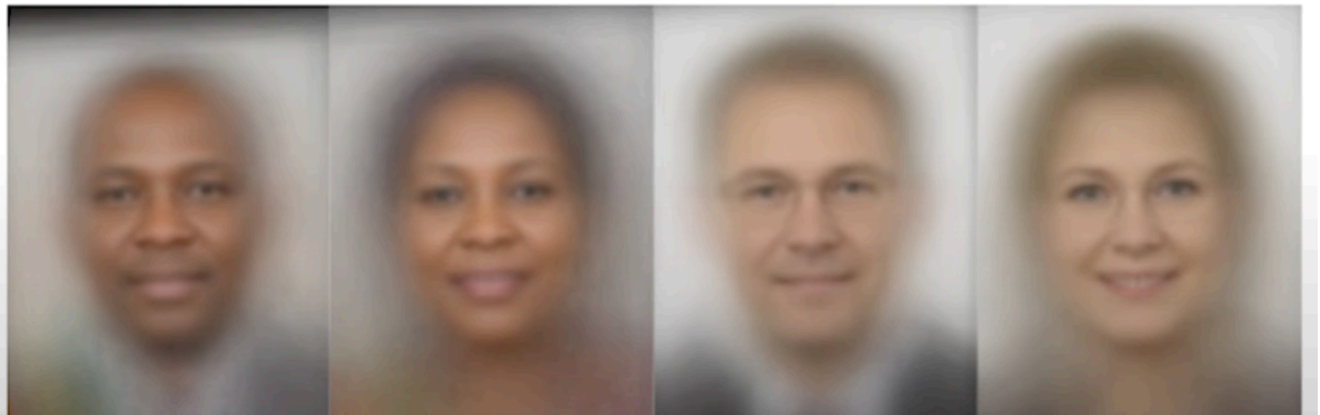
Buolamwini and Gebru, 2018

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%



Lower performance in a group can generate a problem in future data.
Think about credit lines.
If in group A loans are assigned with high accuracy and in group B loans are assigned with low accuracy then over time we will get a dataset where in group A many loans are paid and in group B not paid.

This is only because the people who were assigned credits in group B were more random.

https://proceedings.mlr.press/v81/buolamwini18a/buolamwini18a.pdf

Disregarding sensitive attributes is not a solution

APPLE POLICY TECH

Apple's credit card is being investigated for discriminating against women

117

Customers say the card offers less credit to women than men

By James Vincent | Nov 11, 2019, 5:57am EST

If you buy something from a Verge link, Vox Media may earn a commission. See our ethics statement.

SHARE

Image: Apple

Apple's new credit card is being investigated by financial regulators after customers complained that the card's lending algorithms discriminated against women.

DHH @dhh · Nov 9, 2019

Replying to @dhh

To be fair, this is an even more egregious version of the same take. THE ALGORITHM is always assumed to be just and correct. It's verdict is thus predestined to be a reflection of your failings and your sins.

> **Isles47** @isles47 · Nov 9, 2019
>
> Replying to @dhh and @AppleCard
>
> Haha this is absurd. Litterally none of the things you list here have any effect on credit approval. Whats her existing line of credit, what's her credit score, what outstanding debt does she have? How old is her original line of credit?

19 86 1.4K

Steve Wozniak @stevewoz · Nov 10, 2019

The same thing happened to us. We have no separate bank accounts or credit cards or assets of any kind. We both have the same high limits on our cards, including our AmEx Centurion card. But 10x on the Apple Card.

33 68 182

WILL KNIGHT BUSINESS 11.19.2019 09:15 AM

The Apple Card Didn't 'See' Gender—and That's the Problem

The way its algorithm determines credit lines makes the risk of bias more acute.

Image: Apple

Apple's new credit card is being investigated by financial regulators after customers complained that the card's lending algorithms discriminated against women.

Steve Wozniak @stevewoz · Nov 10, 2019

The same thing happened to us. We have no separate bank accounts or credit cards or assets of any kind. We both have the same high limits on our cards, including our AmEx Centurion card. But 10x on the Apple Card.

33 68 182

The risk of „gaming the fairness”

Computer Science > Machine Learning

[Submitted on 20 Jul 2020]

Fairwashing Explanations with Off-Manifold Detergent

Christopher J. Anders, Plamen Pasliev, Ann-Kathrin Dombrowski, Klaus-Robert Müller, Pan Kessel

Explanation methods promise to make black-box classifiers more transparent. As a result, it is hoped that they can act as proof for a sensible, fair and trustworthy decision-making process of the algorithm and thereby increase its acceptance by the end-users. In this paper, we show both theoretically and experimentally that these hopes are presently unfounded. Specifically, we show that, for any classifier g, one can always construct another classifier $\tilde{g}$ which has the same behavior on the data (same train, validation, and test error) but has arbitrarily manipulated explanation maps. We derive this statement theoretically using differential geometry and demonstrate it experimentally for various explanation methods, architectures, and datasets. Motivated by our theoretical insights, we then propose a modification of existing explanation methods which makes them significantly more robust.

Comments: 22 pages with 43 figures, to be published in ICML2020
Subjects: **Machine Learning (cs.LG)**; Machine Learning (stat.ML)
Cite as: arXiv:2007.09969 **[cs.LG]**
(or arXiv:2007.09969v1 **[cs.LG]** for this version)

Submission history

From: Christopher J. Anders [view email]
[v1] Mon, 20 Jul 2020 09:42:06 UTC (4,823 KB)

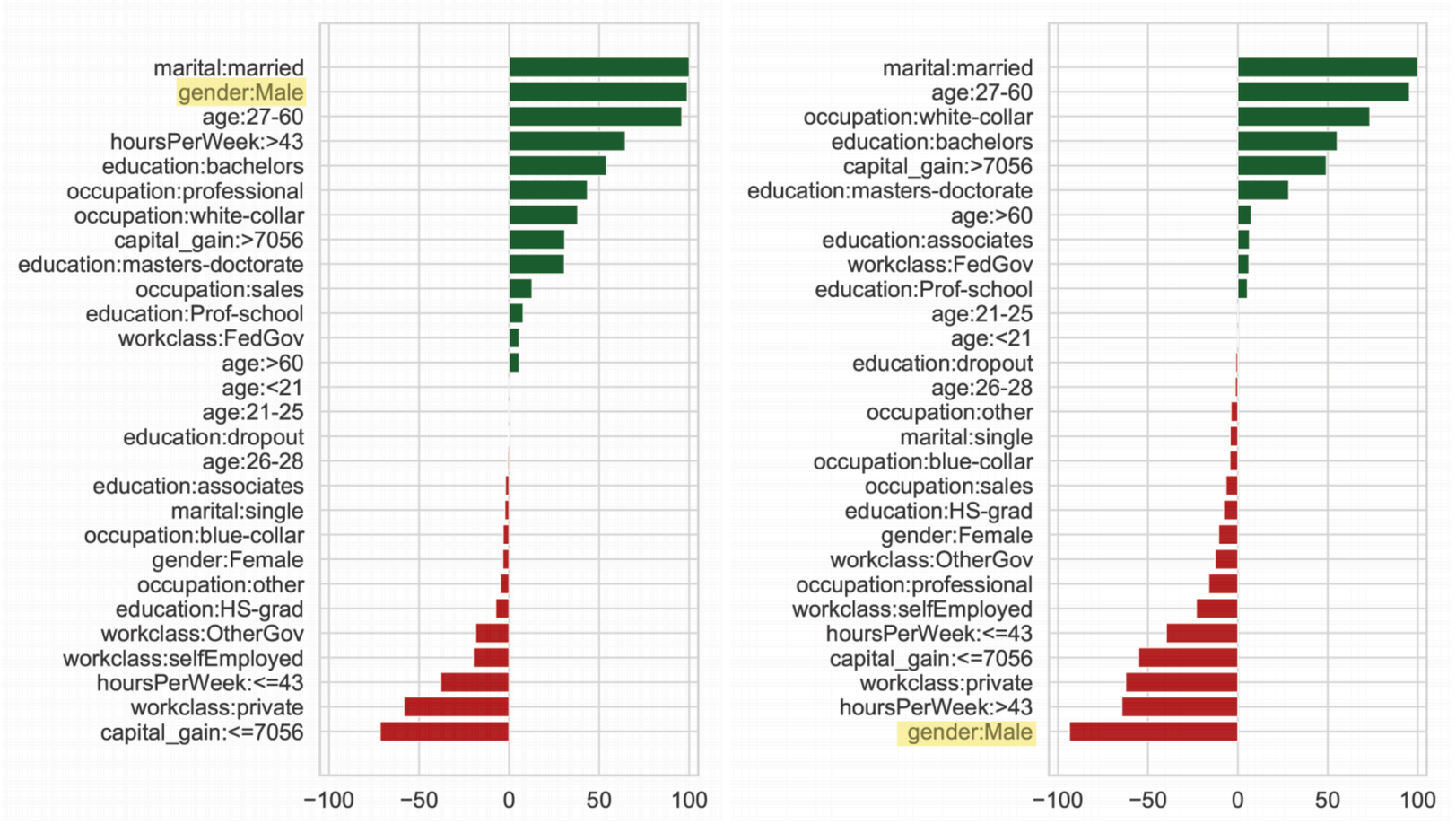
https://arxiv.org/abs/2007.09969

Fairwashing: the risk of rationalization

Ulrich Aïvodji [1] **Hiromi Arai** [2 3] **Olivier Fortineau** [4] **Sébastien Gambs** [1] **Satoshi Hara** [5] **Alain Tapp** [6 7]

Abstract

Black-box explanation is the problem of explaining how a machine learning model – whose internal logic is hidden to the auditor and generally complex – produces its outcomes. Current approaches for solving this problem include model explanation, outcome explanation as well as model inspection. While these techniques can be beneficial by providing interpretability, they can be used in a negative manner to perform fairwashing, which we define as promoting the false perception that a machine learning model respects some ethical values. In particular, we demonstrate that it is possible to systematically rationalize decisions taken by an unfair black-box model using the model explanation as well as the outcome explanation approaches with a given fairness metric. Our solution, LaundryML, is based on a regularized rule list enumeration algorithm whose objective is to search for fair rule lists approximating an unfair black-box model. We empirically evaluate our rationalization technique on black-box models trained on real-world datasets and show that one can obtain rule lists with high fidelity to the black-box model while being considerably less unfair at the same time.



https://arxiv.org/abs/1901.09749

Fairness measures

Notation

Y	true class, (1 - is preferred, favourable outcome)
S	predicted score
$\widehat{Y} := 1_{S>c}$	decision
A	protected attribute

	$Y=1$	$Y=0$	
$\widehat{Y}=1$	TP	FP	P
$\widehat{Y}=0$	FN	TN	N
	π_1	π_0	

Group fairness / statistical parity / independence / demographic parity

$$P(\hat{Y} = 1|A = a) = P(\hat{Y} = 1|A = b) \qquad \hat{Y} \perp A$$

Predicted class is independent from protected attribute

	$Y = 1$	$Y = 0$	
$\hat{Y} = 1$	TP	FP	P
$\hat{Y} = 0$	FN	TN	N
	π_1	π_0	

Group fairness / statistical parity / independence / demographic parity

$$P(\hat{Y} = 1|A = a) = P(\hat{Y} = 1|A = b) \qquad \hat{Y} \perp A$$

Predicted class is independent from protected attribute

„four-fifth rule" - selection rate for any disadvantaged group that is less than four-fifths of that for the group with the highest rate

$$80\% \leq \frac{P(\hat{Y}=1|A=a)}{P(\hat{Y}=1|A=b)} \leq 125\%$$

Group fairness / statistical parity / independence / demographic parity

$$P(\hat{Y} = 1|A = a) = P(\hat{Y} = 1|A = b) \qquad \hat{Y} \perp A$$

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„four-fifth rule" - selection rate for any disadvantaged group that is less than four-fifths of that for the group with the highest rate

$$80\% \leq \frac{P(\hat{Y}=1|A=a)}{P(\hat{Y}=1|A=b)} \leq 125\%$$

Sounds like a good idea, but is easy to fool.

For example, in class a we use a valid classifier while in class b we make decisions randomly.

Perfect classificator does not satisfy this parity if classes are not balanced.

Equal opportunity

$$P(\widehat{Y} = 1|A = a, Y = 1) = P(\widehat{Y} = 1|A = b, Y = 1)$$

Equal True Positive Rate TPR = TP/(TP+FN) for each subgroup

If he/she pays the credit then should have an equal chance to get it.

	$Y = 1$	$Y = 0$	
$\widehat{Y} = 1$	TP	FP	P
$\widehat{Y} = 0$	FN	TN	N
	π_1	π_0	

Predictive equality

$$P(\hat{Y} = 1 | A = a, Y = 0) = P(\hat{Y} = 1 | A = b, Y = 0)$$

Equal False Positive Rate FPR = FP/(FP+TN) for each subgroup

	$Y = 1$	$Y = 0$	
$\hat{Y} = 1$	TP	FP	P
$\hat{Y} = 0$	FN	TN	N
	π_1	π_0	

Equalized odds, Separation, Positive Rate Parity

$$P(\widehat{Y}=1|A=a,Y=1)=P(\widehat{Y}=1|A=b,Y=1)$$
$$P(\widehat{Y}=1|A=a,Y=0)=P(\widehat{Y}=1|A=b,Y=0)$$

$$\widehat{Y} \perp A \mid Y$$

Equal True Positive Rate TPR = TP/(TP+FN) for each subgroup and

equal False Positive Rate FPR = FP/(FP+TN) for each subgroup

Predicted class is independent from protected attribute given true class

	$Y=1$	$Y=0$	
$\widehat{Y}=1$	TP	FP	P
$\widehat{Y}=0$	FN	TN	N
	π_1	π_0	

Positive Predictive Parity

$$P(Y = 1|A = a, \widehat{Y} = 1) = P(Y = 1|A = b, \widehat{Y} = 1)$$

Equal Positive Predictive Value PPV = TP / (TP + FP) for each subgroup

If he/she gets the credit then should have an equal chance to pay it.

	$Y = 1$	$Y = 0$	
$\widehat{Y} = 1$	TP	FP	P
$\widehat{Y} = 0$	FN	TN	N
	π_1	π_0	

Negative Predictive Parity

$$P(Y = 1|A = a, \widehat{Y} = 0) = P(Y = 1|A = b, \widehat{Y} = 0)$$

Equal Negative Predictive Value NPV = NP / (NP + NP) for each subgroup

	$Y = 1$	$Y = 0$	
$\widehat{Y} = 1$	TP	FP	P
$\widehat{Y} = 0$	FN	TN	N
	π_1	π_0	

Predictive Rate Parity, Sufficiency

$$P(Y = 1|A = a, \widehat{Y} = 1) = P(Y = 1|A = b, \widehat{Y} = 1)$$
$$P(Y = 1|A = a, \widehat{Y} = 0) = P(Y = 1|A = b, \widehat{Y} = 0)$$

$$Y \perp A \mid \widehat{Y}$$

Equal Positive Predictive Value PPV = TP / (TP + FP) for each subgroup and equal Negative Predictive Value NPV = NP / (NP + NP) for each subgroup

True class is independent from protected attribute given predicted class

	$Y = 1$	$Y = 0$	
$\widehat{Y} = 1$	TP	FP	P
$\widehat{Y} = 0$	FN	TN	N
	π_1	π_0	

Whether to sentence a prisoner

Demographic parity:

the rate of sentenced prisoners should be equal in each group

fair from society's perspective

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Equal opportunity:

The fraction of innocents sentenced should be equal in subgroups

fair from the prisoner's perspective (ProPublica)

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

Predictive Rate Parity:

Among the convicted, there should be an equal fraction of innocents

fair from the judge's perspective (Northpointe)

	$Y=1$	$Y=0$	
$\hat{Y}=1$	TP	FP	P
$\hat{Y}=0$	FN	TN	N
	π_1	π_0	

The Fairness Trade-off (the impossibility theorem)

Except for trivial cases all these criteria cannot be satisfied jointly.

In fact each two out of {Sufficiency, Separation, Independence}
are mutually exclusive.

Bias mitigation strategies

Data Pre-processing

change data to improve model performance, for example, use subsampling or case weighting

Model In-processing

modify the optimized criterion to include fairness functions, e.g. through adversarial training

Model Post-processing

modify the resulting model scores or final decisions, e.g., using different thresholds

Hands on example with the fairmodels package

Statistics > Machine Learning

[Submitted on 1 Apr 2021]

fairmodels: A Flexible Tool For Bias Detection, Visualization, And Mitigation

Jakub Wiśniewski, Przemysław Biecek

Machine learning decision systems are getting omnipresent in our lives. From dating apps to rating loan seekers, algorithms affect both our well-being and future. Typically, however, these systems are not infallible. Moreover, complex predictive models are really eager to learn social biases present in historical data that can lead to increasing discrimination. If we want to create models responsibly then we need tools for in-depth validation of models also from the perspective of potential discrimination. This article introduces an R package fairmodels that helps to validate fairness and eliminate bias in classification models in an easy and flexible fashion. The fairmodels package offers a model-agnostic approach to bias detection, visualization and mitigation. The implemented set of functions and fairness metrics enables model fairness validation from different perspectives. The package includes a series of methods for bias mitigation that aim to diminish the discrimination in the model. The package is designed not only to examine a single model, but also to facilitate comparisons between multiple models.

Comments: 15 pages, 9 figures

Subjects: **Machine Learning (stat.ML)**; Machine Learning (cs.LG); Mathematical Software (cs.MS); Applications (stat.AP)

Cite as: arXiv:2104.00507 **[stat.ML]**

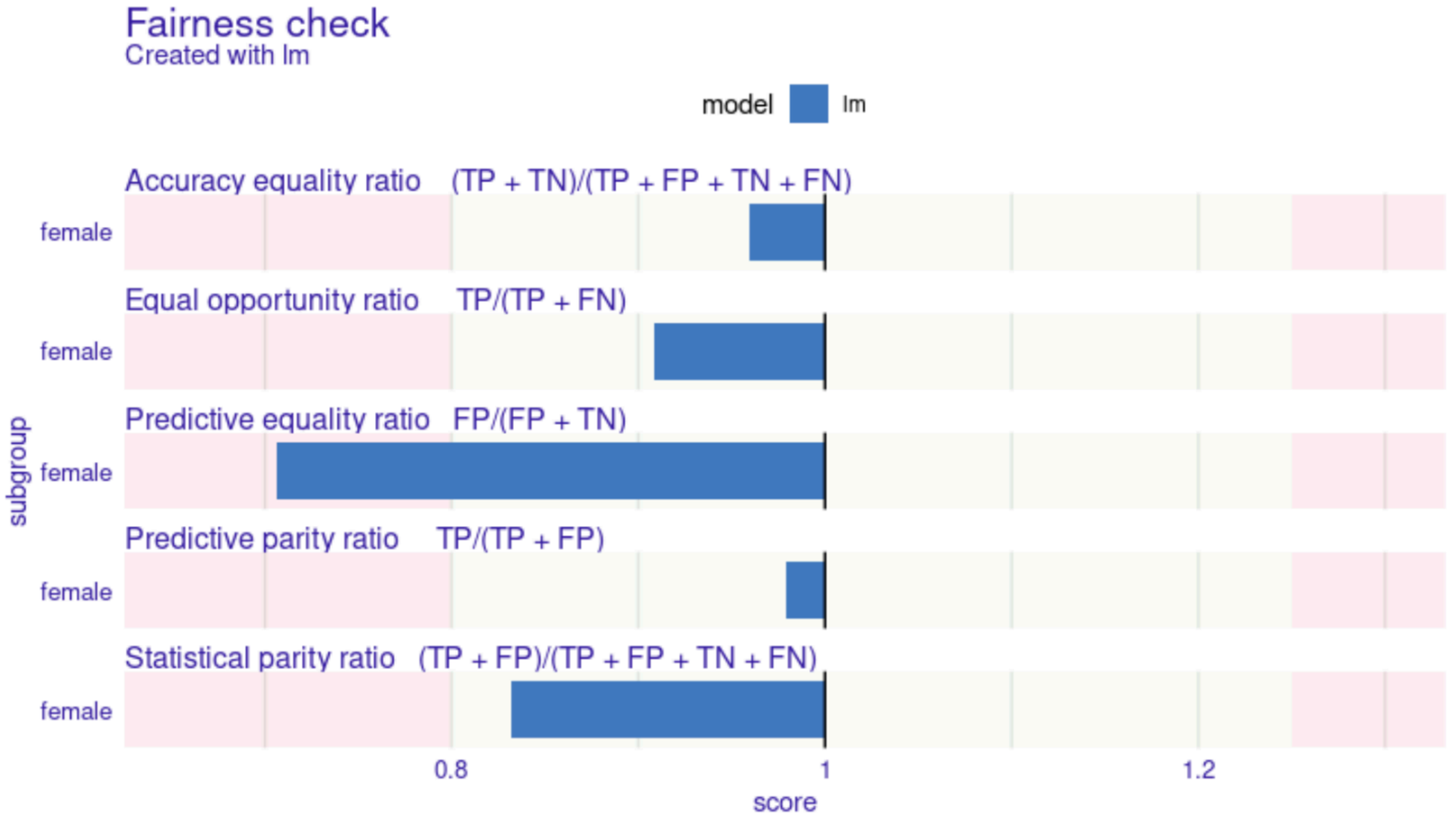
(or arXiv:2104.00507v1 **[stat.ML]** for this version)

Submission history

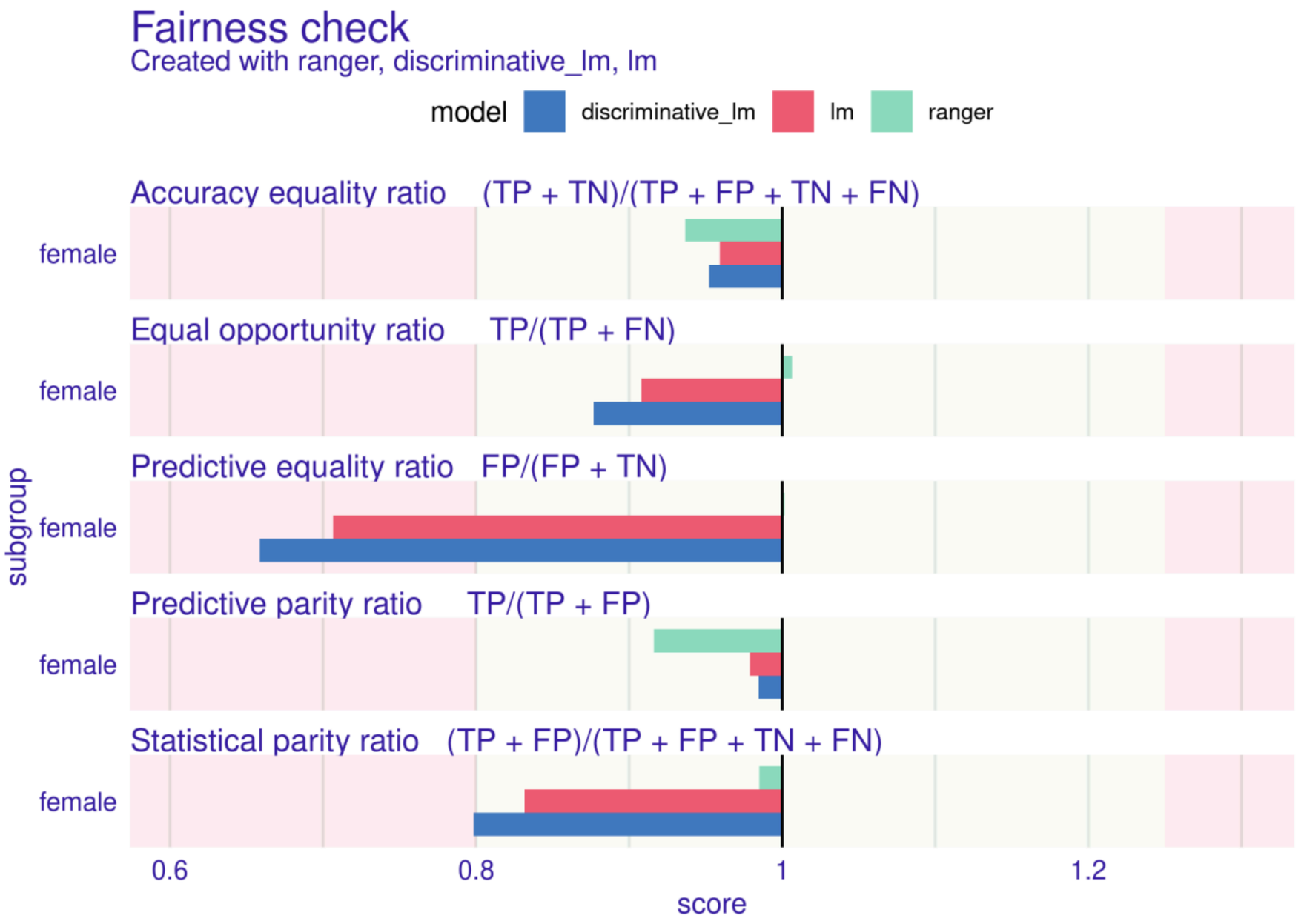
From: Przemyslaw Biecek [view email]

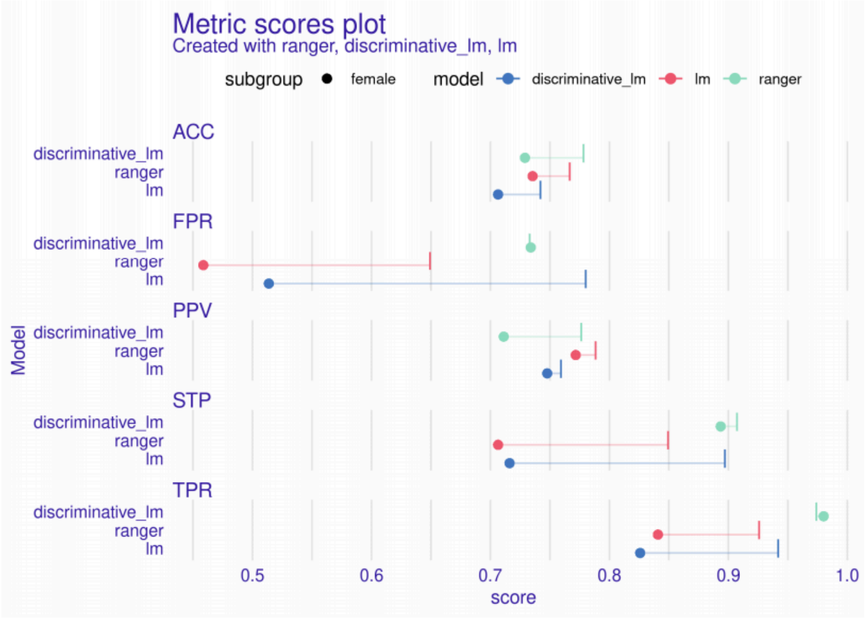
[v1] Thu, 1 Apr 2021 15:06:13 UTC (1,920 KB)

Wiśniewski et al, 2020, https://arxiv.org/abs/2104.00507

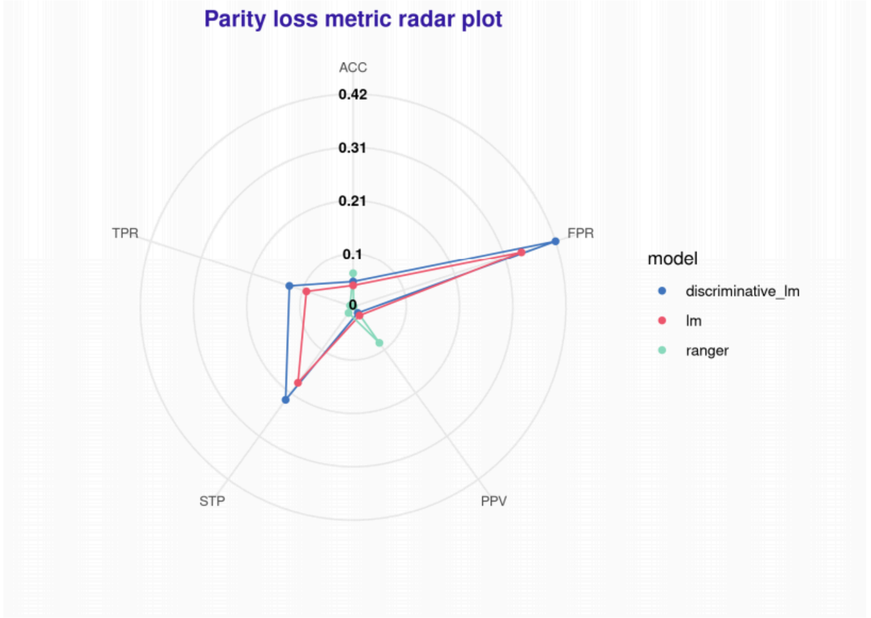


The four-fifths rule (Code of Federal Regulations, 1978)
"A selection rate for any race, sex, or ethnic group which is less than four-fifths (4 / 5) (or eighty percent) of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact[...]."

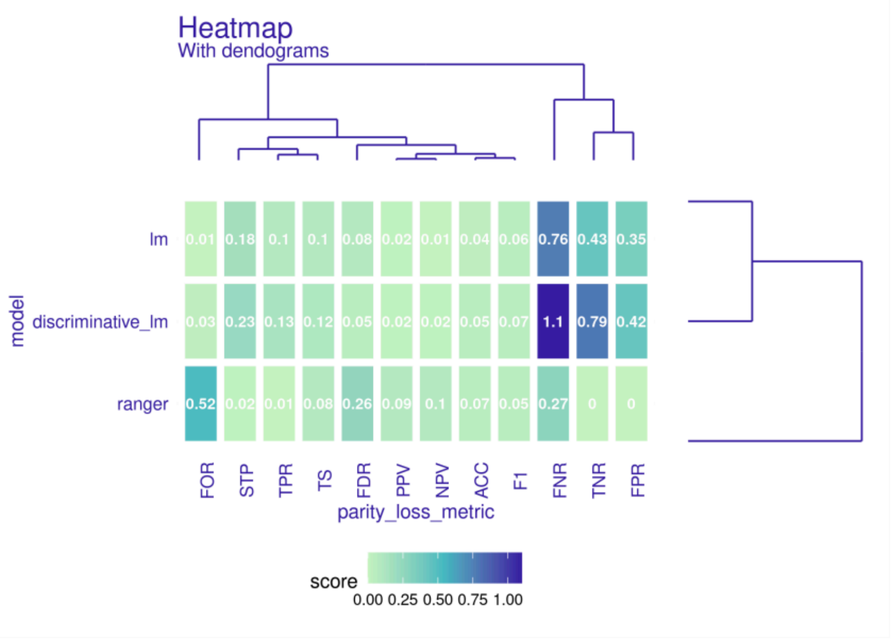

Fairness check
Created with ranger, discriminative_lm, lm
model
discriminative_lm
lm
ranger
Accuracy equality ratio (TP + TN)/(TP + FP + TN + FN)
Equal opportunity ratio TP/(TP + FN)
Predictive equality ratio FP/(FP + TN)
Predictive parity ratio TP/(TP + FP)
Statistical parity ratio (TP + FP)/(TP + FP + TN + FN)
female
subgroup
0.6
0.8
1
1.2
score



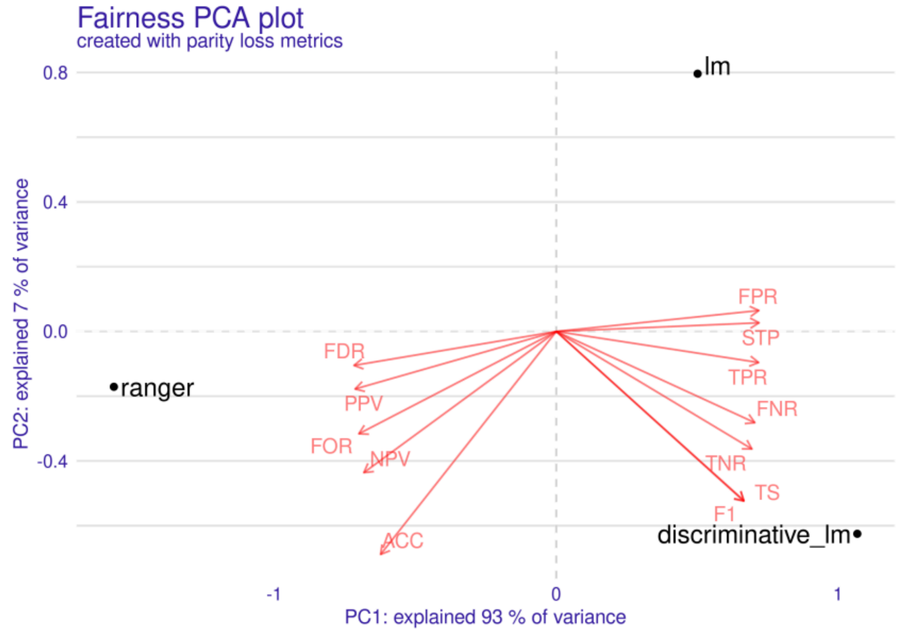
(a) metric_scores



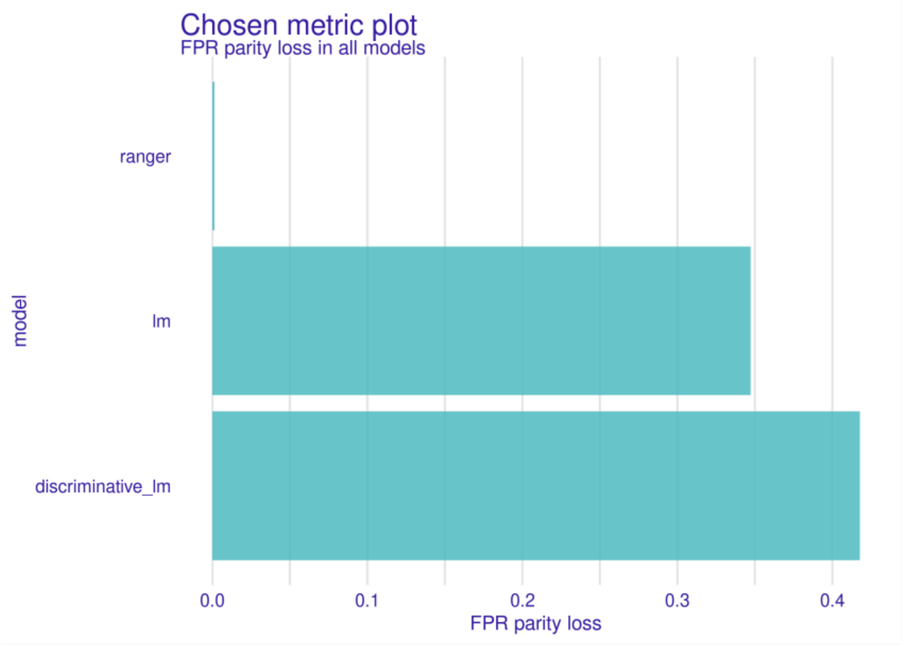
(b) fairness_radar



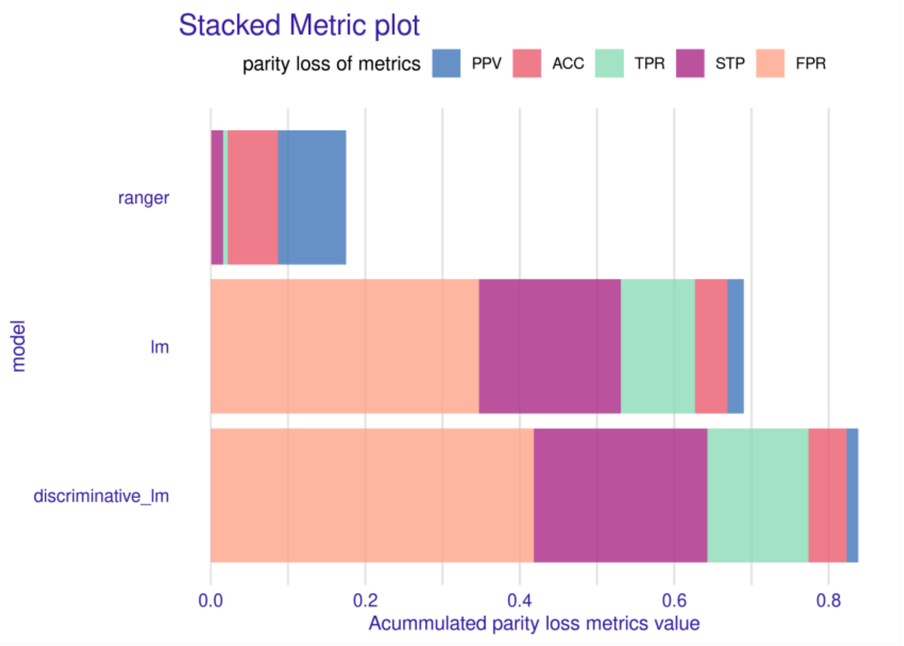
(c) fairness_heatmap



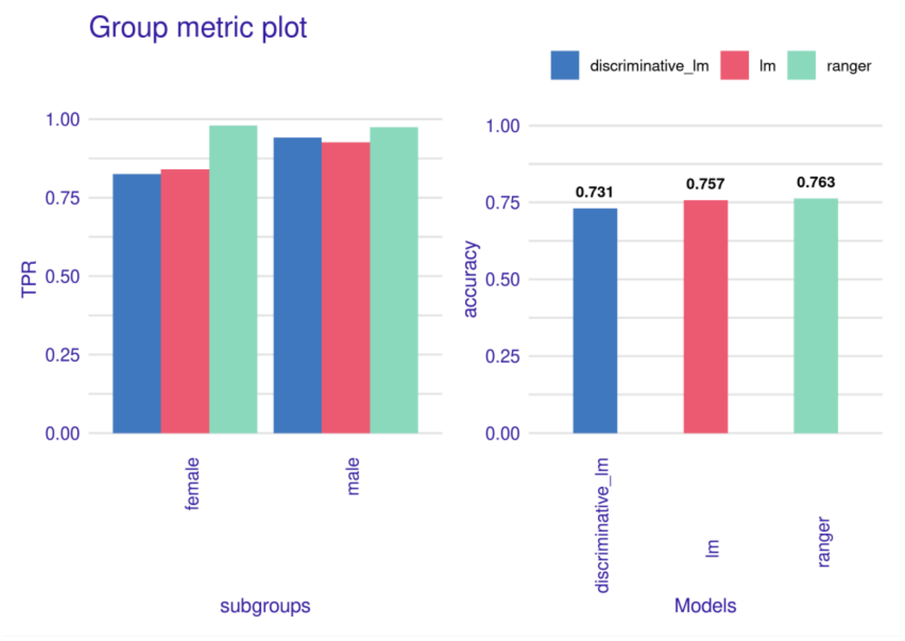
(d) fairness_pca



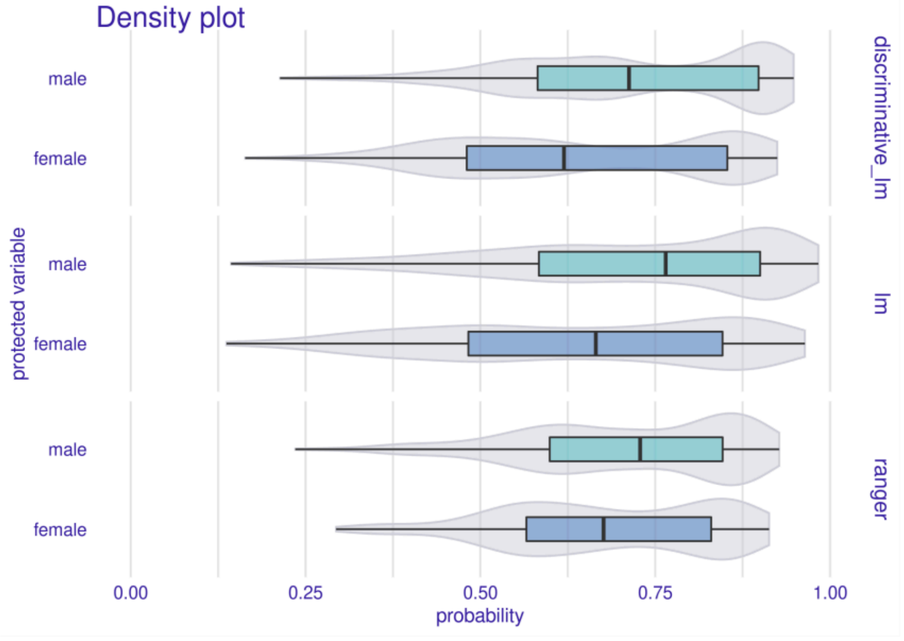
(e) choose_metric



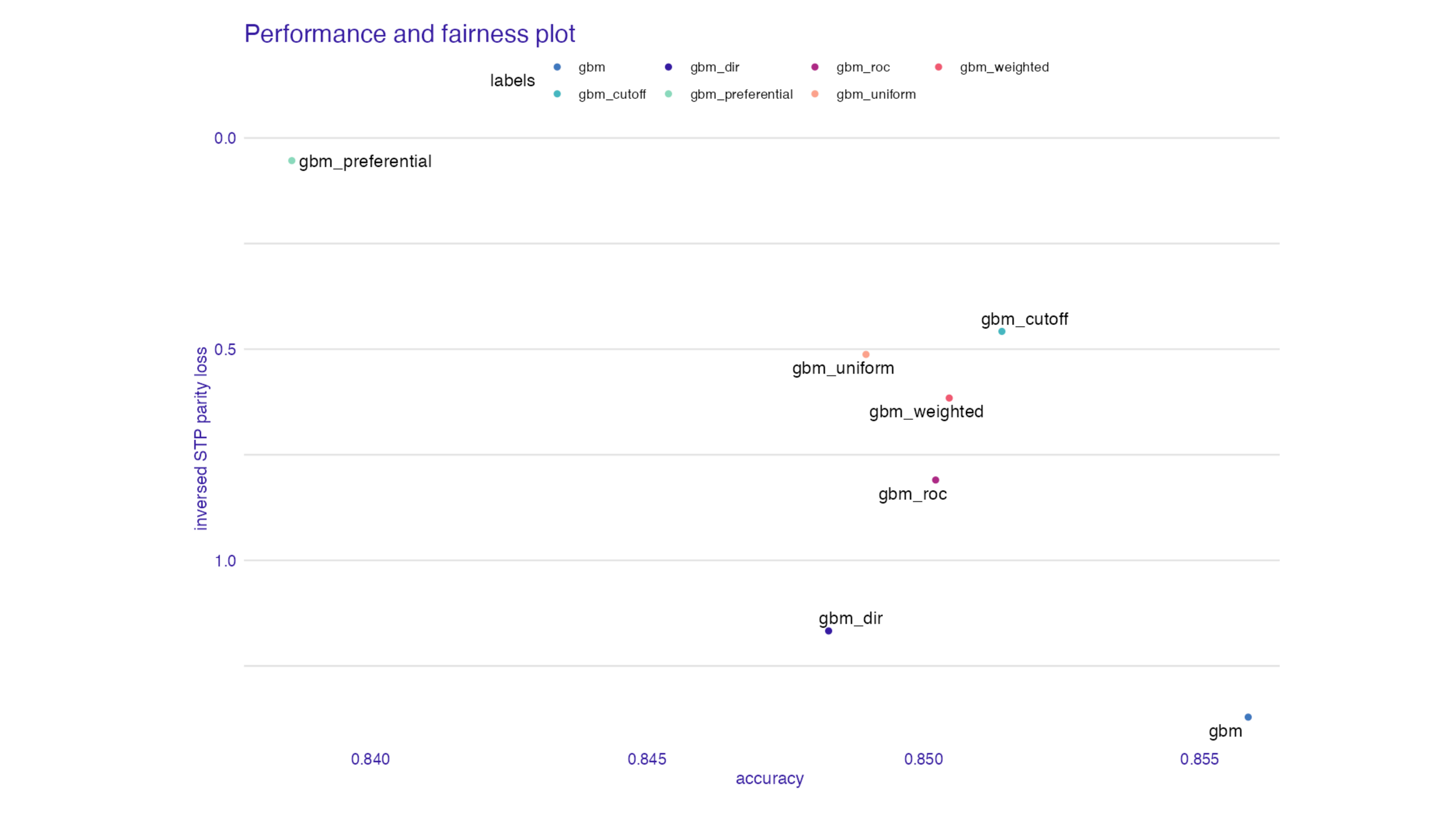
(f) stack_metrics



(g) group_metric



(h) plot_density


Performance and fairness plot
labels
gbm
gbm_dir
gbm_roc
gbm_weighted
gbm_cutoff
gbm_preferential
gbm_uniform
0.0
0.5
1.0
inversed STP parity loss
gbm_preferential
gbm_cutoff
gbm_uniform
gbm_weighted
gbm_roc
gbm_dir
gbm
0.840
0.845
0.850
0.855
accuracy

AI Fairness 360 - Demo

Data — Check — Mitigate — Compare

1. Choose sample data set

Bias occurs in data used to train a model. We have provided three sample datasets that you can use to explore bias checking and mitigation. Each dataset contains attributes that should be protected to avoid bias.

◯ **Compas (ProPublica recidivism)**

Predict a criminal defendant's likelihood of reoffending.
Protected Attributes:
- **Sex**, privileged: ***Female***, unprivileged: ***Male***
- **Race**, privileged: ***Caucasian***, unprivileged: ***Not Caucasian***

Learn more

◯ **German credit scoring**

Predict an individual's credit risk.
Protected Attributes:
- **Sex**, privileged: ***Male***, unprivileged: ***Female***
- **Age**, privileged: ***Old***, unprivileged: ***Young***

Learn more

◯ **Adult census income**

Predict whether income exceeds $50K/yr based on census data.
Protected Attributes:
- **Race**, privileged: ***White***, unprivileged: ***Non-white***
- **Sex**, privileged: ***Male***, unprivileged: ***Female***

Learn more

http://aif360.mybluemix.net/data

Optimized Pre-Processing

Learns a probabilistic transformation that can modify the features and the labels in the training data.

Adversarial Debiasing

Learns a classifier that maximizes prediction accuracy and simultaneously reduces an adversary's ability to determine the protected attribute from the predictions. This approach leads to a fair classifier as the predictions cannot carry any group discrimination information that the adversary can exploit.

Reject Option Based Classification

Changes predictions from a classifier to make them fairer. Provides favorable outcomes to unprivileged groups and unfavorable outcomes to privileged groups in a confidence band around the decision boundary with the highest uncertainty.

http://aif360.mybluemix.net/data

4. Compare original vs. mitigated results

Dataset: German credit scoring

Mitigation: **Reject Option Based Classification algorithm applied**

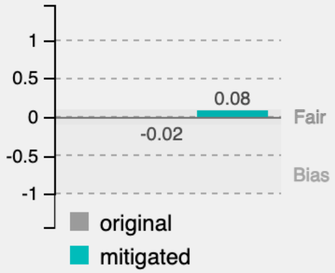
Protected Attribute: Sex

Privileged Group: ***Male***, Unprivileged Group: ***Female***

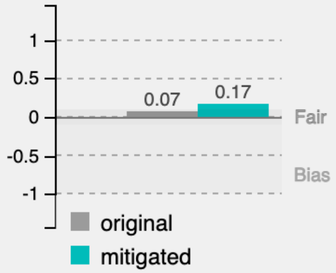
Accuracy after mitigation changed from 75% to 77%

Bias against unprivileged group unchanged after mitigation (0 of 5 metrics indicate bias)

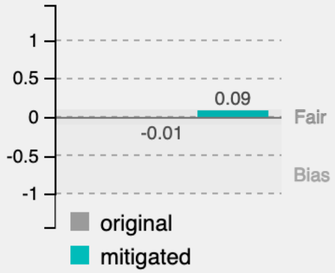
Statistical Parity Difference



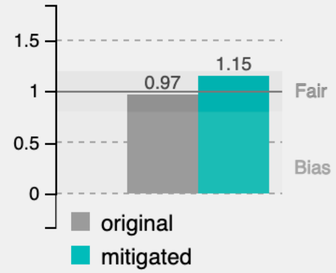
Equal Opportunity Difference



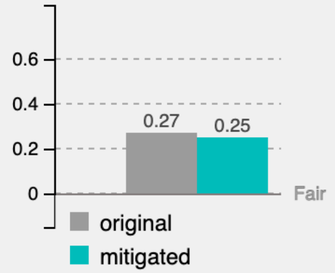
Average Odds Difference



Disparate Impact



Theil Index



http://aif360.mybluemix.net/data

More materials:
https://tinyurl.com/xkdd-fairness