Verification and Explanation of Unfairness in Machine Learning

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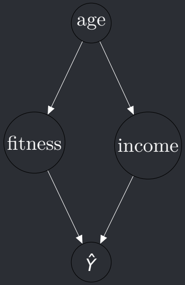
(Un)Fairness in Machine Learning

Prediction of eligibility of health insurance

- Sensitive features, $\mathbf{A} = \{\text{age}\}$
- Non-sensitive features, $\mathbf{X} = \{\text{fitness, income}\}$



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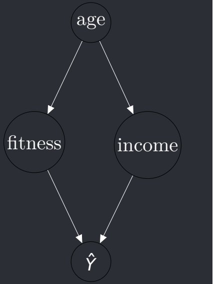

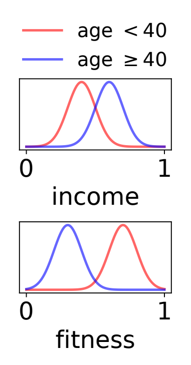

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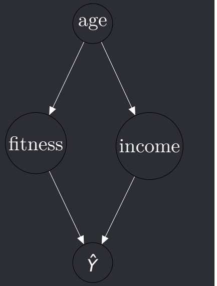

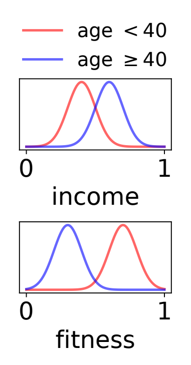

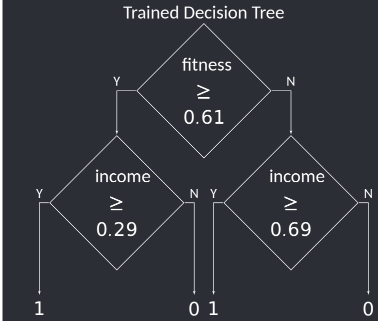

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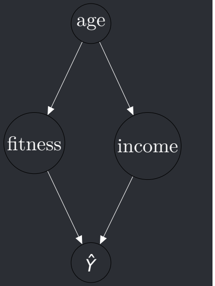

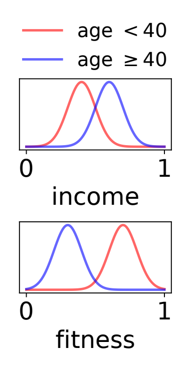

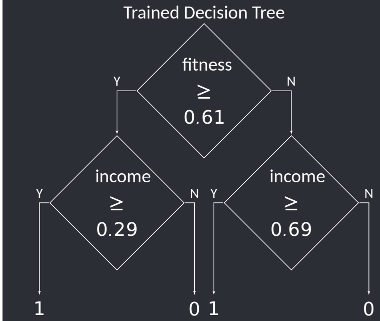

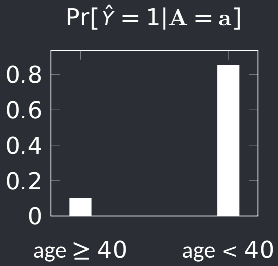

Motivation

- Machine learning classifiers may become unfair to certain demographic groups

- Multiple fairness definitions and algorithms have been proposed to improve fairness

- What are still missing is scalable algorithms for verification and explanation of fairness

- Today, we focus on
  - **Fairness Verification**: A rigorous estimate of fairness of a classifier
  - **Fairness Explanation**: Identifying the source of unfairness of a classifier through the lens of input features

Outline

1. Motivation
2. Fairness Verification of Boolean Formulas
3. Fairness Verification of Linear Classifiers with Correlated Features
4. Fairness Explanation: A Model-agnostic Approach

Justicia: A Stochastic SAT Approach to Formally Verify Fairness [1]

Given

- a binary classifier $\mathscr{A} : (\mathbf{X}, \mathbf{A}) \rightarrow \hat{Y} \in \{0, 1\}$ and
- a probability distribution $(\mathbf{X}, \mathbf{A}, Y) \sim \mathscr{D}$,

verify whether $\mathscr{A}$ achieves fairness w.r.t. $\mathscr{D}$

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$\Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$ is called the conditional PPV (Positive Predictive Value)

Statistical parity: $\mathscr{A}$ satisfies ϵ-statistical parity if for $\epsilon \in [0, 1]$,

$$\max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] - \min_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] \leq \epsilon$$

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Our Approach: Compute the maximum and minimum of $\Pr[\hat{Y} = 1|\mathbf{A} = \mathbf{a}]$ by *a reduction to stochastic SAT*

Satisfiability (SAT) problem

A Recap

Given a Boolean formula ϕ in CNF (Conjunctive Normal Form) defined over Boolean variables $\mathbf{X}$, the SAT problem finds a satisfying assignment of $\mathbf{X}$ that evaluates ϕ to true

$$\phi = (X_1 \lor \neg X_2) \land (\neg X_1 \lor X_2 \lor X_3) \land \neg X_1$$

- SAT solution: $X_1 = \text{false}$, $X_2 = \text{false}$, $X_3 = \text{true}$

Stochastic SAT (SSAT)

A Brief Introduction

An SSAT formula Φ has a prefix and a CNF formula ϕ

$$\Phi = \underbrace{q_1 X_1, \ldots, q_n X_n}_{\text{prefix}}, \phi$$

- q_i is an universal ($\forall$), existential ($\exists$), or randomized $\reflectbox{R}^{p_i}$ quantifier with $p_i = \Pr[X_i = \text{ true}]$
- SSAT computes the probability of satisfaction $\Pr[\Phi]$

Stochastic SAT (SSAT)

The Semantics

Let X be the left-most variable in the prefix of Φ. The recursive semantics of a SSAT formula are

1. $\Pr[\text{true}] = 1$, $\Pr[\text{false}] = 0$
2. $\Pr[\Phi] = \max_X\{\Pr[\Phi|_X], \Pr[\Phi|_{\neg X}]\}$ if X is existentially quantified ($\exists$)
3. $\Pr[\Phi] = \min_X\{\Pr[\Phi|_X], \Pr[\Phi|_{\neg X}]\}$ if X is universally quantified ($\forall$)
4. $\Pr[\Phi] = p\Pr[\Phi|_X] + (1-p)\Pr[\Phi|_{\neg X}]$ if X is randomized quantified ($ꓤ^p$)

Stochastic SAT (SSAT)

A Tale of Two Encodings

- **Existential-random SSAT formula**

$$\Phi_{\mathrm{ER}} = \exists x_2, \exists x_3, \rotatebox[origin=c]{180}{R}^{0.25} x_1,\ (x_1 \lor \neg x_2) \land (\neg x_1 \lor x_2 \lor x_3) \land \neg x_1$$

- $\Pr[\Phi_{\mathrm{ER}}] = 0.75$
- Optimal assignment (maximization): $x_2 =$ false, $x_3 =$ false

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$$\Phi_{\text{ER}} = \exists x_2, \exists x_3, \text{ꓤ}^{0.25} x_1,\ (x_1 \vee \neg x_2) \wedge (\neg x_1 \vee x_2 \vee x_3) \wedge \neg x_1$$

  - $\Pr[\Phi_{\text{ER}}] = 0.75$
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- **Universal-random SSAT formula**

$$\Phi_{\text{UR}} = \forall x_2, \forall x_3, \text{ꓤ}^{0.25} x_1,\ (x_1 \vee \neg x_2) \wedge (\neg x_1 \vee x_2 \vee x_3) \wedge \neg x_1$$

  - $\Pr[\Phi_{\text{UR}}] = 0$
  - Optimal assignment (minimization): $x_2 = \text{true}$, $x_3 = \text{false}$

Justicia: Fairness Verification with SSAT

Consider

- features $\mathbf{X} \cup \mathbf{A}$ are Boolean
- predicted class $\hat{Y}$ is a CNF formula $\phi_{\hat{Y}}$ defined on $\mathbf{X} \cup \mathbf{A}$

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Two Steps to Justicia

1. Computing $\max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$, is equivalent to solving

$$\Phi_{\text{ER}} \triangleq \underbrace{\exists A_1, \ldots, \exists A_n,}_{\text{sensitive features}} \underbrace{\text{Я}^{p_1} X_1, \ldots, \text{Я}^{p_m} X_m,}_{\text{non-sensitive features}} \phi_{\hat{Y}}.$$

2. For computing $\min_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$, we substitute $\exists$ with $\forall$ for sensitive features, and observe $\Pr[\Phi_{\text{UR}}] = 1 - \Pr[\Phi_{\text{ER}}(\neg \phi_{\hat{Y}})]$.

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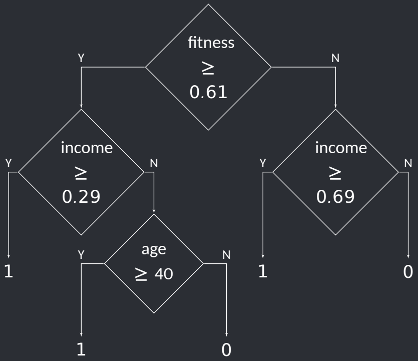
Use an SSAT solver to solve the ER-SSAT problems [2].

An Illustration

Decision Tree



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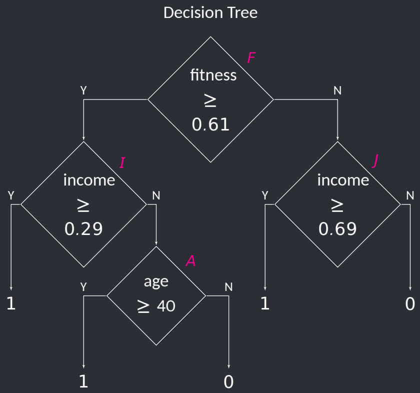

- CNF representation: $(\neg F \vee I \vee A) \wedge (F \vee J)$
- $\Pr[F] = 0.41, \Pr[I] = 0.93, \Pr[J] = 0.09$
- To compute $\max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$, we construct

$$\Phi_{ER} = \exists A, \rotatebox[origin=c]{180}{R}^{0.41} F, \rotatebox[origin=c]{180}{R}^{0.93} I, \rotatebox[origin=c]{180}{R}^{0.09} J,\ (\neg F \vee I \vee A) \wedge (F \vee J)$$

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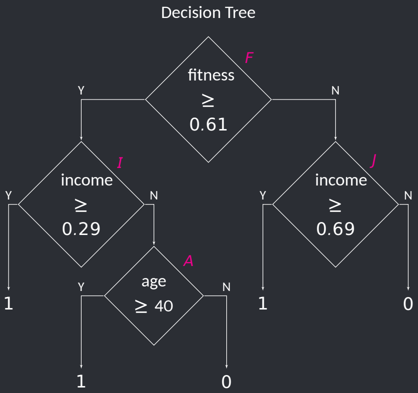
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- $\max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] = \Pr[\Phi_{\mathrm{ER}}] = 0.46$

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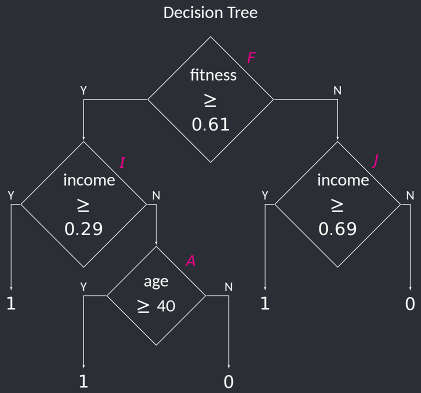

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- $\max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] = \Pr[\Phi_{\text{ER}}] = 0.46$
- Similarly, $\min_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] = 0.43$
- Statistical parity is $0.46 - 0.43 = 0.03$

Theoretical Analysis

Psuedologarithmic Sample Complexity

Theorem (A PAC Bound for Justicia)

With probability $1 - \delta$*, Justicia can estimate Statistical Parity (SP) up to a multiplicative error* $2\epsilon_0$*, i.e.* $\widehat{\mathrm{SP}} \leq 2\epsilon_0 \mathrm{SP}$*, if it has access to*

$$k = O\left(\left(n + \ln\left(\frac{1}{\delta}\right)\right)\frac{\ln m}{\ln \epsilon_0}\right)$$

samples from the data-generating distribution.

Here, m *and* n *are the number of variables with randomised and existential quantifiers respectively. Note that* $\delta \in (0, 1)$ *and* $\epsilon_0 > 1$*.*

Experimental Analysis

Robustness and Compound Attribute Level Analysis

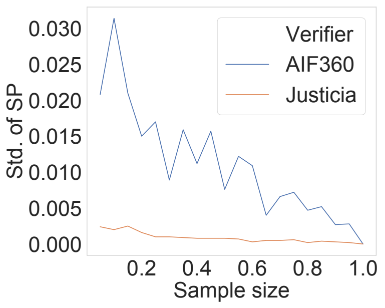

Figure: Robustness between probabilistic (Justicia) and dataset centric (AIF360 [3]) verifiers

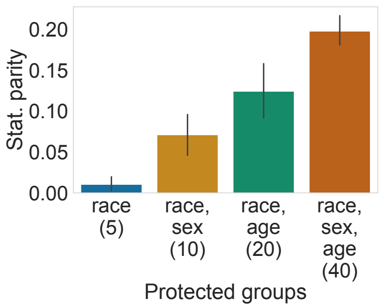

Figure: Verifying compound sensitive/protected groups with Justicia

Experimental Results

Faster than the Fastest

State-of-the-art probabilistic fairness verifiers

- FairSquare: computes weighted volume of logical programs using SMT reduction [4]
- VeriFair: probabilistic verification via sampling [5]

Dataset	FairSquare	VeriFair	Justicia
Ricci	4.8	5.3	0.1
Titanic	16	1.2	0.1
COMPAS	36.9	15.9	0.1
Adult	—	295.6	0.2

Table: Runtime of different verifiers in terms of execution time (in seconds) with decision tree classifiers. '—' refers to timeout.

Summary of Justicia

What Justicia can do?

- Justicia is a SSAT based probabilistic fairness verifier
- First method to verify compound sensitive groups
- More scalable in verifying decision trees and classifiers in Boolean formulas

What Justicia cannot do?

- Classifiers have to be expressed as Boolean formulas, which is computationally expensive even for linear classifiers
- Assumption of probabilistic independence of features leads to incorrect estimates

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FVGM: Algorithmic Fairness Verification with Graphical Models [6]

Fairness verification of Linear Classifiers

Challenges of earlier fairness verifiers

- **Scalability:** SSAT or SMT-based reduction of linear classifiers is computationally expensive
- **Accuracy:** Feature correlation is imprecisely modelled

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Proposed solutions

- **Scalability:** Novel stochastic subset-sum problem (S3P) based reduction
- **Accuracy:** Feature correlations represented as a Bayesian network

Linear Classifiers

Let

- w_{X_i} be the the weight/coefficient of non-sensitive feature X_i
- w_{A_j}be the the weight/coefficient of sensitive feature A_j
- τ is the offset parameter

The prediction of a binary linear classifier

$$\hat{Y} = \mathbb{1}\Big[\sum_i w_{X_i} X_i + \sum_j w_{A_j} A_j \geq \tau\Big].$$

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by a reduction to S3P

A Detour to Subset-sum Problem

- $\mathbf{B} \triangleq \{B_i\}_{i=1}^{|\mathbf{B}|}$ be a set of Boolean variables
- $w_i \in \mathbb{Z}$ be the weight of B_i
- a constant threshold $\tau \in \mathbb{Z}$

Given a constraint

$$\sum_{i=1}^{|\mathbf{B}|} w_i B_i = \tau$$

the subset-sum problem computes $\mathbf{b} \in \{0, 1\}^{|\mathbf{B}|}$ such that the constraint evaluates to true when $\mathbf{B}$ is substituted with $\mathbf{b}$

Example:

- weights $\{-7, -3, -2, 9000, 5, 8\}$ and $\tau = 0$
- $\mathbf{b} = [0, 1, 1, 0, 1, 0]$ is the solution of the subset-sum problem, since $-3 - 2 + 5 = 0$

Stochastic Subset-sum Problem (S3P)

A Counting Analogue of the Subset-Sum Problem

S3P computes the *probability* of a subset of $\mathbf{B}$ with sum of weights of non-zero variables to be at least τ. Formally,

$$s(\mathbf{B}, \tau) \triangleq \Pr\left[\sum_i w_i B_i \geq \tau\right] \in [0, 1].$$

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Similar to SSAT, we consider a quantifier $q_i \in \{ ꓤ^{p_i}, \exists, \forall \}$ for each B_i in S3P

Stochastic Subset-sum Problem (S3P)

The Semantics

Let $\mathrm{B}[2:n] \triangleq \{B_j\}_{j=2}^{n}$ be the subset of B without the first variable B_1.

$s(\mathrm{B}, \tau)$ is recursively defined as

$$s(\mathrm{B}, \tau) = \begin{cases} \mathbb{1}[\tau \leq 0], & \text{if } \mathbf{B} = \emptyset \\ s(\mathrm{B}[2:n], \tau - \max\{w_1, 0\}), & \text{if } q_1 = \exists \\ s(\mathrm{B}[2:n], \tau - \min\{w_1, 0\}), & \text{if } q_1 = \forall \\ p_1 \times s(\mathrm{B}[2:n], \tau - w_1) + (1 - p_1) \times s(\mathrm{B}[2:n], \tau), & \text{if } q_1 = \text{Я}^{p_1} \end{cases}$$

Stochastic Subset-sum Problem (S3P)

Differences of S3P *with SSAT*

- Computation of $\exists$ and $\forall$ quantified variables is linear in S3P but exponential in SSAT.

- There is a pseudo-polynomial dynamic programming algorithm for S3P compared to the $\mathrm{NP}^{\mathrm{PP}}$-hardness of ER-SSAT and UR-SSAT.

FVGM: Fairness Verification of Linear Classifiers

1. Preprocess a linear classifier
    - discretize each continuous feature X to a set of Boolean features $\mathbf{B}$ using histogram
    - if w is the weight of X and μ_i is the mean of feature values in the i-th bin, then the weight of $B_i \in \mathbf{B}$ is $w\mu_i$

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2. Learn a Bayesian network on discretized features[1]

3. To compute $\max_a \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$,
   - assign $\exists$ quantifier to sensitive features $\mathbf{A}$
   - assign $\reflectbox{R}$ quantifier to non-sensitive features $\mathbf{X}$
   - solve S3P problem

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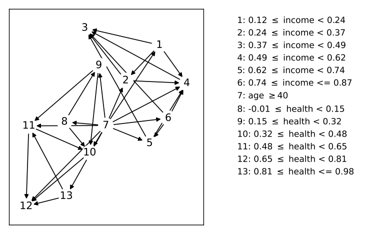
4. To compute $\min_a \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$, assign ∀ quantifier to $\mathbf{A}$ while keeping Я quantifier on $\mathbf{X}$

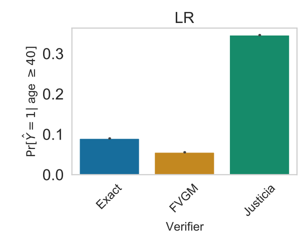
Experimental Analysis

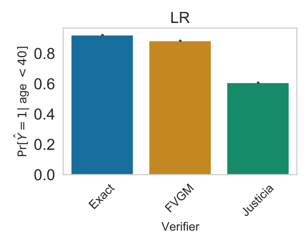
Accuracy

- Sensitive features, $\mathbf{A} = \{\text{age}\}$
- Non-sensitive features, $\mathbf{X} = \{\text{health, income}\}$
- We discretize $\mathbf{X}$ to Boolean features



1: 0.12 ≤ income < 0.24
2: 0.24 ≤ income < 0.37
3: 0.37 ≤ income < 0.49
4: 0.49 ≤ income < 0.62
5: 0.62 ≤ income < 0.74
6: 0.74 ≤ income <= 0.87
7: age ≥ 40
8: -0.01 ≤ health < 0.15
9: 0.15 ≤ health < 0.32
10: 0.32 ≤ health < 0.48
11: 0.48 ≤ health < 0.65
12: 0.65 ≤ health < 0.81
13: 0.81 ≤ health <= 0.98





Experimental Analysis

Scalability

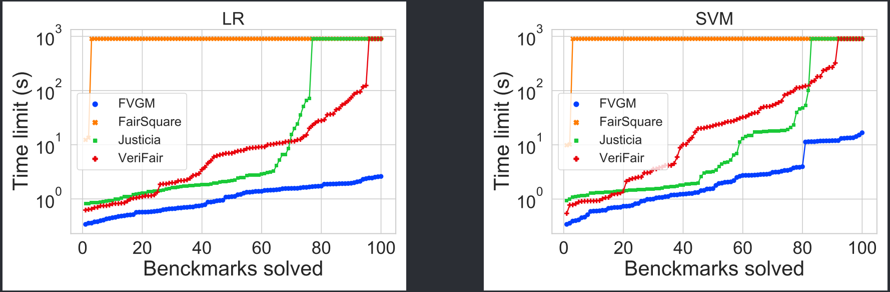


Figure: A cactus plot to present the scalability of different fairness verifiers on Linear Regression (LR) classifiers and Support Vector Machine (SVM)

Summary of FVGM

- FVGM is an efficient fairness verification framework for linear classifiers based on a novel stochastic subset-sum problem (S3P).
- FVGM is the first method to include feature correlations using a Bayesian network.
- FVGM demonstrates higher *scalability* and higher *accuracy* in comparison with earlier fairness verifiers.

Outline

1. Motivation

2. Fairness Verification of Boolean Formulas

3. Fairness Verification of Linear Classifiers with Correlated Features

4. Fairness Explanation: A Model-agnostic Approach

Fairness Explanation

- Identification of the source of unfairness is important to take affirmative actions
- Data contains bias and classifiers trained on the data inherit the bias.

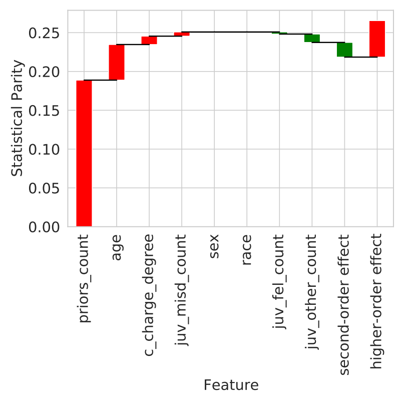


Figure: Explaining statistical parity in COMPAS recidivism prediction dataset for the feature ’sex’

Computing the Fairness Explanations

A Model-agnostic Approach

Observations

- Fairness, particularly group fairness, is a global property of the classifier.
- Fairness computation is equivalent to computing *the sensitivity of the classifier* w.r.t. different sensitive groups

Our approach: Extend global sensitivity analysis techniques from functional analysis to classification for explainning fairness.

FairXplain: Key Ideas

Idea 1

Statistical parity can be computed using the difference between variance of outcomes for sensitive groups

If $p_{\mathbf{a}} \triangleq \max_{\mathbf{a}} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}]$ and $p_{\mathbf{a}'} \triangleq \min_{\mathbf{a}'} \Pr[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}']$,

$$\text{Statistical Parity} = \frac{\text{Var}[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}] - \text{Var}[\hat{Y} = 1 | \mathbf{A} = \mathbf{a}'])}{1 - (p_{\mathbf{a}} + p_{\mathbf{a}'})}$$

$$= \frac{\sum_{i=1}^{n} \overbrace{(V_i^{(\mathbf{a})} - V_i^{(\mathbf{a}')})}^{\text{1-th order}} + \sum_{i<j}^{n} \overbrace{(V_{ij}^{(\mathbf{a})} - V_{ij}^{(\mathbf{a}')})}^{\text{2-th order}} + \cdots + \overbrace{(V_{12\ldots n}^{(\mathbf{a})} - V_{12\ldots n}^{(\mathbf{a}')})}^{n\text{-th order}}}{1 - (p_{\mathbf{a}} + p_{\mathbf{a}'})}$$

$$V_i^{(\mathbf{a})} = \text{Var}_{X_i}[\text{E}_{X_{\sim i}}[\hat{Y} = 1 | X_i, \mathbf{A} = \mathbf{a}]], \quad V_{ij}^{(\mathbf{a})} = \text{Var}_{X_{ij}}[\text{E}_{X_{\sim ij}}[\hat{Y} = 1 | X_i, X_j, \mathbf{A} = \mathbf{a}]] - V_i^{(\mathbf{a})} - V_j^{(\mathbf{a})}$$

FairXplain: Key Ideas

Idea 2

If we can decompose the variance in terms of the basis functions of the classifier, we can decompose the first and higher order variances as the variances of these decompositions.

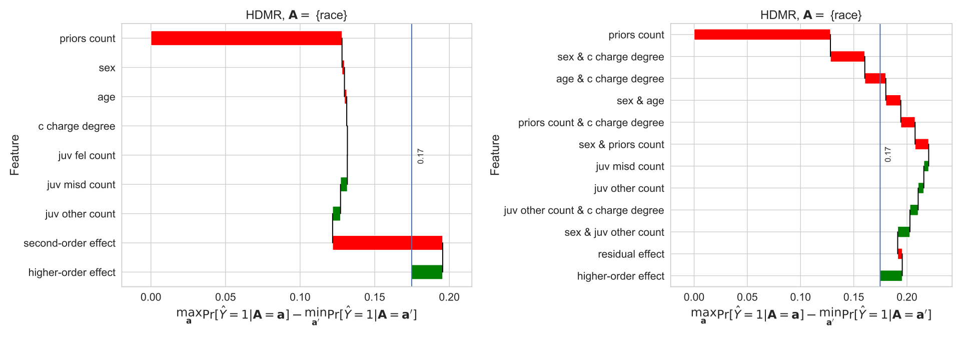
$$f_{\{i\}}(\mathbf{X}_{\{i\}}) \approx \sum_{r=-1}^{m+1} \alpha_r^i B_r(\mathbf{X}_{\{i\}})$$

$$f_{\{i,j\}}(\mathbf{X}_{\{i,j\}}) \approx \sum_{p=-1}^{m+1} \sum_{q=-1}^{m+1} \beta_{pq}^{ij} B_p(\mathbf{X}_{\{i\}}) B_q(\mathbf{X}_{\{j\}})$$

$$f_{\{i,j,k\}}(\mathbf{X}_{\{i,j,k\}}) \approx \sum_{p=-1}^{m+1} \sum_{q=-1}^{m+1} \sum_{r=-1}^{m+1} \gamma_{pqr}^{ijk} B_p(\mathbf{X}_{\{i\}}) B_q(\mathbf{X}_{\{j\}}) B_r(\mathbf{X}_{\{j\}})$$

Explaining Statistical Parity in COMPAS Dataset

Higher Order Effects are Decisive

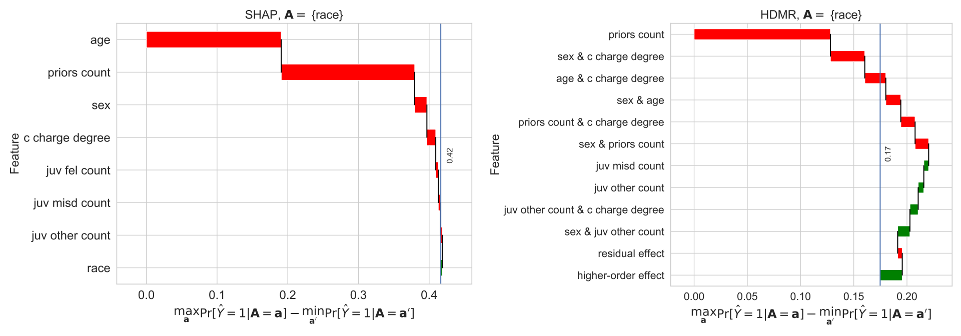


(a) FairXplain: First order effects

(b) FairXplain: First and second order effect

Explaining Statistical Parity in COMPAS Dataset

Local Explanations cannot Explain Unfairness



(c) Shapley Explanations

(d) FairXplain: First and second order effect

Conclusion

- **Fairness verification** and **explanation** are important problems in estimating the bias of classifiers and identifying the source of bias

- **Fairness verifiers**, Justicia and FVGM, improve upon existing fairness verifiers in terms of scalability and accuracy

- **Fairness explanation** shows the potential in identifying the effect of individual features or their interactions on the unfairness of the classifier. We currently focus in it.

- As a future work, we aim to design fairness enhancing algorithms relying on fairness verification and explanation

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Want to detect unfairness in your favourite classifier?

Use our Python library: “pip install justicia”

https://github.com/meelgroup/justicia