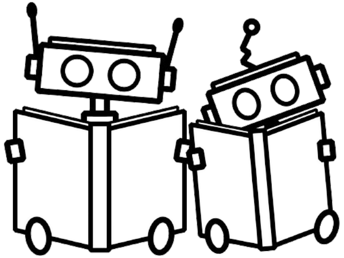
Arbitrariness and Social Prediction:

The Confounding Role of Variance in Fair Classification

A. Feder Cooper
Cornell University | The GenLaw Center



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Arbitrariness and fairness

Existing fairness practices…

Look at **error rates across groups**

Arbitrariness and fairness

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typically, for a **single** model

Arbitrariness and fairness

Existing fairness practices…

Look at **error rates across groups** (**definite**)

typically, for a **single** model (**feasible**)

Arbitrariness and fairness

Existing fairness practices…

Look at **error rates across groups** (**definite**),
typically, for **a single model** (**feasible**)

This can lead to **arbitrary** outcomes

(**Cooper** & Abrams, *AIES '21* Oral; **Cooper*** et al. *ICLR '21* Workshop Oral, **Cooper*** et al. *FAccT '22*)

Individual models → distributions over possible models

(**Cooper** et al. *CSLAW '22*)

An intuition for arbitrariness

Training 100 different logistic regression models on **COMPAS** using bootstrapping

(Dataset used to predict prison recidivism)

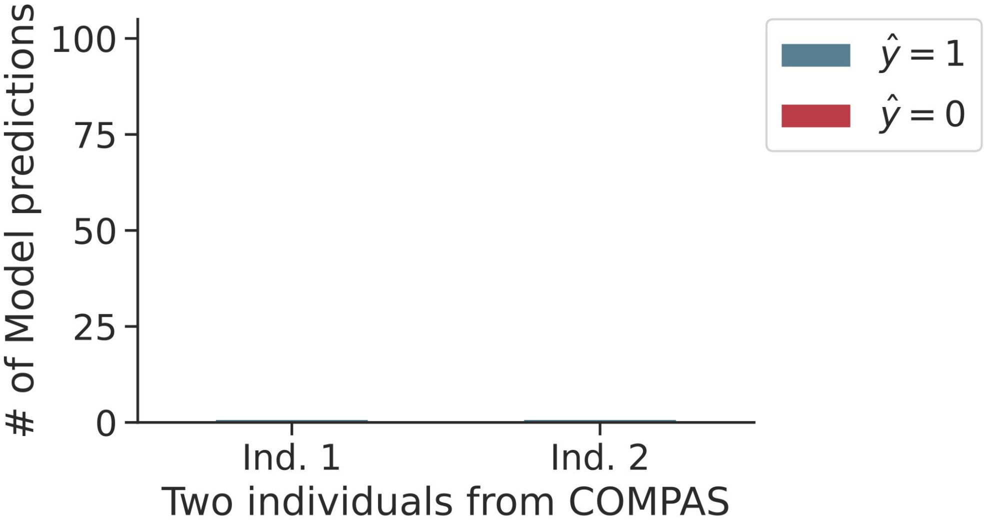
An intuition for arbitrariness

Training 100 different logistic regression models on COMPAS using **bootstrapping**

(split into train/test sets)

(resample train set)

Arbitrariness and fairness



(= recidivates)

(= does not recidivate)

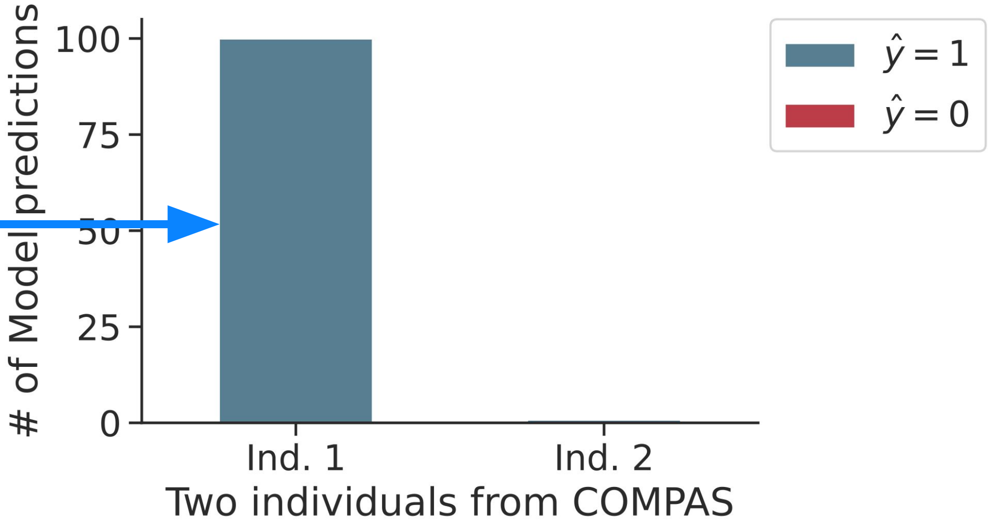
Training 100 different logistic regression models on COMPAS using bootstrapping

Looking at the resulting predictions for 2 individuals in the test set

Arbitrariness and fairness

Learning process is **really confident**

All 100 models predict the same outcome for Ind. 1



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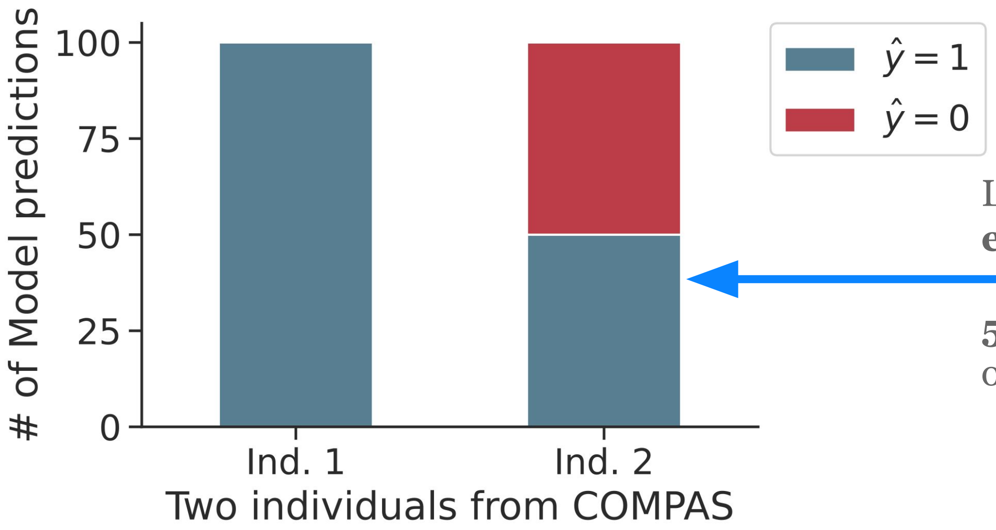

(= recidivates)

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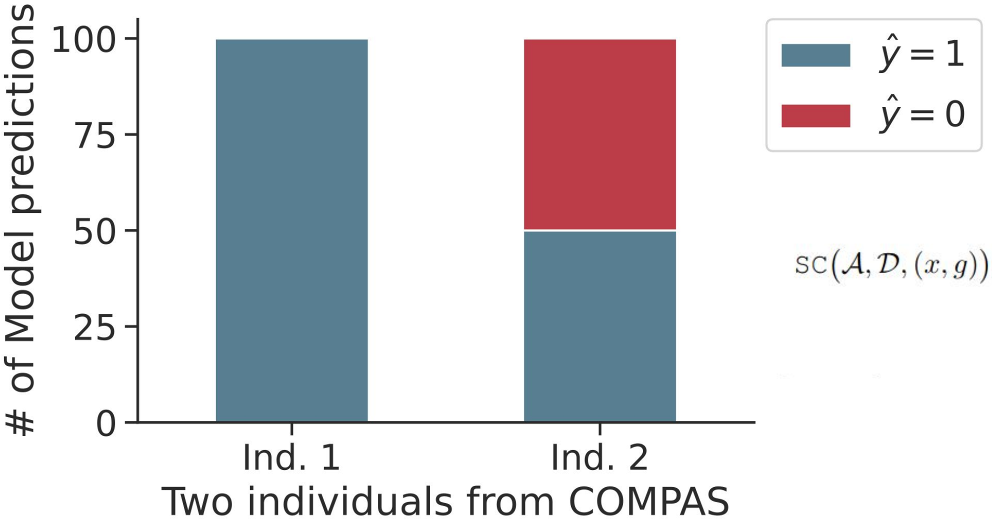
Learning process is **effectively random**

50 models predict each outcome for Ind. 2

Training 100 different logistic regression models on COMPAS using bootstrapping

Looking at the resulting predictions for 2 individuals in the test set

Arbitrariness and fairness



(= recidivates)

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$$\begin{aligned}\mathrm{SC}(\mathcal{A}, \mathcal{D}, (x, g)) &\triangleq \mathbb{P}_{h_{D_i}\sim\mu, h_{D_j}\sim\mu}\{h_{D_i}(x) = h_{D_j}(x)\} \\ &= \frac{1}{n(n-1)} \sum_{i \neq j} \mathbb{1}[h_{D_i}(x) = h_{D_j}(x)].\end{aligned}$$

We turn this picture into a metric (***self-consistency***) to capture ***arbitrariness***

Our contributions

Quantifying ***arbitrariness*** via ***self-consistency***

Developing an algorithm that ***abstains*** from making arbitrary predictions

Running a large-scale empirical study on the ***role of arbitrariness in fair classification***

Packaging a large-scale dataset (won't get into this, but at the end will explain why)

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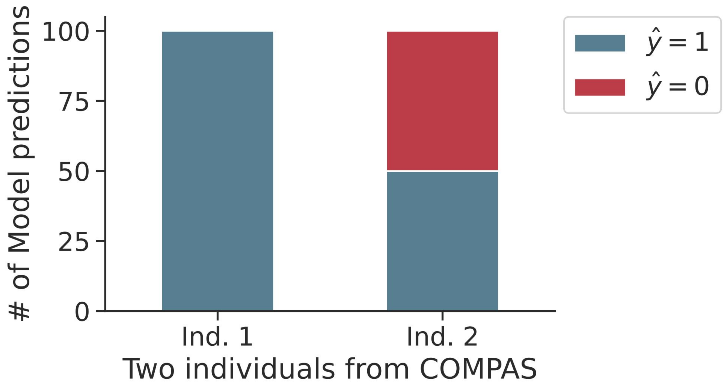
From intuition to metric

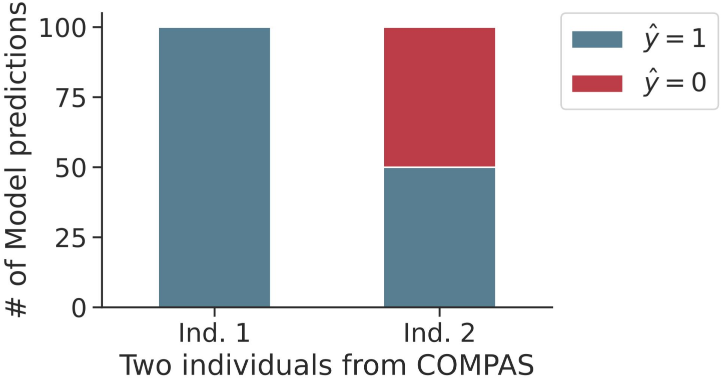


From intuition to metric

$$\textit{self-consistency} = 1 - \frac{2B_0B_1}{B(B-1)}.$$

Defined in terms of # of bootstrap replicates B

B_0 = the number of 0 predictions
B_1 = the number of 1 predictions



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$$\textbf{\textit{self-consistency}}^{*} = 1 - \frac{2B_0B_1}{B(B-1)}.$$

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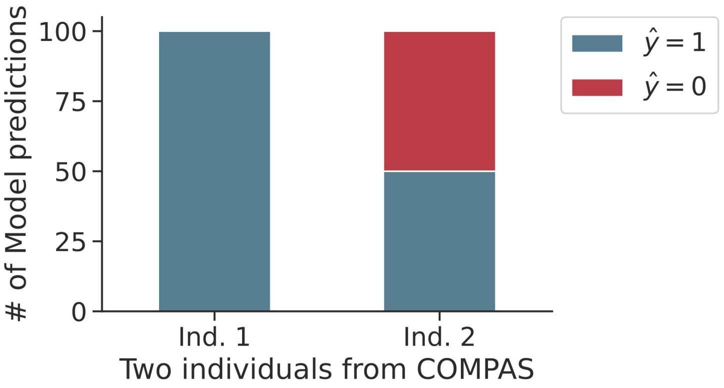

*This is our **empirical approximation definition**

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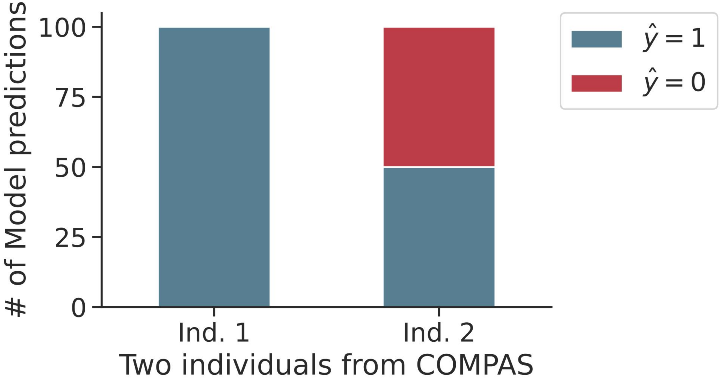
Interpretation

a value on [~0.5, 1]



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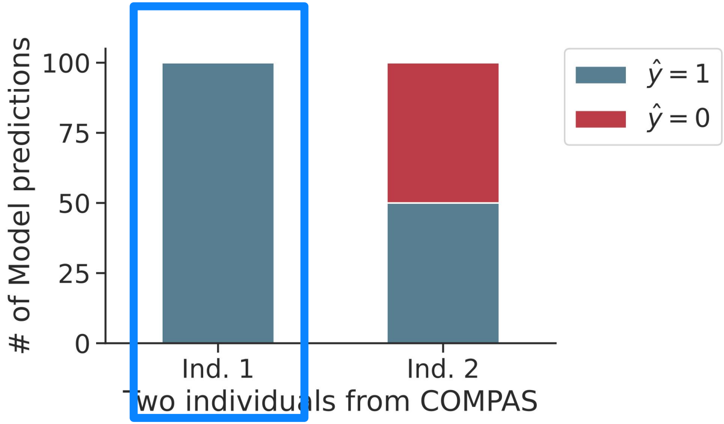

***B* = 100 logistic regression models**

Ind. 1: $B_0 = 0$, $B_1 = 100$

Ind. 2: $B_0 = 50$, $B_1 = 50$

From intuition to metric

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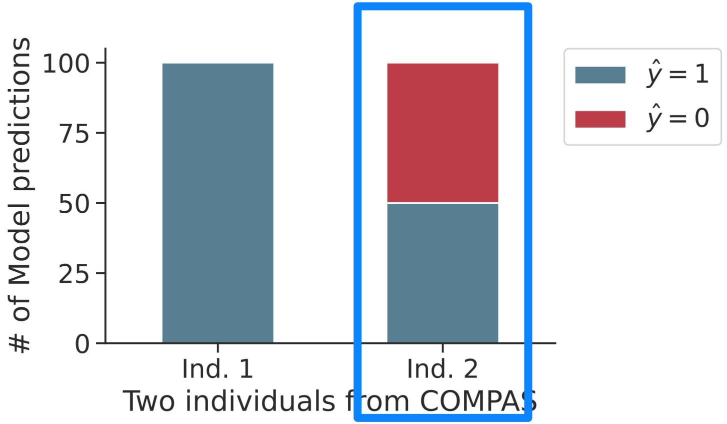

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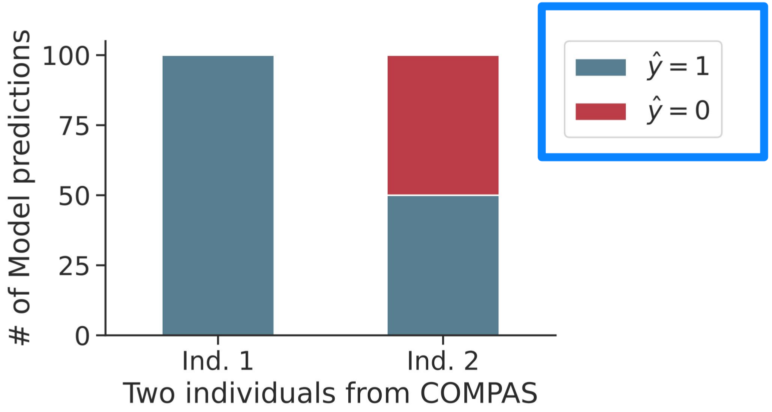
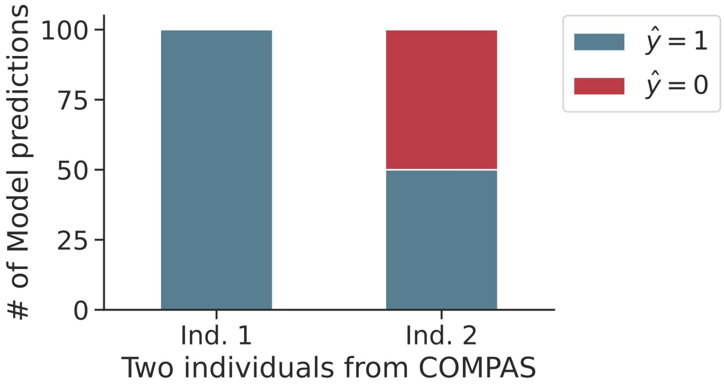
Interpretation

a value on [~0.5, 1]

does ***not*** depend on dataset labels y



Illustrating self-consistency



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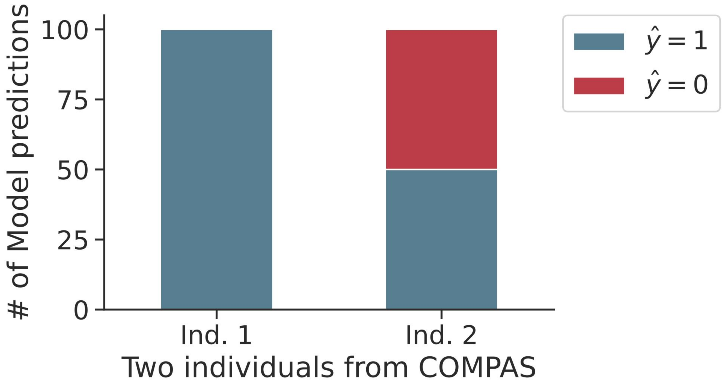

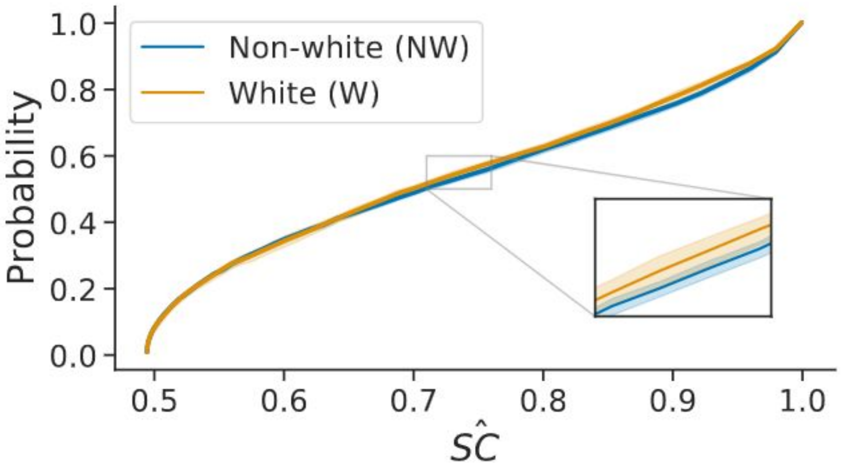

COMPAS, random forests, B=101
(mean +/- STD over 10 trials)

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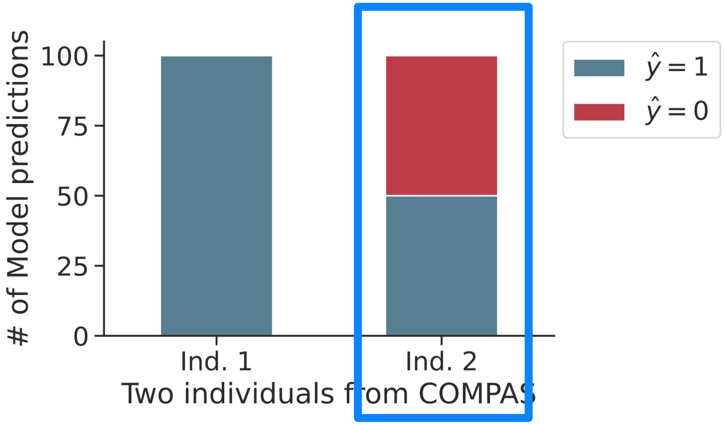
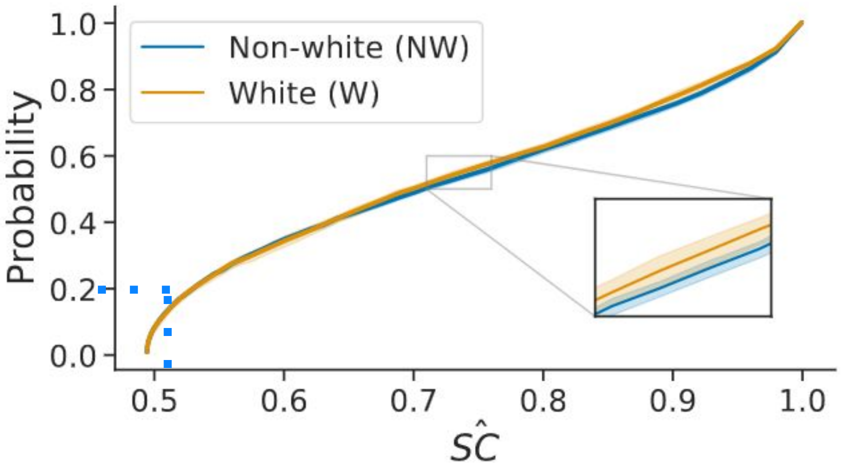


About 20% of COMPAS looks like Ind. 2

Their predictions are ***arbitrary***



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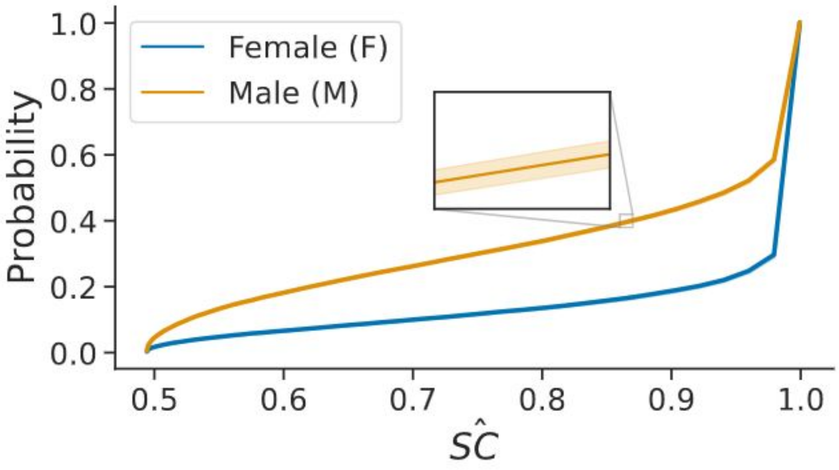

Old Adult, random forests, B=101
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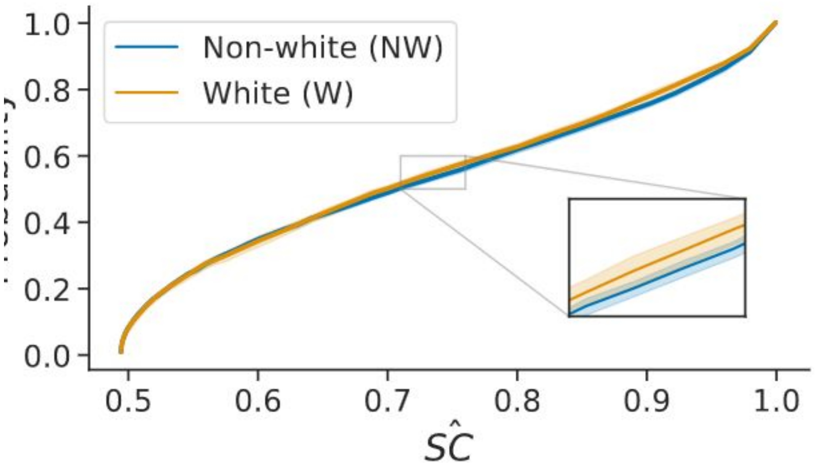

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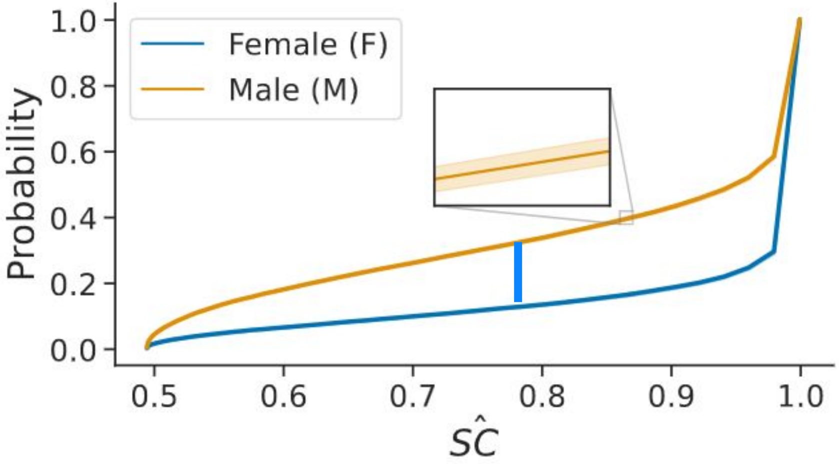

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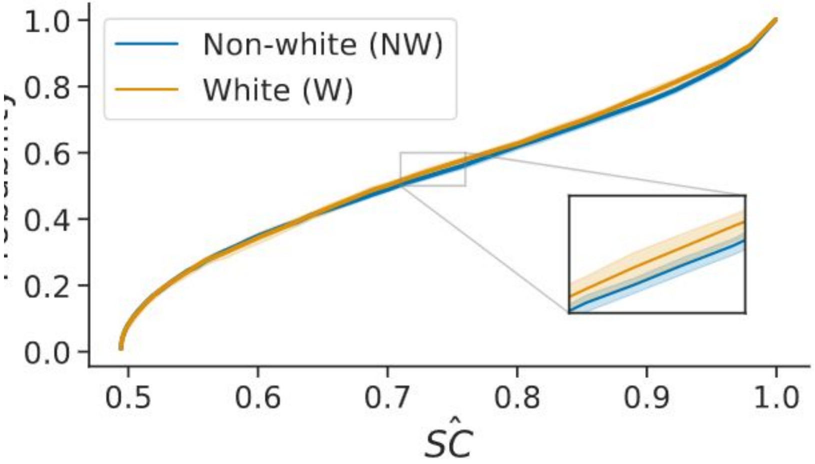
systematic arbitrariness
(actually happens rarely in practice)



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Our algorithm (really really quickly)

Self-consistency is derived from variance (High self-consistency → low variance)...

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→ Leo Breiman's 1996 bagging algorithm

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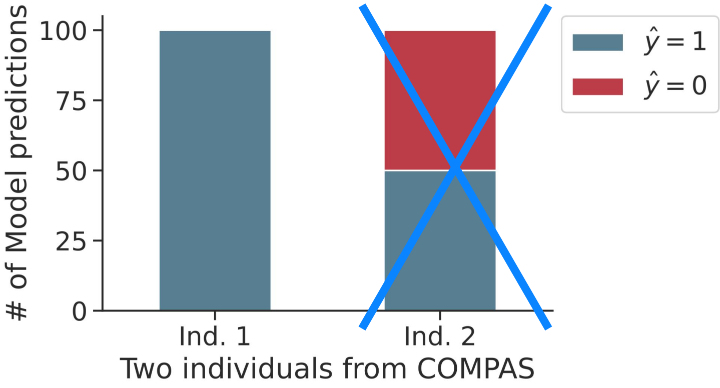
Self-consistency is derived from variance (High self-consistency → low variance)...

...so let's try to do variance reduction to improve self-consistency

→ Leo Breiman's 1996 bagging algorithm (with a twist)

Abstain if too self-inconsistent



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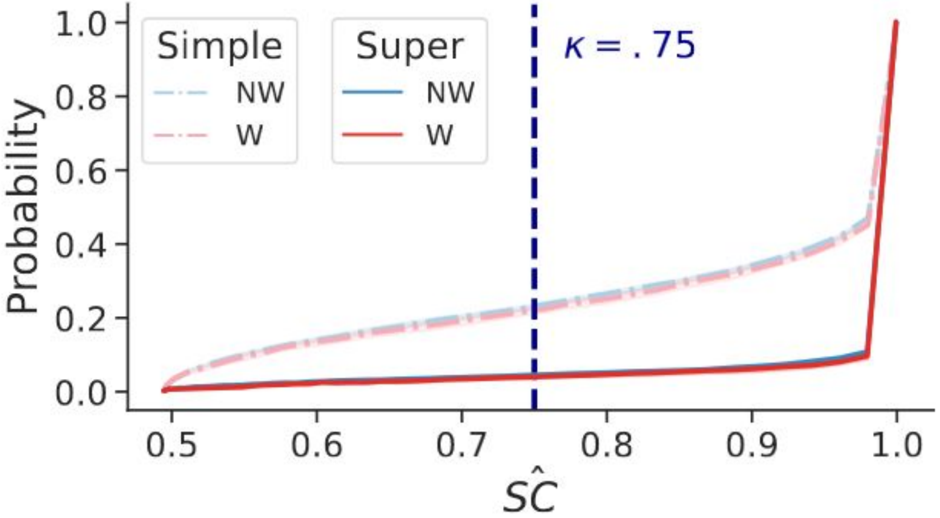

COMPAS, logistic regression, B=101
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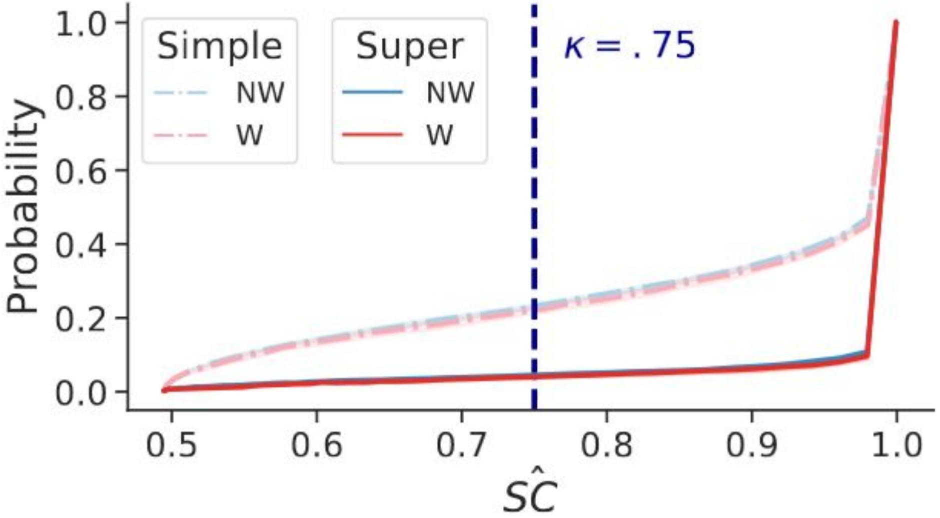
An example from our results: COMPAS

Fairness metrics

Examine false positive rate disparities



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We yield results that are very close-to-fair (<2% disparity in FPR) (and **super** variant abstains <5%)

	Simple	Super
$\Delta\hat{\mathrm{FPR}}$	$3.0 \pm 1.4\%$	$1.8 \pm 1.0\%$
$\hat{\mathrm{FPR}}_{\mathrm{NW}}$	$11.4 \pm 1.0\%$	$12.9 \pm .8\%$
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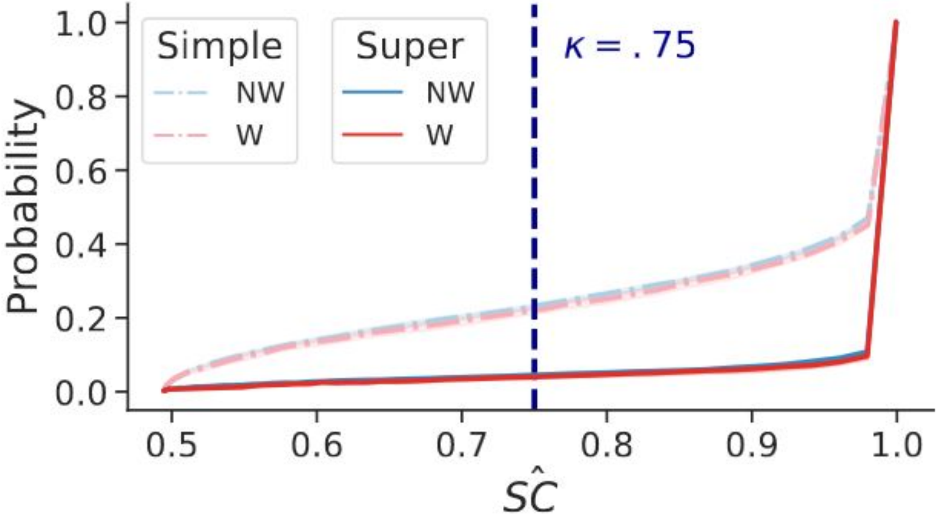

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And we haven't run any algorithmic fairness method!

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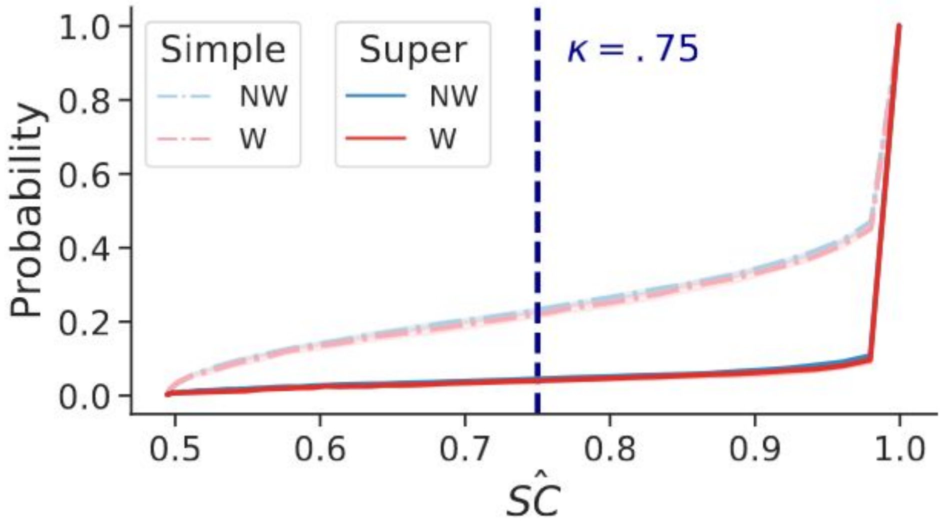

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Summarizing our experiments

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Datasets:

- **(South) German Credit**
- **COMPAS**
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- **Taiwan Credit**

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    - **NY - 2017**
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Models: logistic regression, decision trees, random forests, MLPs, SVMs (**most common fair classification models**)

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Overall, these patterns hold (and more)

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We improve self-consistency, attain accuracy, *and* (in almost every single case) **achieve close-to-fairness** ...

... *without* using a single field-standard theory-backed technique that aims to improve fairness

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There are huge takeaways here

(Please ask me about the details)

Takeaways

This finding is **really shocking**

What does it mean for empirical rigor and reproducibility of existing approaches?

Do fairness interventions actually improve fairness in practice?

Are conclusions from prior empirical work confounded by a more general problem of arbitrariness in predictions?

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Arbitrariness is rampant when predicting on social data.

How practically useful are prior theoretical formulation choices?

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The Confounding Role of Variance in Fair Classification

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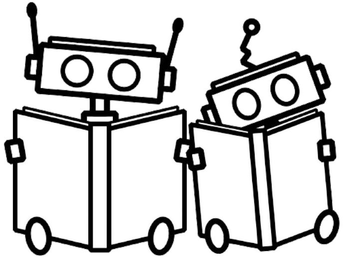
Thank you!



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