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
- Under/over sampling 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

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

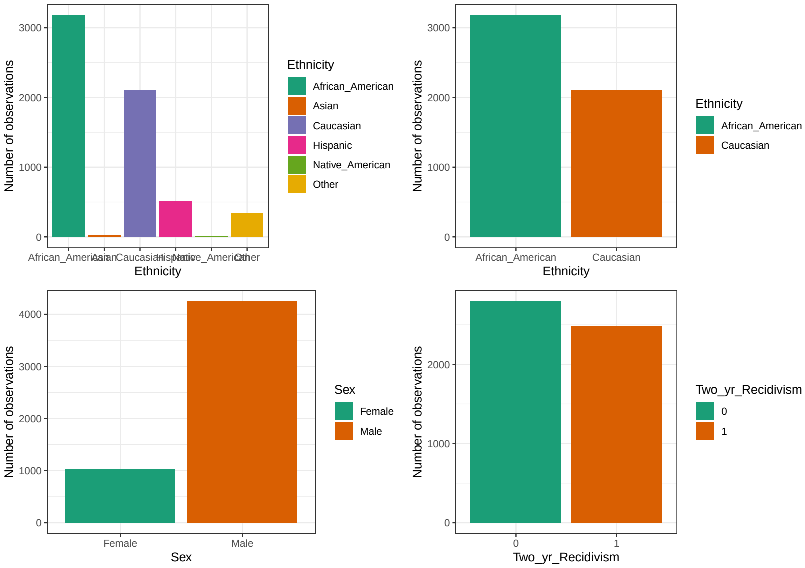
Data Frame Summary
COMPAS
Dimensions: 5278 x 7
Duplicates: 4706

No	Variable	Stats / Values	Freqs (% of Valid)
1	Two_yr_Recidivism [factor]	1. 0 2. 1	2795 (53.0%) 2483 (47.0%)
2	Number_of_Priors [integer]	Mean (sd) : 3.5 (4.9) min $<$ med $<$ max: 0 $<$ 2 $<$ 38 IQR (CV) : 5 (1.4)	36 distinct values
3	Above45 [factor]	1. 0 2. 1	4182 (79.2%) 1096 (20.8%)
4	Below25 [factor]	1. 0 2. 1	4122 (78.1%) 1156 (21.9%)
5	Misdemeanor [factor]	1. 0 2. 1	3440 (65.2%) 1838 (34.8%)
6	Ethnicity [factor]	1. African_American 2. Caucasian	3175 (60.2%) 2103 (39.8%)
7	Sex [factor]	1. Female 2. Male	1031 (19.5%) 4247 (80.5%)

Data

Variable	Type	Values
Two_yr_Recidivism	Factor	1 / 0
Number_of_Priors	Numerical	Mean (sd) : 3.5 (4.9)
Above45	Factor	1 / 0
Below25	Factor	1 / 0
Misdemeanor	Factor	1 / 0
Ethnicity	Factor	African_American / Caucasian
Sex	Factor	Female / Male

Descriptives



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

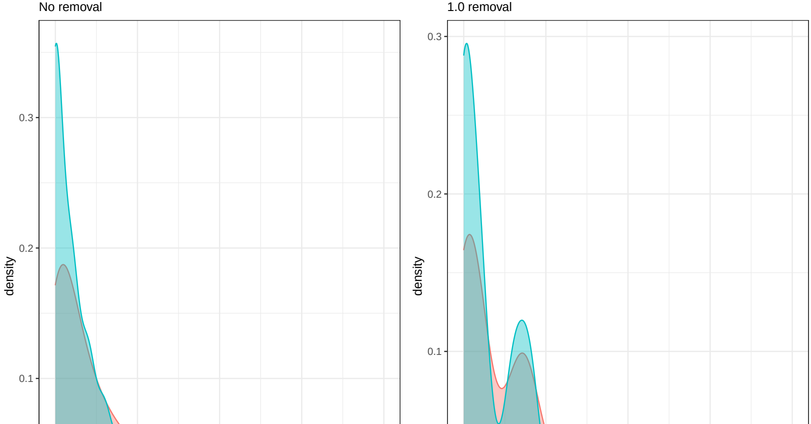
```
## Warning: namespace 'xgboost' is not available and has be
## by .GlobalEnv when processing object 'fobject1'
```

Disparate Impact Removal

Removes differences between groups while preserving it within the groups. Example: Number of priors.

```
## Warning: Removed 71 rows containing non-finite values (s
```

```
## Warning: Removed 71 rows containing non-finite values (s
```



Resampling

Using undersampling and oversampling to even out inequalities between the depraved and privileged groups having positive and negative outcome attributes respectively.

Table 5: Joint distribution of Ethnicity and Recidivism

	African_American	Caucasian
0	1514	1281
1	1661	822

Note: 1 = Recidivism

Uniform Resampling

Aim: Make the joint distribution of `Ethnicity` and `Two_yr_Recidivism` uniform by duplicating some observations and removing others.

Table 6: Joint distribution of Ethnicity and Recidivism, uniform resampling

	African_American	Caucasian
0	1352	885
1	1201	786

Note: 1 = Recidivism

Preferential Resampling

- Very similar to uniform
- Borderline observations skipped or duplicated more often
- Evaluated by logistic regression

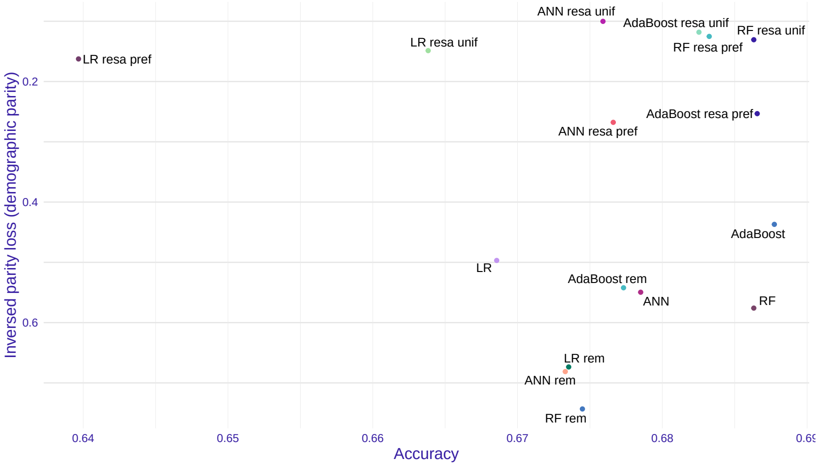
Table 7: Joint distribution of Ethnicity and Recidivism, preferential resampling

	African_American	Caucasian
0	1352	885
1	1201	786

Note: 1 = Recidivism

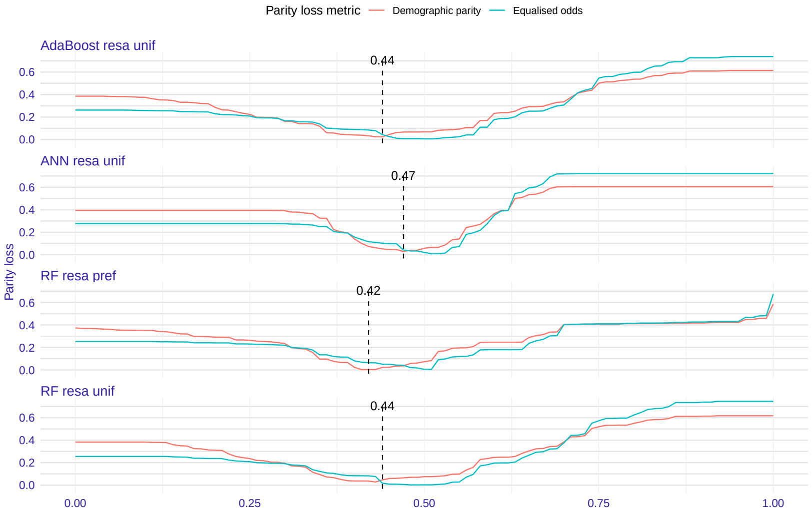
Comparison

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



Threshold Adjustment

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



Comparing Models with Different Thresholds

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

Evaluation on Test Data - Comparison

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

Final Model Performance and Conclusion

- The resampling methods seems to have best effect on minimising parity loss while also preserving accuracy rates
- Random Forest looked most promising, but while tested on new data Logistic Regression, Artifical Neural Network and AdaBoost were equally strong competitors

Table 8: Performance

recall	precision	accuracy	auc
0.717	0.654	0.649	0.7

General Conclusions

- It is possible to build models who satisfy some fairness criteria without a too large drop in accuracy
- Decisions for fair models include: fairness measure, evaluation metrics and choice of methods
- Less complex methods can be found amongst resampling and threshold adjustment
- As always, what type of data we are dealing with will largely impact the results of different methods (for example why disparate impact remover didn't work)

References

Datta, Amit, Michael Carl Tschantz, and Anupam Datta. 2015. "Automated Experiments on Ad Privacy Settings." *Proceedings on Privacy Enhancing Technologies* 2015 (1): 92–112. https://doi.org/https://doi.org/10.1515/popets-2015-0007.

Obermeyer, Ziad, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. 2019. "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations." *Science* 366 (6464): 447. https://doi.org/10.1126/science.aax2342.