

Machine Learning Bias

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Outline

1. How Bias Sneaks In (Biased Factors)

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2. How Bias Sneaks In (Biased Measures)
3. Ethics of Type 1 versus Type 2 Errors
4. Right to Review and Black Box Algorithms

Supervised Machine Learning

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By design, SML will always try and be biased.

Supervised Machine Learning

SML models are designed to find any patterns they can to help predict outcomes / classify records.

Because sexism, racism, xenophobia, homophobia, etc. shape outcomes in the world,

~> SMLs generally **perform better** when they are sexist/racist/xenophobic/homophobic!

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If supervisors tend to discriminate against women, then our SML will look for signals that an applicant is a woman, since they can use this to give women lower reviews, better matching the training data.

Proxies

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In COMPAS, **race wasn't in the model.**

Biased By Design

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So long as society has biases, Machine Learning has an affirmative incentive to be biased too!

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Picking unbiased outcomes is not as easy as it seems...

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Arrests are pretty objective, right?

FIGURE 6A.

Rates of Drug Use and Sales, by Race

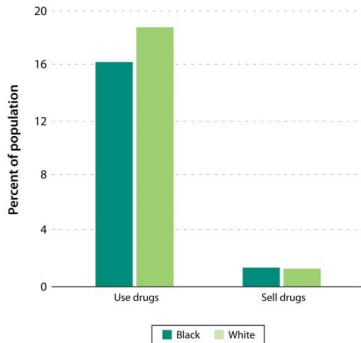
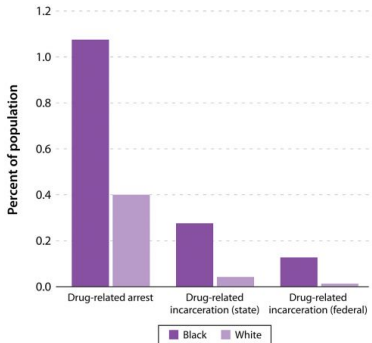


FIGURE 6B.

Rates of Drug-Related Criminal Justice Measures, by Race



At the state level, blacks are about 6.5 times as likely as whites to be incarcerated for drug-related crimes.

Source: BLS n.d.c; Carson 2015; Census Bureau n.d.; FBI 2015; authors' calculations.

Probability of arrest \neq probability of committing a crime

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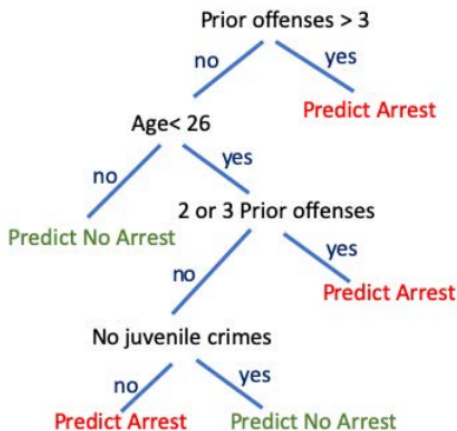
- Same accuracy scores for Black and White suspects!
- But... very different rates of false positives and false negatives.

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An interpretable decision tree to predict whether an individual will be arrested in the future. Hu et al. NeurIPS 2019