# Data Science as Decision Tool: Algorithmic Fairness

## Methods for Detecting Automated Discrimination

Caitlin Kuhlman PhD Candidate
Computer Science Department, Worcester Polytechnic Institute

WPI

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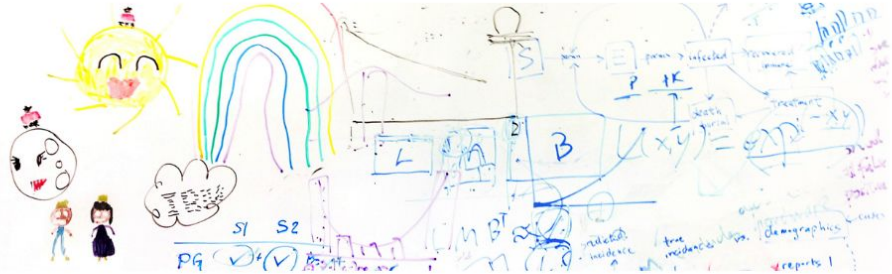

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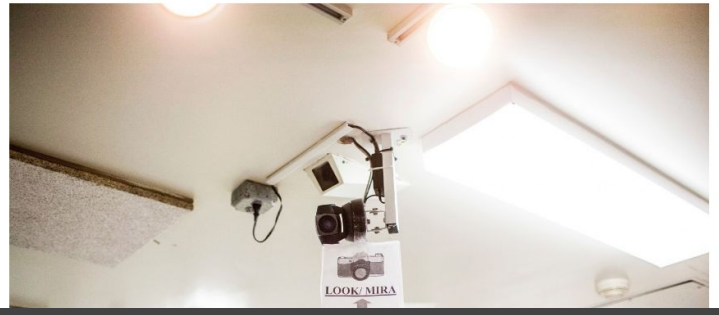
Business

# Racial profiling, by a computer? Police facial-ID tech raises civil rights concerns.




The New York Times

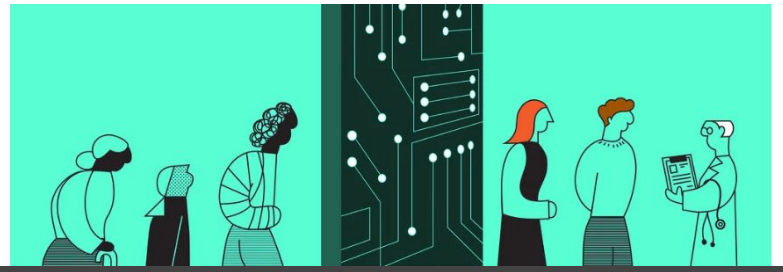
Opinion

# A.I. Could Worsen Health Disparities

In a health system riddled with inequity, we risk making dangerous biases automated and invisible.

By Dhruv Khullar

Dr. Khullar is an assistant professor of health care policy and research.



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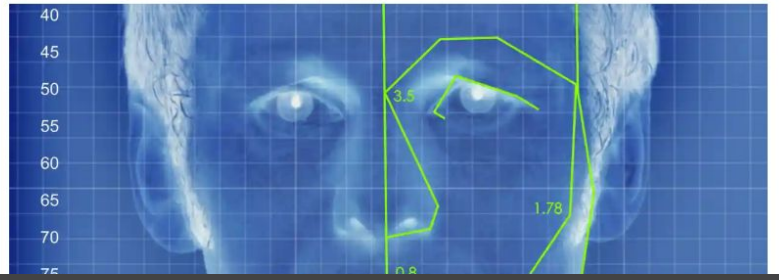
# New AI can guess whether you're gay or straight from a photograph

**An algorithm deduced the sexuality of people on a dating site with up to 91% accuracy, raising tricky ethical questions**



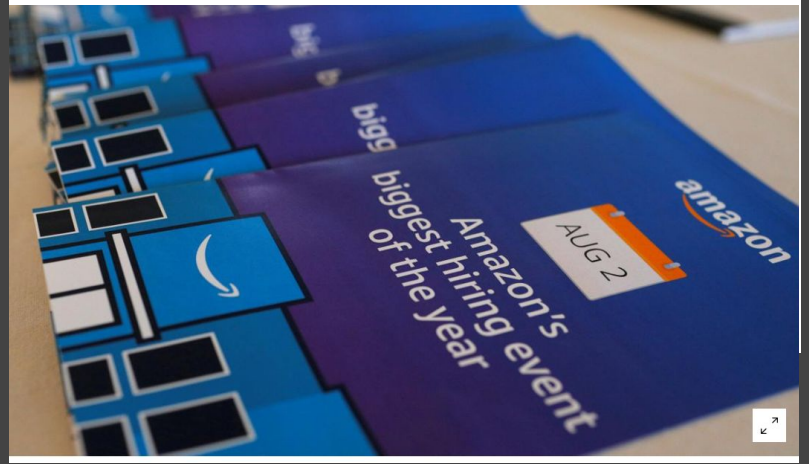

SundayReview | OPINION

# Artificial Intelligence's White Guy Problem

By KATE CRAWFORD JUNE 25, 2016

REUTERS World Business Markets Politics TV

# Amazon scraps secret AI recruiting tool that showed bias against women

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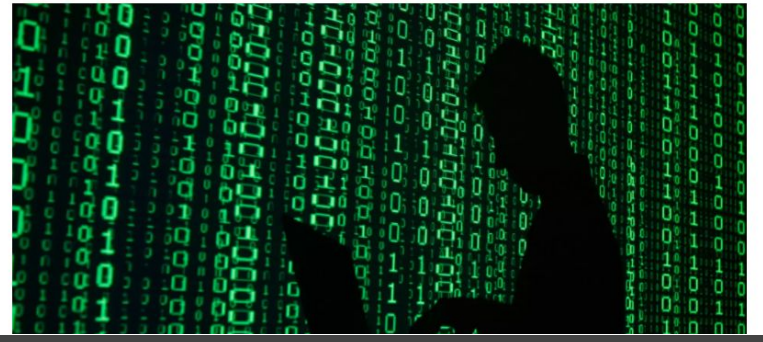
# AI robots are sexist and racist, experts warn



# Who Cares?

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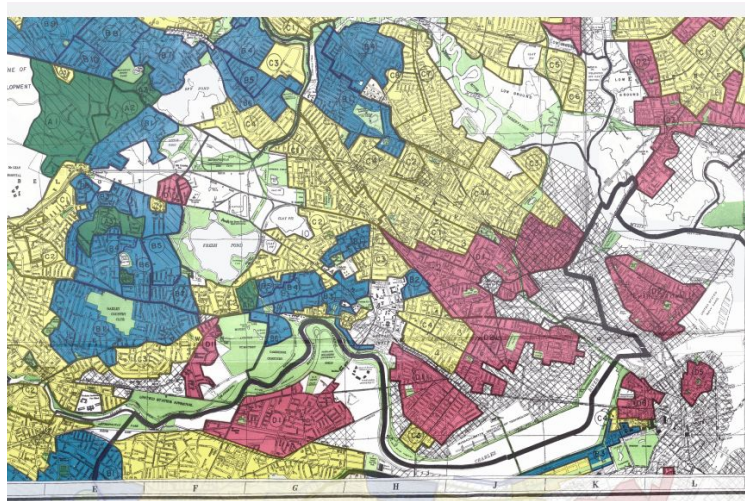

## Regulated Domains:

- Credit (Equal Opportunity Act)
- Housing (Fair Housing Act)
- Education, Employment, Public Accommodation (Civil Rights Act)

## Protected Attributes:

- Race, Religion, National Origin, Familial Status. . . (Civil Rights Act)
- Sex (Equal Pay Act, Civil Rights Act)
- Age (Age Discrimination in Employment Act)
- Disability (Americans with Disabilities Act)
- Genetic Information (Genetic Information Nondiscrimination Act)
- . . .

*Extends to marketing and advertising

NIPS Tutorial, Hardt, Moritz 2017 http://fairml.how/tutorial
https://dsl.richmond.edu/panorama/redlining

# Who Cares?

**Standards:**

- Proposed IEEE standard 7003 “Algorithmic Bias Considerations”

**New Regulations:**

- General Data Protection Regulation (GDPR)
  - Right to Explanation
  - Washington Privacy act
  - California Consumer Privacy Act

https://standards.ieee.org/develop/project/7003.html
Goodman, Bryce, and Seth Flaxman. European Union regulations on algorithmic decision-making and a" right to explanation". *arXiv:1606.08813* (2016).
https://fatconference.org/

# Who Cares?

AAAI / ACM conference on
ARTIFICIAL INTELLIGENCE, ETHICS, AND SOCIETY

## Conferences and Workshops

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# Overview

Algorithmic Fairness studies ways in which automated systems may perpetuate or exacerbate unfair bias and inequity.

We will investigate 3 examples of ways unfair bias can enter a data mining pipeline:

1. Historical Bias
2. Data Collection
3. Validation Techniques

# Learning Objectives

1. Recognize ways in which unfair bias might be introduced into a data mining pipeline.
2. Perform analysis to verify whether a predictive model is fair.
3. Discuss what data mining outcomes we should consider beyond accuracy.
4. Get hands-on experience with open tools for conducting transparent, reproducible research.

# Reproducible Research

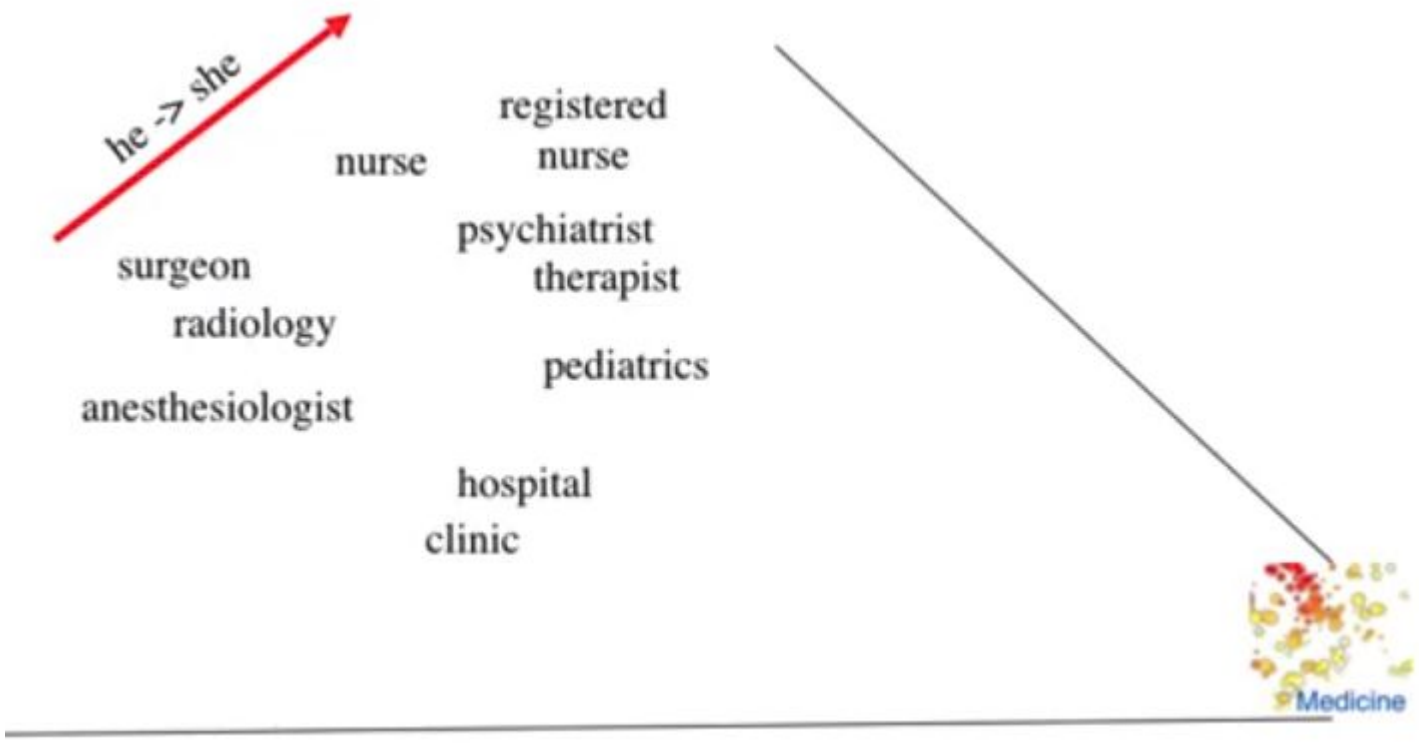
- Github
  - https://github.com/caitlinkuhlman/bpdmtutorial
- Jupyter notebooks
  - https://www.anaconda.com
- Python libraries
  - https://scikit-learn.org
  - https://pandas.pydata.org

# Example 1: Historical Bias

# Historical Bias: Gender Steotypes in NLP

| he: ___ | she: __ |
|---|---|
| uncle | aunt |
| lion | lioness |
| surgeon | nurse |
| architect | interior designer |
| beer | cocktail |
| professor | associate professor |

… many more




Bolukbasi, Tolga, et al. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." *Advances in Neural Information Processing Systems*. 2016.
https://www.youtube.com/watch?v=aZariglogXc

# Example 2: Data Collection

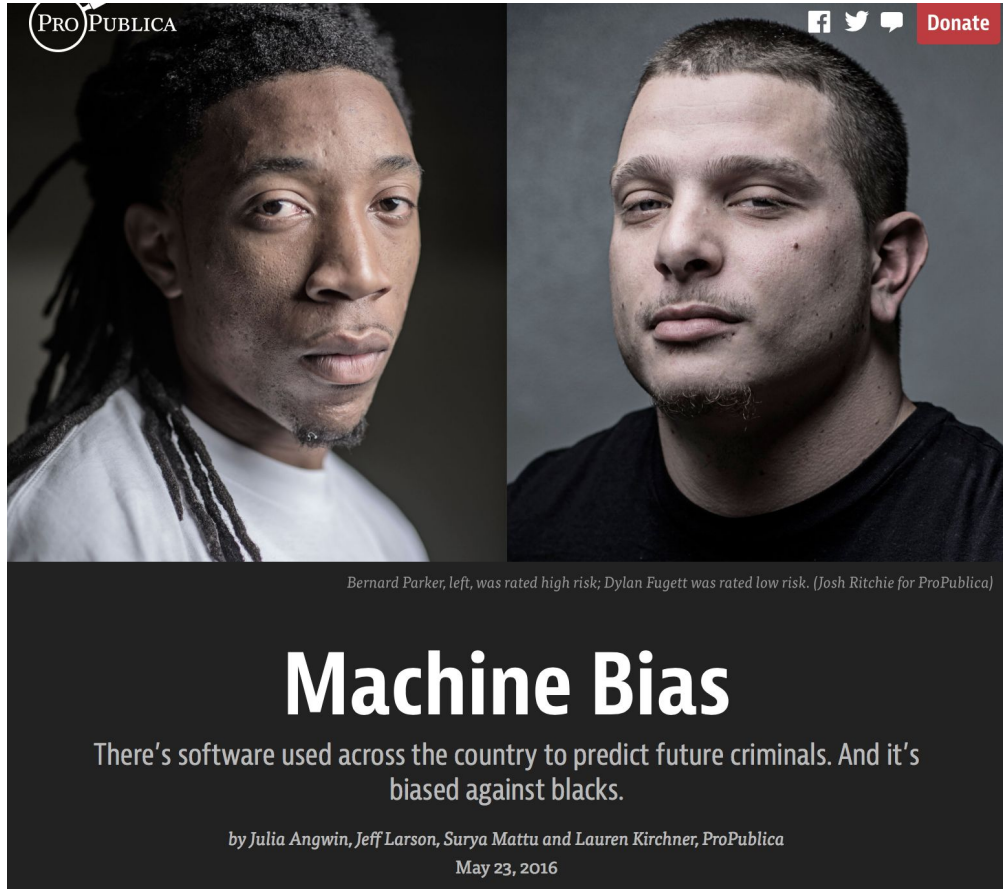
# Data Collection: Bias in Computer Vision

| 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% |

Buolamwini, Joy, and Timnit Gebru. "Gender shades: Intersectional accuracy disparities in commercial gender classification." *Conference on Fairness, Accountability and Transparency*. 2018.
http://gendershades.org/overview.html

# Example 3: Validation Techniques

# Validation Techniques: Risk Scoring




| Fairness Criteria |
| --- |
| Calibration |
| Balance for Negative Class |
| Balance for Positive Class |

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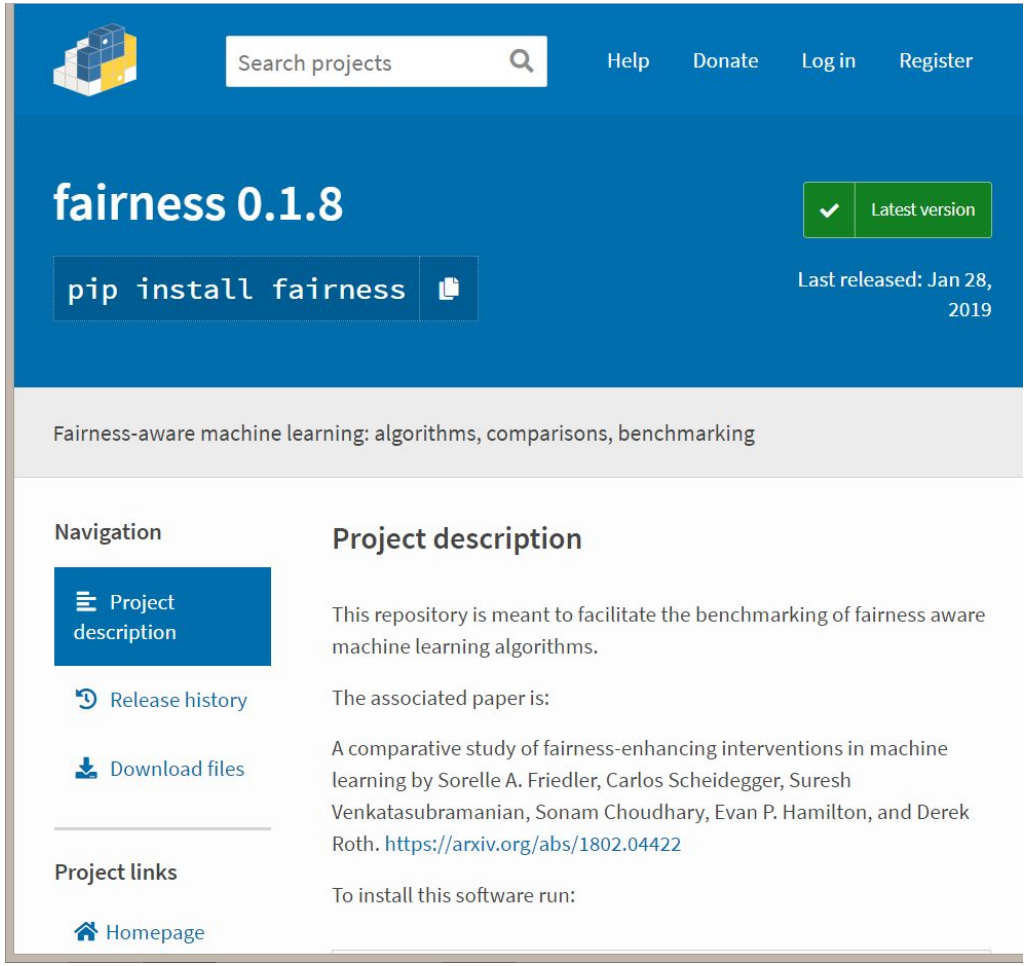
Mutually exclusive measurements of fairness

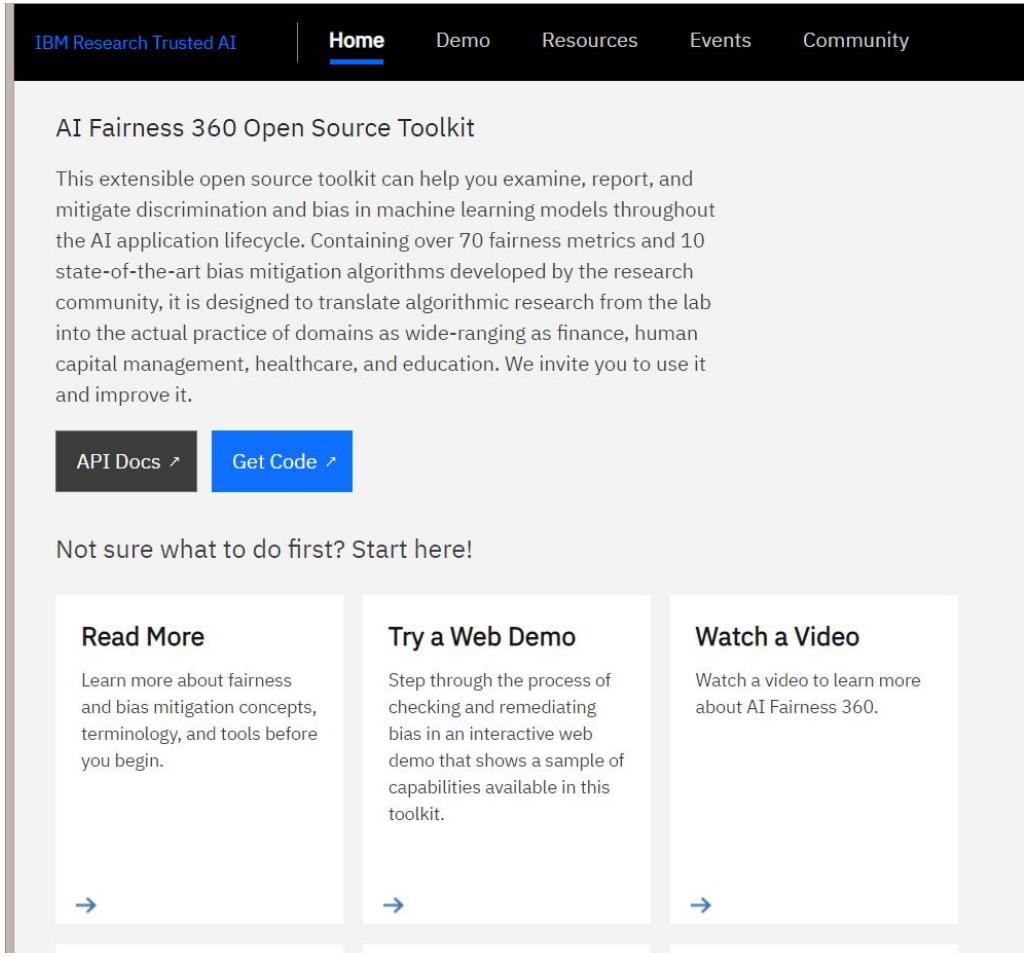

Angwin, Julia, et al. "Machine bias: There's software used across the country to predict future criminals. and it's biased against blacks." *ProPublica, May* 23 (2016).
Chouldechova, Alexandra. "Fair prediction with disparate impact: A study of bias in recidivism prediction instruments." arXiv preprint arXiv:1703.00056 (2017).
Kleinberg, Jon, Sendhil Mullainathan, and Manish Raghavan. "Inherent trade-offs in the fair determination of risk scores." arXiv preprint arXiv:1609.05807(2016).

# More Resources

# Fairness Libraries

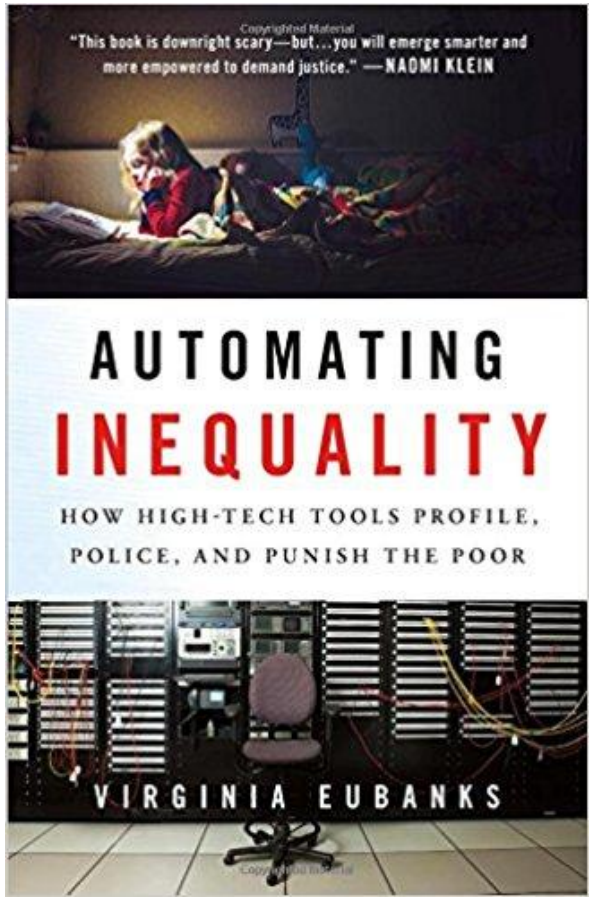


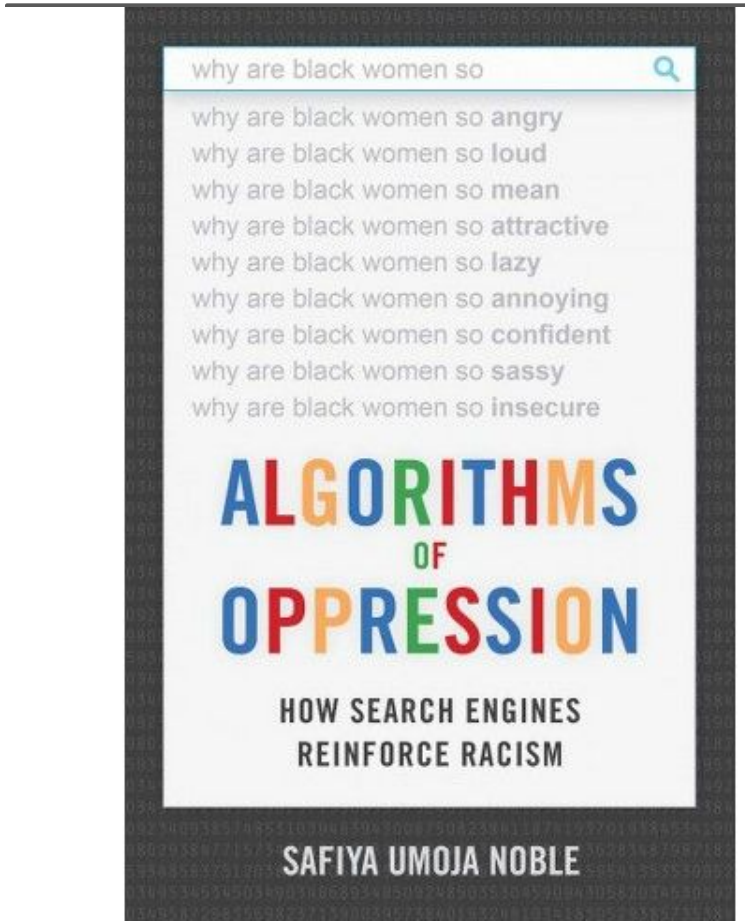

https://pypi.org/project/fairness

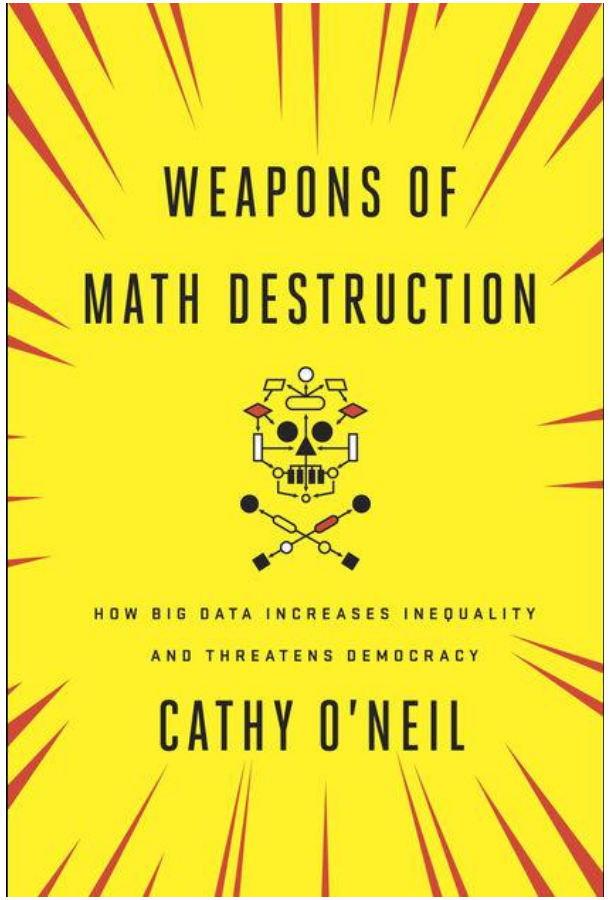



http://aif360.mybluemix.net/

# Books




Eubanks, Virginia. "Automating inequality: how high-tech tools profile, police, and punish the poor." (2018).
O'Neil, Cathy. *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway Books, 2017.
Noble, Safiya Umoja. *Algorithms of Oppression: How search engines reinforce racism*. NYU Press, 2018.

**News Articles**

https://www.nytimes.com/2017/11/21/magazine/can-ai-be-taught-to-explain-itself.html
http://www.telegraph.co.uk/news/2017/08/24/ai-robots-sexist-racist-experts-warn/
https://www.washingtonpost.com/business/economy/face-recognition-tech/2016/10/17/986929ea-41f0-44a2-b2b9-90b495230dce_story.html?utm_term=.491efe7bec56
https://medium.com/@mrtz/how-big-data-is-unfair-9aa544d739de
https://www.theguardian.com/inequality/2017/aug/08/rise-of-the-racist-robots-how-ai-is-learning-all-our-worst-impulses
https://www.nytimes.com/2019/01/31/opinion/ai-bias-healthcare.html
https://www.theguardian.com/technology/2017/sep/07/new-artificial-intelligence-can-tell-whether-youre-gay-or-straight-from-a-photograph

Crawford, Kate. "Artificial intelligence's white guy problem." The New York Times (2016).

Angwin, Julia, et al. "Machine bias: There's software used across the country to predict future criminals. and it's biased against blacks." *ProPublica, May* 23 (2016).

**Resources**

https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm
Machine Bias Interactive Tutorial: https://github.com/caitlinkuhlman/bpdmtutorial
NIPS Fairness Tutorial: http://fairml.how/tutorial
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IEEE Proposed fairness standard https://standards.ieee.org/develop/project/7003.html

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7. Zafar, Muhammad Bilal, Isabel Valera, Manuel Gomez Rodriguez, and Krishna P. Gummadi. "Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment." In Proceedings of the 26th International Conference on World Wide Web, pp. 1171-1180. International World Wide Web Conferences Steering Committee, 2017.

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