

Cornell Bowers C-IS
College of Computing
and Information Science

Machine Learning Variance, Arbitrariness, and Due Process

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Presenting work in collaboration with

Madiha Zahrah Choksi (Cornell Tech), **Solon Barocas** (Microsoft Research & Cornell),
James Grimmelmann (Cornell Law & Tech), **Christopher De Sa** (Cornell), and **Siddhartha Sen** (Microsoft Research)

ML does not remove unwanted variability

Recent legal literature claims ML will remove the “noise” of human decision-making

E.g., “**Governing by Algorithm? No Noise and (Potentially) Less Bias**” (Sunstein)

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In reality, it’s more complicated than that

A similar problem of instability can be seen in ML when we analyze
statistical variance

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A similar problem of instability can be seen in ML when we analyze
statistical variance

We show

how statistical variance can be interpreted as **arbitrariness** in ML

why this type of arbitrariness is important for legal analyses of ML rules,
technological due process, and a few other things (to be scoped out)

An intuition for arbitrariness

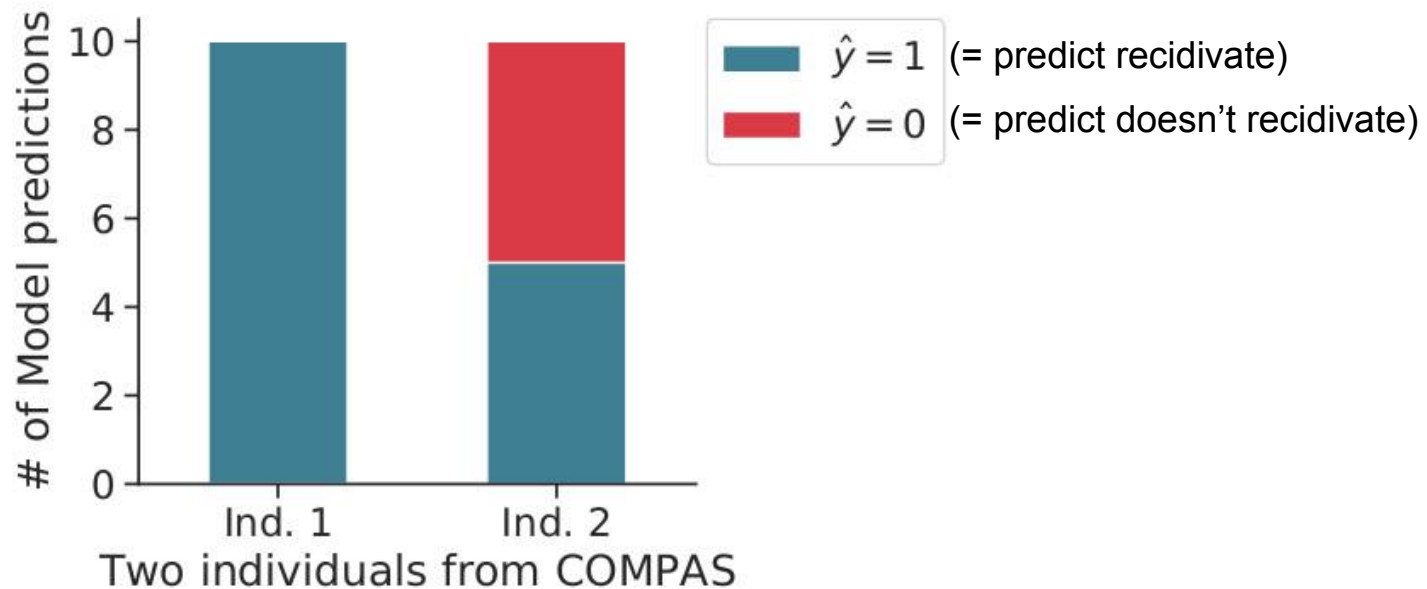
Training 10 different logistic regression models on COMPAS using bootstrapping

(Dataset used to predict
whether or not a person
will recidivate)

An intuition for arbitrariness

Training 10 different logistic regression models on COMPAS using **bootstrapping**
(split into train/test sets)
(resample train set)

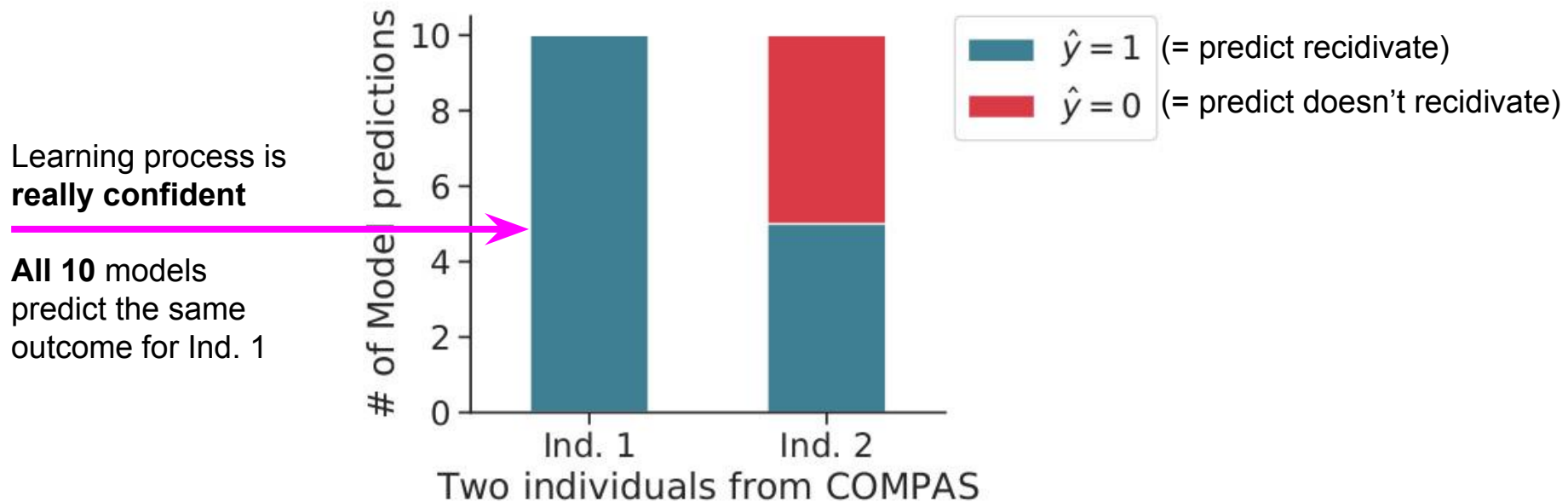
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Looking at the resulting predictions for 2 individuals in the test set (not used in training)

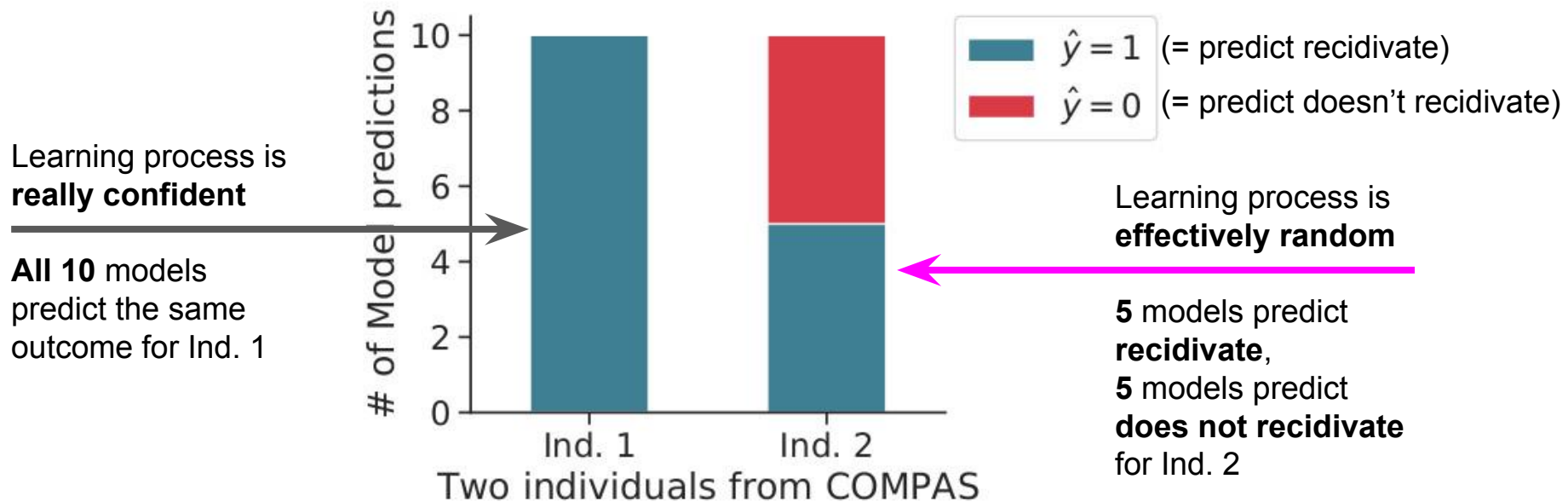
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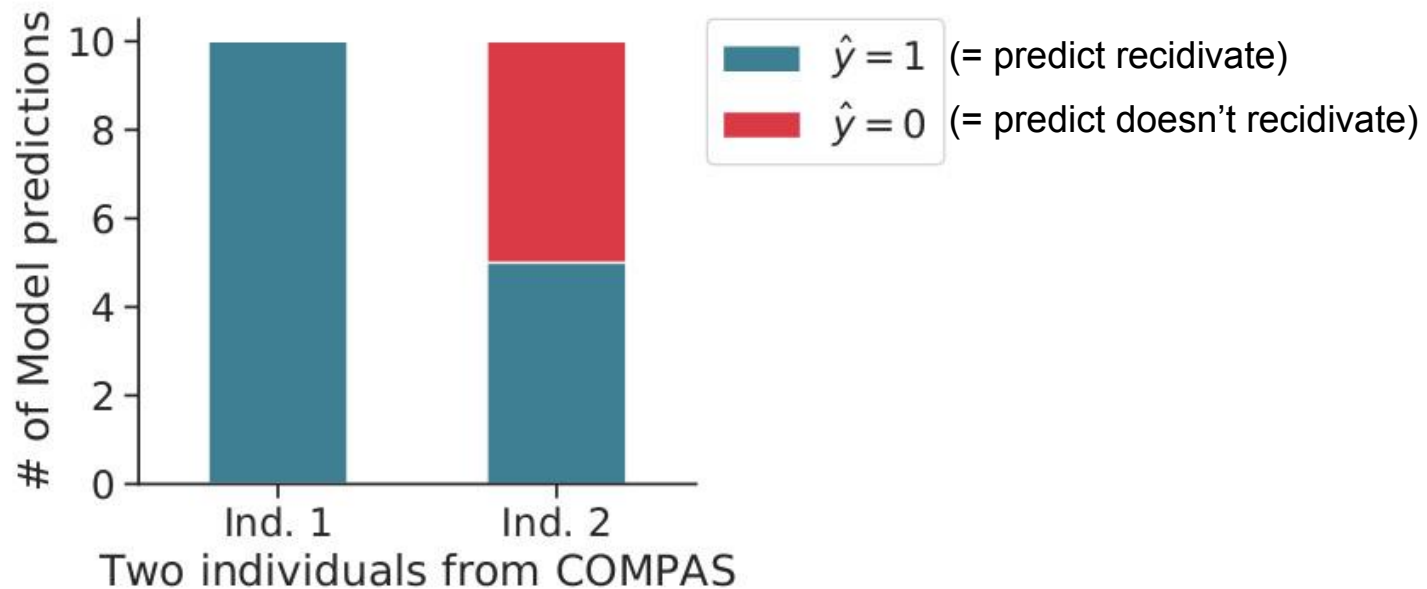
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What does this mean for the law?



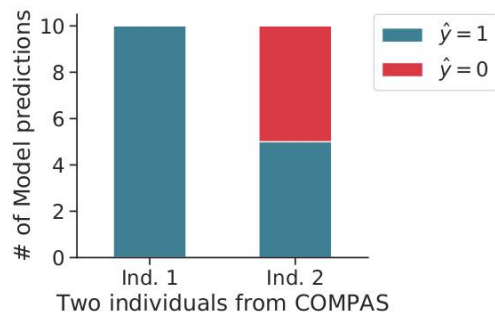
The randomness that leads to these results **is a feature of ML**

We need to change how legal and regulatory
work talks about randomness

Non-determinism

Non-deterministic

Supplying the **same** inputs can produce **different** outputs.



Reasoning about *distributions over outcomes*

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Instead of thinking about

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We will think about **distributions**

over **possible models** with different **deterministic decision rules**

(where the distribution of rules is influenced by non-determinism in training)

ML randomness in the legal literature

In a **single model**, randomness can cause a **deterministic decision rule** to (nevertheless) **always** produce the **same output** for the **same input**

“Governing by Algorithm? No Noise and (Potentially) Less Bias” (Sunstein)

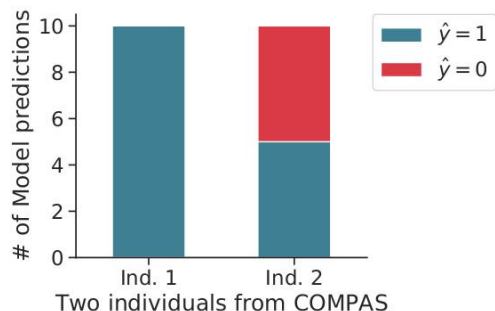
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In a **single model**, randomness can cause a **deterministic decision rule** to exhibit **big variations** in outputs when there are **small variations** in inputs

“Small Change Makes a Big Difference” (Bambauer, et al.)

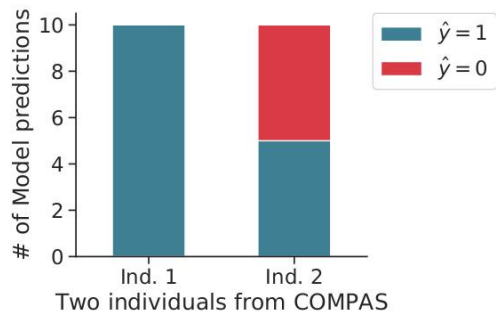
“Treat like alike” (TLA) principle (which has various critiques in the law)

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“**The Algorithmic Leviathan**” (Creel and Hellman)

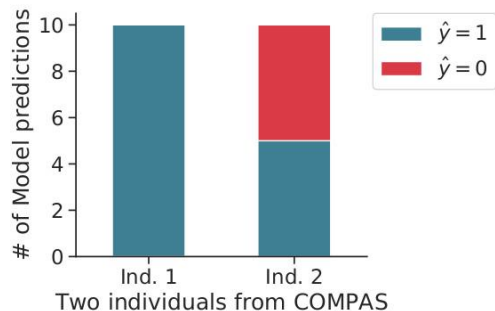
“To the extent that an algorithm governs the decision, it will produce the **same result when run on the same inputs**. If the algorithm contains a degree of **randomness** within it, ... it is **still reproducible** at a higher level of abstraction”

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presents under-explored implications for technological due process

suggests novel insights into when and how legal rules can break down

If you're interested in computer science results on this topic,
please check out our ML paper!

(which by accident also broke fundamental, important things in fair classification
& suggested serious scientific reproducibility problems in the subfield)

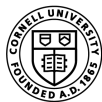
Variance, Self-Consistency, and Arbitrariness in Fair Classification

A. Feder Cooper¹ **Solon Barocas**^{2,3} **Christopher De Sa**¹ **Siddhartha Sen**²

[Under Submission '23;

title is getting changed;

maybe please wait a week to read because
I'm updating it]



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