Bias and Fairness in ML

Fairness

Fairness Definitions

Equality of Treatment

- Fairness through Unawareness
  - An algorithm is fair if protected attributes are not explicitly used in the decision-making process
- Counterfactual Fairness
  - An algorithm is fair if its output remains the same when the protected attribute is flipped to its counterfactual value

Equality of Outcomes

- Demographic Parity
  - Members of groups have an equal probability of being assigned to the positive class
- Conditional Statistical Parity
  - Demographic parity holds given a set of legitimate factors
- Fairness Through Awareness
  - An algorithm is fair if it gives similar predictions to similar individuals

Fairness Definitions

Equality of Performance/ Error

- Predictive Parity
  - Equalizing $FDR_g = \frac{FP_g}{FP_g + TP_g}$
- Sufficiency
  - Equalizing FDR_g and $FOR_g = \frac{FN_g}{FN_g + TN_g}$
- Equal Opportunity
  - Equalizing $FNR_g = \frac{FN_g}{FN_g + TP_g}$
- Equalized Odds
  - Equalizing FNR_g and $FPR_g = \frac{FP_g}{FP_g + TN_g}$
- Treatment Equality
  - Equalizing $\frac{FP_g}{FN_g}$
- Test Fairness
  - Considers complete score distribution across groups

Table: Confusion matrix

		Prediction 0	Prediction 1	
Reference	0	TN	FP	N'
	1	FN	TP	P'
		N	P	

→ Notions are in conflict with each other and with overall accuracy

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$\rightarrow$ *Notions are in conflict with each other and with overall accuracy*

Fairness Definitions

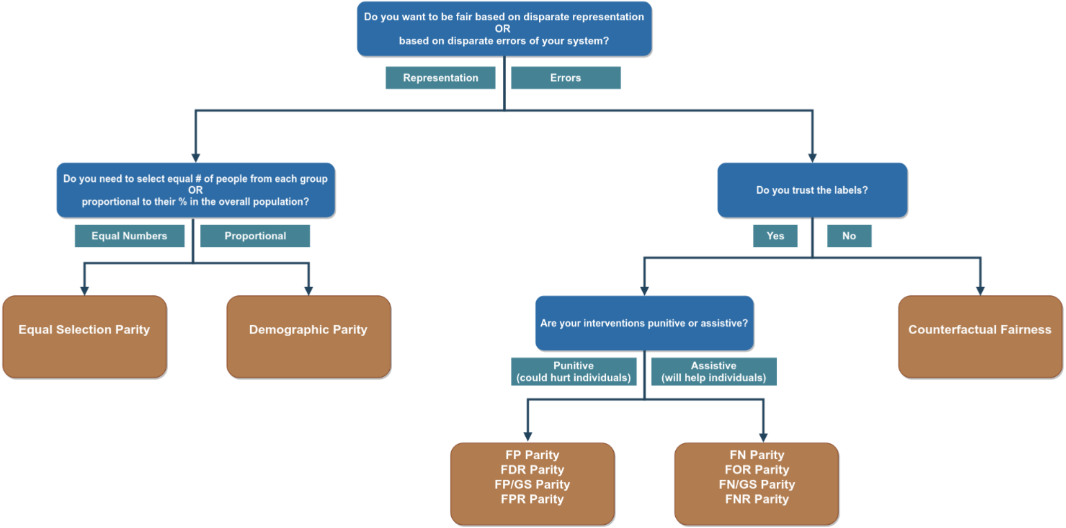
1. Individual Fairness: Give similar predictions to similar individuals
2. Group Fairness: Treat different groups equally
3. Subgroup Fairness: Extend group fairness to large collection of subgroups

Table: Categorizing Fairness Notions (Mehrabi et al. 2019)

	Group	Individual
Demographic parity	x	
Conditional statistical parity	x	
Equalized odds	x	
Equal opportunity	x	
Fairness through unawareness		x
Fairness through awareness		x
Counterfactual fairness		x

Fairness Definitions

Figure: Choosing Fairness Metrics (Saleiro et al. 2018)



Methods for Fair ML

Some Potential Solutions (Berk et al. 2017)

1. Pre-processing
   - Eliminating sources of unfairness in data before model training
     - Remove linear dependence between legitimate and protected predictors
     - Re-label some response values to make base rates comparable
     - Perturb class membership for protected attributes for some cases
2. In-processing
   - Making fairness adjustments as part of the model building process
     - Add fairness penalty to loss function
3. Post-processing
   - Adjust model output post-training to make it more fair
     - Randomly re-assign some predicted class labels

Software Resources

Resources for R

- PDP, ICE, ALE
  - Plot model surfaces: `plotmo`
  - Partial Dependence Plots: `pdp`
  - ICE plots: `ICEbox`
  - ALE plots: `ALEPlot`
- Interpretable Machine Learning in R: `iml`
- Descriptive mAchine Learning EXplanations: `DALEX`

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