Investigating discrimination bias in predictive modelling

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Background: The Problem

In recent years, many scandalous examples have shown that statistical models trained on large amounts of data can “act” discriminatory. Examples include:

- Adds of high-income jobs being shown less frequently to women, presumable becasue they’ve been predicted to be less interested or suitable[1]
- Black people’s health status being underestimated, leading to inappropriate healtch care measures[2]
- Black people begin predicted a higher risk for crime recidivism, leading to higher penalties[3]

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[1] Datta, Tschantz, and Datta (2015)
[2] Obermeyer et al. (2019)
[3] ProPublica (2016)

Project Aims

- How can we quantify fairness in order to be able to evaluate algorithmic fairness?
- What methods are available to increase algorithmic fairness? In what type of situations do they apply? (i.e. In what kind of situations can we expect them to be successful?)

Background: Why Discrimination Bias?

- Correlation between outcome y and protected charateristic x_p
- Correlation between important predictors $\boldsymbol{x}_i$ and protected carachteristic x_p
- Undersampling of groups with protected carachteristic x_p

Possible Solutions

Pre-Processing	**Training**	**Prediction**
Resampling	Penalty	Threshold
Mapping	Model bias	adjustments
Altering labels	Tuning for fairness	Alter predictions

We've chosen to work with resampling and threshold adjustment.

Possible Goals

Demographic parity

$$P(Y = 1|X = 1) = P(Y = 1|X = 0)$$

Equalized odds

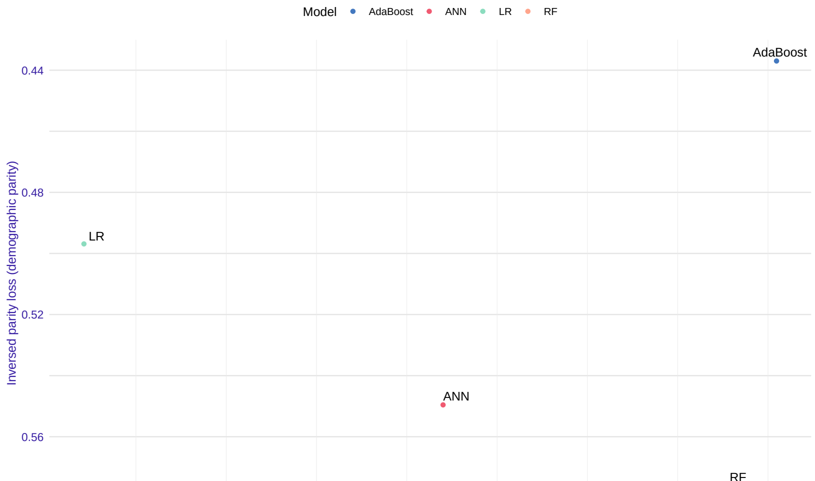
$$P(G = 1|X = 0, Y = 1) = P(G = 1|X = 1, Y = 1)$$

Models

Model	Tuning
Random Forest	Predictors at each split
Artificial neural net	Number of hidden nodes
Logistic ridge regression	Penalisation
K-nearest neighbour (left out)	Number of neighbours
AdaBoost	Predictors at each split

Accuracy and Fairness for the Initial Models

```
## Warning: namespace 'xgboost' is not available and has be
## by .GlobalEnv when processing object 'fobject1'
```



Disparate Impact Removal

Preferential Resampling

Uniform Resampling

Comparison

Final Model Performance

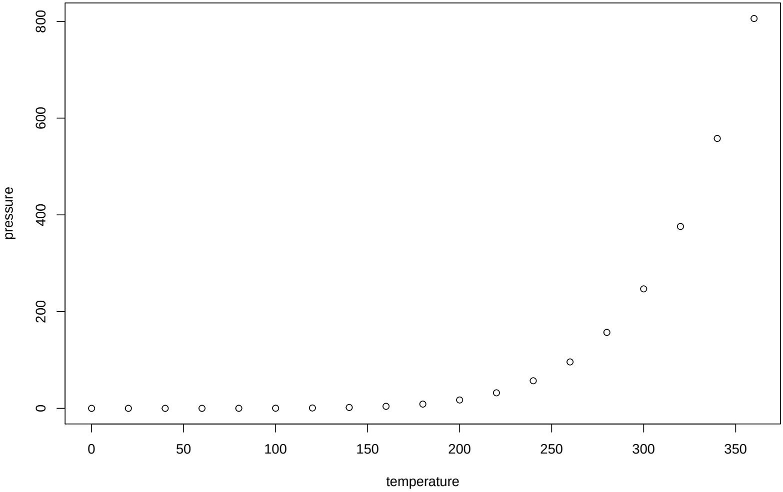
Conclusions

Slide with R Output

```r
summary(cars)
```

```
##      speed           dist       
##  Min.   : 4.0   Min.   :  2.00  
##  1st Qu.:12.0   1st Qu.: 26.00  
##  Median :15.0   Median : 36.00  
##  Mean   :15.4   Mean   : 42.98  
##  3rd Qu.:19.0   3rd Qu.: 56.00  
##  Max.   :25.0   Max.   :120.00  
```

Slide with Plot



Datta, Amit, Michael Carl Tschantz, and Anupam Datta. 2015. "Automated Experiments on Ad Privacy Settings." *Proceedings on*