Using Data Science to Achieve Fair and Equitable Outcomes

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Reducing jail recidivism with proactive mental health interventions (Johnson County, KS) Reducing Incarceration through Prioritized Interventions. Bauman et. Al. ACM COMPASS 2018

11 MILLION

people move through 3,100 Jails

22 BILLION

in cost

64% suffer from mental illness

68%

have a substance abuse disorder

44% suffer from chronic health problems



Children in at least 4MM US households are exposed to high levels of lead

Impaired Attention

Hearing Loss

Lower IQ

Lack of Motor Skills

Learning Disability

Memory Problems

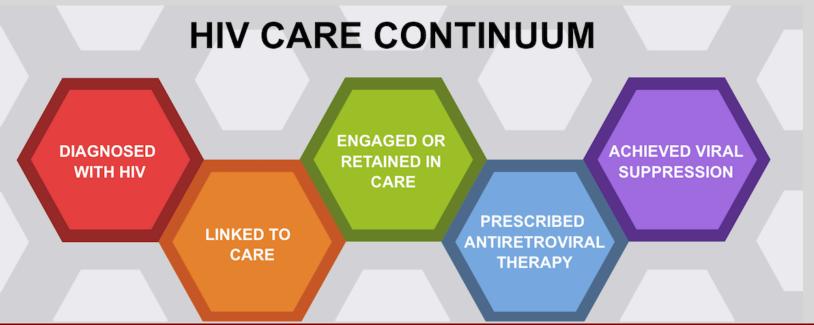
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Increasing Retention in Care for HIV+ Patients

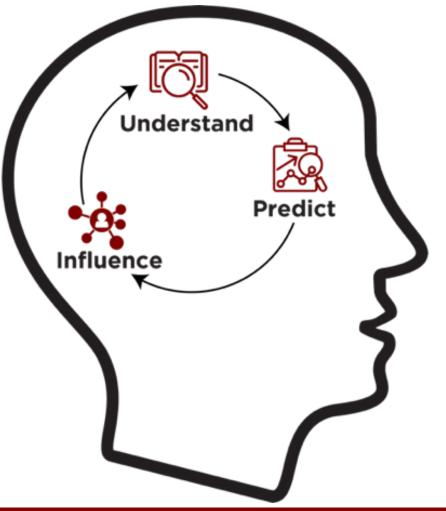
Predictive Analytics for Retention in Care in an Urban HIV Clinic. Ramachandran et al. Nature Scientific Reports 2020







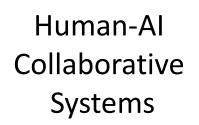
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How do we develop Human-ML collaborative systems to help make decisions that lead to fair and equitable outcomes?

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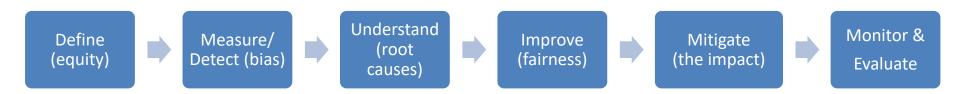






Allocation of Limited Resources Balancing goals of equity, efficiency, and effectiveness

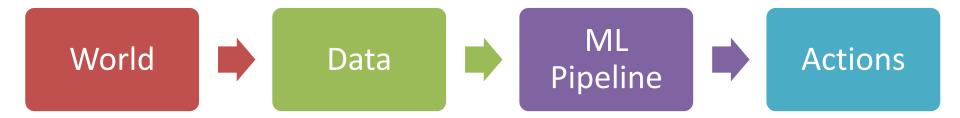
The focus is not just be on making the ML model fair but rather on making the overall system and outcomes fair







Bias (in outcomes) can come from any of these four components



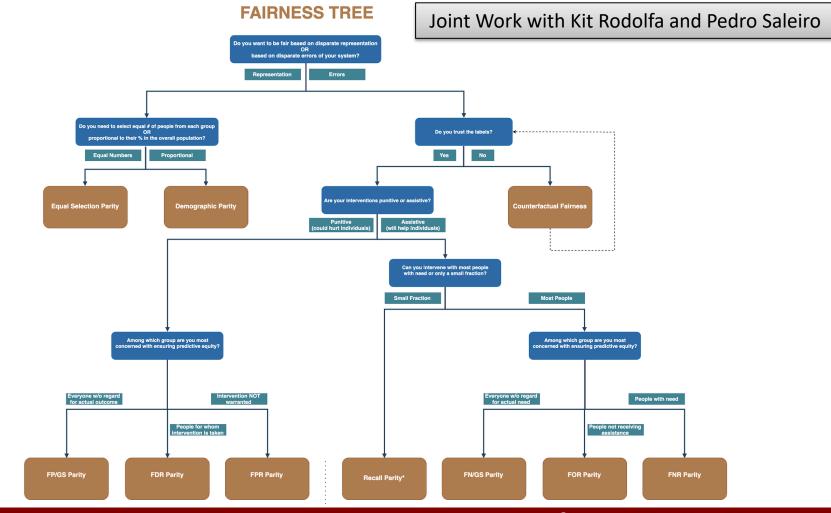
Sample Bias Measurement Bias Label Bias System Developers Complexity or flaws Design Choices

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Many Bias Measures: How do we select what we care about?

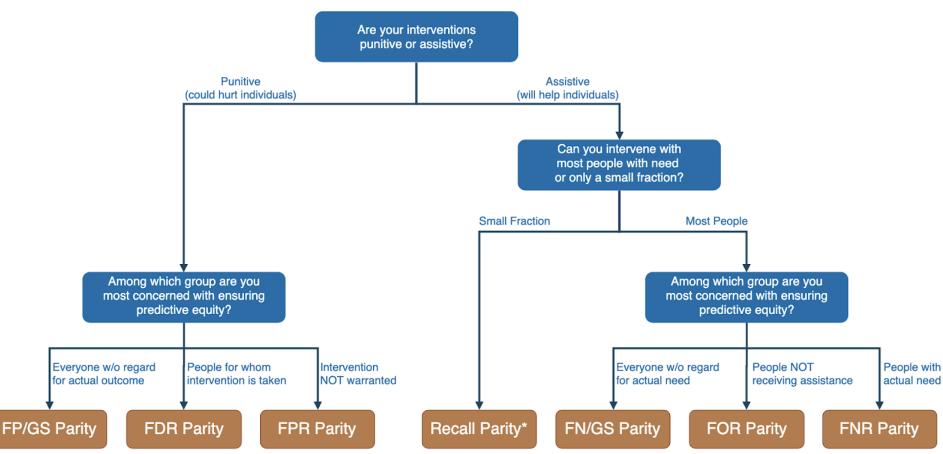
- Statistical/Demographic Parity
- Impact Parity
- False Discovery Rate Parity
- False Omission Rate Parity
- False Positive Rate Parity
- False Negative Rate Parity
- ...





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Zoomed in Version



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Aequitas Open Source Bias & Fairness Audit Tool

Aequitas: Bias Audit Tool

http://datasciencepublicpolicy.org/aequitas

Joint Work with Pedro Saleiro

Bias and Fairness Audit Report

Generated by Aequitas for [Large US City] Criminal Justice Project January 29, 2018

Project Goal: Identify individuals likely to get booked/charged by police in the near future
Performance Metric: Accuracy (Precision) in the top 150 identified individuals
Bias Metrics Considered: Demographic Disparity, Impact Disparity, FPR Disparity, FNR Disparity, FOR
Disparity, FDR Disparity
Reference Groups: Race/Ethnicity – White, Gender: Male, Age: None

Model Audited: #841 (Random Forest)

Model Performance: 73%

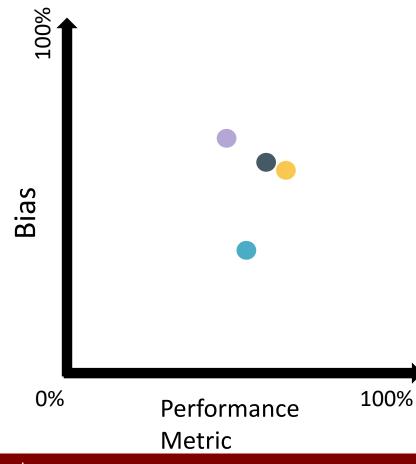
Aequitas has found that Model 841 is **BIASED**. The Bias is in the following attributes:

Race = Black is biased in Demographic Disparity (6X), Impact Disparity 1.8X), FPR Disparity (5X), FOR Disparity (1.5X), FDR Disparity (1.7X)

46% (66) of the selected group (n=150), while only making up 24% of the total population.
FDR (30%) is 1.7X higher than Reference FDR (18%).
FOR (6%) is 1.5X higher than Reference FOR (4%).
FPR (0.02%) is 5X higher than Reference FPR (0.004%)



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Data from 1M patients from 2006 to 2018

Outcome: Type 2 Diabetes diagnoses in the 3 years period after a provider visit.



Performance Metric: Recall/Sensitivity@k (k= # of patients screened based on resources)

Group Metric: False Omission Rate

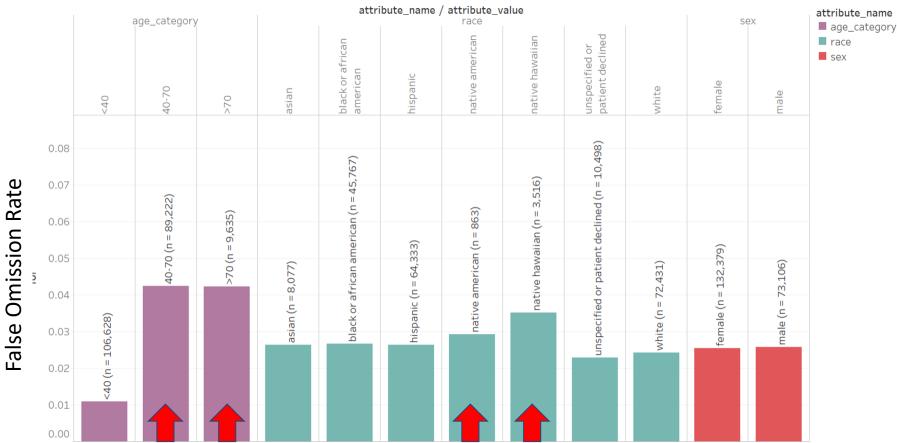
Protected Attributes: Age, Ethnicity and Sex

Test Set:

205,485 patients that visit a doctor during 2014

3.4% prevalence (7,154 diabetes diagnoses in 3 years interval after visit)

Current Practice (at provider)



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Current Practice vs "Best Overall" Model

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AllianceChicago
 Best Recall Visits

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Current Practice vs "Best Overall" vs "Best Hispanic" Model

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Current Practice vs "Best Overall" vs "Race Fair" Model

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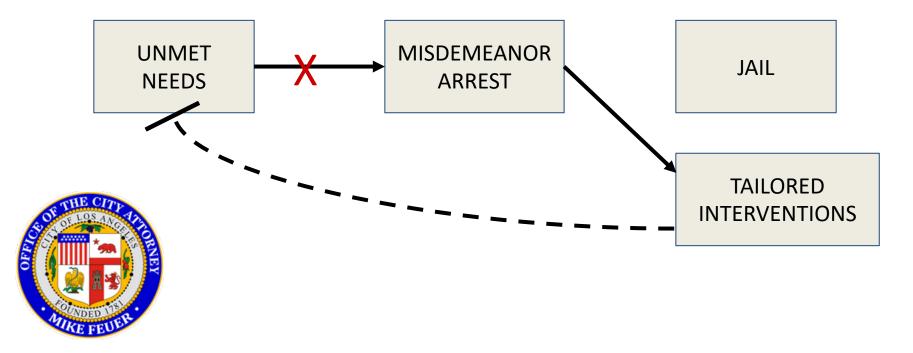
Case Study: Reducing Misdemeanor Recidivism through **Diversion and Social Service Programs**

Predictive Fairness to Reduce Misdemeanor Recidivism Through Social Service Interventions. Rodolfa et al. ACM FAT* 2020



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Case Study: Breaking the Cycle



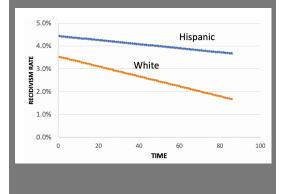
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Policy Menu

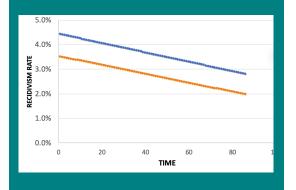
Designing for Efficiency

72.7% Efficient



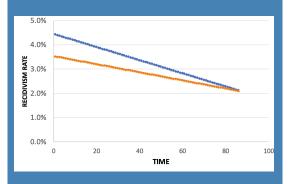
Equality

Additional Cost: 2%



Equity

Additional Cost: 2%



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code at github.com/dssg