Improving Fairness Generalization Through a Sample-Robust Optimization Method

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Context

- The paper is published in the **Machine Learning** journal, in July 2022
- Link to the paper `link.springer.com/article/10.1007/s10994-022-06191-y`
- Preprint: `https://hal.archives-ouvertes.fr/hal-03709547`
- Open source code `https://github.com/ferryjul/FairnessSampleRobustness`

Context

- Fairness in machine learning
- Statistical measures
- Generalisation of fairness on unseen data is one of the open challenges for trustworthy machine learning

The COMPAS Example [Angwin et al., 2016]

- Binary classification task: Recidivism within two years
- Sensitive attribute: Ethnicity (African-American/Caucasian)
- Protected Groups:
  - $\mathcal{A}$: African-American individuals;
  - $\mathcal{B}$: Caucasian individuals;

Statistical Fairness

- Principle: ensure that some measure $\mathcal{M}$ *differs by no more than* ϵ between several *protected* groups
- In the particular case of two protected groups ($\mathcal{A}$) and ($\mathcal{B}$), one need to ensure that $|\mathcal{M}(\mathcal{A}) - \mathcal{M}(\mathcal{B})| < \epsilon$

Supervised Fair Learning: A Bi-Objective Optimization Problem

- Notation: $\mathcal{D}$ initial dataset, h prediction model, ϵ unfairness tolerance
- Let unf$(\cdot)$ be an unfairness oracle. A common formulation of the Fair Learning problem is:

$$\begin{aligned} \underset{h \in \mathcal{H}}{\arg\min} \quad & f_{obj}(h, \mathcal{D}) \\ \text{s.t.} \quad & \text{unf}(h, \mathcal{D}) \leq \epsilon \end{aligned} \tag{1}$$

  where one wants to build model h minimizing objective function f_{obj} and exhibiting unfairness withing an ϵ threshold (on training dataset $\mathcal{D}$)
- The fairness constraint does not generalize well in practice [Cotter et al., 2018, 2019]

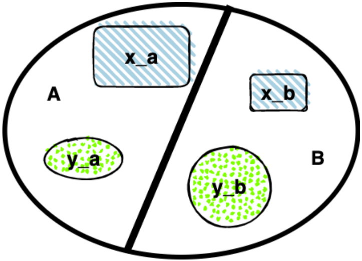
Distributionally Robust Optimization (DRO)

- Instead of minimizing objective function f_{obj} for a given distribution $\mathcal{P}$, DRO aims at minimizing f_{obj} for a worst-case distribution among a *perturbation set* of $\mathcal{P}$ [Sagawa et al., 2019] $\mathcal{B}(\mathcal{P})$

Perturbation Set based on the Jaccard Distance

- Let $\mathcal{D}_1$ and $\mathcal{D}_2$ be two sample sets. The Jaccard distance between $\mathcal{D}_1$ and $\mathcal{D}_2$ is defined as follows: $J_\delta(\mathcal{D}_1, \mathcal{D}_2) = 1 - \frac{|\mathcal{D}_1 \cap \mathcal{D}_2|}{|\mathcal{D}_1 \cup \mathcal{D}_2|}$

Robustness Evaluation via an Integer Program



- Let $\mathcal{D}'$ be the subset of $\mathcal{D}$ where the colored sets are removed
- If h is not fair on $\mathcal{D}'$, then h is not robust on the perturbation set defined with the distance between $\mathcal{D}$ and $\mathcal{D}'$

The Integer Program

$$\begin{aligned}
&\min && n && (2)\\
&\text{s.t.} && n = x_a + x_b + y_a + y_b && (3)\\
& && \left|\frac{M_a - x_a}{N_a - x_a - y_a} - \frac{M_b - x_b}{N_b - x_b - y_b}\right| > \epsilon && (4)\\
&0 \leq x_a \leq M_a && 0 \leq x_b \leq M_b &&\\
&0 \leq y_a \leq M_a - M_a && 0 \leq y_b \leq N_b - M_b &&\\
&x_a + y_a < N_a && x_b + y_b < N_b &&
\end{aligned}$$

- The optimal value can be used to identified the largest perturbation set where the robustness constraint is satisfied

Setup description

- We compare:
  - `FairCORELS` [Aïvodji et al., 2019]
  - TFCO: TensorFlow Constrained Optimization
  - Exact and Heuristic approaches
- Four fairness metrics:
  - Statistical Parity [Dwork et al., 2012]
  - Predictive Equality [Chouldechova, 2017]
  - Equal Opportunity [Hardt et al., 2016]
  - Equalized Odds [Hardt et al., 2016]
- Four biased datasets:
  - Adult Income dataset [Frank and Asuncion, 2010]
  - COMPAS dataset [Angwin et al., 2016]
  - Default Credit dataset [Yeh and Lien, 2009]
  - Bank Marketing dataset [Moro et al., 2014]
- The Integer Program is solved using the constraint programming solver OrTools

Experimental Results (FairCORELS) I

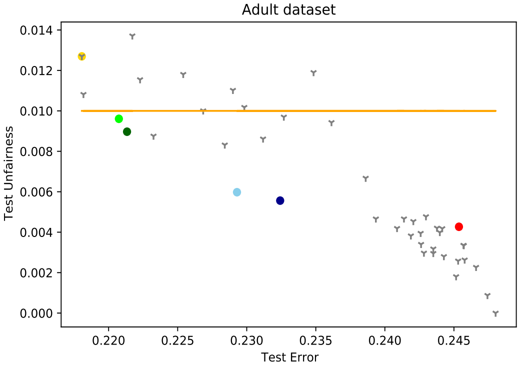


Figure: Test error and unfairness of models generated by `FairCORELS` using our exact and heuristic sample-robust fair methods (Statistical Parity metric, $\epsilon = 0.01$)

Summary

- We address the problem of fairness generalisation via an approach based on Distributionally Robust Optimization
- We empirically show that our approach is competitive to the state-of-the-art with two learning models on many datasets in the literature using different fairness measures

Future Work

- Can we find an efficient way to approximate the best parameters ?
- How to extend the work with other distance functions ?

Thank you!

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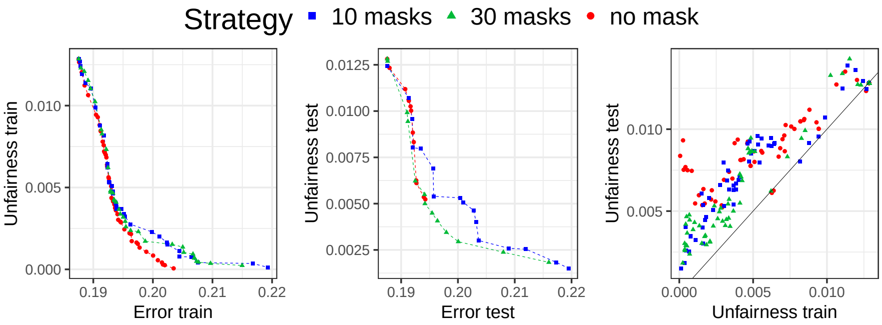

Figure: Results obtained on the Default Credit dataset, for the Predictive Equality metric

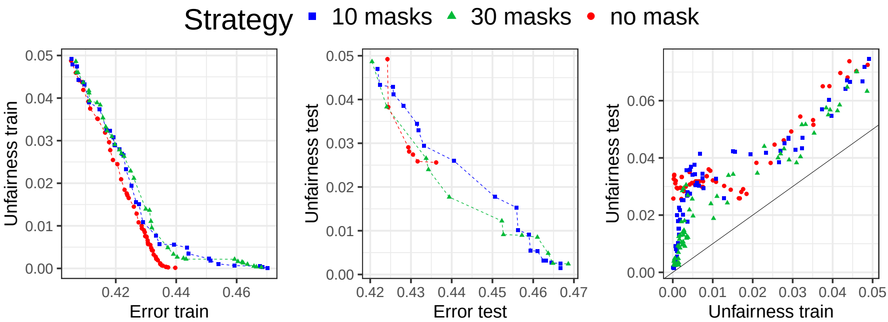

Figure: Results obtained on the COMPAS dataset, for the Statistical Parity metric

Rule Lists: Definition

Rule lists [Rivest, 1987] are classifiers formed by an ordered list of *if-then* rules with antecedents in the *if* clauses and predictions in the *then* clauses. More precisely, a rule list $r = (\{p_{k,k\in\{1..K\}}\}, \{q_{k,k\in\{1..K\}}\}, q_0)$ consists of K distinct association rules $p_k \rightarrow q_k$, in which p_k is the antecedent of the association rule and q_k its associated consequent, followed by a default prediction q_0.

A possible rule list for the example dataset of slide ?? (with 100% accuracy)

```
if [Education:Dropout] then [low]
else if [Gender:Male AND Age>45] then [high]
else [low]
```

FairCORELS Problem Formulation

- Based on the CORELS algorithm [Angelino et al., 2017a,b]
- FairCORELS [Aïvodji et al., 2019] returns rule list r^* that is a solution to the following problem:

$$\begin{aligned} \underset{r \in \mathcal{R}}{\arg\min} \quad & \mathrm{misc}(h, \mathcal{D}) + \lambda . K_r \\ \text{s.t.} \quad & \mathrm{unf}(h, \mathcal{D}) \leq \epsilon \end{aligned}$$

where:

- $\mathcal{R}$ is the space of rule lists
- $\mathcal{D}$ denotes the training dataset
- K_r is the length of rule list r
- λ is a regularization parameter balancing sparsity and accuracy
- $\mathrm{misc}(\cdot)$ is the misclassification error and $\mathrm{unf}(\cdot)$ measures unfairness

FairCORELS search space

- FairCORELS represents the search space of rule lists as a prefix tree (trie)
- FairCORELS leverages several bounds to efficiently explore this search space (including CORELS' original bounds)

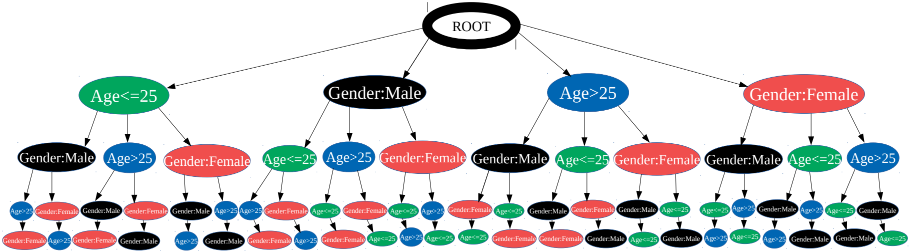

Figure: Example prefix tree with 4 attributes