Bursting the Burden Bubble?

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

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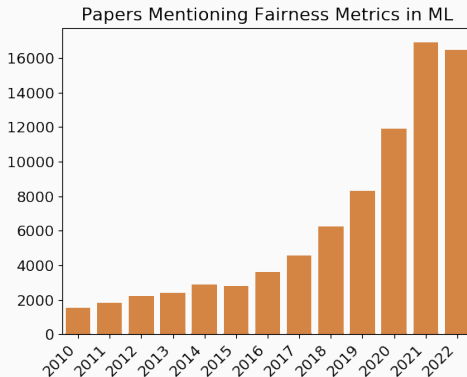*November 8, 2022*

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Outline

Fairness

- What is fairness?
- Many aspects of fairness

- What is fairness?
- Many aspects of fairness metrics
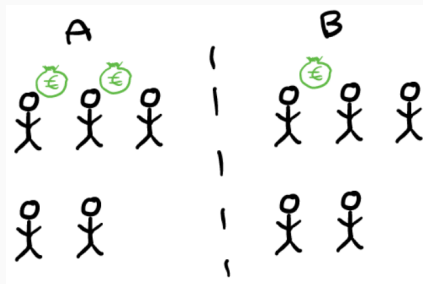
Statistical/Demographic Parity (SP_S) [2]:
Ratio of acceptance rates (AR_S).

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

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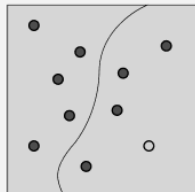

$$\frac{1/5}{2/5} = 0.5 < 0.8$$
No parity!

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

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

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[1]Counterfactual Explanations for Robustness, Transparency, Interpretability, and Fairness of Artificial Intelligence models
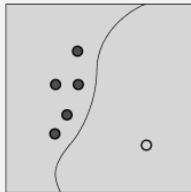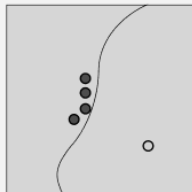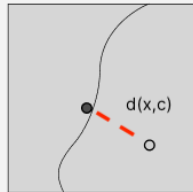
Initiate random points around original datapoint
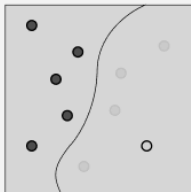
Restrict to points with different classification

Choose points with best fitness scores, apply mutation or crossover

Repeat selection, mutation and crossover steps to form new generations

Pick most fit counterfactual after final 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
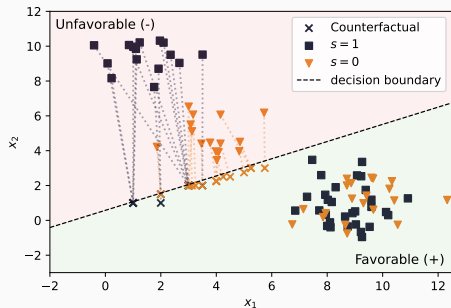
- Goal: Highlighting theoretical difference between metrics
- What the metrics measure:
    - Burden: Estimated distance to counterfactual
    - SP: Rate of favorably classified
- Approach:
    - Dataset D_A: $AR_{S=0} = AR_{S=1}$, $Burden_{S=0} > Burden_{S=1}$
    - Dataset D_B: $AR_{S=0} > AR_{S=1}$, $Burden_{S=0} < Burden_{S=1}$
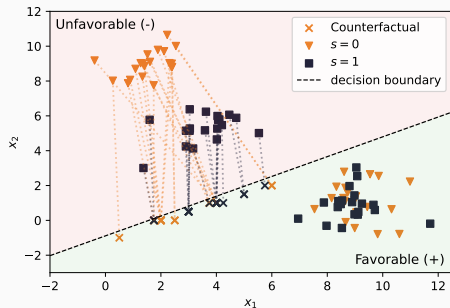
(a) D_A, where Burden and statpar disagree on the presence of unfairness.

(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

Conclusions

- 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

- 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?

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The Comparisons of Data Mining Techniques for the Predictive Accuracy of Probability of Default of Credit Card Clients.
Expert Systems with Applications, 36(2):2473––2480, March 2009.

yochem/**bursting-burden**

📝 Accompanying code for our paper "Bursting the Burden Bubble: An Assessment of Sharma et al.'s Counterfactual-Based Fairness Metric"

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Contributor

⊙ 0
Issues

☆ 4
Stars

⑂ 0
Forks

github.com/yochem/bursting-burden