

Ensuring Fairness with Transparent Auditing of Quantitative Bias in AI Systems

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AI Bias

- AI is widely used in decision making:
 - School admission.
 - Loan approval.
 - Hiring.
 - Policing.
 - Censorship.
 - etc..
- Decision making by AI may be biased.
- Bias can come from several sources:
 - Biased data. ML is designed to replicate this.
 - Missing data. The datasets might not be representative.
 - Biased algorithms. The objective functions might introduce bias.
 - Sensitive attributes: Age, Gender, ..., etc..

Protected Attributes

What are the protected(sensitive) attributes?

Age	Gender	Occupation	Income	Education
28	M	Engineering	\$80,000	Master
28	F	Engineering	\$65,000	Master
45	M	Medicine	\$100,000	Doctorate
40	F	Legal	\$150,000	Law Degree
32	M	Education	\$55,000	Bachelor

Table: Example Dataset

Fairness Through Unawareness

The most straightforward solution to fairness seems to be that just simply dropping all the protected columns.

- This is called fairness through unawareness.
- Formally it's

$$X_i = X_j \rightarrow \hat{Y}_i = \hat{Y}_j$$

where i, j are individuals; X is the set of attributes except protected attributes; and \hat{Y} is the prediction.

- Also known as fairness through blindness and anti-classification.

Fairness Through Unawareness

The downside of this is there could still be “proxy” attributes that correlate with protected attributes: like Occupation still correlates with Income.

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Table: Example Dataset

Demographic Parity

Formally, it requires that

$$|P[\hat{Y} = 1|S = 1] - P[\hat{Y} = 1|S \neq 1]| \leq \epsilon$$

where $\hat{Y} = 1$ represents acceptance(positive); $S = 1$ represents privileged group; $S \neq 1$ represents unprivileged group where S is some protected attributes.

Let's set $\epsilon = 0.2$. If for some job opening, male is the privileged group and there are 10 female applicants and 100 male applicants, and there are 8 accepted females and 90 accepted males:

$$|8/10 - 90/100| = 0.1 < \epsilon \quad \text{so this is fair}$$

while if there were 1 accepted females and 50 accepted males:

$$|1/10 - 50/100| = 0.4 > \epsilon \quad \text{so this is unfair}$$

Disadvantages of Demographic Parity

- A fully accurate classifier may be considered unfair.
- The notion permits that we accept the qualified applicants in one demographic, but random individuals in another, so long as the percentages of acceptance match.
- For example, the case with 90 qualified males and only 1 qualified females.

Equalized Odds

- Equalized odds is designed to address the downsides of the previous two by taking into accounts the “ground truths” and consider the difference between false-positive rates and true-positive rates of the groups.
- Formally, it requires that

$$\begin{aligned} |P[\hat{Y} = 1|S = 1, Y = 0] - P[\hat{Y} = 1|S \neq 1, Y = 0]| &\leq \epsilon \\ |P[\hat{Y} = 1|S = 1, Y = 1] - P[\hat{Y} = 1|S \neq 1, Y = 1]| &\leq \epsilon \end{aligned}$$

where Y represents ground truths.

- A fully accurate classifier will necessarily satisfy the two equalized odds constraints.

Equal Opportunity

- It is a relaxation of equalized odds.
- Formally, it requires that

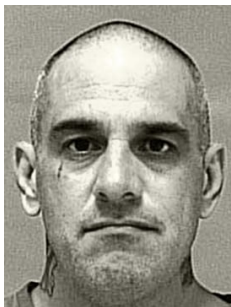
$$|P[\hat{Y} = 1|S = 1, Y = 1] - P[\hat{Y} = 1|S \neq 1, Y = 1]| \leq \epsilon$$

where Y represents ground truths.

COMPAS

recidivism *noun*

the tendency of a convicted criminal to reoffend.



- Prior Offenses: 2 armed robberies, 1 attempted armed robbery
- Subsequent Offenses: 1 grand theft
- Risk Score: 3



- Prior Offenses: 4 juvenile misdemeanors
- Subsequent Offenses: None
- Risk Score: 8

COMPAS

- COMPAS is an algorithm used by U.S. courts for predicting recidivism based on a questionnaire and background information.
- In 2016, ProPublica found that the algorithm is biased.
Black defendants were often predicted to be at a higher risk of recidivism than they actually were. White defendants were often predicted to be less risky than they were.
- The false-positive rates vary significantly across black people and white people, violating equalized odds.
- Supreme Court ruled that it can be considered by judges during sentencing, but there must be warnings about the tool's "limitations and cautions."

¹(Link) ProPublica - How We Analyzed the COMPAS Recidivism Algorithm

²(Link) Vsauce2 - The Dangerous Math Used To Predict Criminals

Other Measures

Fairness Measure	Definition
Disparate Impact	$\frac{P[\hat{Y}=1 S \neq 1]}{P[\hat{Y}=1 S=1]} \geq 1 - \epsilon$
Demographic Parity	$ P[\hat{Y} = 1 S = 1] - P[\hat{Y} = 1 S \neq 1] \leq \epsilon$
Conditional Statistical Parity	$ P[\hat{Y} = 1 S = 1, L = l] - P[\hat{Y} = 1 S \neq 1, L = l] \leq \epsilon$
Overall Accuracy Equality	$ P[Y = \hat{Y} S = 1] - P[Y = \hat{Y} S \neq 1] \leq \epsilon$
Mean Difference	$ E[\hat{Y} S = 1] - E[\hat{Y} S \neq 1] \leq \epsilon$
Equalized Odds	$ P[\hat{Y} = 1 S = 1, Y = 0] - P[\hat{Y} = 1 S \neq 1, Y = 0] \leq \epsilon$
	$ P[\hat{Y} = 1 S = 1, Y = 1] - P[\hat{Y} = 1 S \neq 1, Y = 1] \leq \epsilon$
Equal Opportunity	$ P[\hat{Y} = 1 S = 1, Y = 1] - P[\hat{Y} = 1 S \neq 1, Y = 1] \leq \epsilon$
Predictive Equality	$ P[\hat{Y} = 1 S = 1, Y = 0] - P[\hat{Y} = 1 S \neq 1, Y = 0] \leq \epsilon$
Conditional Use Accuracy Equality	$ P[Y = 1 S = 1, \hat{Y} = 1] - P[Y = 1 S \neq 1, \hat{Y} = 1] \leq \epsilon$
	$ P[Y = 0 S = 1, \hat{Y} = 0] - P[Y = 0 S \neq 1, \hat{Y} = 0] \leq \epsilon$
Predictive Parity	$ P[Y = 1 S = 1, \hat{Y} = 1] - P[Y = 1 S \neq 1, \hat{Y} = 1] \leq \epsilon$
Equal Calibration	$ P[Y = 1 S = 1, \hat{V} = v] - P[Y = 1 S \neq 1, \hat{V} = v] \leq \epsilon$
Positive Balance	$ E[\hat{V} Y = 1, S = 1] - E[\hat{V} Y = 1, S \neq 1] \leq \epsilon$
Negative Balance	$ E[\hat{V} Y = 0, S = 1] - E[\hat{V} Y = 0, S \neq 1] \leq \epsilon$

Table: Fairness measures.

Framework

We made a tool to calculate these measures.

Our framework consists of 3 parties: data provider, model maker, and auditor.

- Data provider has access to the real world data. For example, a census bureau.
- Model maker designs AI models that is to be used on data. They can use our tool on their in-house data to test their models.
- Auditor is some 3rd-party that takes real data and a model or model result. They can use our tool to determine the fairness of the model.

Predicate

We first introduce the idea of a predicate.

- A predicate is a decider that determines if some condition holds for some given input.
- Formally, it is a function that takes some type α and returns True or False.
- For example, an “adult(x)” predicate might take a person x ’s data and returns if they are over 18 year old.

Abstraction

Our framework tool abstracts the fairness measures:

- A row is a lookup table or dictionary. $r_n(\text{"sex"}) = \text{"Female"}$ means r_n 's sex is female.
- A privileged predicate R takes a row and determines if it belongs to the privileged group. For example, $R(r_i) := r_i(\text{"race"}) == \text{"Caucasian"}$ means the privileged group is those with race being Caucasian.
- A positive predicate \hat{P} takes a row and determines if its prediction is positive. For example, $\hat{P}(r_i) := \text{int}(r_i(\text{"score"})) > 7$ means a row's prediction is positive if its score is greater than 7.
- A ground truth predicate T takes a row and gives the ground truth of the result. For example, $T(r_i) := r_i(\text{"recid"}) == \text{True}$ indicates a row's actual recidivism.

Definition

We can use these abstractions to define fairness measures. For equal opportunity, recall its formal definition:

$$|P[\hat{Y} = 1|S = 1, Y = 1] - P[\hat{Y} = 1|S \neq 1, Y = 1]| \leq \epsilon$$

To model Y , \hat{Y} , and S , we define the corresponding T , \hat{P} , and R .

- $Y = 1$ if and only if T is true
- $\hat{Y} = 1$ if and only if \hat{P} is true
- $S = 1$ if and only if R is true
- and vice versa

This way, we can calculate equal opportunity as a function:

$$\text{equal_opportunity}(\epsilon, R, \hat{P}, T)$$

Definition

$$\text{equal_opportunity}(\epsilon, R, \hat{P}, T)$$

This is implemented in our tool as a Python function:

```
1 def equal_opportunity(  
2     ratio,  
3     privileged_predicate,  
4     positive_predicate,  
5     truth_predicate) -> bool:  
6     ...
```

Application

For demonstration, we analyzed the COMPAS dataset. Let's set the predicates:

$$R(r_i) := r_i(\text{"race"}) \neq \text{"African-American"}$$

$$\hat{P}(r_i) := r_i(\text{"score_text"}) \in \{\text{"Medium"}, \text{"High"}\}$$

$$T(r_i) := r_i(\text{"two_year_recid"}) == \text{True}$$

These predicates can be published for transparency.

Application

$$R(r_i) := r_i(\text{"race"}) \neq \text{"African-American"}$$
$$\hat{P}(r_i) := r_i(\text{"score_text"}) \in \{\text{"Medium"}, \text{"High"}\}$$
$$T(r_i) := r_i(\text{"two_year_recid"}) == \text{True}$$

These predicates can then be encoded with Python functions:

```
1 equal_opportunity(  
2     0.2,  
3     lambda row: row['race'] == 'African-American',  
4     lambda row: row['score_text']  
5         in {'Medium', 'High'},  
6     lambda row: row['is_recid'] == '1')
```

Application

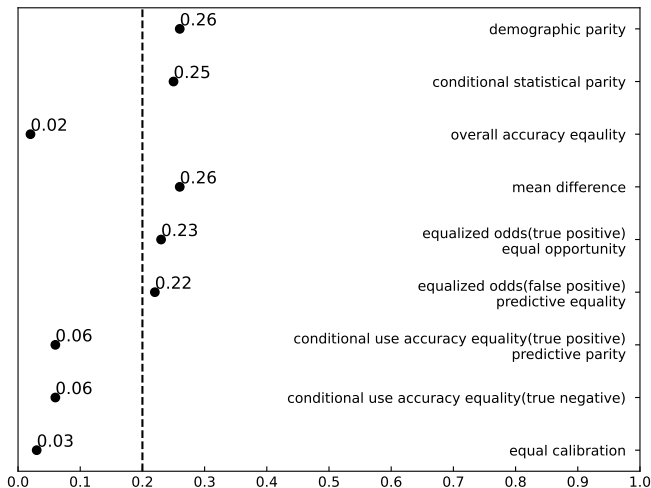


Figure: Unprivileged Group: African-American

Application

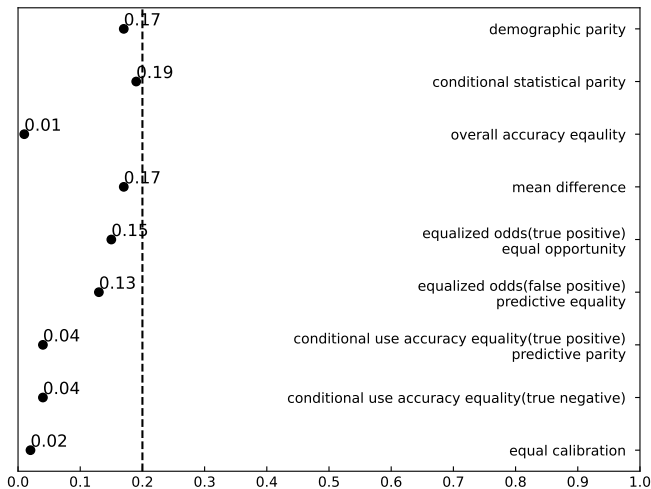


Figure: Unprivileged Group: Caucasian

Application

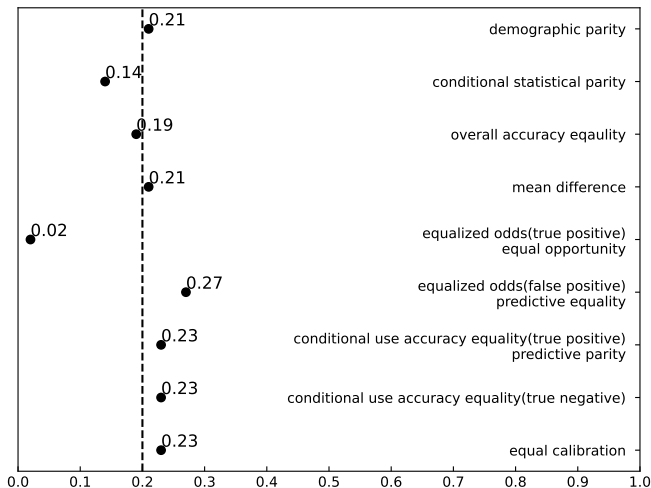


Figure: Unprivileged Group: Asian (32 rows)

Conclusion

- Decision making by AI may be biased.
- With our framework tool, auditors can comprehensively review the fairness of an AI system.

This slides is available at <https://github.com/RexYuan/Shu>.