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EXPLAINABILITY FOR FAIR MACHINE LEARNING

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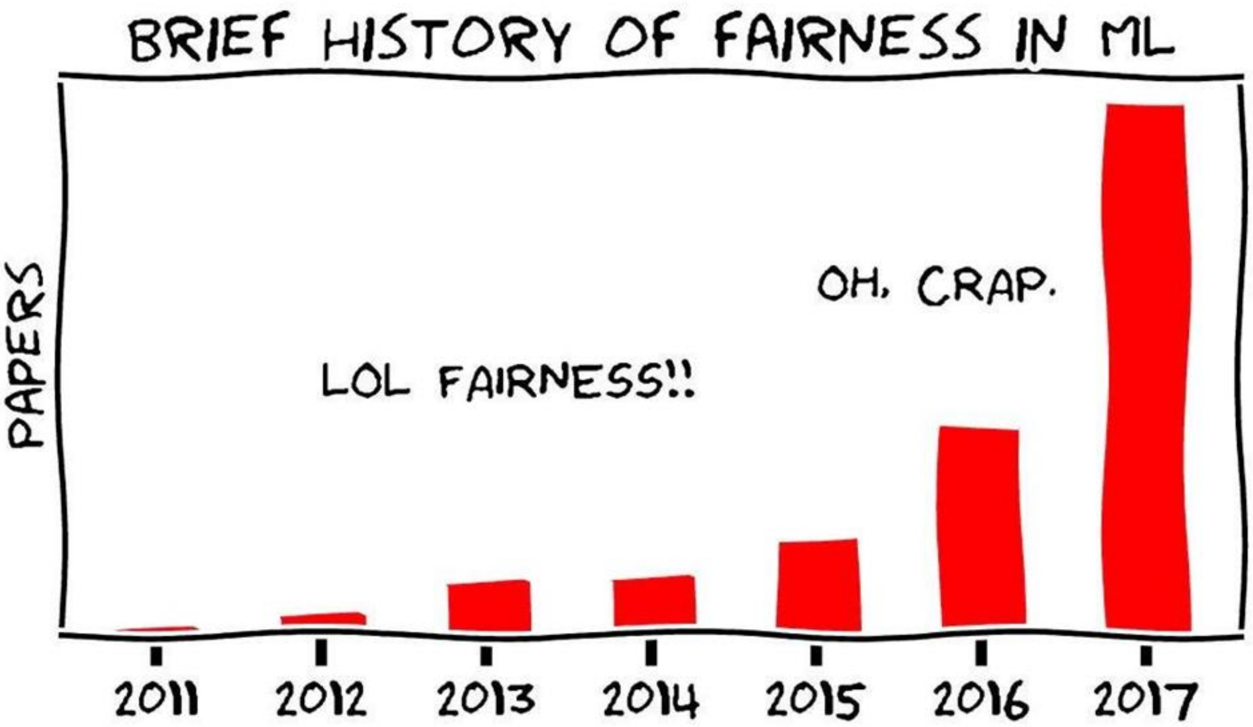
Fair Machine Learning



Fair Machine Learning - Challenges

- **Defining fairness** is hard:
  - Many competing definitions, often incompatible with each other
    - statistics-based, causal-reasoning-based, etc.
    - focus on group outcomes vs. individual outcomes
  - Requires contextual understanding

Name	Closest relative	Note
Statistical parity	Independence	Equivalent
Group fairness	Independence	Equivalent
Demographic parity	Independence	Equivalent
Conditional statistical parity	Independence	Relaxation
Equal opportunity	Separation	Relaxation
Equalized odds	Separation	Equivalent
Conditional procedure accuracy equality	Separation	Equivalent
Disparate mistreatment	Separation	Equivalent
Balance for positive class	Separation	Relaxation
Balance for negative class	Separation	Relaxation
Predictive equality	Separation	Relaxation
Conditional use accuracy equality	Sufficiency	Equivalence
Predictive parity	Sufficiency	Relaxation
Calibration	Sufficiency	Equivalence

Fairness definitions - Example

- **demographic parity: “f(x) be unconditionally independent of sensitive attr. a.”**

if 100 female students and 100 male students apply to Harvard University, **demographic parity** is achieved if **the percentage of** female students admitted is **the same** as **the percentage of** male students admitted, **irrespective of whether one group is on average more qualified than the other**.

Fairness definitions - Example

- **equalized odds: “f(x) be independent of sensitive attr. a given y”**

if 100 female students and 100 male students apply to Harvard University, equalized odds is achieved if **qualified** female and male students both have **the same chance** of being **admitted**, and **unqualified** female and male students have **the same chance** of being **rejected.**

Female students

	Qualified	Unqualified
Admitted	45	2
Rejected	45	8
Total	90	10

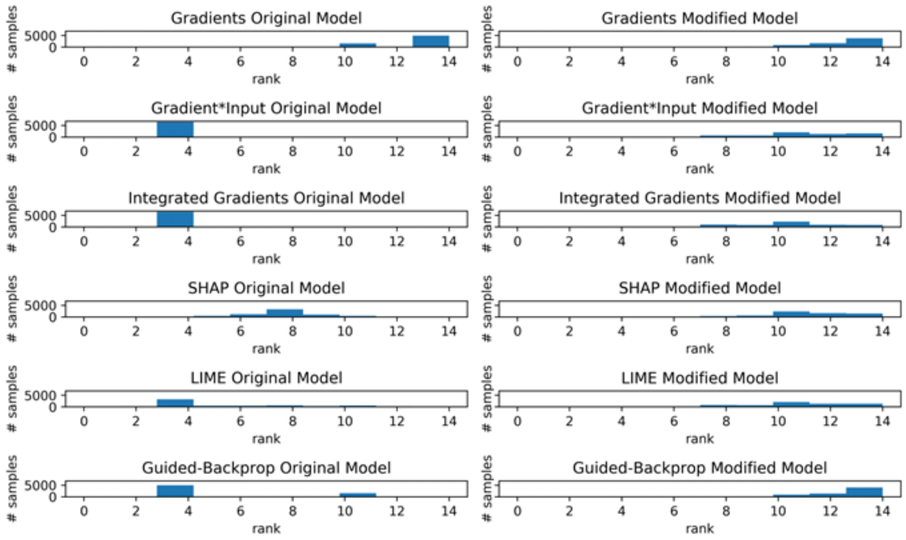
Male students

	Qualified	Unqualified
Admitted	5	18
Rejected	5	72
Total	10	90

Fair Machine Learning - Challenges

- Explanation methods can be **manipulated**
    - [*You shouldn't trust me: Learning models which conceal unfairness from multiple explanation methods*, Dimanov, ECAI, 2020]

Demonstrates that an explanation attack can easily mask a model's discriminatory use of a sensitive feature without hurting accuracy [Dimanov, 2020]



Importance ranking histograms for gender as the sensitive feature on the adult test set of the original (left) and modified (right) models.

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Fair Machine Learning - Proposed Solution

- A **unified** approach that works for many **group-fairness** criteria
  - demographic parity, equalised odds, conditional demographic parity
  - for each definition, choose Shapley value functions that attribute overall fairness to individual features.
- **Cannot hide unfairness** by manipulating explanations
  - Fairness Shapley values collectively must sum to the chosen fairness metric

Methodology

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Explaining Model Accuracy

- If the team earns a total value $v(N)$, the Shapley value $\phi_v(i)$ attributes a portion to player i according to:

$$\phi_v(i) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(n-|S|-1)!}{n!}\left[v(S \cup \{i\}) - v(S)\right] \tag{1}$$

- Binary classification problem:

$$f_y(x) = (1-y)(1-f(x)) + y\,f(x) \tag{2}$$

- Define a value function by marginalising over out-of-coalition features:

$$v_{f_y(x)}(S) = \mathbb{E}_{p(x')}\left[f_y(x_S \sqcup x'_{N \setminus S})\right] \tag{3}$$

- Global explanation of the model's performance:

$$\Phi_f(i) = \mathbb{E}_{p(x,y)}\left[\phi_{f_y(x)}(i)\right] \tag{4}$$

- Aggregating global Shapley values

$$\sum_i \Phi_f(i) = \mathbb{E}_{p(x,y)}\left[f_y(x)\right] - \mathbb{E}_{p(x')p(y)}\left[f_y(x')\right] \tag{5}$$

Expected accuracy for a model which samples a predicted label according to the predicted probability

The accuracy that is not attributable to any of the features and is related to the class balance

Methodology

- Explainable Fairness:
  - How Shapley value paradigm can be adapted to explain fairness.
- Meta Algorithm:
  - Motivation: axiomatic properties of Shapley values
  - Applying existing training-time fairness interventions, wherein one trains a perturbation to the original model, rather than a new model entirely.

Explaining Model Fairness

- To explain fairness in a model's decisions, they define a new value function that captures this effect

Demographic parity calls for $f(x)$ to be unconditionally independent of a

$$g_a(x) = f(x) \cdot \frac{(-1)^a}{p(a)} \qquad (6)$$

a: sensitive attribute

- The value function on coalitions is defined through marginalisation:

$$v_{g_a(x)}(S) = \mathbb{E}_{p(x')}\left[g_a(x_S \sqcup x'_{N \setminus S})\right] \qquad (7)$$

$$\Phi_g(i) = \mathbb{E}_{p(x,a)}\left[\phi_{g_a(x)}(i)\right] \qquad (8)$$

The joint distribution of features and protected attribute from which the data is sampled

$$\sum_i \Phi_g(i) = \int dx\, p(x|a=0)\, f(x) - \int dx\, p(x|a=1)\, f(x) \qquad (9)$$

Each feature's marginal contribution to the overall demographic disparity in the model

Learning Corrective Perturbations

- The linearity axiom of the Shapley values guarantees that the fairness Shapley values of a linear ensemble of models are the corresponding linear combination of Shapley values of the underlying models.
- Motivated by this they consider the problem of learning an additive perturbation to an existing model in order to impose fairness.

$$f_\theta = f + \delta_\theta \tag{10}$$

$$\delta_\theta(f(x), x, a) = \sigma\Big(\sigma^{-1}(f(x)) + \underline{\tilde{\delta}_\theta\big(f(x), x, a\big)}\Big) - f(x). \tag{11}$$

Any training-time fairness algorithm used to learn the auxiliary perturbation
e.g. Agarwal et al. (2018) and Zhang et al. (2018)

The key idea is to reduce fair classification to a sequence of cost-sensitive classification problems, whose solutions yield a randomized classifier with the lowest (empirical) error subject to the desired constraints.

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Experiments & Results

Datasets

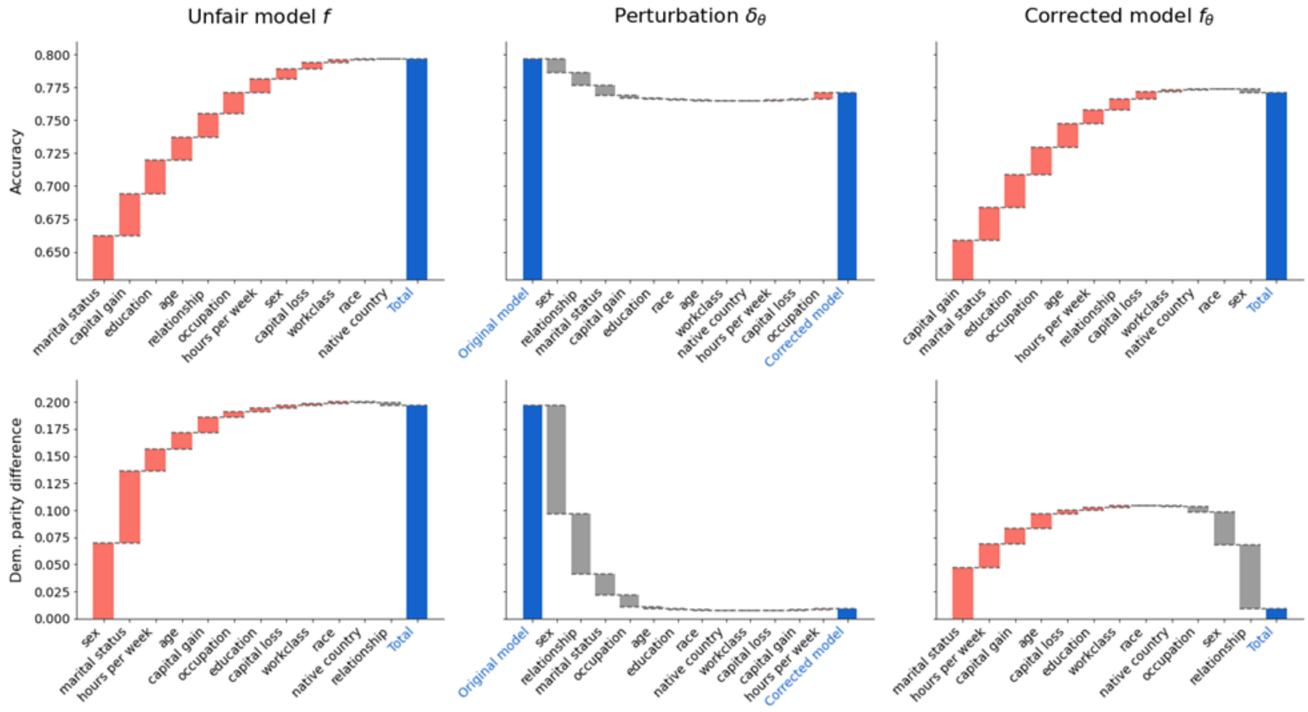
1. Adult dataset - UCI Machine Learning Repository (Dua & Graff, 2017)

   *Task: predict whether an individual **earns more than $50K per year** based on their **demographics***

1. COMPAS recidivism dataset (Larson et al., 2016)

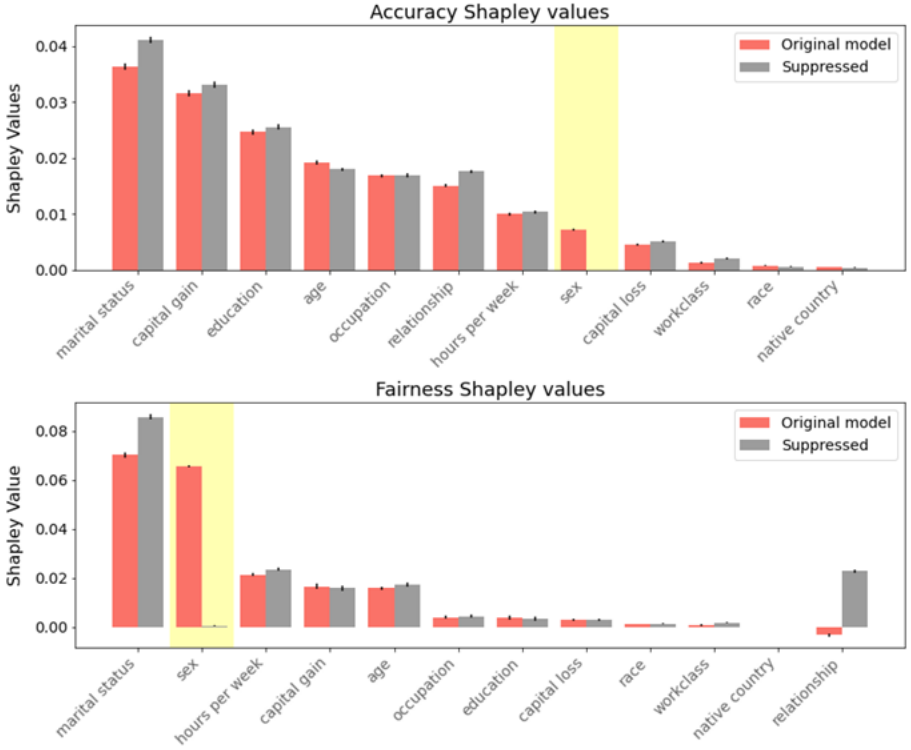
   *Task: predict **recidivism risk** based on **demographics***

Explainability



- Marital Status
- Sex
- Relationship

Robustness of Fairness Explanation



- Suppressing the importance of the sex feature.
- Demographic Parity Difference: 0.193 -> 0.184

Learnt Perturbations - Performance

Table 1: Accuracy associated with decreasing demographic parity thresholds.

	Method	**Accuracy [%] at demographic parity difference** 0.1	0.08	0.06	0.04	0.02	0.01	0.005
Adult	Agarwal et al.	84.71	84.32	83.94	83.82	83.29	83.29	-
	Agarwal et al. - perturbed	84.69	84.43	83.82	83.82	83.35	83.23	-
	Zhang et al.	84.65	84.18	84.06	83.58	83.18	83.15	83.15
	Zhang et al. - perturbed	84.74	84.48	83.78	83.61	83.14	82.99	82.96
	Feldman et al. (post)	84.69	84.35	84.12	83.67	83.32	83.30	83.01
COMPAS	Agarwal et al.	74.05	74.05	73.77	73.67	73.11	73.11	73.01
	Agarwal et al. - perturbed	74.24	74.24	73.86	73.86	73.20	72.73	72.73
	Zhang et al.	75.19	75.19	75.19	74.62	74.15	74.15	74.15
	Zhang et al. - perturbed	74.24	74.24	74.24	73.30	73.30	73.20	72.73
	Feldman et al. (post)	74.81	74.81	74.81	74.24	74.24	73.20	72.35

- No significant reduction under the fairness definition of **demographic darity**.

Learnt Perturbations - Performance

Table 2: Accuracy associated with decreasing equalised odds thresholds.

		Accuracy [%] at equalised odds difference						
	Method	0.1	0.08	0.06	0.04	0.02	0.01	0.005
Adult	Agarwal et al.	85.32	85.32	85.13	84.30	84.18	-	-
	Agarwal et al. - perturbed	85.43	85.43	85.31	84.34	84.21	-	-
	Zhang et al.	85.13	85.04	85.04	84.86	84.33	75.43	75.43
	Zhang et al. - perturbed	85.26	85.11	85.06	84.97	84.23	83.53	-
	Hardt et al.	82.77	82.77	82.77	82.77	82.77	82.77	82.77
COMPAS	Agarwal et al.	75.19	75.19	74.05	74.05	73.86	73.39	73.39
	Agarwal et al. - perturbed	74.43	74.43	74.43	73.86	73.39	73.39	73.39
	Zhang et al.	74.62	74.62	74.62	74.62	74.62	73.48	53.12
	Zhang et al. - perturbed	74.34	74.34	74.34	74.34	73.48	72.44	72.44
	Hardt et al.	71.31	71.31	71.31	70.45	68.75	-	-

- No significant reduction under the fairness definition of **equalised odds**.

Learnt Perturbations - Flexibility

- Fully **model-agnostic** with respect to the original model, as any model structure or access requirements **apply only to the perturbation**, and not the original model.

- If the original model is complex, we have the option of **training a lightweight perturbation** to the complex model, and may not need to rerun an expensive training procedure.

Learnt Perturbations - Stability

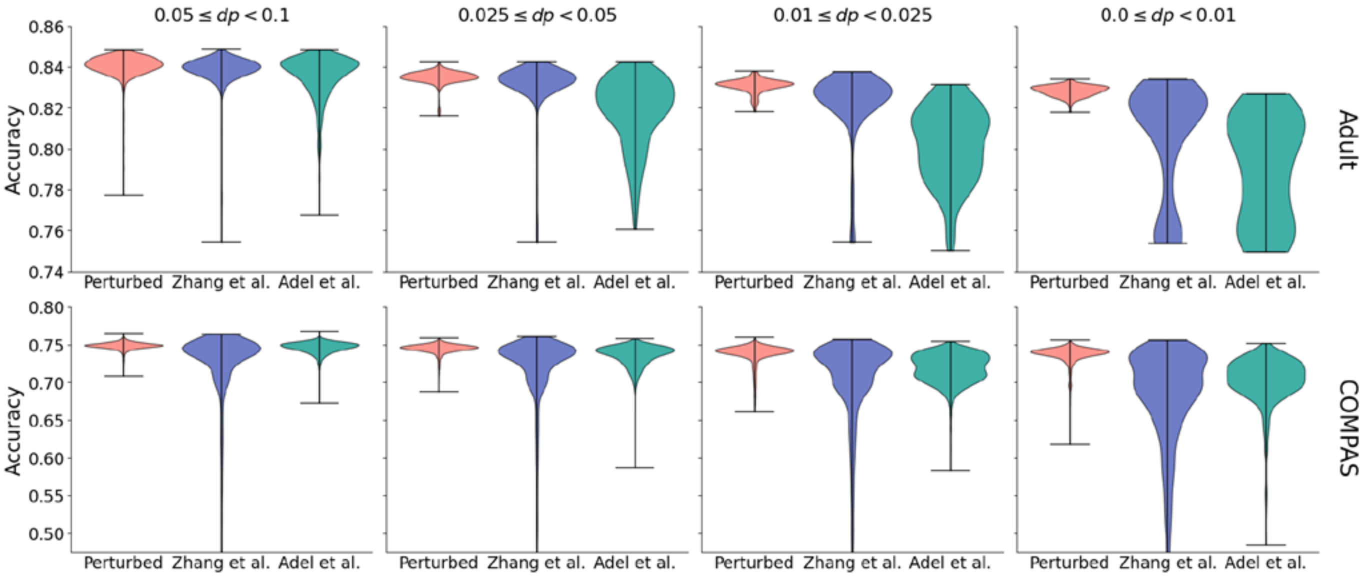


Figure 3: Accuracy violin plots of experimental outcomes binned by achieved level of fairness.

- The proposed perturbative approach has **<u>less variance</u>** and **<u>higher mean accuracy</u>**.

Limitations & Discussion question

- What do you think are the advantages and disadvantages of the perturbation method proposed in the paper against other training-time fairness algorithm?

- From the fairness shapley value, if we observe that a certain feature contributes a lot to the unfairness (e.g., marital status in demographic parity difference), is it always correct to remove that particular feature from the model?

- After reading this paper, what's your opinion about using interpretability methods to validate the fairness of machine learning models?

Thanks & Questions