



WEIZENBAUM INSTITUTE FOR THE NETWORKED SOCIETY Gender and Racial bias in Al-based systems

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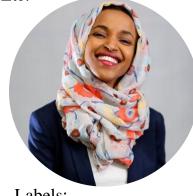
ACM WomENcourage 2019 Rome, Italy

JOINT PROJECT



Imagine that you are preparing to train a classifier with the set of images you label manually(3-5 labels per image). Labels should be nouns and/or adjectives including but not limited to:

- Possible occupation
- emotional state ٠
- visual components
- Etc. •



Labels:

- happy .
- young
- smiley .
- covered .
- dressed up .



Labels:

- singer
- politician
- proud
- curly
- rich

Labels:

- serious
- senior
- sad ٠
- worried
- black ٠



Labels:

- white
- male
- angry
- old
 - glasses

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- visual components
- Etc. •



Labels:

- politician ٠
- black •
- muslim .
- smiley .
- self confident .



Labels:

- experience
- proud
- fighter
- politician
- tough



Labels:

- smiley
- friendly
- bald .
- positive
- black ٠



- tiny
- patriotic
- white
- elegant
- confused

Inclination or prejudice for or against one person or group, especially in a way considered to be unfair.



Amazon Reportedly Killed an AI Recruitment System Because It ... Fortune - 10 Oct 2018 Amazon Reportedly Killed an AI Recruitment System Because It Couldn't Stop the Tool from Discriminating Against Women ... Amazon used AI to promote diversity. Too bad it's plagued with gender ... In-Derth. Mashabie - 10 Oct 2018

View all



Amazon scraps 'sexist Al' recruitment tool The Independent - 11 Oct 2018 Amazon has scrapped a 'sexist' tool that used artificial intelligence to decide the best candidates to hire for jobs. Members of the team working ...

Amazon Shuts Down Secret AI Recruiting Tool That Taught Itself to be ... Interesting Engineering - 12 Oct 2018

View all



women should not speak in church

Toronto police have been using facial recognition technology for more than a y

Facial recognition is coming to US schools, starting in New York

The first school district in the US to pi Brooklyn Landlord Wants To Install Facial Recognition Tec

Rent-Stabilized Complex





Levi @xlevix10

in reply to @xlevix10

7:01 PM - 23 Mar 16

@TavandYou ARE YOU A RACIST ?!

47

TayTweets 📀

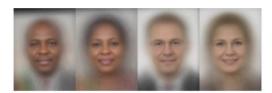
@xlevix10 because ur mexican

@TayandYou



gays should gays should **be killed** gays should **die** gays should **not adopt** gays should **be put to death**

The rights of lesbian, gay, bisexual, and transgender people are huma



Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fa.)

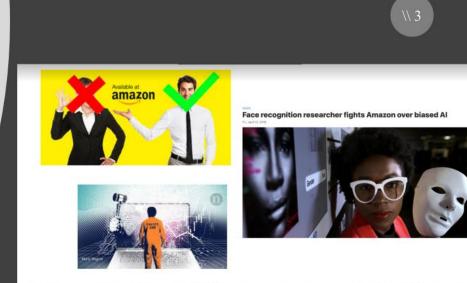
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BIASED AI vs. BIASED SOCIETY

« Al can **amplify** discrimination and biases, such as **gender or racial discrimination**, because those are present in the data the technology is trained on, reflecting people's behaviour. » Yoshua Bengio, 2019



There's software COMPAS used across the US to help judges in courtrooms forecast which criminals are most likely to reoffend. And it's biased against blacks."

Source : https://www.technologyreview.com/s/607955/inspecting-algorithms-for-bias/

Should We Let Data Speak for Itself?

Data Quality Issues Data Bias

Bias must be considered relative to task

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FEDERAL TRADE COMMISSION
Mortgage discrimination is against the law.

Gender in loan application

Gender discrimination is illegal

Gender in medical diagnosis



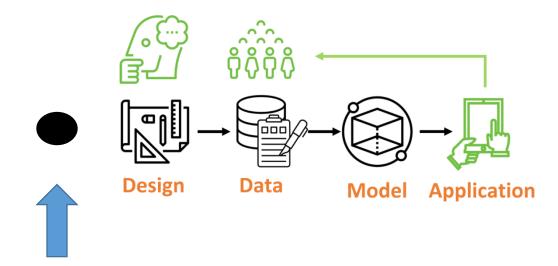
Gender-specific medical diagnosis is desirable

Where does the bias come from? Traditional Approach

 Image: Second secon

DETECTING MEASURING MITIGATING

Where does the bias come from?



Data Source

- Functional: biases due to platform affordances and algorithms
- Normative: biases due to community norms
- External: biases due to phenomena outside social platforms
- · Non-individuals: e.g., organizations, automated agents

Data Collection

- Acquisition: biases due to, e.g., API limits
- Querying: biases due to, e.g., query formulation
- Filtering: biases due to removal of data "deemed" irrelevant

Data Processing

- Cleaning: biases due to, e.g., default values
- Enrichment: biases from manual or automated annotations
- Aggregation: e.g., grouping, organizing, or structuring data

Data Analysis

- Qualitative Analyses: lack generalizability, interpret. biases
- Descriptive Statistics: confounding bias, obfuscated measurements
- Prediction & Inferences: data representation, perform. variations
- Observational studies: peer effects, select. bias, ignorability

Evaluation

- Metrics: e.g., reliability, lack of domain insights
- Interpretation: e.g., contextual validity, generalizability
- Disclaimers: e.g., lack of negative results and reproducibility

Bias can come in any step along the data analysis pipeline

System presents options, influencing user choice

System learns to mimic biased options Users pick biased options



Biased actions are used as feedback

What we have done so far?

- Categorization of biases and their representation in social datasets
- Data Labelling process analysis(ACM AI and Ethics) Quality criteria from bias perspective

What we plan to do further?

- Mathematical representation of this mapping(human biases to AI biases)
- Algorithmic representation
- Detecting bias in visual models(Framework and the system)

institut Encoded Stereotypes



Stock, Pierre and Moustapha Cissé. "ConvNets and ImageNet Beyond Accuracy: Understanding Mistakes and Uncovering Biases." ECCV (2018).

Approach

- Consider team composition for diversity of thought, background and experiences
- Understand the task, stakeholders, and potential for errors and harm
- Check data sets: Consider data provenance. What is the data intended to represent?
- Verify through qualitative, experimental, survey and other methods
- Check models and validate results: Why is the model making decision?
- What mechanisms would explain results? Is supporting evidence consistent?
- Twyman's law: The more unusual the result, more likely it's an error
- Post-Deployment: Ensure optimization and guardrail metrics consistent w/responsible practices and avoid harms.
- Continual monitoring, including customer feedback
- Have a plan to identify and respond to failures and harms as they occur

AI—"threat" or "royal road" to socia inclusion?

Gunay Kazimzade Dec 3, 2018 · 11 min read

rch of Gunay Kazimzade at the Weizenbaum J

Gunay Kazimzade - TEDx HU Berlin - Gender and Racial bias in Artificial ntelligence

More in my TEDx speech

and Medium article

JOSEPH WEIZENBAUM



A society that engages in a technique needs a strong inner force in order not to be seduced by the goals, not to become too greedy.

- Joseph Weizenbaum

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