

Designing Against Bias in Machine Learning and AI

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Designing Against Bias: Identifying and Mitigating Bias in Machine Learning and AI

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OUTLINE

Overview of Bias in ML and AI

Root Causes of Bias

Measuring Bias

Designing Against Bias

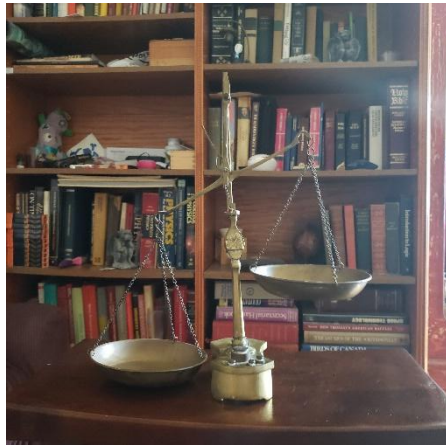
Conclusions



OVERVIEW OF BIAS IN ML AND AI

Bias in Machine Learning Algorithms

Taking human decisions out of the process was supposed to make things more fair...



...but often it hasn't

=> What went wrong??

Racial Bias: Bail and Parole Algorithms

The “Solution”: ML says who gets bail or parole

COMPAS Algorithm:

$$\begin{aligned} \text{RISK} &= \text{AGE} * \text{Weight 1} \\ &+ \text{AGE AT FIRST ARREST} * \text{Weight 2} \\ &+ \text{HISTORY OF VIOLENCE} * \text{Weight 3} \\ &+ \text{EDUCATION LEVEL} * \text{Weight 4} \\ &+ \text{HISTORY OF NONCOMPLIANCE} * \text{Weight 5} \end{aligned}$$

The Problem: using the algorithm results in the exact same bias



Gender Bias: Amazon Resume Screening

The “Solution”: ML picks top resumes

Amazon Algorithm:

Resume Quality = ? + ? + ? + ? + ? ...

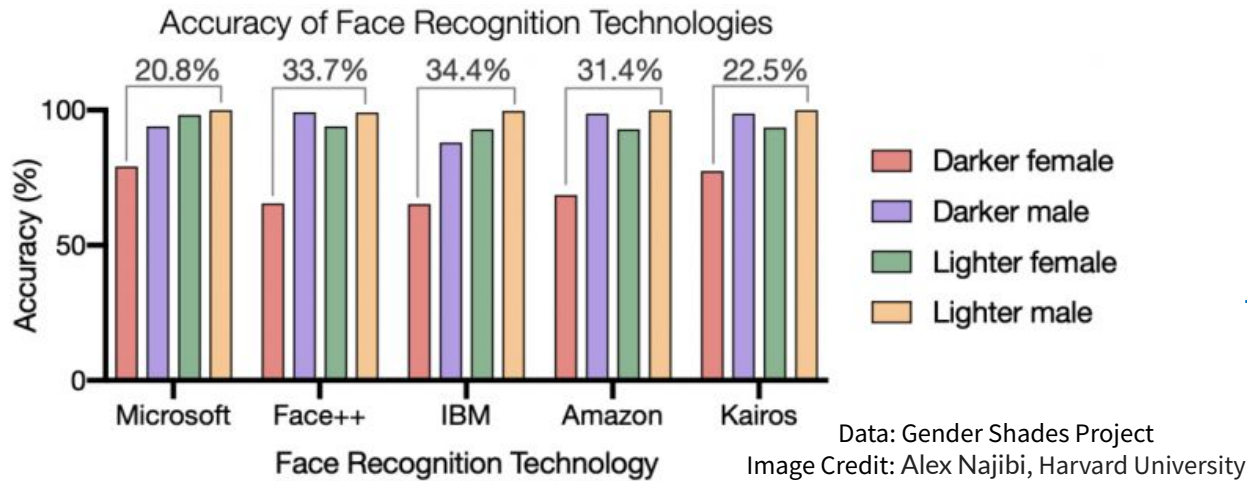


Image Credit: [flazingo_photos](#) - CC BY-SA 2.0

The Problem: the algorithm is biased against women applicants

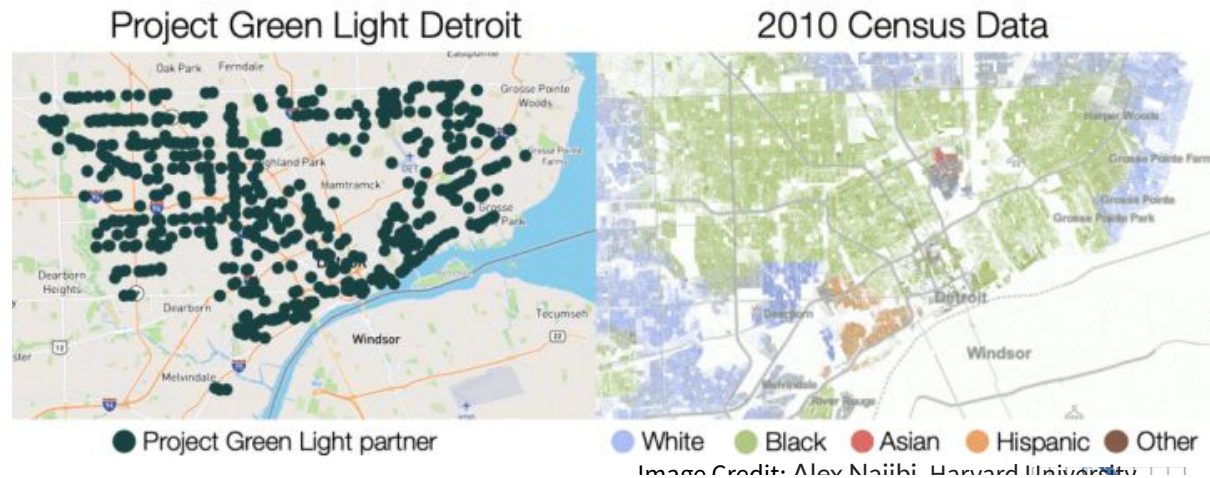
ROOT CAUSES OF BIAS

Root Causes of Bias: Selection Bias



Algorithm trained using biased subset

Usage results in disparate impact



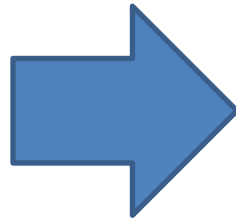
=> Biased Training Population = Biased Results

Root Causes of Bias: The History Problem

ML replaces human decision making

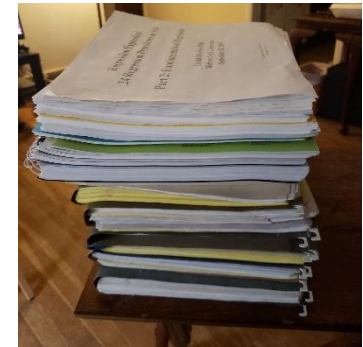


Image Credit: [David Davies](#) -CC BY-SA 2.0



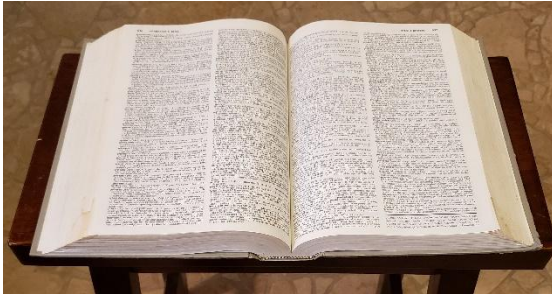
```
library(tensorflow)
library(keras)
model <- keras_model_sequential() %>%
  layer_conv_2d(filters = 32,
    kernel_size = c(3,3), activation = "relu",
```

The algorithm is trained using
earlier, biased human decisions



=> Bias In = Bias Out

Root Causes of Bias: Spaghetti Problem



DATA DICTIONARY

Hundreds or even thousands
of potential predictors

Algorithm trained uncritically
using “anything that sticks”



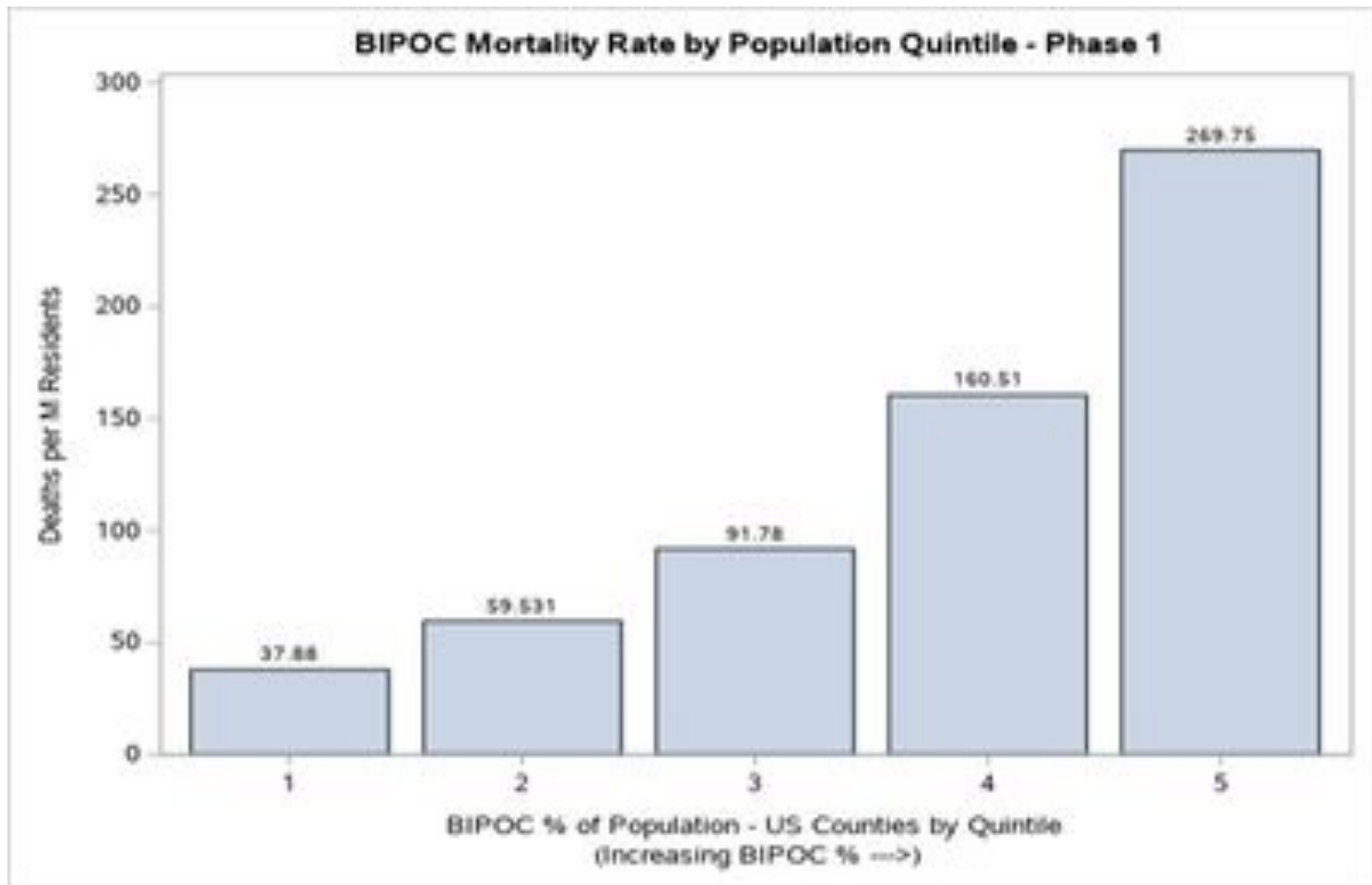
Image Credit: snackdinner.com

=> Biased Predictors = Biased Outcome

STATISTICAL MEASURES OF BIAS

Measuring Bias: Disparate Impact

Example: COVID-19 Initial Mortality



Measuring Bias: Disparate Impact

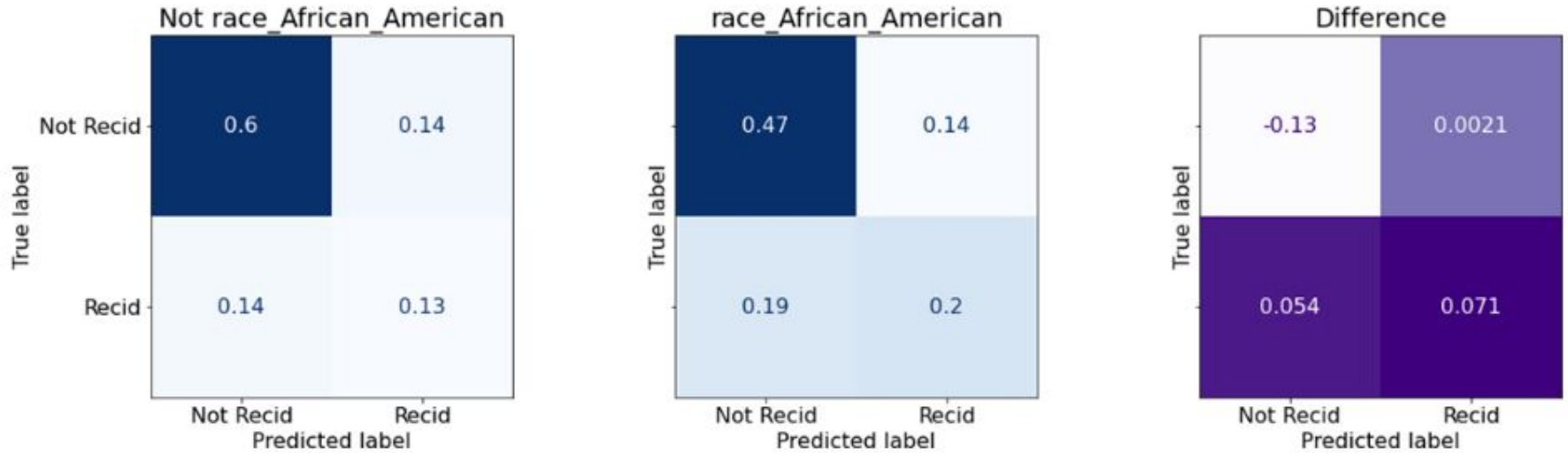
Odds Ratios for demographic factors compare highest % prevalence (60%+) vs. lowest (<5%)

Black / African American	10.1
Cardiovascular Disease	9.3
Chronic Lung Disease	5.9
Prison Populations	5.5
Indigenous	3.3
Poverty (High % Below Poverty Line)	2.9
High Population Density	1.9

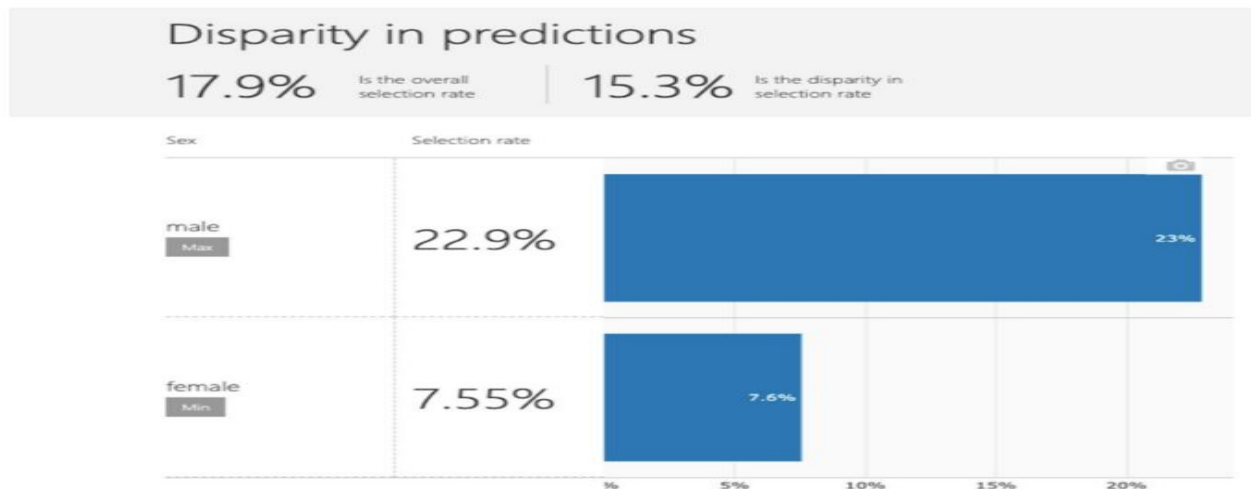
Prison numbers compared to overall US population. Reported by Saloner et al, COVID-19 Cases and Deaths in Federal and State Prisons, JAMA, August 11, 2020



Measuring Bias: Fairlearn Algorithm

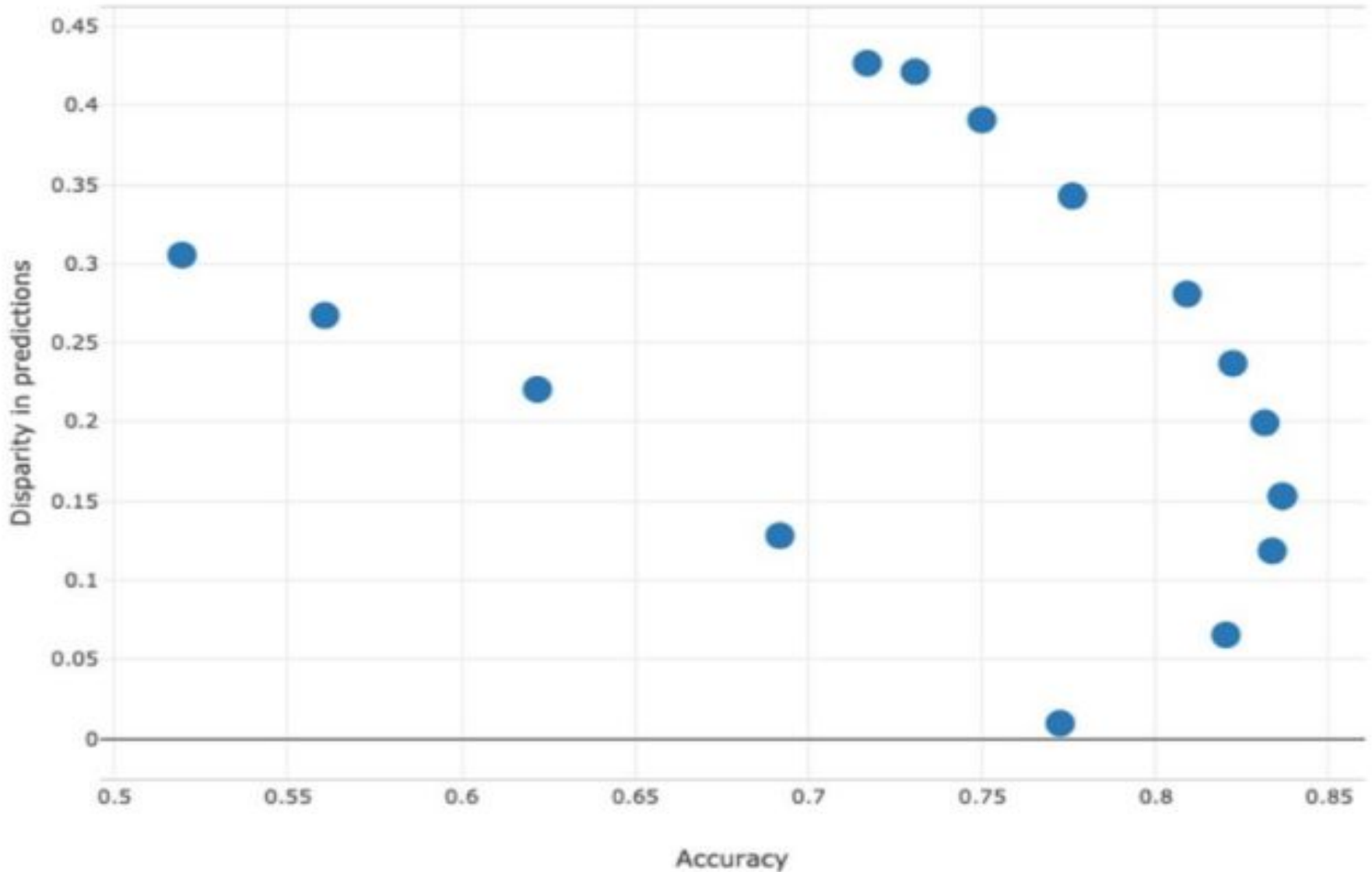


Confusion matrices for African-American defendants vs rest, and difference, for Fairlearn-adjusted model



DESIGNING AGAINST BIAS IN ML AND AI

Designing Against Bias: Fairlearn



Designing Against Bias: Bias-Minimized Comparison Algorithm

1. Develop a new predictive algorithm
2. Create a second model - the BMCA - by removing predictors that might confer bias
3. Test the new model against the BMCA to estimate the amount of bias in any variables causing concern

CONCLUSIONS

Best Practices for Design to Minimize Bias

1. Parsimonious Models
2. Screen all predictors for bias
3. Transparent Methods, not Black Box
4. Develop the model using new outcomes screened for bias - not past human decisions
5. Test for bias w/ FairLearn, BCMA, etc.
6. Present using Odds Ratios or Relative Risk
7. Open Source the data and algorithm



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<https://www.databricks.com/blog/2022/09/16/mitigating-bias-machine-learning-shap-and-fairlearn.html>

US Census Bureau Demographic Data

<https://www.census.gov/programs-surveys/ces/data/restricted-use-data/demographic-data.html>



Questions?

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