

Warning:

The following content may be disturbing to some people. It shows examples of bias & discrimination generated by AI models.

It is reproduced for educational purposes; to raise awareness and foster discussion about to how mitigate AI bias.

Please exercise caution.



Bias in machine learning

Some examples



Racial Bias



This 'Racist soap dispenser' at Facebook office does not work for black people

OCTOBER 24, 2019 | 4 MIN READ

Racial Bias Found in a Major Health Care Risk Algorithm

Black patients lose out on critical care when systems equate health needs with costs

BY STARRE VARTAN



As organizations increasingly replace human decision-making with algorithms, they may assume these computer programs lack our biases. But algorithms still reflect the real world, which means they can unintentionally perpetuate existing inequality. A study published Thursday in Science has found that a health care risk-prediction algorithm, a major example of tools used on more than 200 million people in the U.S., demonstrated racial bias—because it relied on a fully metric for determining need.

MACHINE BIAS

Facebook Enabled Advertisers to Reach 'Jew Haters'

After being contacted by ProPublica, Facebook removed several anti-Semitic ad categories and promised to improve monitoring.

by Julia Angwin, Madeleine Varner and Ariana Tobin, Sept. 14, 2017, 4 p.m. EDT

Source: Michelle Carney

Gender Bias



Microsoft Tay





Overcoming Racial Bias In AI Systems And Startlingly Even In AI Self-Driving Cars Racial bias in a medical algorithm favors white patients over sicker black patients

AI expert calls for end to UK use of 'racially biased' algorithms

AI Bias Could Put Women's Lives At Risk - A Challenge For Regulators

Gender bias in Al: building fairer algorithms

Bias in AI: A problem recognized but still unresolved

Amazon, Apple, Google, IBM, and Microsoft worse at transcribing black people's voices than white people's with Al voice recognition, study finds

Millions of black people affected by racial bias in health-care algorithms

When It Comes to Gorillas, Google Photos Remains Blind

Study reveals rampant racism in decision-making software used by US hospitals – and highlights ways to correct it.

Google promised a fix after its photo-categorization software labeled black people as gorillas in 2015. More than two years later, it hasn't found one.

The Week in Tech: Algorithmic Bias Is Bad. Uncovering It Is Good.

Google 'fixed' its racist algorithm by removing gorillas from its image-labeling tech

Artificial Intelligence has a gender bias problem – just ask Siri

The Best Algorithms Struggle to Recognize Black Faces Equally

US government tests find even top-performing facial recognition systems misidentify blacks at rates five to 10 times higher than they do whites.

Now Is The Time To Act To End Bias In Al

As decisions made by algorithms come to control more and more aspects of modern life, we need to act swiftly to make sure those decisions are actually fair. As of right now, they're often not.





Sure, here is an illustration of a 1943 German soldier:



(8) Canarata more

Type, talk, or share a photo









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9

ayeshakhanna Google's generative Al chatbot produced shocking images of 1943 German soldiers—spotlighting an East Asian woman and an African man as German soldiers! What went haywire?

Believe it or not, Google messed up because in its attempt to have its chatbot be inclusive and diverse, it overcompensated and became biased in the opposite direction, inadvertently rewriting history in the process.

Let's rewind and understand the issue: Bias in Al has long been problematic. This bias often stems from training data that lacks diversity or reflects societal prejudices. For example, biased facial recognition











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Let's rewind and understand the issue: Bias in AI has long been problematic. This bias often stems from training data that lacks diversity or reflects societal prejudices. For example, biased facial recognition software can increase wrongful arrests

Here's how you can make sure your Gen AI chatbot isn't behaving irrationally:

- Representative training data
- Continuous monitoring
- Transparent communication
- Diverse teams

of people of color.

It's not foolproof but it's a systematic way to represent the truth correctly rather than generating untruths.

• • •

Is Machine Learning Dangerous?

- "Doomsday" scenarios not likely any time soon Algorithms are not "intelligent" enough
- But machine learning can potentially be misused, misleading, and/or invasiveImportant to consider implications of what you build

Definitions

Definitions are hard





the Sim

arXiv.org > cs > arXiv:1710.00794

Search or Art

Computer Science > Artificial Intelligence

What Does Explainable AI Really Mean? A New Conceptualization of Perspectives

Derek Doran, Sarah Schulz, Tarek R. Besold

(Submitted on 2 Oct 2017)

We characterize three notions of explainable AI that cut across research fields: opaque systems that offer no insight into its algo- rithmic mechanisms; interpretable systems where users can mathemat- ically analyze its algorithmic mechanisms; and comprehensible systems that emit symbols enabling user-driven explanations of how a conclusion is reached. The paper is motivated by a corpus analysis of NIPS, ACL, COGSCI, and ICCV/ECCV paper titles showing differences in how work on explainable AI is positioned in various fields. We close by introducing a fourth notion: truly explainable systems, where automated reasoning is central to output crafted explanations without requiring human post processing as final step of the generative process.



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Contestability and Professionals: From Explanations to Engagement with Algorithmic Systems

15 Pages • Posted: 10 Jan 2019

Daniel Kluttz

University of California, Berkeley School of Information

Nitin Kohli

UC Berkeley School of Information

Deirdre K. Mulligan

University of California, Berkeley - School of Information

Date Written: August 24, 2018

Proceedings of Machine Learning Research 81:1-15, 2018

Conference on Fairness, Accountability, and Transparency

Discrimination in Online Advertising A Multidisciplinary Inquiry

Amit Datta Anupam Datta Carnegie Mellon University

Jael Makagon Deirdre K. Mulligan University of California, Berkeley

Michael Carl Tschantz
International Computer Science Institute

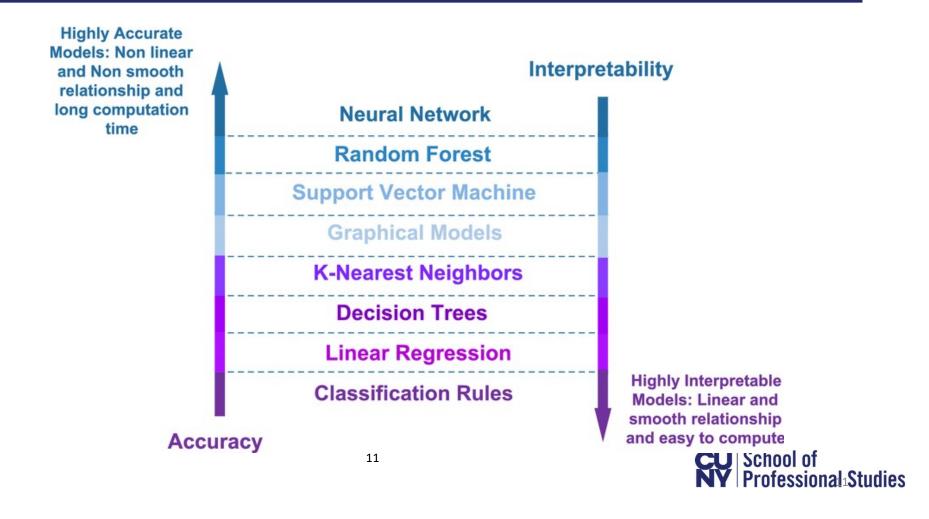
AMITDATTA@CMU.EDU DANUPAM@CMU.EDU

JAEL@BERKELEY.EDU DMULLIGAN@BERKELEY.EDU

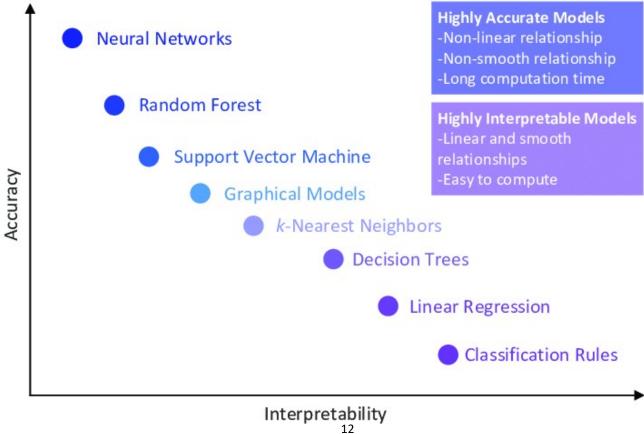
MCT@ICSI.BERKELEY.EDU



Interpretability



Interpretability





Mitigating Bias



Sources of bias in Al

1. Sampling Bias

Occurs when the training data is not representative of the population it serves, leading to poor performance and biased predictions for certain groups.

2. Algorithmic Bias

Results from the design and implementation of the algorithm, which may prioritize certain attributes and lead to unfair outcomes.

3. Representation Bias

Happens when a dataset does not accurately represent the population it is meant to model, leading to inaccurate predictions.

4. Confirmation Bias

Materializes when an AI system is used to confirm pre-existing biases or beliefs held by its creators or users.

5. Measurement Bias

Emerges when data collection or measurement systematically over- or underrepresents certain groups.

6. Interaction Bias

Occurs when an AI system interacts with humans in a biased manner, resulting in unfair treatment.

7. Generative Bias

Occurs in generative AI models, like those used for creating synthetic data, images, or text

Types of AI Bias

1. Algorithm

- Systematic
- Consistent

2. Cognitive

Human input

3. Confirmation

Pre-existing

4. Learning models & data

- Supervised: Diversity of stakeholders
- Unsupervised

5. Balanced Team

• Varied AI team: Racially, Economically, Gender, Innovators, Creators, Consumers

6. Emerging Risks

• Typically GenAl e.g. copyright infringement

How to avoid bias

1. Data processing

- Mindful of each step
- Pre-processing
- In-processing
- Post-processing

2. Continuous Monitoring

- Real-world data
- Third party

3. Confirmation

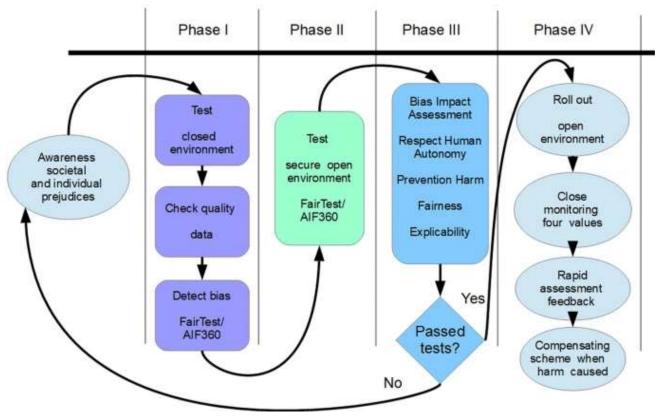
Pre-existing

4. Out-group homogeneity

Assumption about group

5. Exclusion

• Data left out



Source: Springer

ways to build Ethics into AI)

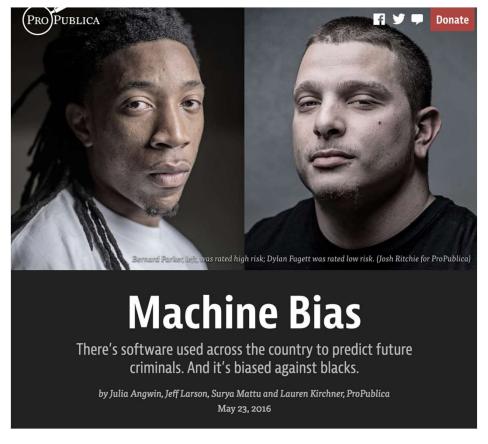
03 Create an Ethical Be Transparent Remove Exclusion Culture Build diverse teams Understand your values Understand the factors involved Prevent data set bias Cultivate an ethical mindset Give users control over their data Conduct social systems analysis Take feedback Prevent association bias Prevent confirmation bias Prevent automation bias Mitigate interaction bias



More case studies

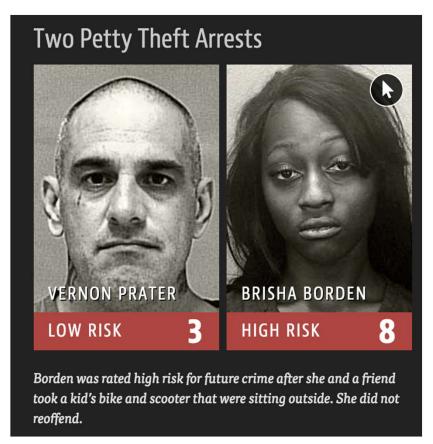


Parole recidivism





Parole recidivism







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%















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Amazon's Face Recognition Falsely Matched 28 Members of Congress With Mugshots



By Jacob Snow, Technology & Civi JULY 26, 2018 | 8:00 AM

TAGS: Face Recognition Technology, Surve









Amazon's face surveillance technology is the target of growing opposition nationwide, and today, there are 28 more causes for concern. In a test the





Source: Michelle Carney