Bursting the Burden Bubble?

An Assessment of Sharma et al.'s Counterfactual-Based Fairness Metric

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Outline

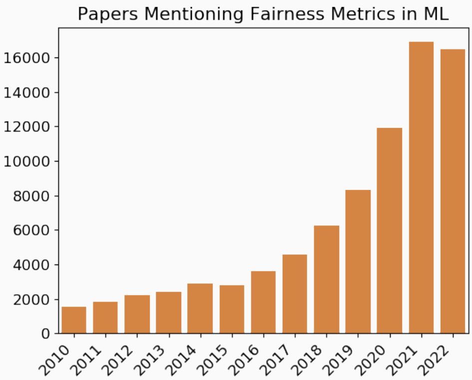
Fairness

Fairness

- What is fairness?
- Many aspects of fairness

Fairness

- What is fairness?
- Many aspects of fairness metrics

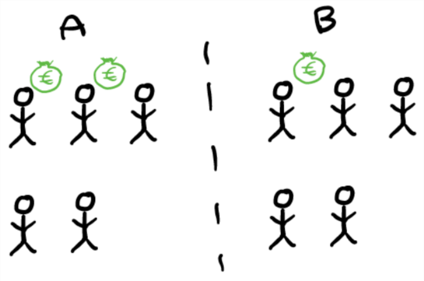


Statistical Parity

Statistical/Demographic Parity (SP_S) [2]:
Ratio of acceptance rates (AR_S).

$$SP_S = \frac{AR_{S=A}}{AR_{S=B}} = \frac{P(\hat{Y}=1|S=A)}{P(\hat{Y}=1|S=B)}$$

Perfect parity: $SP_S = 1$
80% rule [1]: $SP_S \geq 0.8$ is acceptable.



$$\frac{1/5}{2/5} = 0.5 < 0.8$$

No parity!

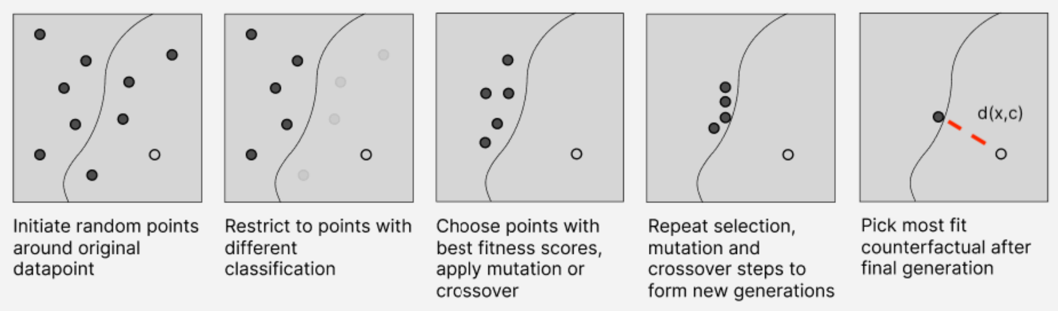
$\hat{Y}$: Model's prediction, S: Sensitive attribute/group

Burden

- Sharma et al.'s CERTIFAI[1] framework [3]
- Cognitive Scale
- Multiple domains
- Model Agnostic
- Counterfactuals
    - Not causal!
    - Generated with genetic algorithm

[1] Counterfactual Explanations for Robustness, Transparency, Interpretability, and Fairness of Artificial Intelligence models

Counterfactual generation



Evolutionary algorithm for the generation of realistic counterfactuals. Illustration adapted from [3].

Burden

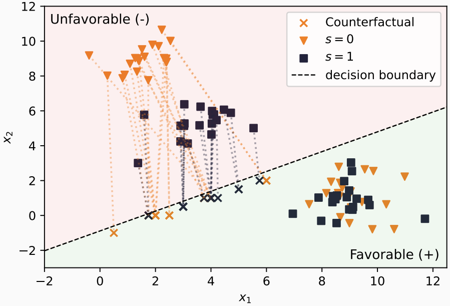
- Distance to counterfactual →individual *recourse*.
- Average distance to counterfactual over instances in a group s, with $\mathbf{c}^*$ the found counterfactual(s):

$$\text{Burden}_{S=s} = \mathbb{E}_{S=s}[d(\mathbf{x}, \mathbf{c}^*)]$$

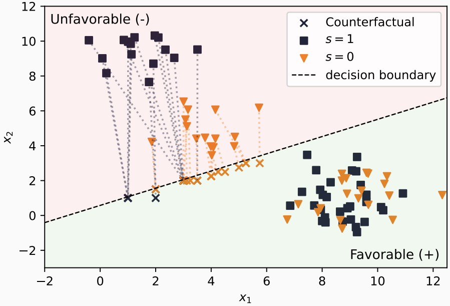
Experiments

Synthetic datasets

- Goal: Highlighting theoretical difference between metrics
- What the metrics measure:
  - Burden: Estimated distance to counterfactual
  - SP: Rate of favorably classified
- Approach:
  - Dataset D_A: $AR_{S=0} = AR_{S=1}$, $\text{Burden}_{S=0} > \text{Burden}_{S=1}$
  - Dataset D_B: $AR_{S=0} > AR_{S=1}$, $\text{Burden}_{S=0} < \text{Burden}_{S=1}$



(a) D_A, where Burden and statpar disagree on the presence of unfairness.



(b) D_B, where Burden and statpar disagree on the direction of unfairness.

Real world dataset

- Default of Credit Card Clients Data Set, “Taiwan” [4]
    - Target: did the person default on loan?
    - 30,000 instances (1000 counterfactuals)
    - 4 Sensitive attributes (dropped for training)
    - All features concerning account balances
- Logistic Regression with 78% accuracy

Results

	Acceptance Rate		SP	Burden		
Dataset	$S=0$	$S=1$	0/1	$S=0$	$S=1$	0/1
D_A	0.500	0.500	1.00	**11.6**	4.65	2.49
D_B	**0.571**	0.667	0.857	3.31	**11.0**	0.302
Taiwan	0.967	**0.948**	1.02	**1.38**	0.940	1.47

Underprivileged group according to metric in **boldface**.

Conclusions

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- Burden can provide more nuance than Statistical Parity
- Computational cost of Burden is high
- Burden can be used in addition to Statistical Parity

Concluding, be mindful when using a single fairness metric!

Future Work

Future Work

- Reduce computational complexity of Burden
- Find real-world datasets with SP and Burden disagree on the direction of unfairness
- Generate counterfactuals for a larger number of datapoints from the Taiwan dataset

Questions?

References i

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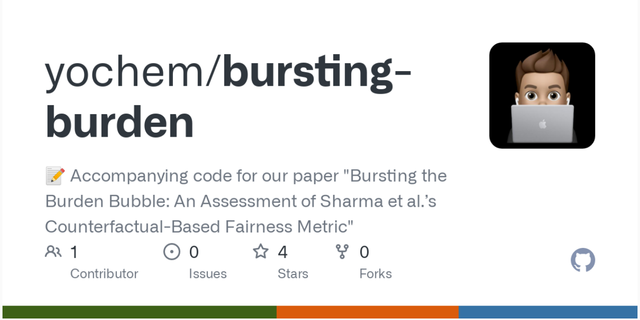
Find the slides, paper and code on GitHub!



github.com/yochem/bursting-burden