

On Formalizing Fairness in Prediction with Machine Learning

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and Transparency in Machine Learning

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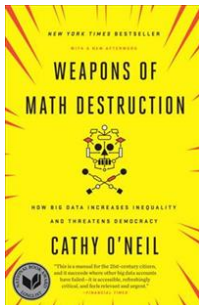
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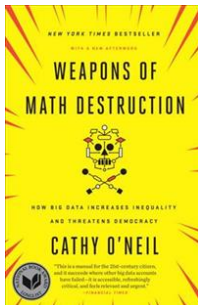
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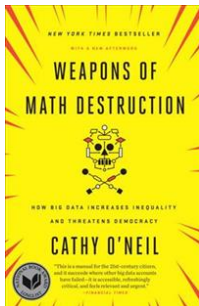
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➔ ICML 2018 Tutorial : Defining and designing fair algorithms by Sam Corbett-Davies and Sharad Goel.

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→ ICML 2018 Tutorial : Defining and designing fair algorithms by Sam Corbett-Davies and Sharad Goel.

*So long as I do not know what the just is, I shall
hardly know whether it is a virtue or not.*

Socrates

What? How? Why?

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- Our Task: Analyze fairness formalizations considered in ML so far.

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- Our Task: Analyze fairness formalizations considered in ML so far.
- Our Method: Juxtapose the formalizations in ML with their corresponding theories in Social Sciences.

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- Our Task: Analyze fairness formalizations considered in ML so far.
- Our Method: Juxtapose the formalizations in ML with their corresponding theories in Social Sciences.
- Our Objective: Start a discussion and propose newer fairness formalizations in ML.

Mathematical Formulation

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- X : Set of individuals i.e. *population*
 A : *Protected* attributes e.g. race, gender etc
 Z : Remaining attributes
 Y : Set of outcomes
- For individual $x_i \in X$, let true outcome (label) be $y_i \in Y$
- Predictor $\mathcal{H} : X \rightarrow Y$ such that $\mathcal{H}(x_i)$ is the predicted outcome for individual x_i
- Group-conditional predictor $\mathcal{H} = \{\mathcal{H}_S\}$ for every $S \subset X$

What is Fair?

- **Parity or preference?** : Statistical Parity or Social Preference?
- **Treatment or impact?** : A property of the process or of its results?

Table 1: The surveyed formalizations of fairness

	Parity	Preference
Treatment	Unawareness Counterfactual measures	Preferred treatment
Impact	Group fairness Individual fairness Equality of opportunity	Preferred impact

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Definition

Protected attributes are not explicitly used in prediction.

- Not sufficient to avoid discrimination.
- ~ “Blind” approach to counter discrimination.
- Various discriminatory practices following race-blind approach Bonilla-Silva (2013) [3], Taslitz (2007) [13].
- Race-blind approach is less efficient than race-conscious approach Fryer (2008) [5].
- Alternatively, some studies show a blind approach can work Glodin (2000) [6].

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Counterfactual Measures

Definition

Changing A while holding attributes which are not causally dependent on A constant will not change the distribution of \mathcal{H} .

- Given $Z = z$ and $A = a$, for all y and $a \neq a'$,
$$\mathbb{P}\{\mathcal{H}_{A=a} = y | Z = z, A = a\} = \mathbb{P}\{\mathcal{H}_{A=a'} = y | Z = z, A = a\}$$
where $\mathcal{H}_{A=a}$ = outcome of \mathcal{H} if A had taken value a .
- Introduced by Kusner et al. [9]. Similar measure introduced independently by Kilbertus et al. [8].
- \sim Counterfactual reasoning given by Lewis (1973) [10]
- Research to indicate that counterfactual reasoning is susceptible to hindsight bias and outcome bias.
- Some argue that counterfactual reasoning may negatively influence identifying causality.

Group Fairness

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Definition

Prob. of an individual from one group getting a particular outcome \approx Prob. of an individual from another group getting same outcome.

- Equivalent to statistical and demographic parity.
- Independent of “ground truth”.
- \sim *Collectivist egalitarianism* from distributive justice.
- Biggest implementation = affirmative action.
- Arguments have been made for and against affirmative action Weisskopf (2004) [14].

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Definition

Similar individuals get similar outcome.

- Mathematically, $\mathcal{H}(x_i) \approx \mathcal{H}(x_j) \mid d(x_i, x_j) \approx 0$ where d is a distance metric for individuals.
- \sim *Individualist egalitarianism* from distributive justice.
- Distance metric is critical to ensure non-discrimination.
- In some domains, reliable distance metric may be unavailable.

Equality of Opportunity

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Definition

True positive rate should be the same for all the groups.

- $\mathbb{P}\{\mathcal{H}(x_i) = 1 \mid y_i = 1, x_i \in S\} = \mathbb{P}\{\mathcal{H}(x_j) = 1 \mid y_j = 1, x_j \in X \setminus S\}$
- *Disparate mistreatment* : Equivalence of misclassification rates across the groups.
- \sim Equality of Opportunity by Rawls (1971) [11].
- Argument that it cannot deal with *stunted ambition* and *selection by bigotry* Arneson (1999) [1].
- Attributes like gender and race not deemed to be affecting an individual's life prospects while numerous surveys conclude otherwise.

Preference-based Fairness

Definition

(Preferred treatment) *A group-conditional predictor in which each group receives more benefit from their respective predictor.*

Definition

(Preferred impact) \mathcal{H} has preferred impact compared to \mathcal{H}' if \mathcal{H} offers at-least as much benefit as \mathcal{H}' for all the groups.

- In certain domains, no single universally accepted beneficial outcome.
- \sim envy-freeness Arnsperger (1994) [2].
- Freedom from envy neither necessary nor sufficient for fairness (Holcombe 1977 [7])
- Envy-freeness formally expressed by *Pareto-efficiency*.
- Finding Pareto-efficient solutions computationally hard.

Equality of Resources

Definition

(Equality of resources) *Unequal distribution of benefits fair when it results from intentional decisions and actions.*
(Dworkin (1981) [4])

- *Ambition-sensitive*
- *Endowment-insensitive*
- In the 2nd property, it differs from equality of opportunity.

Equality of Capability of Functioning

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Definition

(Equality of capability of functioning) *In order to equalize capabilities, people should be compensated for their unequal powers to convert opportunities into functionings. (Sen (1992) [12])*

- Functionings = various states of existence and activities that an individual can undertake.
- Calls for addressing inequalities due to social endowments (e.g. gender) as well as natural endowments (e.g. sex).
- Used in the foundations of human development paradigm by the United Nations.
- High informational requirement and difficult to express mathematically.

Summary and Further Directions

- Juxtaposed ML fairness formalizations with theories from distributive justice.
- Critique and analysis from the social sciences literature.
- Nominate two notions from the social sciences literature as prospective ML fairness formalizations.
- Use of social science literature while choosing fairness formalizations in particular domains.
- Fair prediction cannot be achieved without considering social issues such as unequal access to resources and social conditioning.
- Acknowledge their impact and attempt to incorporate them in fairness formalizations.

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Thank you all.

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