314 Main St. Cambridge

#IBMTHINK2022

MIT-IBM Watson AI Lab

Industry Showcase

AI Fairness Workshop

May 9, 2022

MIT-IBM
Watson AI Lab

IBM Research

AI Fairness

Mikhail Yurochkin and Onkar Bhardwaj

Roadmap

AI is prone to biases

Definitions of algorithmic fairness

Practical fairness methods

- Identifying fairness violations
- Training fair models
- Post-processing for fairness

Fairness: A case study

Example: Sentiment analysis – classify words as positive or negative

Positive: *admire, adorable, joy, lucky, talented, ...*

Negative: *aggressive, distrust, nasty, radical, ...*

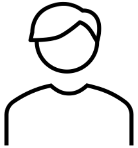
Deep Learning + Word Embeddings -> **95%** test accuracy.

Success ?

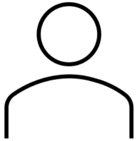
Deployment Concerns

What is a sentiment of a name?

Common European-American names:
Adam, Ryan, Paul, ... , Courtney, Meredith, Megan, ...

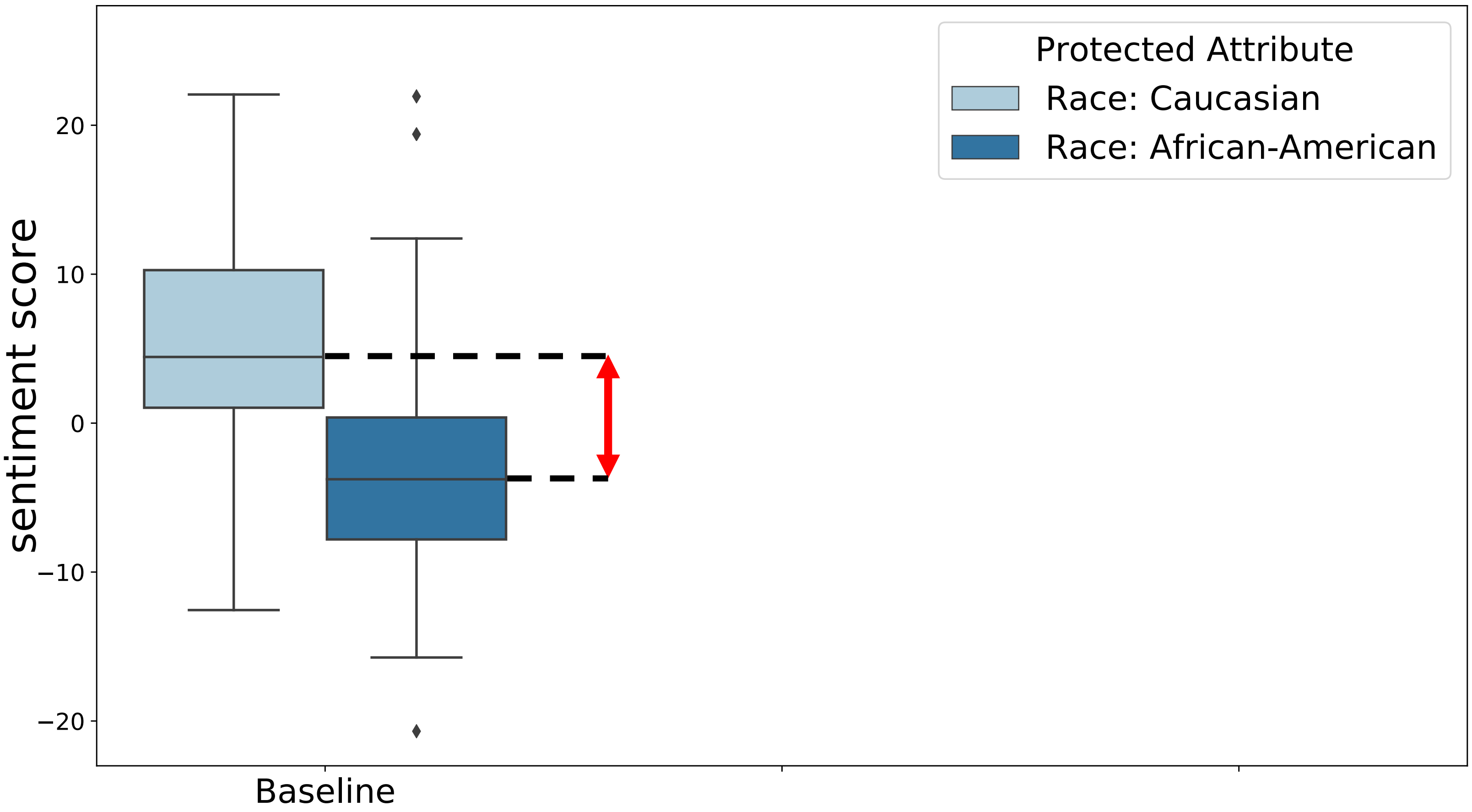


Common African-American names:
Alonzo, Leroy, Tyree, ... , Shereen, Sharise, Tawanda, ...

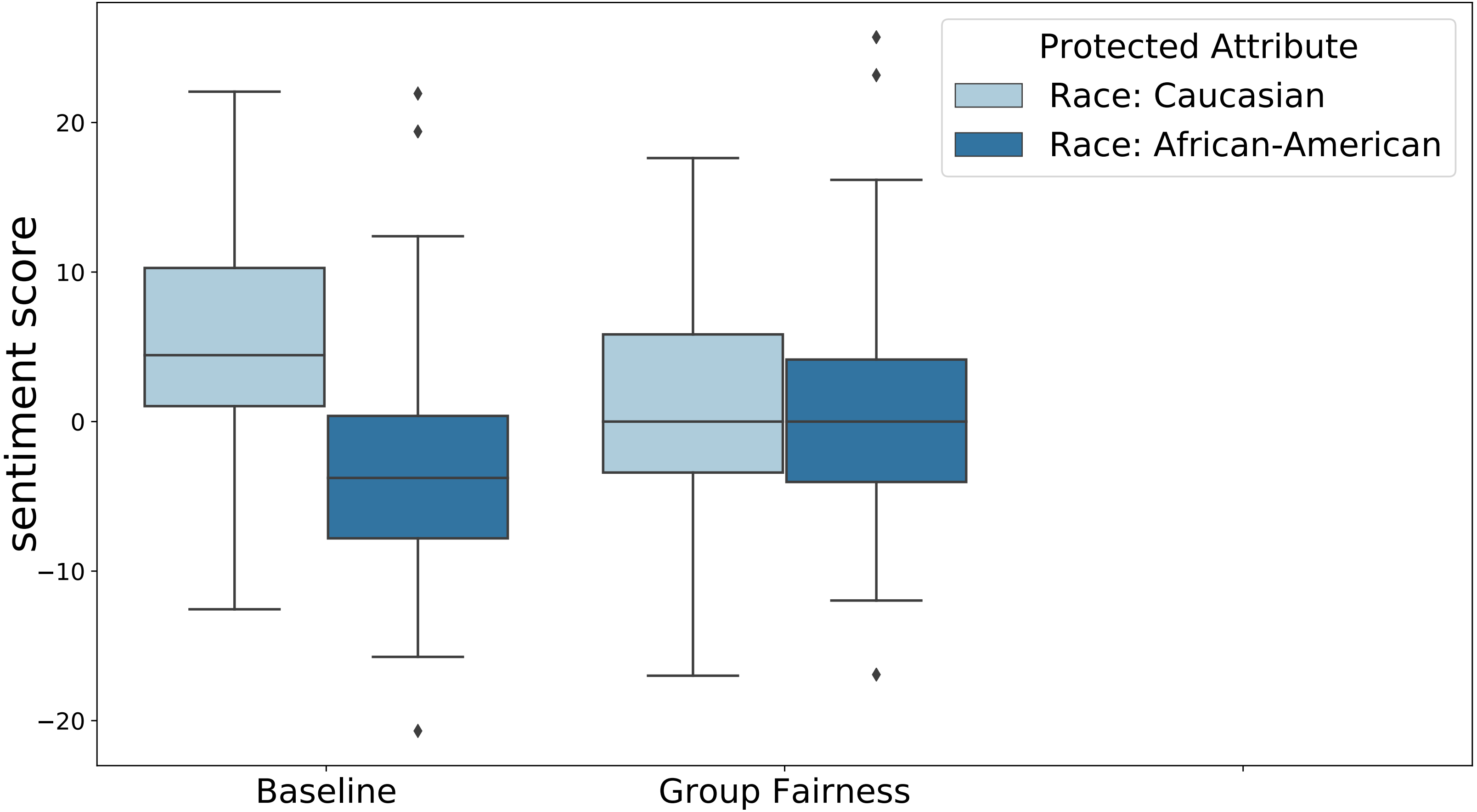


Names are from "Semantics derived automatically from language corpora contain human-like biases" (Caliskan et al., 2017)

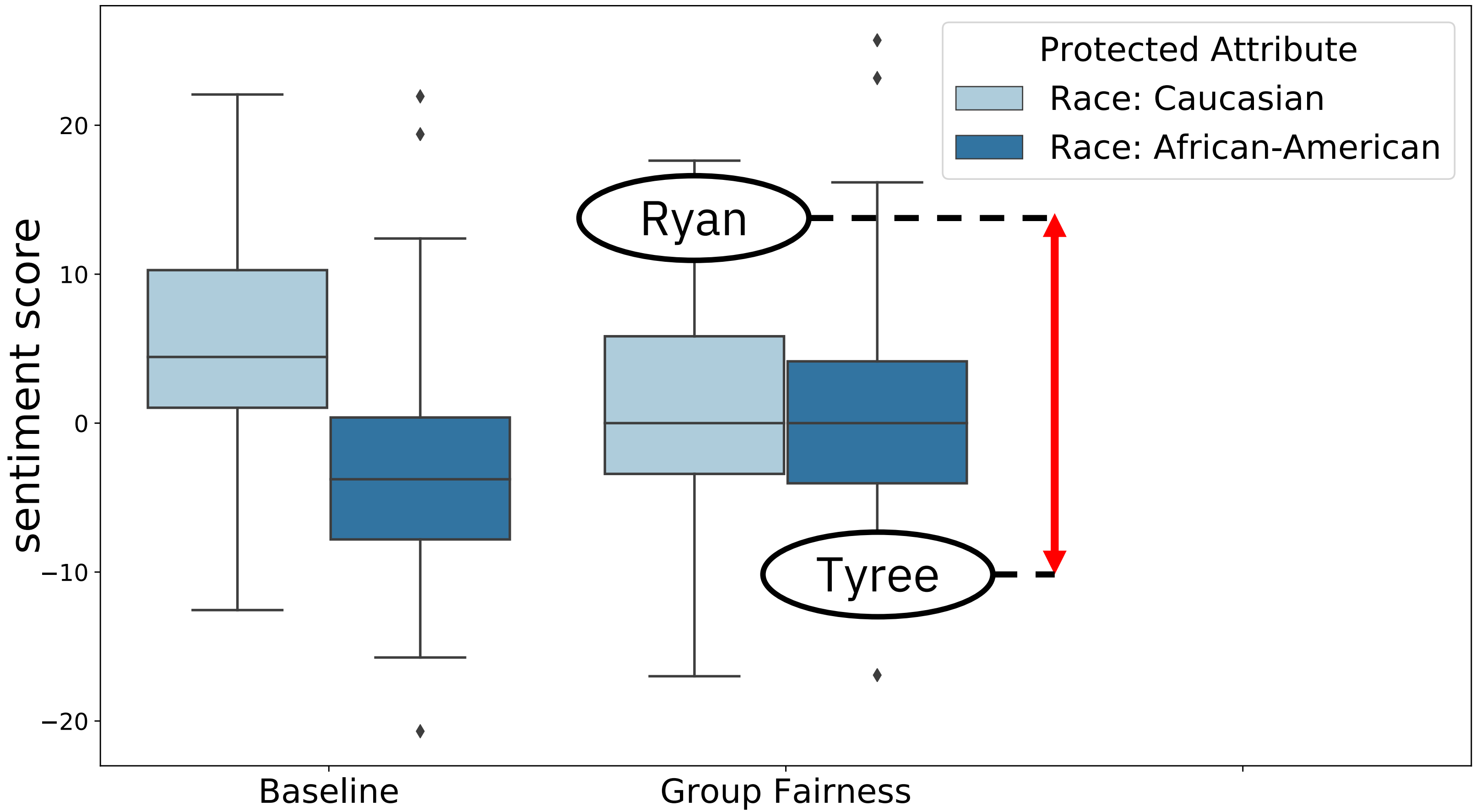
Fairness Violations



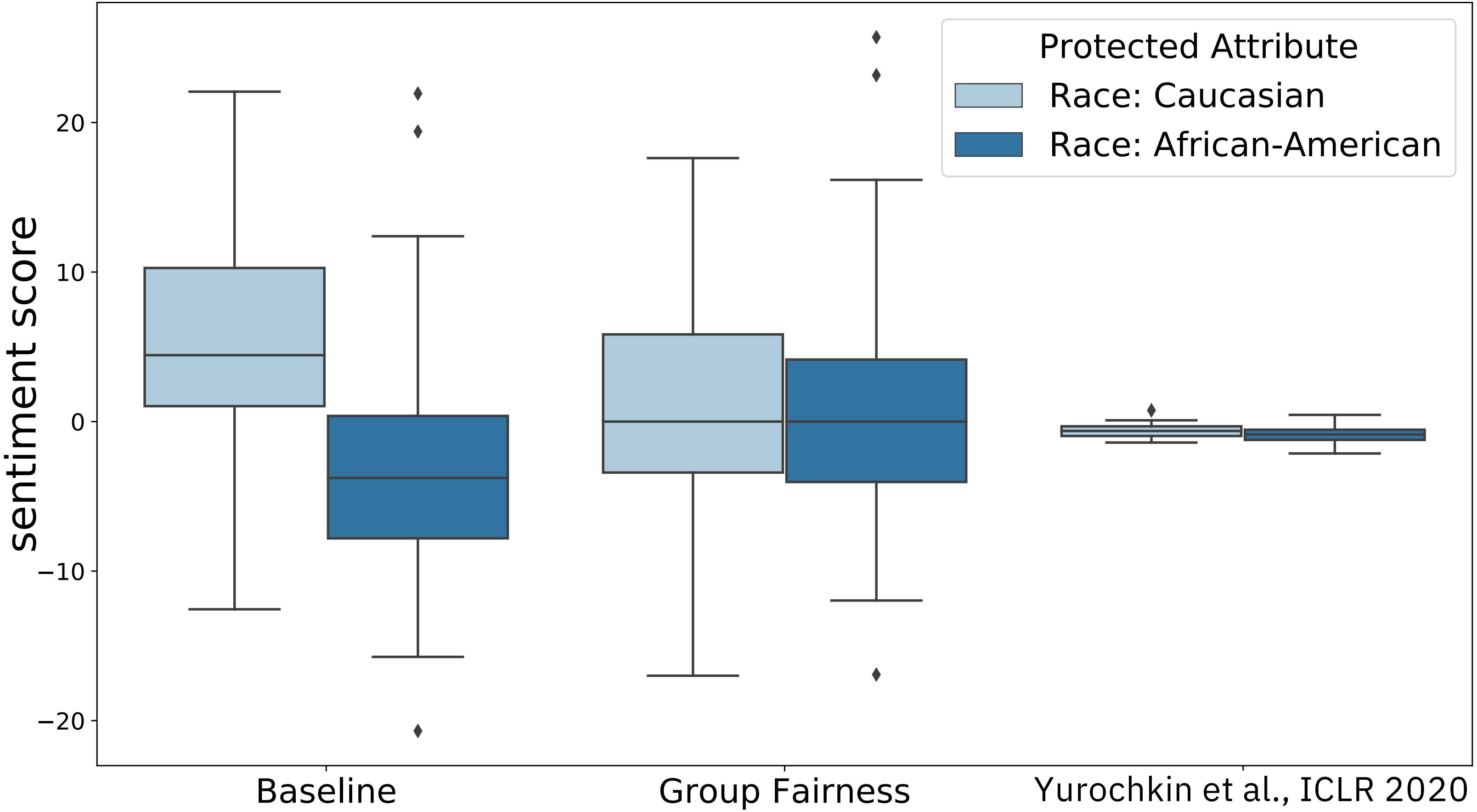
Does Group Fairness help?



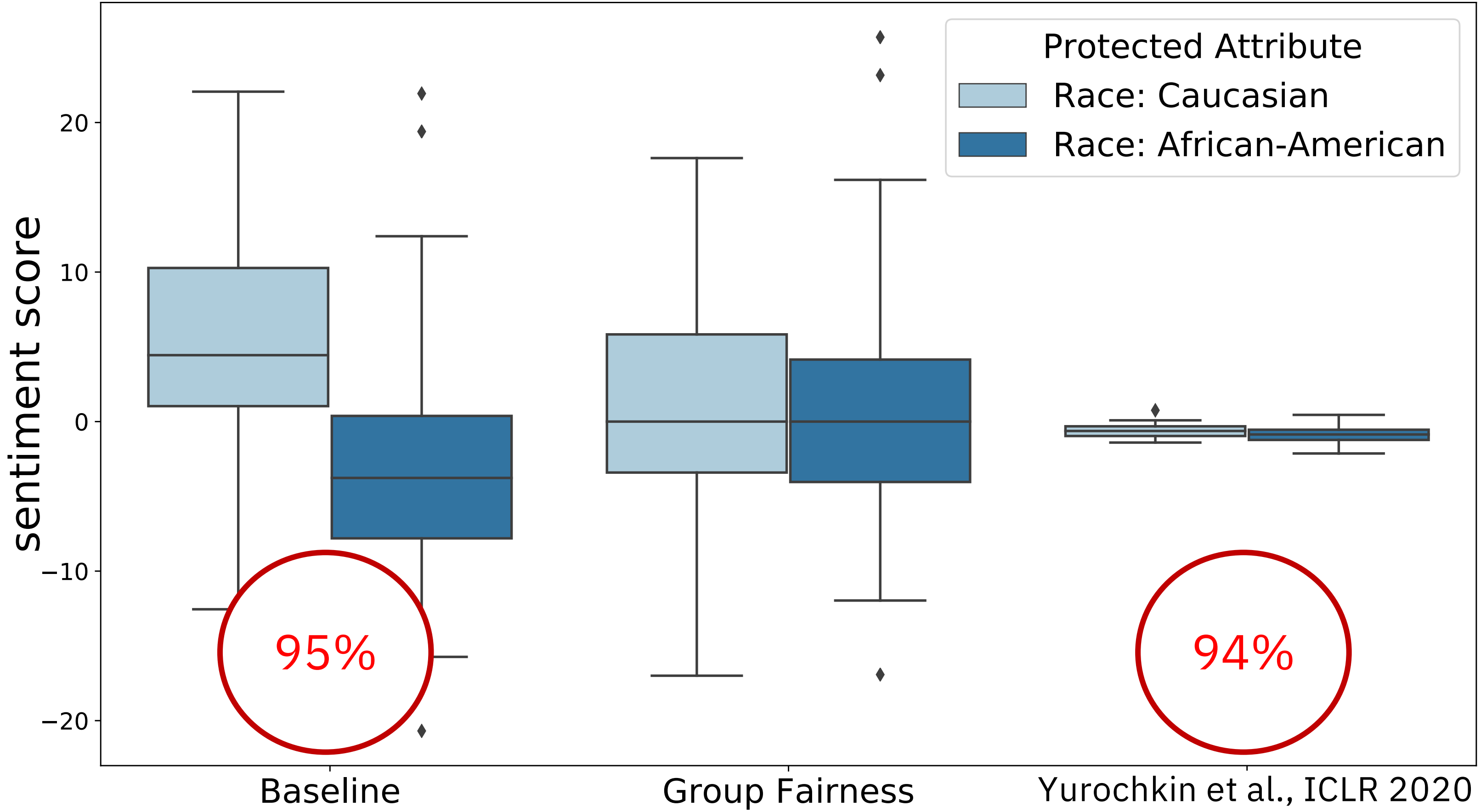
Fairness is Violated for Individuals



Individual Fairness



Accuracy is Preserved



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Group Fairness

Algorithm performs similarly on groups of individuals

$$Y - \text{true label}$$

$$A - \text{protected attribute}$$

$$\hat{Y} - \text{prediction}$$

Demographic Parity: $\hat{Y} \perp\!\!\!\perp A$

Equalized Odds: $\hat{Y} \perp\!\!\!\perp A \mid Y$

Evaluating Group Fairness

Demographic Parity: $\hat{Y} \perp\!\!\!\perp A$

Compare average outcome for men and women

Test data: $(x_1, a_1), \ldots, (x_N, a_N)$;
model to audit $h : \mathcal{X} \to \mathcal{Y}$

$$\text{Output DP} = \left| \frac{\sum_i \mathcal{I}(a_i = \text{male}, h(x_i) = 1)}{\sum_i \mathcal{I}(a_i = \text{male})} - \frac{\sum_i \mathcal{I}(a_i = \text{female}, h(x_i) = 1)}{\sum_i \mathcal{I}(a_i = \text{female})} \right|$$

Evaluating Group Fairness

Equalized Odds: $\hat{Y} \perp\!\!\!\perp A \mid Y$

Compare class accuracies for men and women

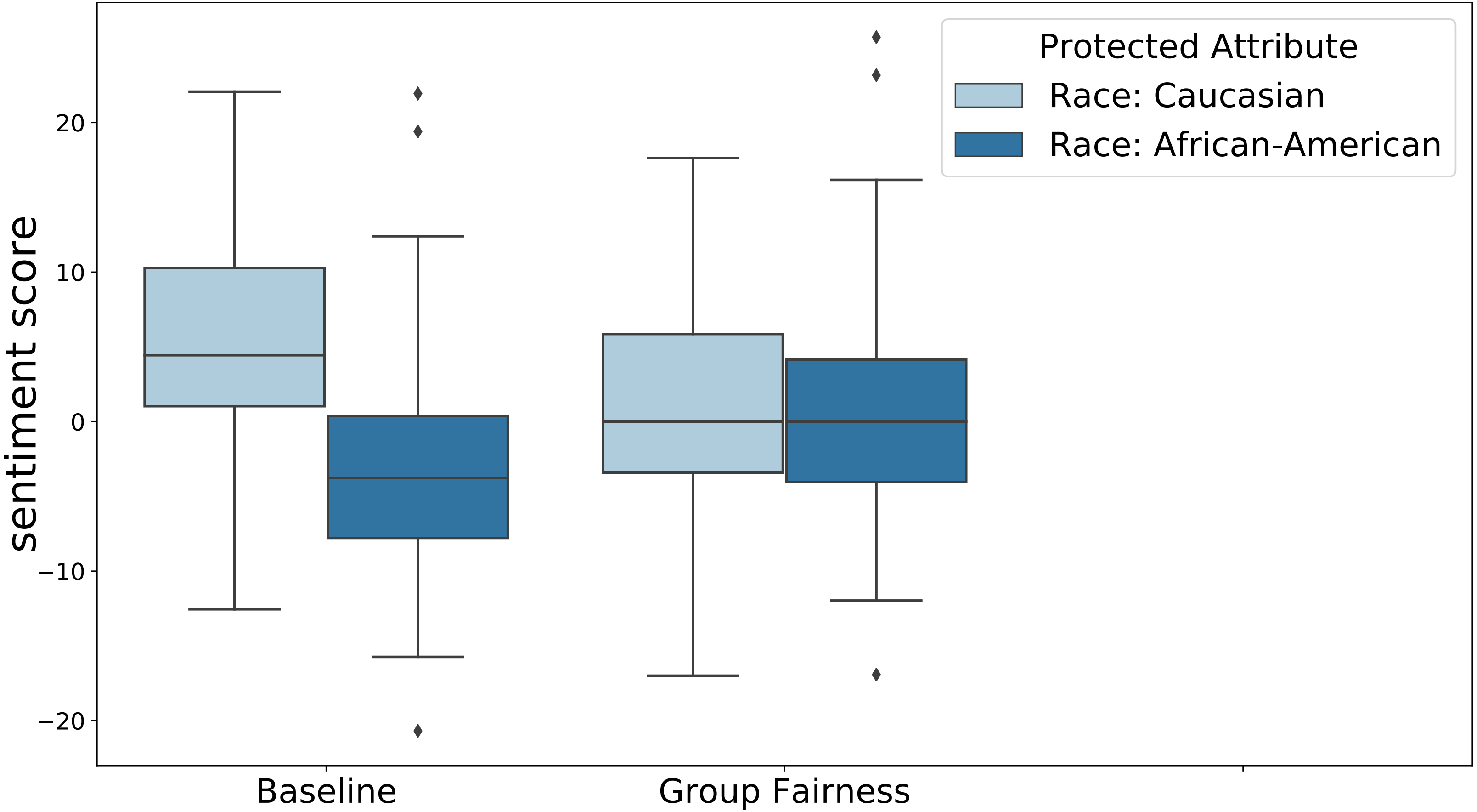
Test data: $(x_1, y_1, a_1), \ldots, (x_N, y_n, a_N)$;
model to audit $h : \mathcal{X} \to \mathcal{Y}$

$$\text{Measure EO}_0 = \left| \frac{\sum_i \mathcal{I}(a_i{=}\text{male}, y_i{=}0, h(x_i){=}0)}{\sum_i \mathcal{I}(a_i{=}\text{male}, y_i{=}0)} - \frac{\sum_i \mathcal{I}(a_i{=}\text{female}, y_i{=}0, h(x_i){=}0)}{\sum_i \mathcal{I}(a_i{=}\text{female}, y_i{=}0)} \right|$$

$$\text{Measure EO}_1 = \left| \frac{\sum_i \mathcal{I}(a_i{=}\text{male}, y_i{=}1, h(x_i){=}1)}{\sum_i \mathcal{I}(a_i{=}\text{male}, y_i{=}1)} - \frac{\sum_i \mathcal{I}(a_i{=}\text{female}, y_i{=}1, h(x_i){=}1)}{\sum_i \mathcal{I}(a_i{=}\text{female}, y_i{=}1)} \right|$$

$$\text{Output EO} = \tfrac{1}{2}(\text{EO}_0 + \text{EO}_1)$$

What Group Fairness definition did we check?



Individual Fairness

(Dwork et al. 2012)

Algorithm treats similar individuals similarly

$$d_{\mathcal{Y}}(h(x_1), h(x_2)) \lesssim d_{\mathcal{X}}(x_1, x_2) \text{ for all } x_1, x_2 \in \mathcal{X}$$

- ML model is a map $h : \mathcal{X} \to \mathcal{Y}$
- $d_{\mathcal{Y}}$ measures similarity between outputs
- **Fair metric** $d_{\mathcal{X}}$ measures similarity between inputs

Evaluating Individual Fairness

Prediction Consistency

Compare predictions on similar inputs

Occupation prediction from a person's biography:

He graduated from law school with honors ➡ Attorney

She graduated from law school with honors ➡ ???Paralegal???

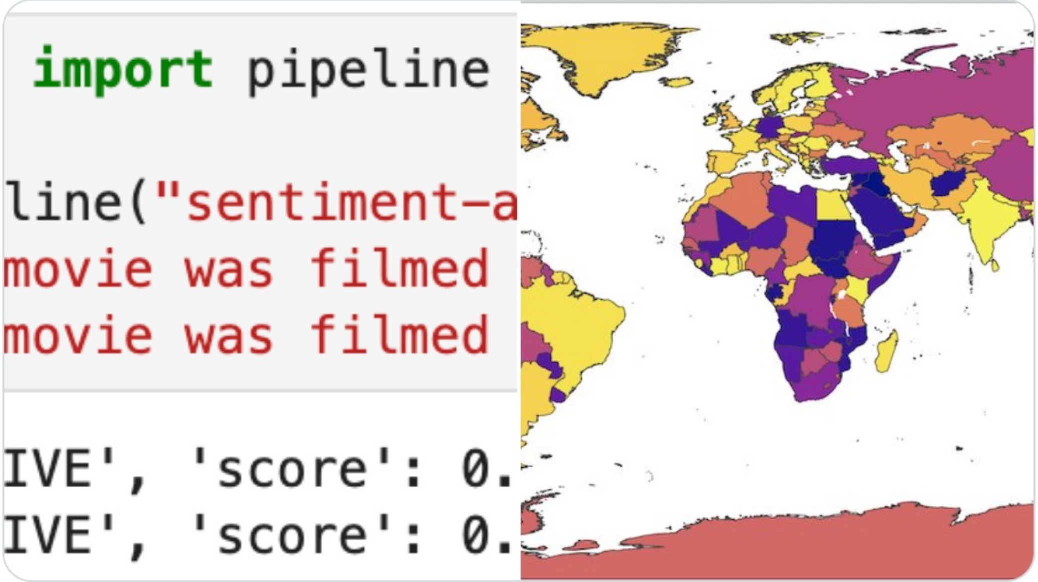
$$\text{Output PC} = \frac{\sum_i \mathcal{I}(h(x_i[he]) = h(x_i[she]))}{N}$$

Questions?

Is “blindness” a solution?

Aurélien Geron
@aureliengeron

I noticed that DistilBERT loves movies filmed in India, but not in Iraq, so I plotted the result for each country: the resulting map is scary. #aibias



12:35 AM · Mar 20, 2022 · Twitter Web App

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```

```
[{'label': 'POSITIVE', 'score': 0.9783285856246948},
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```

Roadmap

AI is prone to biases

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Identifying Fairness violations

Group Fairness: measure DP (EO) on audit data

Test data: $(x_1, a_1), \ldots, (x_N, a_N)$;
model to audit $h : \mathcal{X} \to \mathcal{Y}$

$$\text{Output DP} = \left| \frac{\sum_i \mathcal{I}(a_i{=}\text{male}, h(x_i){=}1)}{\sum_i \mathcal{I}(a_i{=}\text{male})} - \frac{\sum_i \mathcal{I}(a_i{=}\text{female}, h(x_i){=}1)}{\sum_i \mathcal{I}(a_i{=}\text{female})} \right|$$

<u>Four-Fifths Rule</u>, US Equal Employment Opportunity Commission:
"selection rate for any race, sex, or ethnic group [must be at least] four-fifths (4/5) (or eighty percent) of the rate for the group with the highest rate"

Identifying Fairness violations

Individual Fairness: Prediction Consistency

Occupation prediction from a person's biography:

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$$\text{Output PC} = \frac{\sum_i \mathcal{I}(h(x_i[he]) = h(x_i[she]))}{N}$$

Individual Fairness in Social Science

Bertrand & Mullainathan (2004) studied racial bias in the US labor market.

- The investigators responded to job ads in Boston and Chicago newspapers with fictitious resumes.
- They randomly assigned African-American or white sounding names to the resumes.
- The investigators concluded there is discrimination against African-Americans: the resumes assigned white names received 50% more callbacks for interviews.

Demonstration

Distributional Individual Fairness (DIF)

Find individual fairness violations algorithmically

$$\mathrm{DIF}(h) \triangleq \left\{ \begin{array}{ll} \sup_{T:\mathcal{X}\to\mathcal{X}} & \mathbb{E}_{P_X}\left[d_{\mathcal{Y}}(h(x), h(T(x)))\right] \\ \text{subject to} & \mathbb{E}_{P_X}\left[d_{\mathcal{X}}(x, T(x))\right] \le \epsilon. \end{array} \right\}$$

- **Auditor** T is a map that finds fairness violations
- $d_{\mathcal{Y}}$ measures similarity between outputs
- **Fair metric** $d_{\mathcal{X}}$ measures similarity between inputs

Yurochkin & Sun, ICLR 2021

Auditing for IF violations

Test data: $(x_1, y_1), \ldots, (x_N, y_N)$;
DIF map $T(x)$ for the model h that we are auditing;
some loss function $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}_+$

Hypothesis (h is individually fair)
H_0 : loss ratio on similar individuals is at most δ

Compute loss ratios $R = \left\{ \frac{\ell(h(T(x_i), y_i)}{\ell(h(x_i), y_i)} \right\}_{i=1}^{N}$

Reject H_0 with confidence $(1-\alpha)$ if $\mathrm{Mean}(R) - \frac{z_{1-\alpha}}{\sqrt{N}} \mathrm{Var}(R) > \delta$

Maity et al., ICLR 2021

Demonstration

Learning fair metrics from data

- Samples with protected attributes
- Groups of comparable samples
- Pairs of comparable and incomparable samples

$$d_{\mathcal{X}}(x_1, x_2) = (x_1 - x_2)^\top \Sigma (x_1 - x_2)$$

Mukherjee et al., ICML 2020

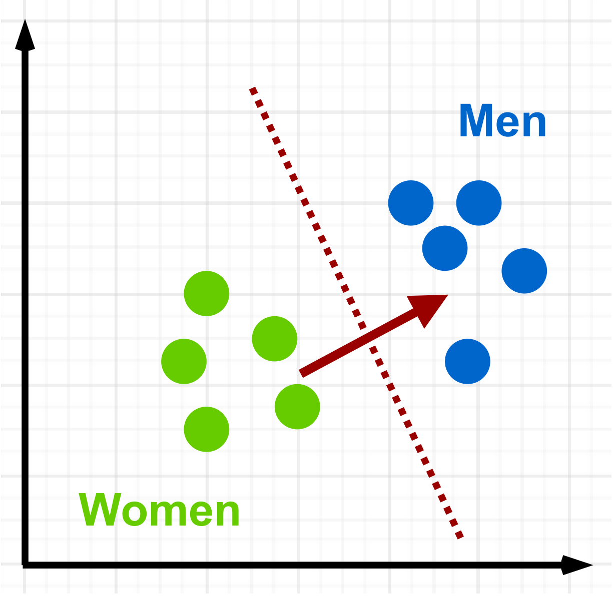
Learning fair metrics from data

Samples with protected attributes:
gender/race information in the Adult dataset

Learn "sensitive" directions with Logistic Regression, i.e. $V = \{v_{\text{gender}}, v_{\text{race}}\}$.

Ignore them in the fair metric: $\Sigma = I - P_{\text{span}(V)}$.

$$d_{\mathcal{X}}(x_1, x_2) = (x_1 - x_2)^\top \Sigma (x_1 - x_2)$$



Yurochkin et al., ICLR 2020

Learning fair metrics from data

Group of comparable samples:
word embeddings of popular baby names

Find directions of major variation with PCA, i.e. $V = \{v_1, \ldots, v_K\}$.

Ignore them in the fair metric: $\Sigma = I - P_{\mathrm{span}(V)}$.

$$d_{\mathcal{X}}(x_1, x_2) = (x_1 - x_2)^\top \Sigma (x_1 - x_2)$$

Mukherjee et al., ICML 2020

Questions?

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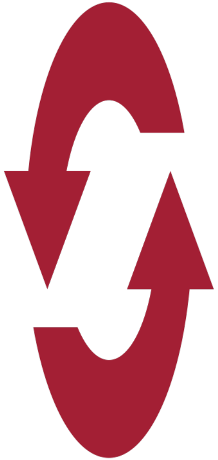
Training Individually Fair models

A variant of adversarial training: Train model accurate on the available data **and** data similar in the fair metric



- Observe data
- Audit model with DIF: Find similar data where algorithm performs differently
- Update model parameters to minimize prediction error **and** DIF
- Repeat

Yurochkin & Sun, ICLR 2021

Sensitive Set Invariance (SenSeI)

$$\min_{h\in\mathcal{H}} L(h) + \rho \mathrm{DIF}(h)$$

$$L(h) \triangleq \mathbb{E}\big[\ell(y, h(x))\big]$$

- $\mathcal{H}$: model class (e.g. neural nets with a certain architecture)
- $\ell : \mathcal{Y} \times \mathcal{Y} \to \mathbb{R}_+$ is a loss function
- ρ: regularization parameter

Yurochkin & Sun, ICLR 2021

Relation to Adversarial Robustness

Adversarial training: Train model accurate on the available data **and** visually similar data. Different "fair" metric.

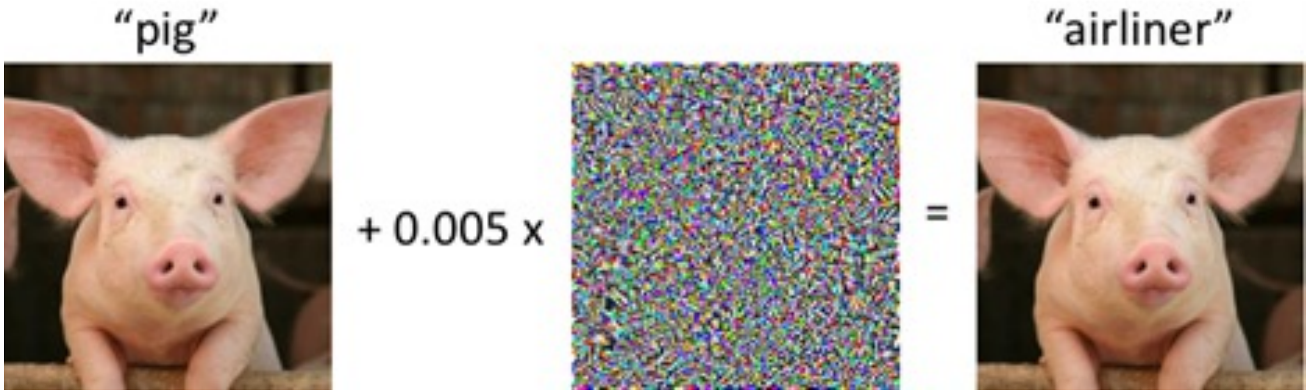


Image is from "A Brief Introduction to Adversarial Examples" (Mądry & Schmidt, 2018)

Demonstration

Training Group Fair models

Optimization with (data-dependent) constraints: Train model accurate on the available data **subject to** group fairness constraints

$$\min_{h \in \mathcal{H}} L(h)$$

$$\text{subject to DP} < \delta, \text{ where}$$

$$\mathrm{DP} = \left| \frac{\sum_i \mathcal{I}(a_i = \text{male},\ h(x_i) = 1)}{\sum_i \mathcal{I}(a_i = \text{male})} - \frac{\sum_i \mathcal{I}(a_i = \text{female},\ h(x_i) = 1)}{\sum_i \mathcal{I}(a_i = \text{female})} \right|$$

Demonstration

What is Your type of Fairness?

Group Fairness:

- Carefully choose GF notion appropriate for the application
- Many open-source solutions (AIF360, Fairlearn, TFCO)
- Check individual fairness!

Individual Fairness:

- Carefully choose data for learning the fair metric
- inFairness package is soon to be open-source
- Check group fairness!

Questions?

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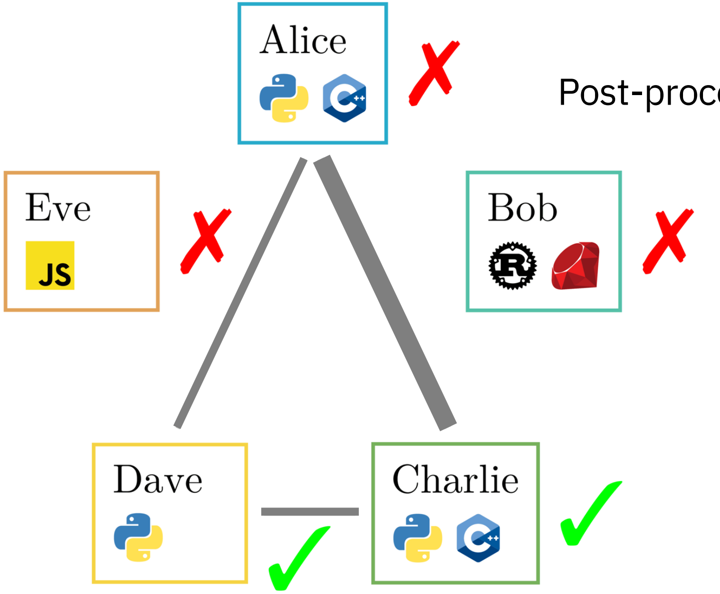
Post-processing for Individual Fairness



Measuring IF on a graph:

$$\sum_{i,j} W_{ij}(f_i - f_j)^2 = 2\mathbf{f}^\top \mathbb{L}\mathbf{f}$$

Original predictions

Graph Laplacian

Post-processed fair predictions

$$\arg\min_{\mathbf{f}} \underbrace{\|\mathbf{f} - \hat{\mathbf{y}}\|_2^2}_{\text{Stay close to original predictions}} + \underbrace{\lambda\, \mathbf{f}^\top \mathbb{L}\mathbf{f}}_{\text{Penalize individual fairness violations}}$$

<u>Closed-form solution!</u>

$$\boxed{\mathbf{f} = (I + \lambda\mathbb{L})^{-1}\hat{\mathbf{y}}}$$

Petersen et al., NeurIPS 2021

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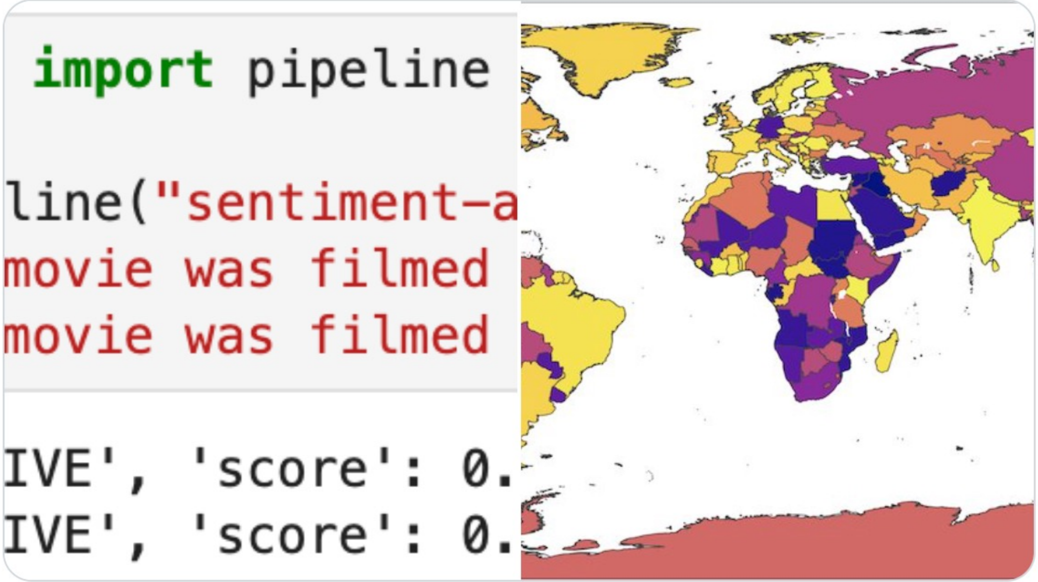

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```

Demonstration

Post-processing for Group Fairness

Optimized Score Transformation for
Consistent Fair Classification
Wei et al., 2021

FairScoreTransformer (FST): Available in AIF360

Algorithmic Fairness pipeline

Choose IF fair metric / GF notion

↓

Audit trained ML model for fairness violations

↓

Post-process trained model to improve fairness

↓

Train Fair model

Questions?

Yuekai 11:44 PM

LOL I'm getting depressed

we write all these papers and all we keep hearing about is the [redacted]uckups

We ask Your input!

Let us know your thoughts in a follow up survey.

Group Fairness References

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- Fairlearn: https://github.com/fairlearn/fairlearn
- TFCO: https://github.com/google-research/tensorflow_constrained_optimization

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- F. Petersen, D. Mukherjee, Y. Sun, and M. Yurochkin. Post-processing for Individual Fairness. NeurIPS 2021.

Blog-posts and Media

AI fairness

In today's data-driven world, machine learning (ML) systems are increasingly used to make high-stakes decisions in domains like criminal justice, education, lending, and medicine. For example, a judge may use an algorithm to assess a defendant's chance of re-offending before deciding to detain or release the defendant. Although replacing humans with ML systems appear to eliminate human biases in the decision-making process, they can perpetuate or even exacerbate biases in the training data. Such biases are especially objectionable when it adversely affects underprivileged groups of users. The most obvious remedy is to remove the biases in the training data, but carefully curating the datasets that modern ML systems are trained on is impractical. This leads to the challenge of developing ML systems that remain "fair" despite biases in the training data.

But what is fair?

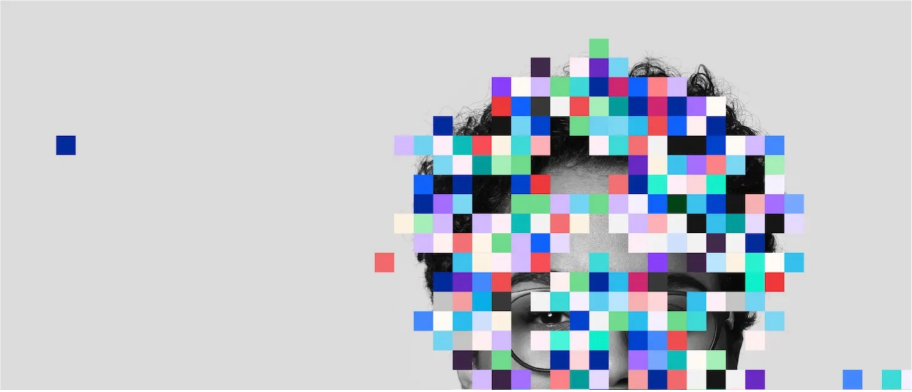
There are two major families of definitions of fairness: **(1) group fairness; (2) individual fairness**. Group fairness requires certain constraints to be satisfied at the population level, e.g. proportion of hired job applicants should be similar across different demographic groups. Individual fairness (also known as *Lipschitz fairness*) states that hiring decisions for any pair of similar applicants (e.g. equally qualified applicants with different names) should be the same.

Research

5 minute read

New research helps make AI fairer in decision-making

Our team developed the first practical procedures and tools for achieving Individual Fairness in machine learning (ML) and artificial intelligence (AI) systems.



inFairness team

Onkar Bhardwaj

Mayank Agarwal

Aldo Pareja

Collaborators

University of Michigan: Yuekai Sun, Amanda Bower, Songkai Xue, Debarghya Mukherjee, Moulinath Banerjee, Alexander Vargo, Fan Zhang, Subha Maity, Hamid Eftekhari

IBM Research: Mark Weber, Ben Hoover, Mayank Agarwal, Aldo Pareja, Onkar Bhardwaj, Uri Kartoun, Bum Chul Kwon, Kenney Ng, Zahra Ashktorab

University of Konstanz: Felix Petersen

Wells Fargo: Sherif Botros, Vanio Markov

Thank You!

Paper links, videos, news, and code are on my website
moonfolk.github.io