

# Week 9 Notes

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**FAIR PREDICTION WITH DISPARATE IMPACT**

# Introduction



Recidivism prediction instruments (RPI's) provide decision makers with an assessment of the likelihood that a criminal defendant will reoffend at a future point in time



COMPAS

Developed by Northpointe Inc.

Risk Assessment used to determine recidivism likelihood



With such heavy impact we need to know if systems are bias

ProPublica Analysis to see if COMPAS is bias

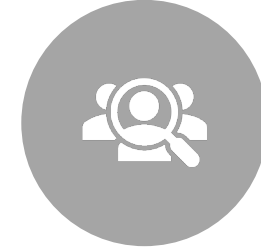
# Notation

- Let  $S=s(x)$  denote the risk Score.
- We let  $R \in \{b, w\}$  denote the group to which an individual belongs
- We denote the outcome indicator by  $Y \in \{0,1\}$ , with  $Y=1$  indicating that the given individual goes on to recidivate.
- We introduce the quantity  $sHR$ , which denotes the high-risk score threshold.
- Defendants whose score  $S$  exceeds  $sHR$  will be referred to as high risk, while the remaining defendants will be referred to as low risk.

# Four Different Fairness Criteria



CALIBRATION



PREDICTIVE PARITY



ERROR RATE BALANCE



STATISTICAL  
(DEMOGRAPHIC) PARITY

## Collaboration

A score  $S=S(x)$  is said to be well-calibrated if it reflects the same likelihood of recidivism irrespective of the individuals' group membership

In their response to the ProPublica investigation, Flores et al. [6] verify that COMPAS is well-calibrated using logistic regression modeling

# Predictive Parity



A score  $s = S(x)$  satisfies predictive parity at a threshold  $s_{HR}$  if the likelihood of recidivism among high-risk offenders is the same regardless of group membership.

$$\mathbb{P}(Y=1 \mid S > s_{HR}, R=b) \\ = \mathbb{P}(Y=1 \mid S > s_{HR}, R=w).$$



Predictive parity at a given threshold  $s_{HR}$  amounts to requiring that the positive predictive value (PPV) of the classifier  $Y^{\wedge} = 1_{S > s_{HR}}$  be the same across groups



Northpointe's refutation of the ProPublica analysis shows that COMPAS satisfies predictive parity for threshold choices of interest.

# Error Rate Balance

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A score  $S = s(x)$  satisfies error rate balance at a threshold  $s_{HR}$  if the false positive and false negative error rates are equal across groups

$$\mathbb{P}(S > s_{HR} \mid Y=0, R=b) = \mathbb{P}(S > s_{HR} \mid Y=0, R=w)$$

$$\mathbb{P}(S < s_{HR} \mid Y=1, R=b) = \mathbb{P}(S < s_{HR} \mid Y=1, R=w)$$

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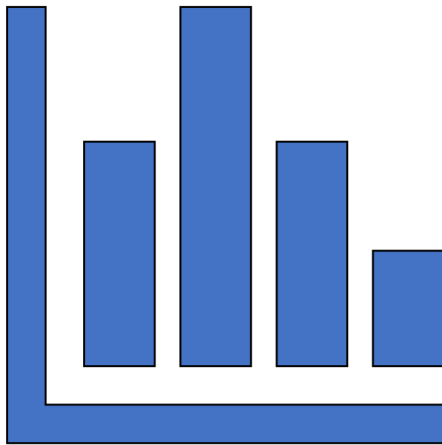
ProPublica analysis considered a threshold or  $s_{HR}=4$ , which they showed leads to considerable imbalance in both false positive and false negative rates.

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Error rate balance is also closely connected to the notions of equalized odds and equal opportunity

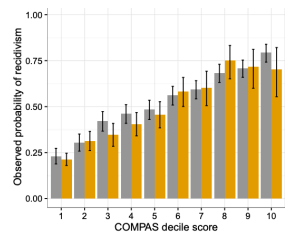


# Statistical (Demographic) Parity

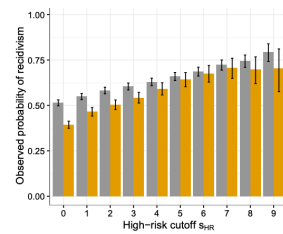


- A score  $S(x)$  satisfies statistical parity at a threshold  $s_{HR}$  if the proportion of individuals classified as high-risk is the same for each group.
- $\mathbb{P}(S > s_{HR}, |R = b) = \mathbb{P}(S > s_{HR}, |R = w)$
- Other names: Demographic parity, equal acceptance rates, group fairness.

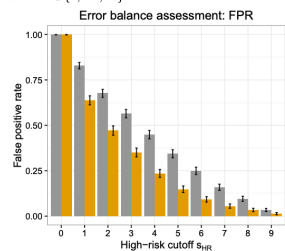
# Does Compas Satisfy



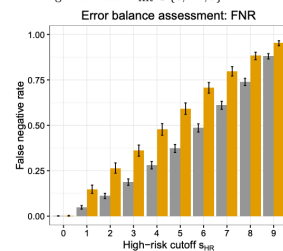
(a) Bars represent empirical estimates of the expressions in (2.1):  $\mathbb{P}(Y = 1 \mid S = s, R = r)$  for decile scores  $s \in \{1, \dots, 10\}$ .



(b) Bars represent empirical estimates of the expressions in (2.2):  $\mathbb{P}(Y = 1 \mid S > s_{HR}, R = r)$  for values of the high-risk cutoff  $s_{HR} \in \{0, \dots, 9\}$ .



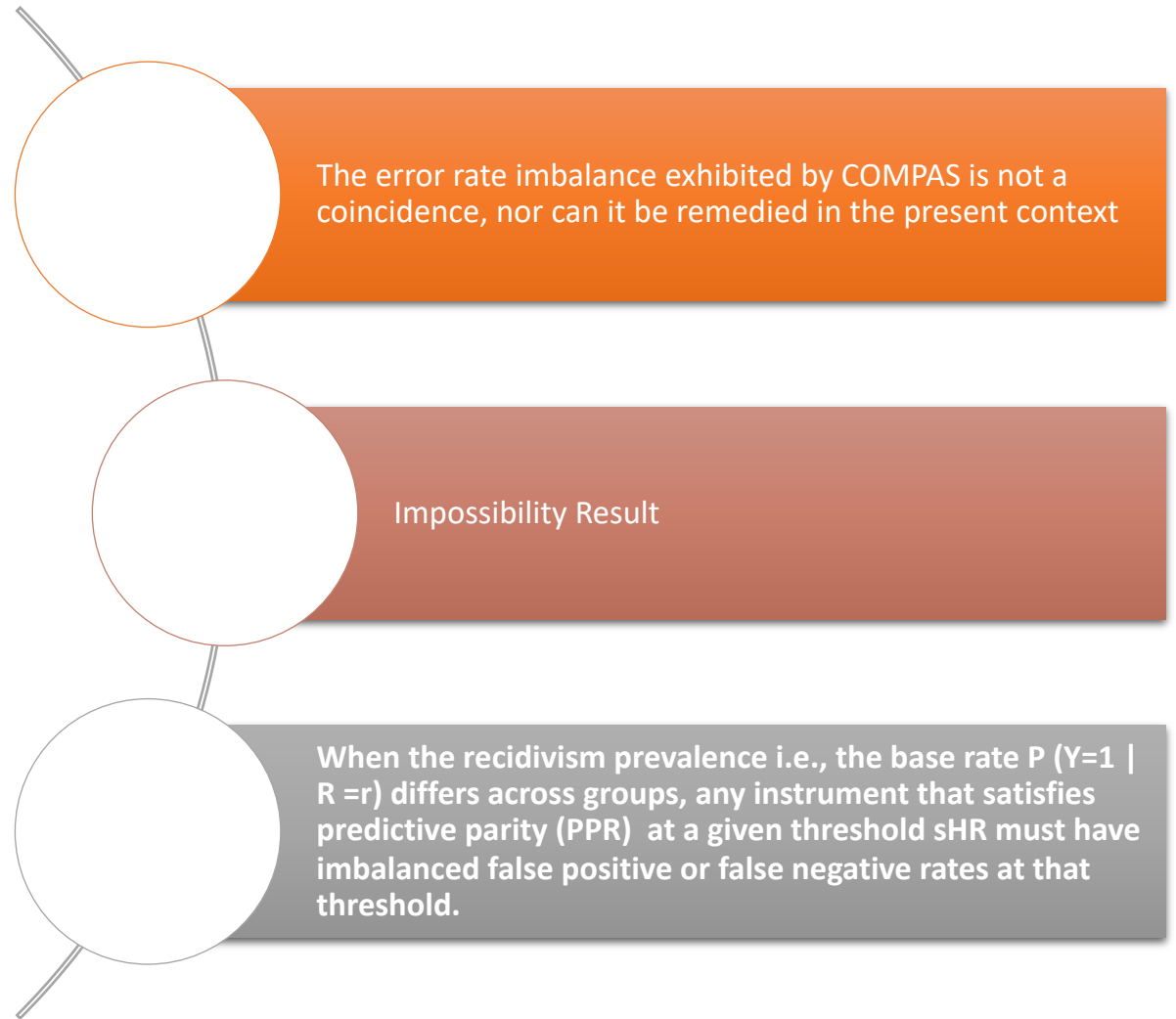
(c) Bars represent observed false positive rates, which are empirical estimates of the expressions in (2.3):  $\mathbb{P}(S > s_{HR} \mid Y = 0, R = r)$  for values of the high-risk cutoff  $s_{HR} \in \{0, \dots, 9\}$ .



(d) Bars represent observed false negative rates, which are empirical estimates of the expressions in (2.4):  $\mathbb{P}(S \leq s_{HR} \mid Y = 1, R = r)$  for values of the high-risk cutoff  $s_{HR} \in \{0, \dots, 9\}$ .

- Calibration Assessment
  - Yes
  - 95% Confidence Intervals Intercept for Black and White groups
- Predictive Parity
  - Yes
  - 95% Confidence Intervals Intercept for Black and White groups
- Error Balance
  - No
  - Higher False Positive Rates for Black Groups is Higher
- Statistical Parity
  - No
  - Higher False Negative Rates for White Groups is Higher

# Conclusion



$$\text{FPR} = \frac{p}{1-p} \frac{1 - \text{PPV}}{\text{PPV}} (1 - \text{FNR}).$$

*THURSDAY OCTOBER 24, 2019*

**EQUALITY OF OPPORTUNITY IN SUPERVISED  
LEARNING**

# Does this lead to disparate impact?

**Corollary 3.1** (Non-Recidivists). *Among individuals who do not recidivate, the difference in average penalty under the MinMax policy is*

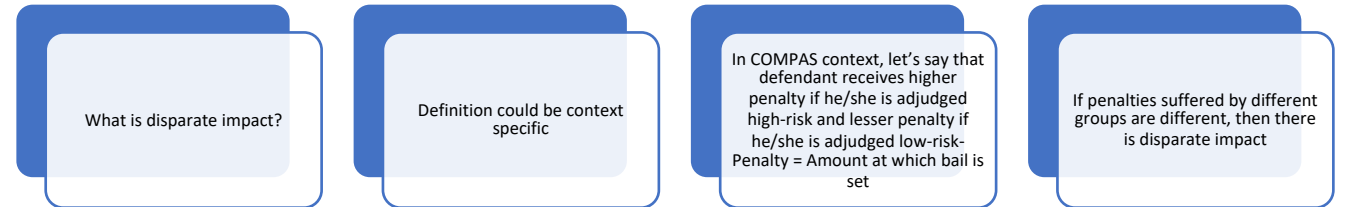
$$\Delta = (t_{\max} - t_{\min})(\text{FPR}_b - \text{FPR}_w), \quad (3.2)$$

where  $\text{FPR}_r$  denotes the false positive rate among individuals in group  $R = r$ .

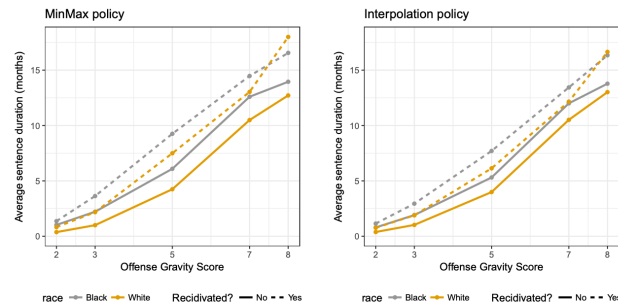
**Corollary 3.2** (Recidivists). *Among individuals who recidivate, the difference in average penalty under the MinMax policy is*

$$\Delta = (t_{\max} - t_{\min})(\text{FNR}_w - \text{FNR}_b), \quad (3.3)$$

where  $\text{FNR}_r$  denotes the false negative rate among individuals in group  $R = r$ .



# Important to see the Distinction



- Unfairness in ML relates more to predictions made by ML model
- Disparate impact deals more with what you do with the predictions
- Might be the case that unfair ML does not lead to disparate impact if it is not actually used to make decisions
  - Just using your ML model to understand how your features are correlated with your target variable

# Three Ways of Fixing Biases



PREPROCESS DATA



POSTPROCESSING DATA



MODIFY ML  
ALGORITHM

# What is their high-level approach?



Don't change anything in the ML training pipeline

Train models like you usually do



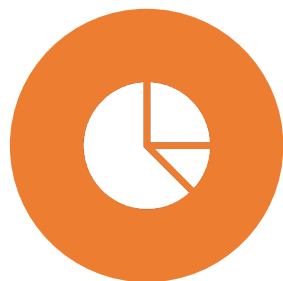
Do some post-processing on the outputs of the ML model

Make it fairer

Make this process oblivious to the training set



## 2 Fairness criteria that they try to establish



Equalized odds

- Across your two categories:  
FPR should be equal, TPR  
should be equal



Equal opportunity



We say that a binary predictor  $\hat{Y}_b$  satisfies equal opportunity with respect to  $A$  and  $Y$  if only satisfied for the positive class



Equal opportunity is a weaker, though still interesting, notion of non-discrimination, and thus typically

$$\Pr\{\hat{Y} = 1 \mid A = 0, Y = y\} = \Pr\{\hat{Y} = 1 \mid A = 1, Y = y\}, \quad y \in \{0, 1\}$$

# Deriving from Binary Predictor

$$\min_{\tilde{Y}} \mathbb{E} \ell(\tilde{Y}, Y) \quad (4.3)$$

$$\text{s.t. } \forall a \in \{0, 1\} : \gamma_a(\tilde{Y}) \in P_a(\hat{Y}) \quad (\text{derived})$$

$$\gamma_0(\tilde{Y}) = \gamma_1(\tilde{Y}) \quad (\text{equalized odds})$$

# Deriving from Binary Predictor pt.2

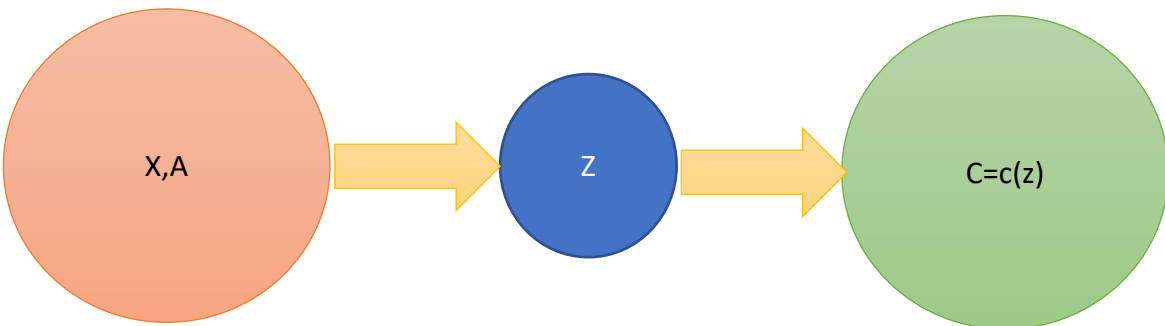
$$\gamma_a(\widehat{Y}) \stackrel{\text{def}}{=} (\Pr\{\widehat{Y} = 1 \mid A = a, Y = 0\}, \Pr\{\widehat{Y} = 1 \mid A = a, Y = 1\}). \quad (4.1)$$

**Lemma 4.2.** *A predictor  $\widehat{Y}$  satisfies:*

1. *equalized odds if and only if  $\gamma_0(\widehat{Y}) = \gamma_1(\widehat{Y})$ , and*
2. *equal opportunity if and only if  $\gamma_0(\widehat{Y})$  and  $\gamma_1(\widehat{Y})$  agree in the second component, i.e.,  $\gamma_0(\widehat{Y})_2 = \gamma_1(\widehat{Y})_2$ .*

$$P_a(\widehat{Y}) \stackrel{\text{def}}{=} \text{convhull}\{(0, 0), \gamma_a(\widehat{Y}), \gamma_a(1 - \widehat{Y}), (1, 1)\} \quad (4.2)$$

# Another Approach: Pre-Processing



Remove the sensitive attribute

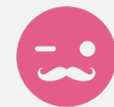


Remove all features with sensitive attribute



Brute Force Method?

For all the features that are somewhat correlated with the sensitive attribute



What is a more sophisticated method?

THAT'S IT!

QUESTIONS?

