Fairness and Machine Learning

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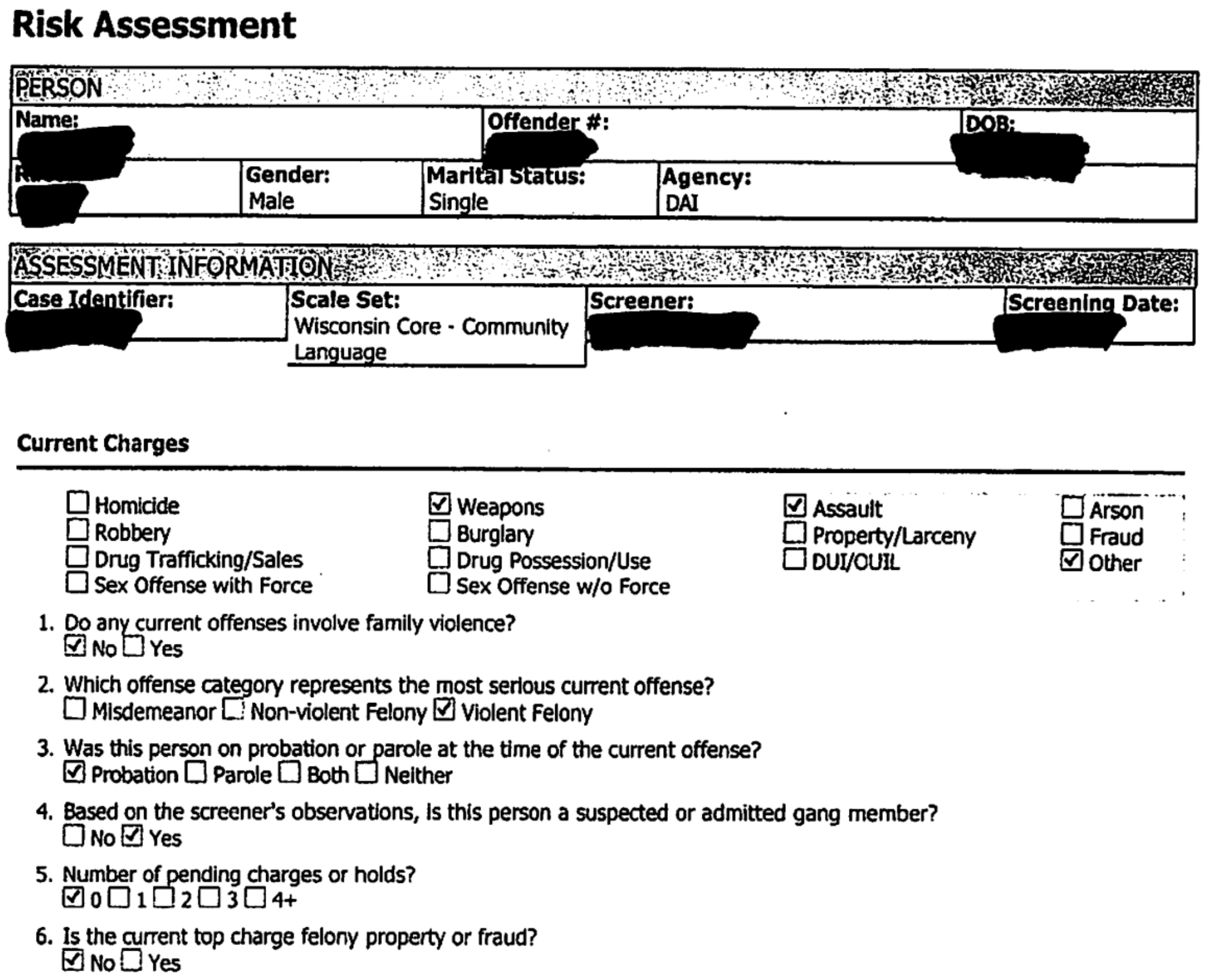
USC CSCI 467, Spring 2023
April 20, 2023

The story of COMPAS

- COMPAS: Proprietary software that estimates risk of defendant committing another crime
- Can be used in determining bail
- Results shown to judges during sentencing in several states



Risk Assessment

PERSON

Name: [redacted]		Offender #: [redacted]	DOB: [redacted]
[redacted]	Gender: Male	Marital Status: Single	Agency: DAI

ASSESSMENT INFORMATION

Case Identifier: [redacted]	Scale Set: Wisconsin Core - Community Language	Screener: [redacted]	Screening Date: [redacted]

Current Charges

☐ Homicide ☑ Weapons ☑ Assault ☐ Arson
☐ Robbery ☐ Burglary ☐ Property/Larceny ☐ Fraud
☐ Drug Trafficking/Sales ☐ Drug Possession/Use ☐ DUI/OUIL ☑ Other
☐ Sex Offense with Force ☐ Sex Offense w/o Force

1. Do any current offenses involve family violence?
   ☑ No ☐ Yes
2. Which offense category represents the most serious current offense?
   ☐ Misdemeanor ☐ Non-violent Felony ☑ Violent Felony
3. Was this person on probation or parole at the time of the current offense?
   ☑ Probation ☐ Parole ☐ Both ☐ Neither
4. Based on the screener's observations, is this person a suspected or admitted gang member?
   ☐ No ☑ Yes
5. Number of pending charges or holds?
   ☑ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4+
6. Is the current top charge felony property or fraud?
   ☑ No ☐ Yes

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

The story of COMPAS

PROPUBLICA

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

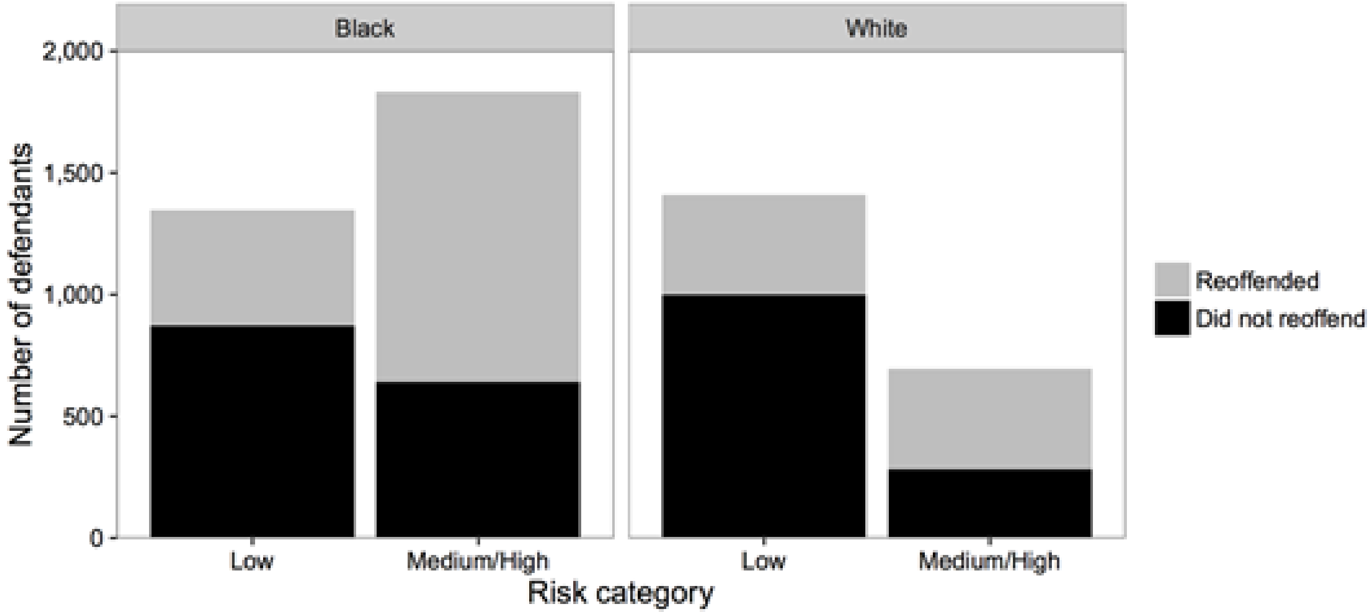
May 23, 2016

- "The formula was **particularly likely to falsely flag black defendants as future criminals**, wrongly labeling them this way at almost twice the rate as white defendants."
- "White defendants were mislabeled as low risk more often than black defendants."

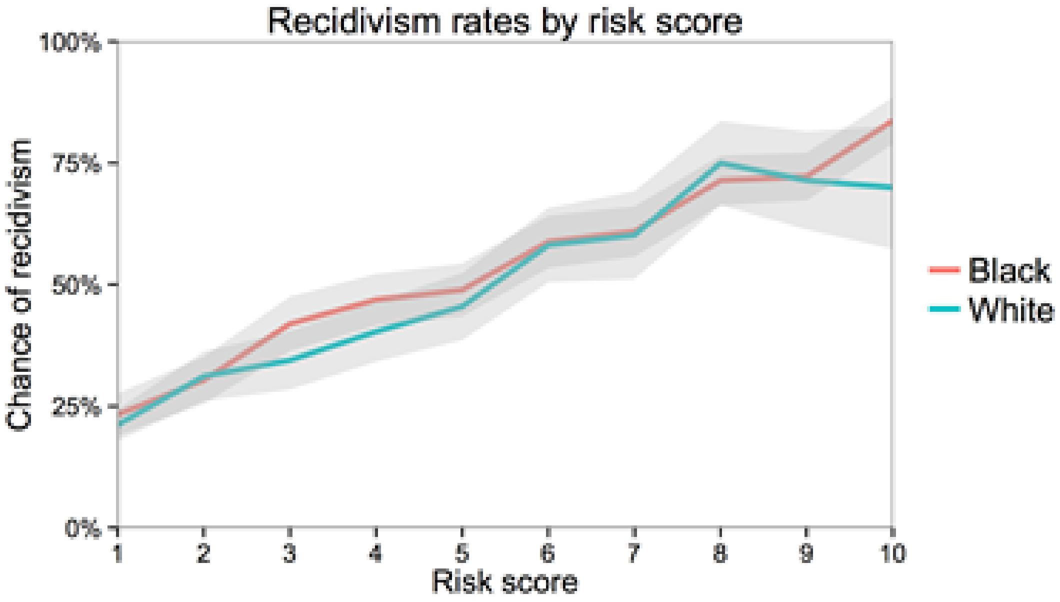
https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Is COMPAS unfair?

Unfair: Black individuals who did not reoffend were more likely to be categorized as high risk



Fair: For given risk score, chance of recidivism same for each population



https://medium.com/soal-food/what-makes-an-algorithm-fair-6ad64d75dd0c

Outline

- Allocative harms
- Unequal accuracy
- Representational harms

Allocation problems

- Problems in which **individuals** are evaluated for receiving certain opportunities or resources
    - Bail or sentencing decisions
    - Receiving loans
    - Job resume filtering (Applicant tracking systems)
    - Automated essay grading

REUTERS

RETAIL   OCTOBER 10, 2018 / 4:04 PM / UPDATED 3 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

By Jeffrey Dastin   8 MIN READ

"In effect, Amazon's system taught itself that male candidates were preferable. ***It penalized resumes that included the word "women's,"*** *as in "women's chess club captain." And it downgraded graduates of two all-women's colleges, according to people familiar with the matter."*

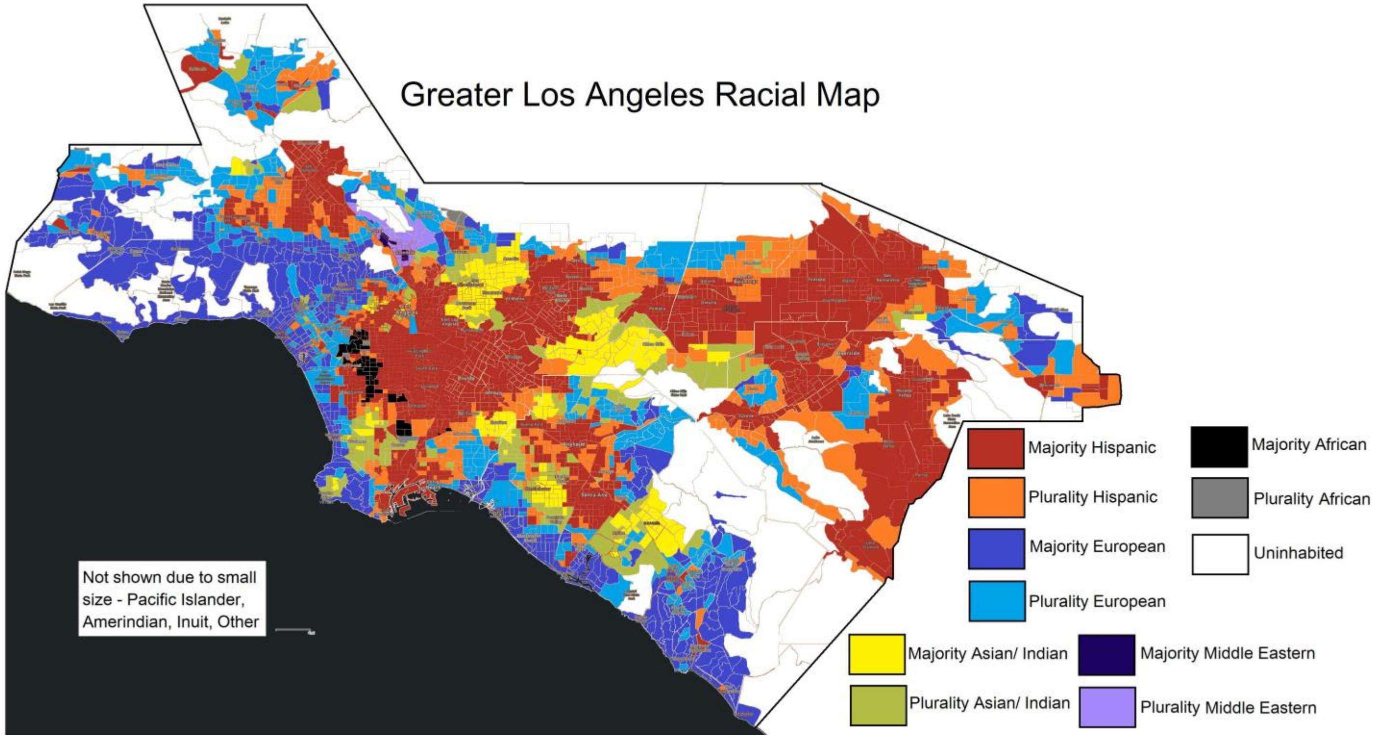
https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G

Basic setup

- X: An individual (or features thereof)
- Y: Something you want to predict
  - E.g., Will this person repay a loan or not (1 if yes, 0 if no)
  - Note: These are often **actual prediction** problems, not labeling—lots of fundamental uncertainty!
- R: Classifier's prediction
  - For now, just think of this as 1 or 0
  - But it can also be a continuous output, such as $P(y=1 \mid x; \theta)$
- A: Sensitive attribute (e.g., gender, race, etc.)
- We ask: Is the model fair to individuals with different values of A?

No fairness through unawareness

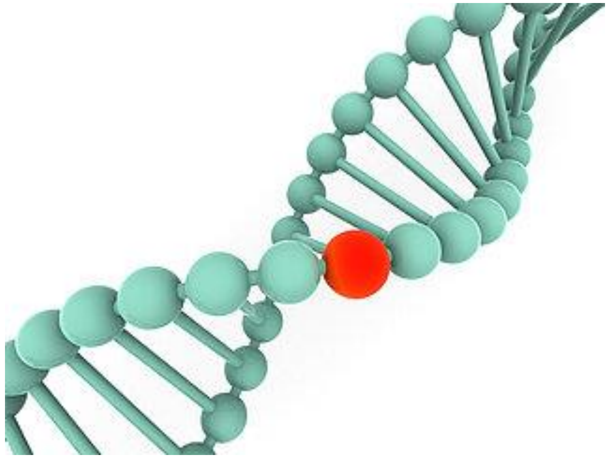
- First attempt: Just don't depend on the sensitive attribute ("blindness")
- Problem: Sensitive attribute can often be reconstructed from other features
  - Suppose you want to be fair across racial groups
  - Even if you don't use race to predict, zip code has a lot of information about race



Barocas, Hardt, and Narayanan. Fairness and Machine Learning: Limitations and Opportunities.

No fairness through unawareness

- Thought experiment: Trying to predict income from genome
  - Is there a “financial success” gene?????
  - Well, there are cues about your ancestry in your genome
  - For various societal reasons, this may correlate with income



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How can we measure (un)fairness?

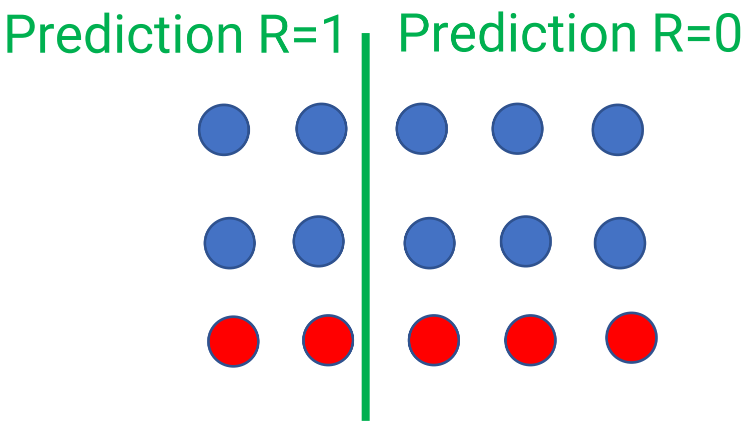
1. Independence (statistical parity)
2. Separation (equalized odds)
3. Sufficiency (calibration within groups)

1. Independence

- Independence: $R \perp A$
  - Equivalently for binary predictor:

    $$P(R = 1 \mid A = a) = P(R = 1 \mid A = b) \forall a, b$$

  - Very weak: says nothing about Y!
    - Can be satisfied by predicting well on group a and randomly with same base rate on group b
  - May also be too strong if $Y \not\perp A$



$$P(R = 1 \mid A = \color{blue}{\bullet}) = 2/5$$

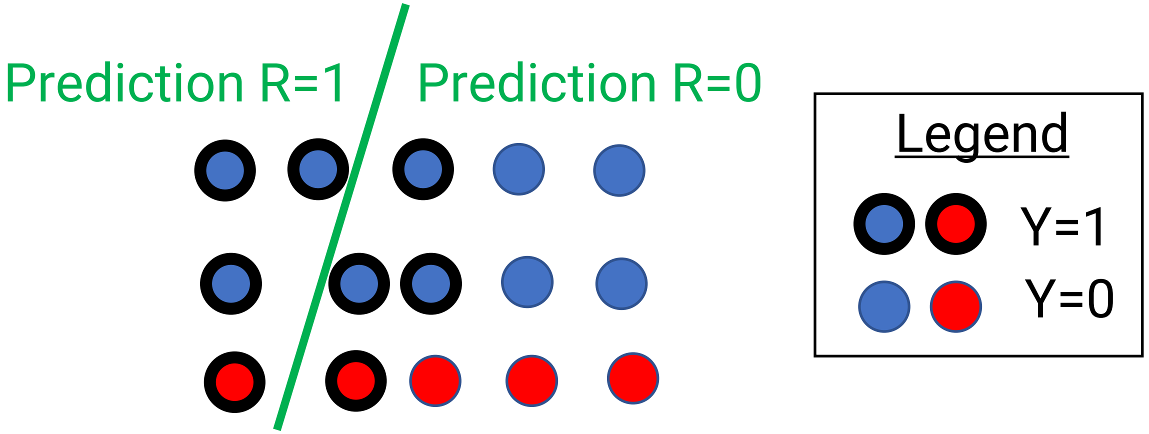
$$P(R = 1 \mid A = \color{red}{\bullet}) = 2/5$$

Barocas, Hardt, and Narayanan. Fairness and Machine Learning: Limitations and Opportunities.

2. Separation / Equalized odds

- Separation: $R \perp A \mid Y$
  - Equivalently for binary predictor:

$$P(R=1 \mid A=a, Y=1) = P(R=1 \mid A=b, Y=1)$$
$$P(R=0 \mid A=a, Y=0) = P(R=0 \mid A=b, Y=0)$$



  - In English: **Recall** on both Y=1's and Y=0's are same for both groups
  - **Recall** defined as

$$\frac{\text{Positives found by classifier}}{\text{Total Positives}}$$

$$P(R=1 \mid A = \textcolor{blue}{\bullet}, Y=1) = 3/6 = 1/2$$
$$P(R=1 \mid A = \textcolor{red}{\bullet}, Y=1) = 1/2$$
$$P(R=0 \mid A = \textcolor{blue}{\bullet}, Y=0) = 4/4 = 1$$
$$P(R=0 \mid A = \textcolor{red}{\bullet}, Y=0) = 3/3 = 1$$

Barocas, Hardt, and Narayanan. Fairness and Machine Learning: Limitations and Opportunities.

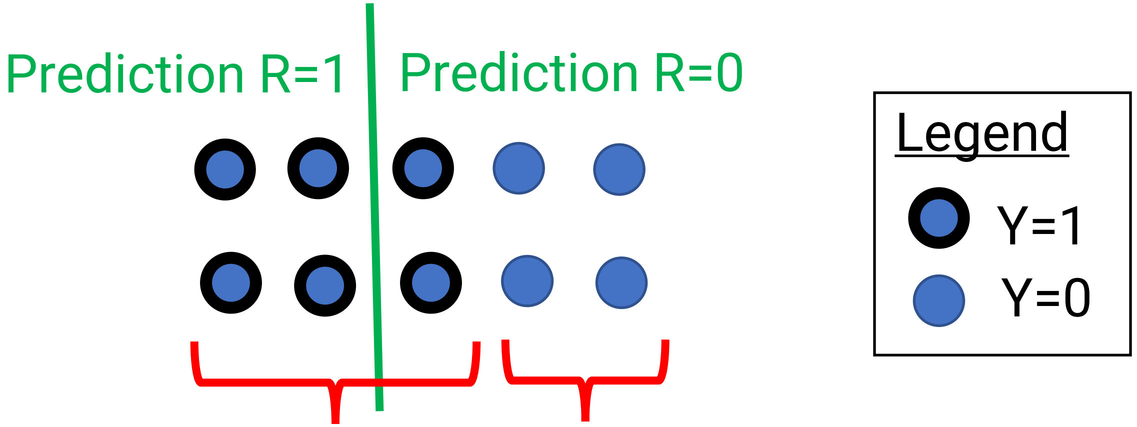
Trade-offs between false positives/negatives

- Setting: We have a *continuous* classifier output R
  - E.g., For input x, R = P(y=1 | x; θ)
- Default classification rule: Predict y=1 if R > 0.5, y=0 otherwise
- But you can choose any threshold!
  - High threshold (e.g. 0.9): Predict fewer 1's
  - Low threshold (e.g. 0.1): Predict fewer 0's
- False positives: Predict 1 but real y=0
  - Higher threshold reduces false positives
  - Measured by **False Positive Rate:**

$$P(R = 1 \mid A, Y = 0)$$

- False negatives: Predict 0 but real y=1
  - Lower threshold reduces false negatives
  - Measured by **True Positive Rate** (same as recall):

$$P(R = 1 \mid A, Y = 1)$$



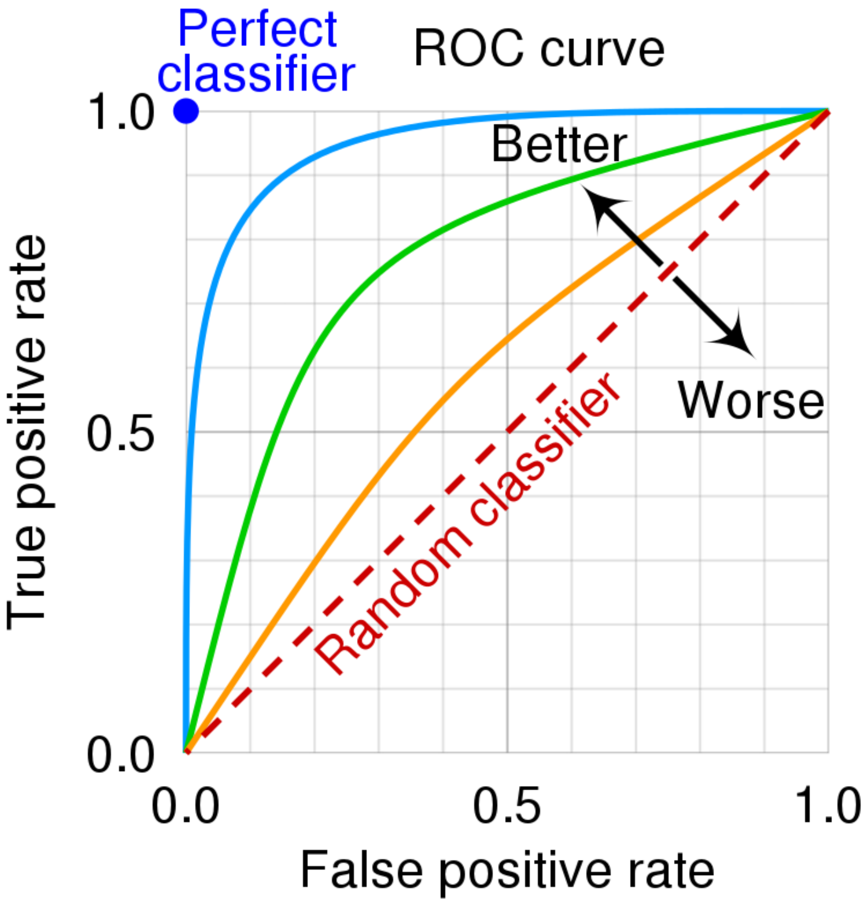
False negatives: **2**
True positive rate: 4/6
(=1 – **2**/6)

False positives: **0**
False positive rate: **0**/4

Split the dataset into two halves (Y=1 and Y=0)
False positives are errors when Y=0
False negatives are errors when Y=1

ROC curves

- Receiver Operating Characteristic (ROC) curve: One way to average model performance across all possible thresholds
  - For each threshold, measure true positive rate & false positive rate
  - Plot these on a curve
- Area under ROC curve (AUROC) summarizes performance
  - Perfect classifier: AUROC=1
  - Random classifier: AUROC=0.5

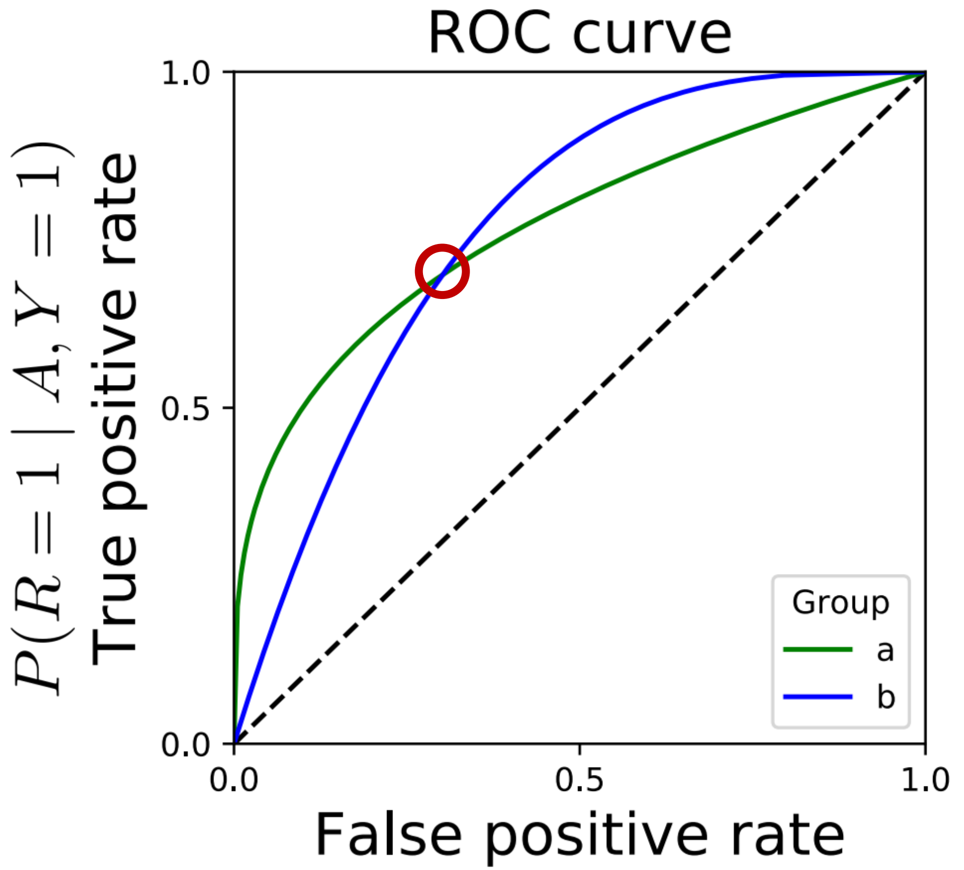


$P(R = 1 \mid A, Y = 1)$

$P(R = 1 \mid A, Y = 0)$

Separation and ROC curves

- Separation: Both groups should be at same point on ROC curve
  - First constraint is on true positive rate
  - Second constraint is on 1 – false positive rate
- May require setting separate thresholds for each group



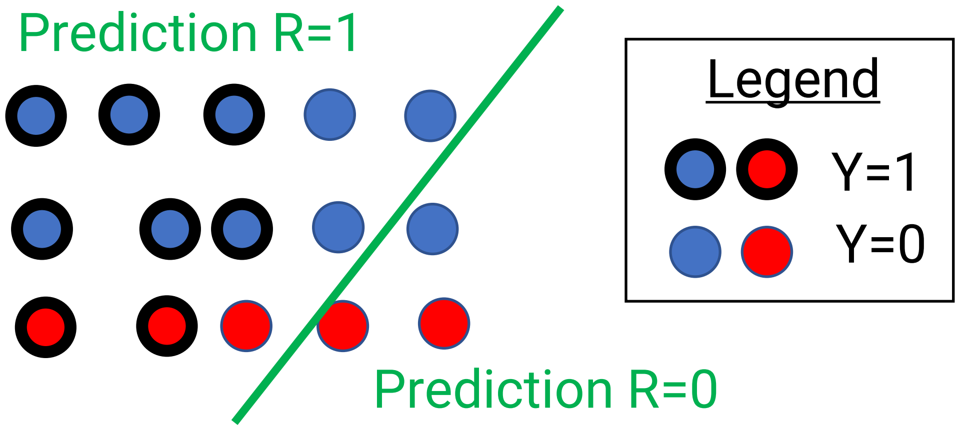
$$P(R = 1 \mid A, Y = 0)$$
$$= 1 - P(R = 0 \mid A, Y = 0)$$

Barocas, Hardt, and Narayanan. Fairness and Machine Learning: Limitations and Opportunities.

3. Sufficiency / Calibration within groups

- Separation: $Y \perp A \mid R$
  - Equivalently for binary predictor:

$$P(Y=1 \mid A=a, R=1) = P(Y=1 \mid A=b, R=1)$$
$$P(Y=0 \mid A=a, R=0) = P(Y=0 \mid A=b, R=0)$$



  - In English: **Precision** on both Y=1’s and Y=0’s are same for both groups
  - **Precision** defined as

$$\frac{\text{Positives found by classifier}}{\text{Things predicted as positive}}$$

$$P(Y=1 \mid A={\color{blue}\bullet}, R=1) = 6/9 = 2/3$$
$$P(Y=1 \mid A={\color{red}\bullet}, R=1) = 2/3$$
$$P(Y=0 \mid A={\color{blue}\bullet}, R=0) = 1/1 = 1$$
$$P(Y=0 \mid A={\color{red}\bullet}, R=0) = 2/2 = 1$$

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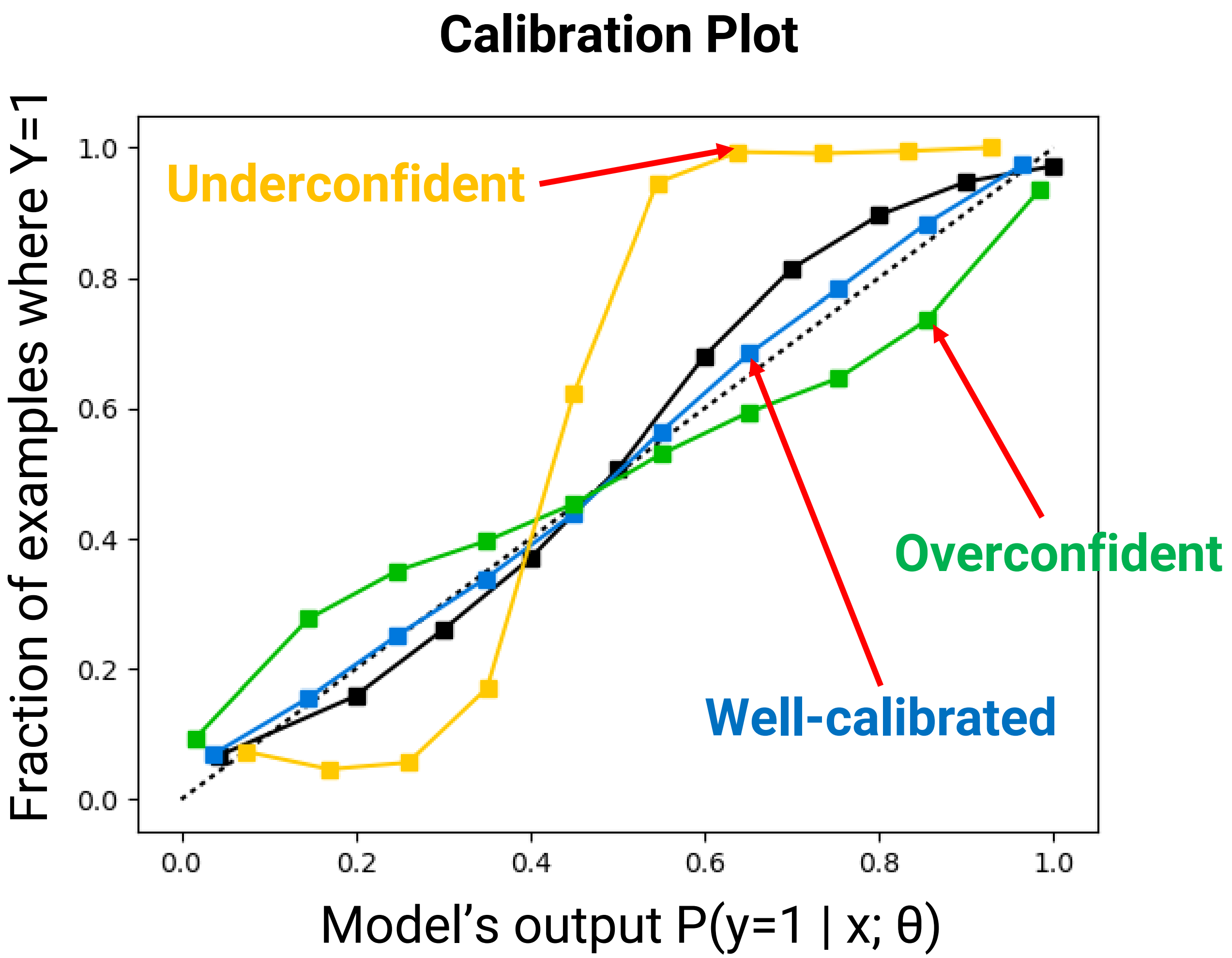
Calibration

- We can instead consider the model output R to be the probability P(y=1 | x; θ)
- With an ideal model, what should $P(Y = 1 \mid A = a, R = 0.8)$ equal?
  - Ideally should equal **0.8**!
- If this holds for all values of R, model is called **well-calibrated**

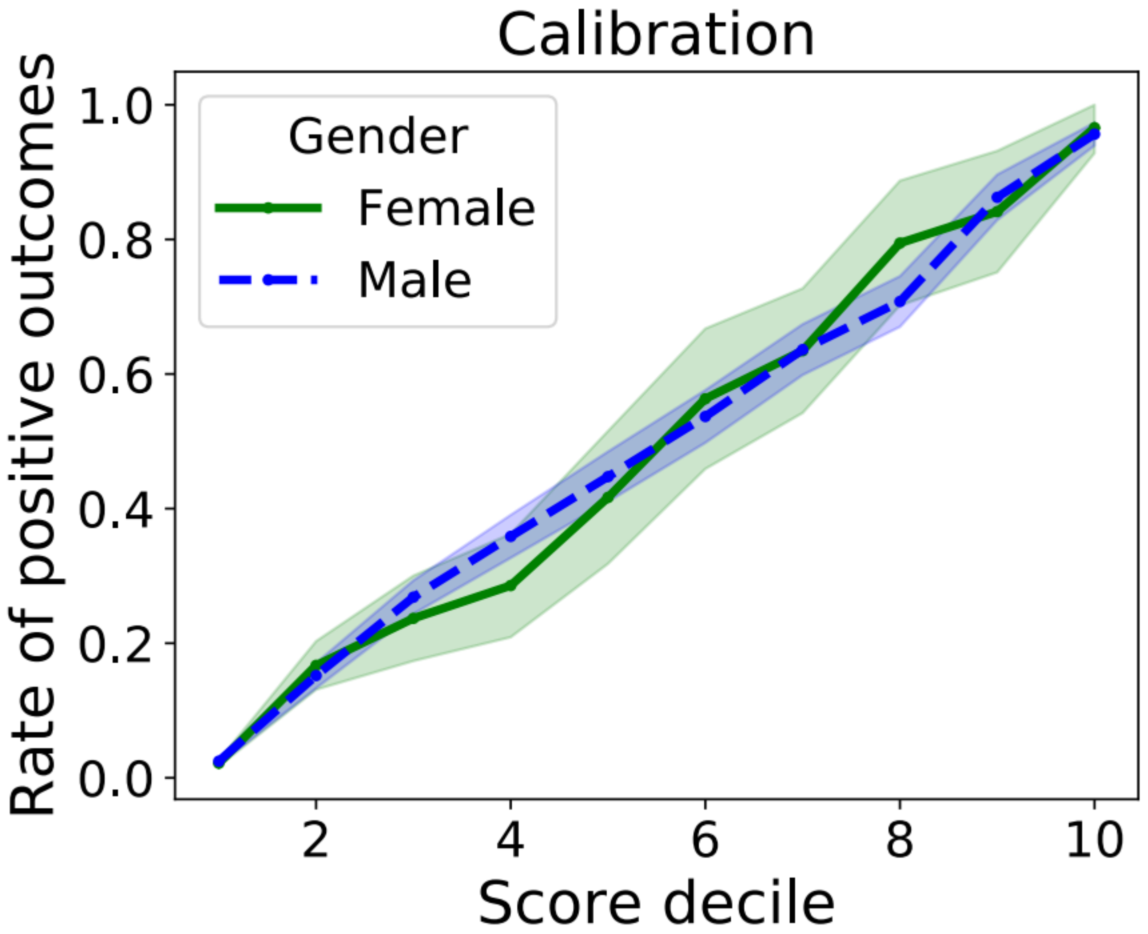


Sufficiency and Calibration

- If R is continuous valued, sufficiency says for each R value, rate of Y=1 should be same between groups

$$P(Y = 1 \mid A = a, R = r) = P(Y = 1 \mid A = b, R = r) \forall r$$

- If model is well-calibrated on each group, then it satisfies sufficiency



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Great, now we can make things fair…?

- Problem: These definitions of fairness are **mutually incompatible** in many natural settings!
- No system (automated or human) can simultaneously be fair in all these ways!

Independence (1) vs. Sufficiency (3)

- Independence and sufficiency only compatible if $Y \perp A$
  - Very strong—usually base rates of Y given A are not the same

$$P(Y \mid A = a) = \sum_r P(R = r \mid A = a) P(Y \mid A = a, R = r)$$

Base rate of Y
in population a

Independence $R \perp A$

Sufficiency $Y \perp A \mid R$

$$= \sum_r P(R = r \mid A = b) P(Y \mid A = b, R = r)$$

$$= P(Y \mid A = b)$$

Base rate of Y
in population b

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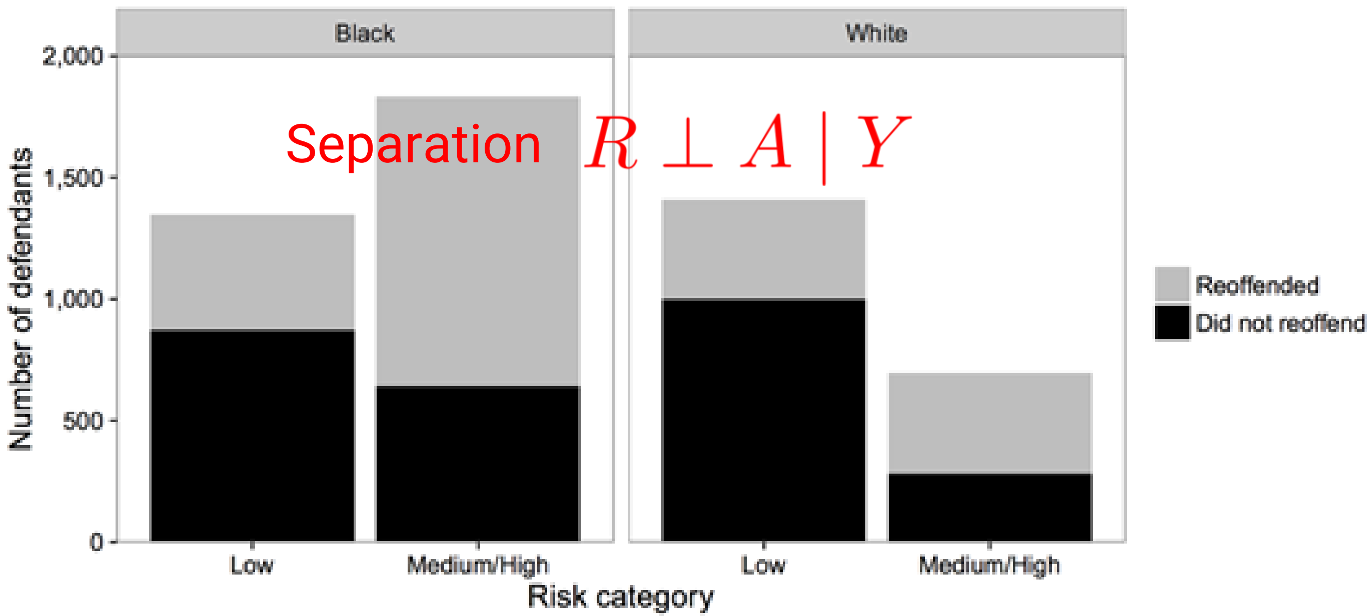
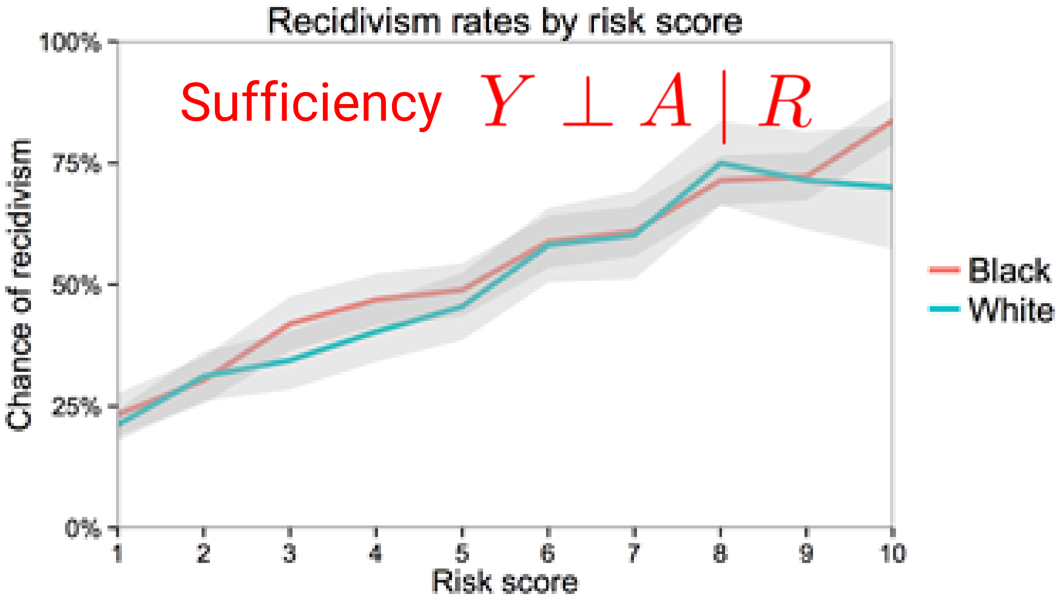
Is COMPAS unfair?

Unfair: Black individuals who did not reoffend were more likely to be categorized as high risk



Fair: For given risk score, chance of recidivism same for each population



https://medium.com/soal-food/what-makes-an-algorithm-fair-6ad64d75dd0c

Where do we go from here?

- There is a fundamental trade-off between different natural notions of fairness
- We should not be surprised when a system fails by some fairness criteria
- Can still try to monitor and improve any given notion of fairness
- Overall assessment of “fairness” will continue to be debatable

Announcements

- Homework 4 released, due Thursday, April 27
- Last section this Friday: EM (k-Means, GMM, HMM), inference algorithms for HMM
- Last class will be a broad overview of all topics

Outline

- Allocative harms
- Unequal accuracy
- Representational harms

Unequal accuracy

- Allocation problems: Each example represents one individual
- In other scenarios, individuals are not examples but users who produce (many) examples

The TIMIT dataset (1988)

- Important early benchmark dataset for speech recognition
  - 6300 utterances, 5 hours
  - 630 speakers, 10 sentences each
- Underrepresentation problem!
- Even today, higher error rate for black vs. white speakers for commercial ASR systems

	Male	Female	Total (%)
White	402	176	578 (91.7%)
Black	15	11	26 (4.1%)
American Indian	2	0	2 (0.3%)
Spanish-American	2	0	2 (0.3%)
Oriental	3	0	3 (0.5%)
Unknown	12	5	17 (2.6%)

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Gender Shades

- 2018 study: Commercial facial recognition systems much less accurate on darker-skinned females than other groups

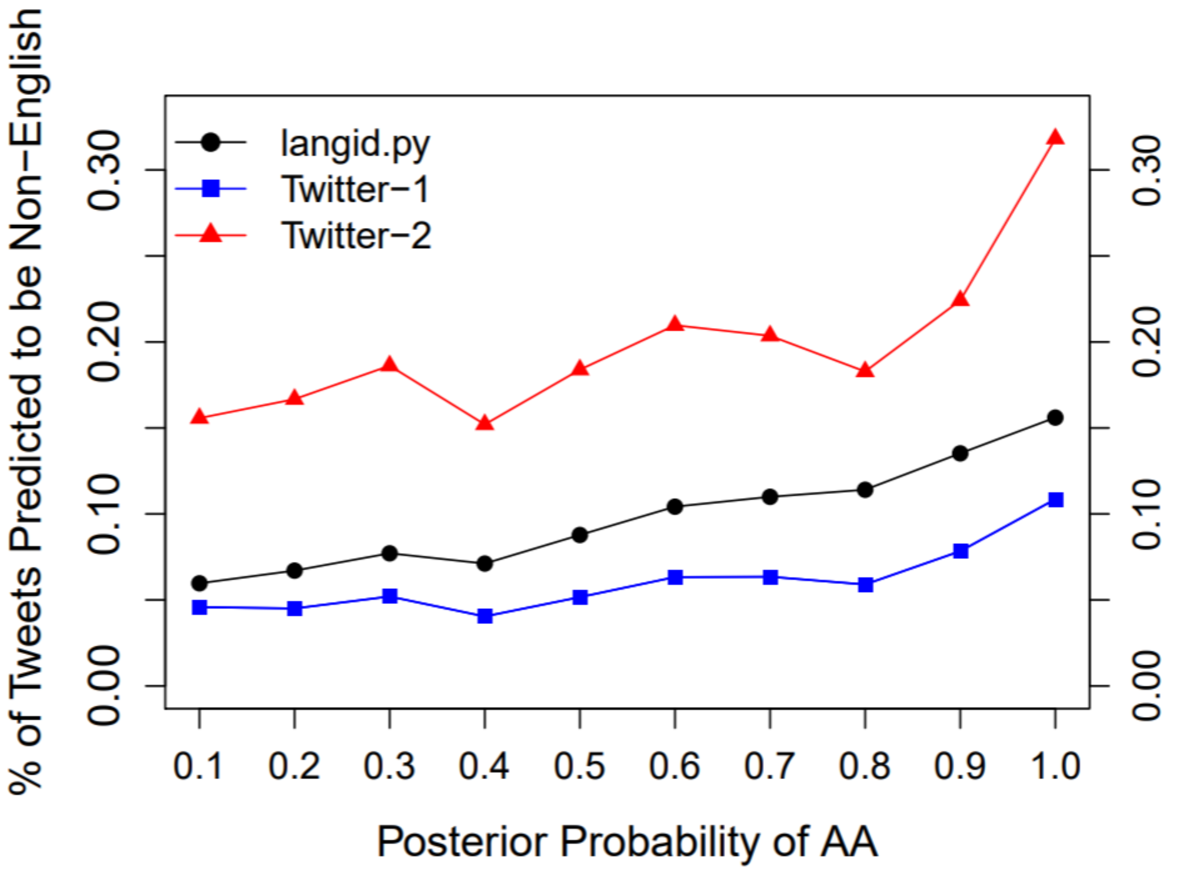
Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

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

Language variation

Language identification systems miscategorize Tweets in African American English (AAE) as non-English at a much higher rate

- May affect users of systems
- May also affect computational analysis of text data



Blodgett, Green, and O'Connor. "Demographic Dialectal Variation in Social Media: A Case Study of African-American English." EMNLP 2016.

Outline

- Allocative harms
- Unequal accuracy
- Representational harms

Representational harms

- Previously
  - Allocative harms: Individuals are examples, they can be treated unfairly
  - Unequal accuracy: Individuals have examples, they can be helped or not helped
- Now: Thinking about broader externalities
  - Are some stereotypes reinforced by the outputs of this system?
  - Harms become evident on longer time scales

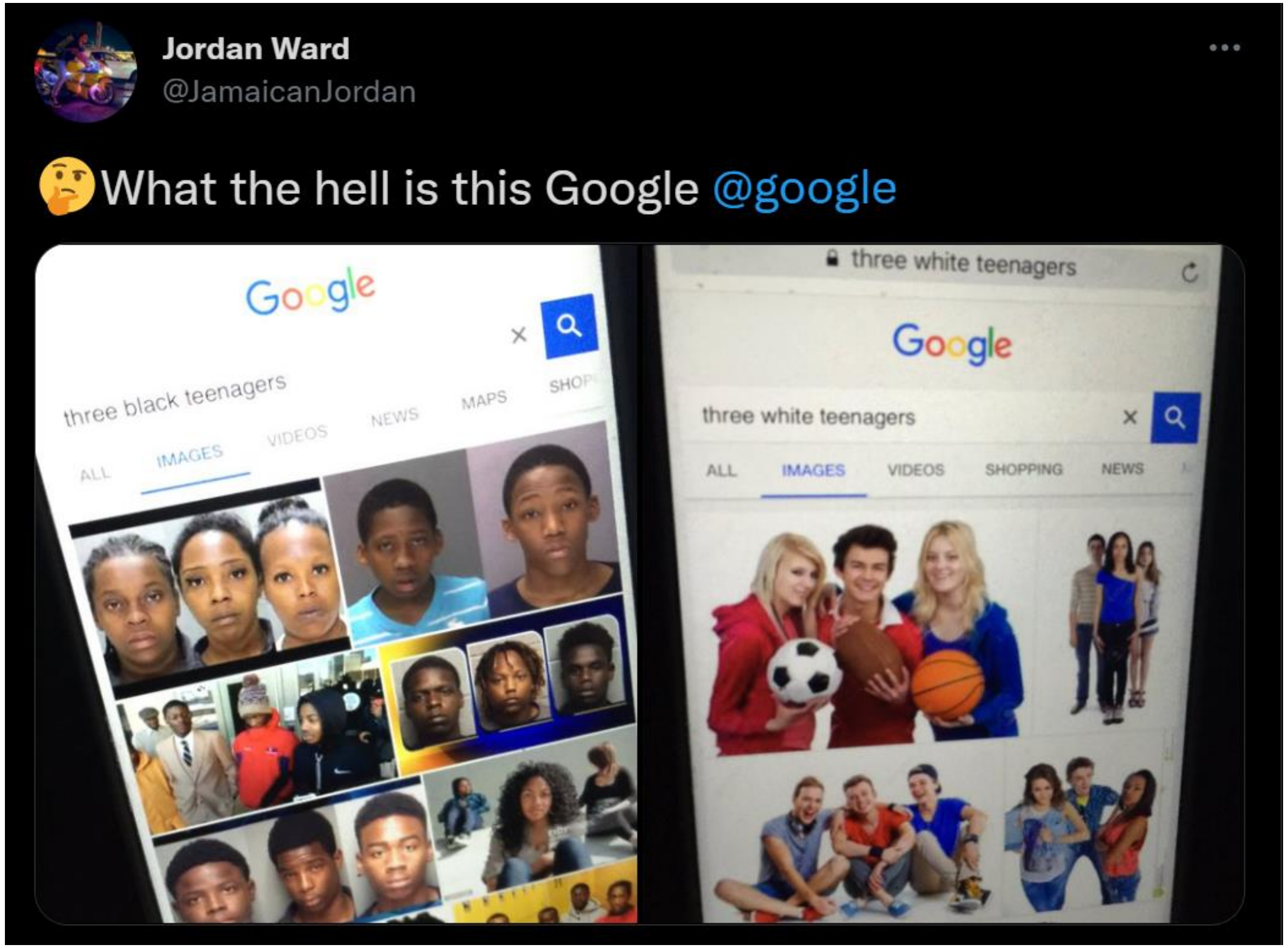
Machine translation and gender

- In some languages, nouns must specify gender
- When translating from gender-neutral language, system must(?) guess
- Representational harm if “doctor” is always assumed to be male

https://ai.googleblog.com/2020/04/a-scalable-approach-to-reducing-gender.html

Search engine results

- Many results may "match" a given search query—which are shown?
- Representational harms can occur despite literal match with query
- Similar issues with gender stereotypes and occupations



https://www.washingtonpost.com/news/morning-mix/wp/2016/06/10/google-faulted-for-racial-bias-in-image-search-results-for-black-teenagers/

Conclusion

- Breadth of potential harms
  - To individuals being evaluated
  - To users attempting to use tools
  - To broader society due to shifts in perception
- Different fairness metrics can be fundamentally at odds