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1 (Some) Fairness Metrics

Independence

- Statistical Parity/Demographic Parity: $P(\hat{Y} = 1|A = a) = P(\hat{Y} = 1|A = b)$
- Conditional Statistical Parity: $P(\hat{Y} = 1 | E = e, A = a) = P(\hat{Y} = 1 | E = e, A = b)$ E is a set of legitimate features that may affect the outcome.

Separation

- Equalized Odds: $P(\hat{Y}=1|Y=y,A=a)=P(\hat{Y}=1|Y=y,A=b) \forall y \in \{0,1\}$ mlr3: fairness.equalized.odds
- Equal Opportunity/ False negative error rate balance: $P(\hat{Y}=1|Y=1,A=a)=P(\hat{Y}=1|Y=1,A=b)$ mlr3: fairness.tpr
- Predictive Equality/ False positive error rate balance: $P(\hat{Y}=1|Y=0,A=a)=P(\hat{Y}=1|Y=0,A=a)$ or $P(\hat{Y}=0|Y=0,A=a)=P(\hat{Y}=0|Y=0,A=b)$ mlr3: fairness.fpr, fairness.tnr
- Treatment Equality: $\frac{\text{FN}}{\text{FP}}\Big|_{A=a} = \frac{\text{FN}}{\text{FP}}\Big|_{A=b}$

Sufficiency

- Predictive parity/ outcome test: $P(Y=1|\hat{Y}=1,A=a)=P(Y=1|\hat{Y}=1,A=b)$ mlr3: fairness.ppv
- Equal true negative rate: $P(Y=0|\hat{Y}=0,A=a)=P(Y=0|\hat{Y}=0,A=b)$ mlr3: fairness.npv
- Equal false omission rate*: $P(Y=1|\hat{Y}=0,A=a)=P(Y=1|\hat{Y}=0,A=b)$ mlr3: fairness.fomr
- Equal false discovery rate*: $P(Y=0|\hat{Y}=1,A=a)=P(Y=0|\hat{Y}=1,A=b)$
- Conditional use accuracy equality: $P(Y=1|\hat{Y}=1,A=a)=P(Y=1|\hat{Y}=1,A=b) \wedge P(Y=0|\hat{Y}=0,A=a)=P(Y=0|\hat{Y}=0,A=b)$

Score-based

- Calibration: P(Y = 1 | S = s, A = a) = P(Y = 1 | S = s, A = b)
- Well-calibration: P(Y=1|S=s,A=a) = P(Y=1|S=s,A=b) = s
- Balance for positive class: $E(S \mid Y = 1, A = a) = E(S \mid Y = 1, A = b)$
- Balance for negative class: $E(S \mid Y = 0, A = a) = E(S \mid Y = 0, A = b)$

Other

 • Overall Accuracy Equality: $P(\hat{Y}=Y|A=a) = P(\hat{Y}=Y|A=b)$ mlr3: fairness.acc

^{*} not officially defined in any of the three papers, but following the same principles as all confusion matrix based metrics

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2 Fairness Methods

- Preprocessing
- Inprocessing
- Postprocessing
- 3 Sources of bias and the feedback loop