Why is My Classifier Discriminatory?

Irene Y. Chen, Fredrik D. Johansson, David Sontag
Massachusetts Institute of Technology (MIT)
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It is **surprisingly easy** to make a discriminatory algorithm.
Zero-one loss
In this paper

1. We want to find the sources of unfairness to guide resource allocation.
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2. We decompose unfairness into bias, variance, and noise.
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2. We decompose unfairness into bias, variance, and noise.

3. We demonstrate methods to guide feature augmentation and training data collection to fix unfairness.
Classification fairness: many factors

Model

- Loss function constraints
  - Kamairan et al, 2010; Zafar et al, 2017

- Representation learning
  - Zemel et al, 2013

- Regularization
  - Kamishima et al, 2007; Bechvod and Ligett, 2017

- Tradeoffs
  - Chouldechova, 2017; Kleinberg et al, 2016; Corbett-Davies et al, 2017
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<table>
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Data
• Data processing
  • Haijan and Domingo-Ferrer, 2013; Feldman et al., 2015
• Cohort selection
• Sample size
• Number of features
• Group distribution
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We should examine fairness algorithms in the context of the data and model.

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Learned model
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- Learned model
- True data function
Why might my classifier be unfair?

Error from **variance** can be solved by collecting more samples.
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   Orange dot model error
Why might my classifier be unfair?

Learned model

Orange dot model error

Blue dot model error
Why might my classifier be unfair?

True data function

$y = 0.5x^2$

$y = x - 1$
Why might my classifier be unfair?

Error from bias can be solved by changing the model class.
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- **Orange dot** model error
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Error from noise can be solved by collecting more features.
How do we define fairness?
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We define fairness in the context of loss like false positive rate, false negative rate, etc.

For example, zero-one loss for data $D$ and prediction $\hat{Y}$:

$$\gamma_a(\hat{Y}, Y, D) := P_D(\hat{Y} \neq Y \mid A = a)$$
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We can then formalize unfairness as group differences.

$$\Gamma(\hat{Y}) := |\gamma_1 - \gamma_0|$$

We rely on accurate $Y$ labels and focus on algorithmic error.
Why might my classifier be unfair?

**Theorem 1:** For error over group $a$ given predictor $\hat{Y}$:

$$\bar{Y}_a(\hat{Y}) = \bar{B}_a(\hat{Y}) + \bar{V}_a(\hat{Y}) + \bar{N}_a$$

Note that $\bar{N}_a$ indicates the expectation of $N_a$ over $X$ and data $D$. 
Why might my classifier be unfair?

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Accordingly, the expected discrimination level $\bar{\Gamma} := |\bar{y}_1 - \bar{y}_0|$ can be decomposed into differences in bias, differences in variance, and differences in noise.

$$\bar{\Gamma} = |(\bar{B}_1 - \bar{B}_0) + (\bar{V}_1 - \bar{V}_0) + (\bar{N}_1 - \bar{N}_0)|$$
We found statistically significant racial differences in zero-one loss.
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2. By subsampling data, we fit inverse power laws to estimate the benefit of more data and reducing variance.
Mortality prediction from MIMIC-III clinical notes

1. We found statistically significant racial differences in zero-one loss.
2. By subsampling data, we fit inverse power laws to estimate the benefit of more data and reducing variance.
3. Using topic modeling, we identified subpopulations to gather more features to reduce noise.
Where do we go from here?

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1. For **accurate and fair models** deployed in real world applications, both the data and model should be considered.

2. Using **easily implemented fairness checks**, we hope others will check their algorithms for bias, variance, and noise--which will guide further efforts to reduce unfairness.
Read our paper: https://arxiv.org/abs/1805.12002

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• **Spotlight talk:** Thurs 12/6 10:20am – 10:25am @ 220 CD.
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Irene Chen  
MIT  
iychen@mit.edu

Fredrik D. Johansson  
MIT  
fredrikj@mit.edu

David Sontag  
MIT  
dsontag@csail.mit.edu

**Abstract**

Recent attempts to achieve fairness in predictive models focus on the balance between fairness and accuracy. In sensitive applications such as healthcare or criminal justice, this trade-off is often undesirable as any increase in prediction error could have devastating consequences. In this work, we argue that the fairness of predictions should be evaluated in context of the data, and that unfairness induced by inadequate samples sizes or unmeasured predictive variables should be addressed through data collection, rather than by constraining the model. We decompose cost-based metrics of discrimination into bias, variance, and noise, and propose actions aimed at estimating and reducing each term. Finally, we perform case-studies on prediction of income, mortality, and review ratings, confirming the value of this analysis. We find that data collection is often a means to reduce discrimination without sacrificing accuracy.

1 Introduction

As machine learning algorithms increasingly affect decision making in society, many have raised concerns about the fairness and biases of these algorithms, especially in applications to healthcare or criminal justice, where human lives are at stake (Angwin et al., 2016; Barocas & Selbst, 2016). It is often hoped that the use of automatic decision support systems trained on observational data will remove human bias and improve accuracy. However, factors such as data quality and model choice may encode unintentional discrimination, resulting in systematic disparate impact.