Building a Robot Judge: Data Science for Decision-Making

11. Algorithms and Decisions II

Using predictions by judges

- **Rewrite the following statements about building inspectors, for the case of judges deciding on bail. For each requirement, give an example of when it won't hold.**
  Under what conditions are predictions sufficient for optimal allocation of inspectors?
  (1) Benefits of fixing problems are mostly homogeneous.
  (2) Establishments do not change behavior in response to the algorithm.
  (3) Inspectors follow a threshold rule.
  (4) Inspectors get feedback on prediction accuracy (before making a decision?).
- When done, compare answers with a neighbor.

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(1) Benefits of detention are mostly homogeneous.

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(3) Judge follows a threshold rule.
- why not?

(4) Judges get feedback on prediction accuracy to assess domain shift.
- why not?
- **important distinction: if decision is about inspecting, versus jailing/treating/etc**

Alternative: Doctor's testing decision

Mullainathan and Obermeyer (2019)

- Consider the problem of a doctor deciding whether to order a test for a heart blockage.
  - if blockage is detected, useful treatment can be given
  - if no blockage, then test was wasted (test is costly to administer)

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  - if blockage is detected, useful treatment can be given
  - if no blockage, then test was wasted (test is costly to administer)
- Optimal testing strategy:
  - form predicted prior probability of a positive test $\hat{Y}(X_i)$
  - test all i with predicted prior probability above some threshold $\bar{Y}$.

When are test result priors sufficient for testing decisions?

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Note: Given (1) through (3), the doctor testing decision is a **prediction problem**.

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- Under what conditions are predictions $\hat{Y}(X)$ sufficient for making the optimal decision D^*?
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2. Environment factors (i.e. decision subjects) do not respond to the algorithm.
   - X is not a function of $D^*(\cdot)$
3. Each decision-maker j follows the algorithm threshold rule.
   - $D(X, \hat{Y}, j) = D^*(\hat{Y})$

Outline

Prediction / Causation / Decisions

Behavioral Responses to Algorithms
- Responses by Subjects
- Responses by Decision-Makers

Selective Labeling

Prediction / Causation / Decisions

Kleinberg, Ludwig, Mullainathan and Obermeyer (AER P&P 2015)

- Rain Dance:
  - farmer 1 is facing a drought, should she pay a shaman to give a rain dance to bring rain?

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  - both want to estimate a function $Y = f(X)$
- One is a prediction problem, and one is a causation problem.
  - which is which?

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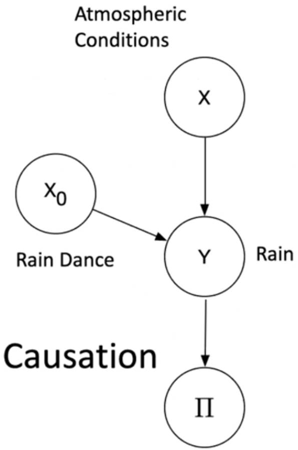
- Umbrella:
  - farmer 2 is walking to work, should she bring an umbrella?
  - $\rightarrow$ **prediction problem (like doctor testing): Will it rain?**

Rain Dances and Umbrellas



- X_0 is the decision, payoff is Π
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Source: Sendhil Mullainathan Slides.

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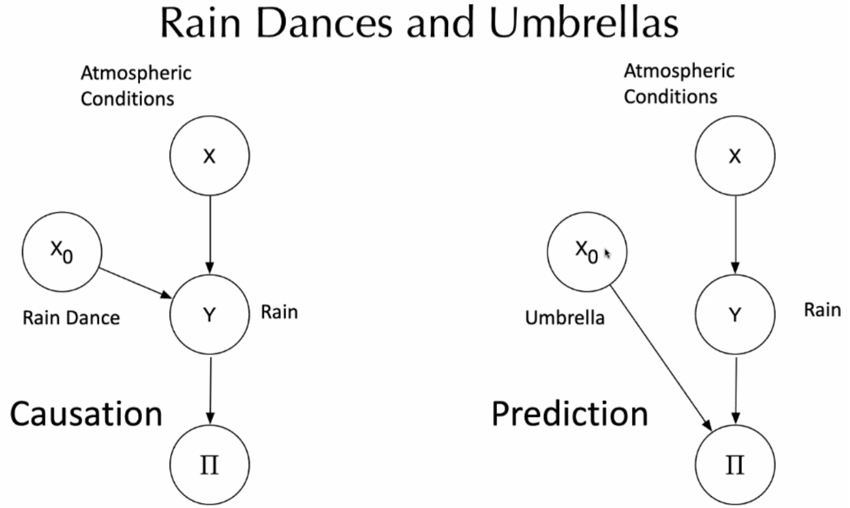

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  - **Prediction**: we care about $X_0 \rightarrow \Pi$, potentially conditional on Y

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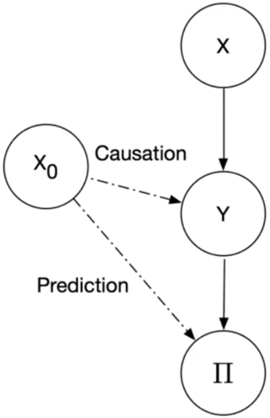
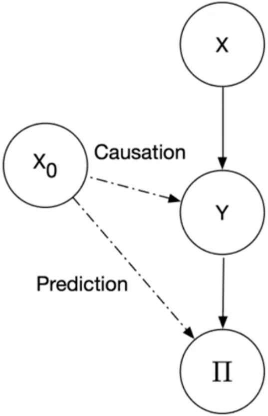
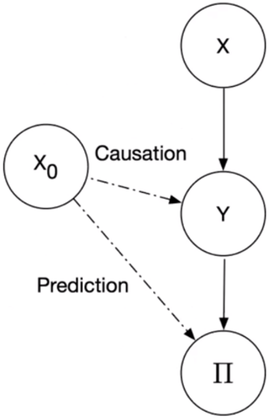
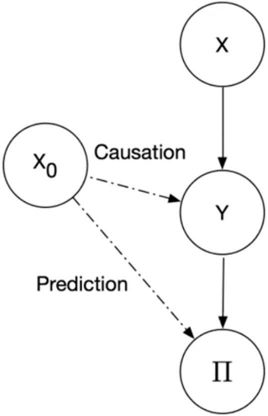

X
X_0
Causation
Y
Prediction
Π



$$\frac{d\Pi}{dX_0} =$$



$$\frac{d\Pi}{dX_0} = \frac{\partial \Pi}{\partial X_0}(Y) + \frac{\partial \Pi}{\partial Y}\frac{\partial Y}{\partial X_0}$$



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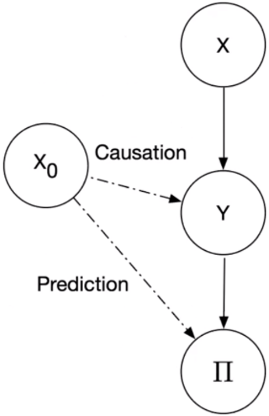
- $\frac{\partial Y}{\partial X_0} = \hat{\rho}$ = the **causal effect** of the decision on Y



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- Rules for good decision-making:
  - good predictions require machine learning
  - consistent causal effect estimates require causal inference and experiments.

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- More generally:
  - ML subjects can pay some cost and manipulate their features to improve their predicted label.

Milli et al, "The Social Cost of Strategic Classification" (2019)

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- The costs $c(\cdot)$ are socially wasteful, but responses to manipulation increase them.
  - $c(\cdot)$ could be different across groups, causing inequity

Bjorkegren et al (2021): Manipulation-Proof Machine Learning

- Assume a cost function for individual i

$$c(X, X') = \frac{1}{2}(X - X')^{\mathsf{T}}\Gamma_i(X - X')$$

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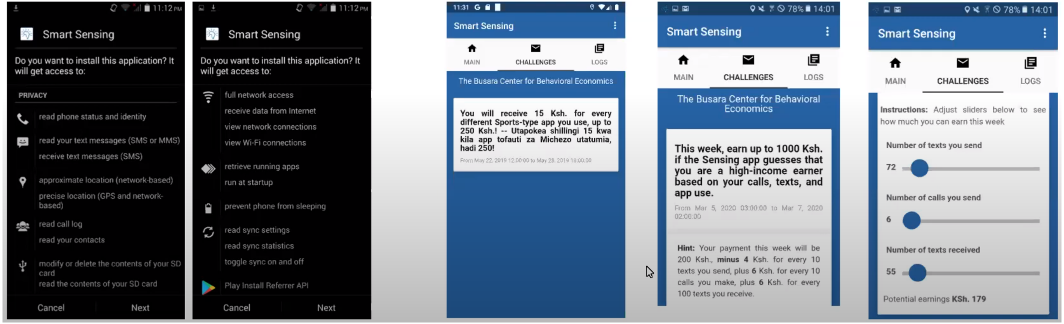
- Principal's "manipulation-proof" decision rule is

$$\begin{aligned}\beta &= \arg\min_{\beta} \sum_i [y_i - \beta^{\mathsf{T}} X_i^*(\beta)]^2 \\ &= \arg\min_{\beta} \sum_i [y_i - \beta^T \underbrace{(X + \Gamma_i^{-1}\beta)}_{\text{strategic response}}]^2\end{aligned}$$

Bjorkegren et al (2021): Experiment

We built a new smartphone app, with Busara Center (Nairobi)

1. App collects **behavioral data** (same as with a digital credit app)
2. App provides **rewards** based on user behavior
3. We experimentally vary **transparency** of the algorithm [timeline]



Bjorkegren et al (2021): Learning cost parameters Γ_i

	Change in observed behavior					
Behavior incentivized	Missed Calls	People Called (Workday)	Battery Charges	Missed Calls (outgoing)	Non-Contact Calls (Weekend)	Text messages sent
Missed Calls	**0.709** **(0.05)****	**0.152** **(0.044)***	0.026 (0.865)	0.825 (0.124)	-0.002 (0.994)	**4.16** **(0.035)****
People Called (Workday)	0.395 (0.165)	**0.227** **(0.0)*****	-0.06 (0.609)	0.121 (0.773)	0.068 (0.7)	-1.537 (0.321)
Battery Charges	-0.053 (0.913)	-0.03 (0.766)	-0.038 (0.85)	-0.616 (0.391)	-0.015 (0.96)	0.687 (0.795)
Missed Calls (outgoing)	0.324 (0.491)	**0.197** **(0.045)***	0.313 (0.11)	**1.187** **(0.089)**	**0.502** **(0.089)***	-0.206 (0.936)
Non-Contact Calls (on Weekend)	-0.056 (0.906)	-0.054 (0.585)	-0.138 (0.481)	**1.234** **(0.078)***	**1.233** **(0.0)*****	-2.022 (0.433)
Text messages sent	-0.052 (0.921)	-0.014 (0.898)	0.005 (0.981)	-0.836 (0.286)	-0.022 (0.948)	**24.508** **(0.0)*****
Week & Individual FE's	✓	✓	✓	✓	✓	✓
N (person-weeks)	7976	7976	7976	7976	7976	7976

Bjorkegren et al (2021): Decision Rule

Robust model selects features that are harder to manipulate

Response variable: **MONTHLY INCOME**	**Naive β (3 coefficients)** ¢/action	**Robust β (3 coefficients)** ¢/action	**Cost α_{jj} of manipulation** ¢/action^2
# Outgoing Calls	0.625	0.542	0.591
# Outgoing SMS	-0.395	-0.107	0.035
# Incoming SMS	0.065	0	0.038
# Evening SMS	0	-0.121	0.058
N (unique individuals)	1377	1377	

Bjorkegren et al (2021): Results

In experiment, robust rule performs better

Response variable: MONTHLY INCOME	Naive β (3 coefficients)	Robust β (3 coefficients)	Cost α_{jj} of manipulation
# Outgoing Calls	0.625	0.542	0.59087919
# Outgoing SMS	-0.395	-0.107	0.03454505
# Incoming SMS	0.065	0	0.03834774
# Evening SMS	0	-0.121	0.05849779
RMSE (w/o Manipulation)	3.553	3.554	
RMSE (with Manipulation)	3.867	3.655	
Δ (%)	8.837%	2.841%	

The naïve model does better when people don't have incentives to game

The robust model does better when people are gaming

The robust model is less impacted by strategic behavior

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3. **Decision-makers respond predictably to the algorithm.**

Decision-makers are usually separate from the algorithm

- So far we have treated the decision D as a deterministic function of $\hat{Y}$: $D = 1$ if $\hat{Y} > \bar{Y}$, $D = 0$ otherwise.
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- But there could be many reasons that this assumption does not hold, e.g.:
  - judges caring about whether a defendant has children or not.
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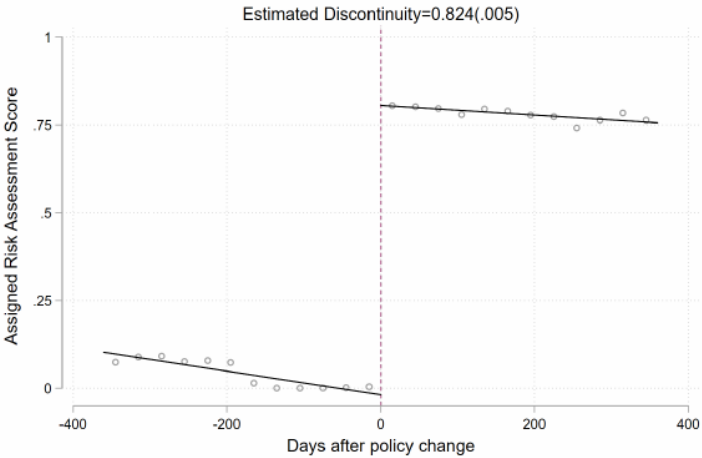
$\rightarrow$ empirical evidence is needed on how decision-makers respond to algorithms.

First Stage: Discrete Reform introducing risk scoring

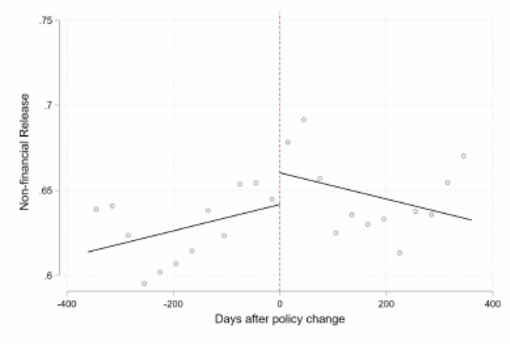
Sloan et al 2018

Figure 4: Regression Discontinuity Results for the Probability of Receiving a Risk Assessment Score

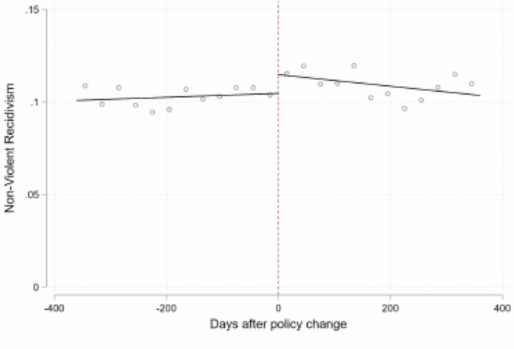


Risk scoring increases release rates and recidivism

Sloan et al 2018



(a) Non-financial Bond



(a) Probability of Non-Violent Recidivism

- In response to risk scoring, judges release more poor defendants.

Stevenson and Doleac: Method

- RD using a continuous risk score – above a discrete cutoff, defendant is labeled "risky".

Stevenson and Doleac: Method

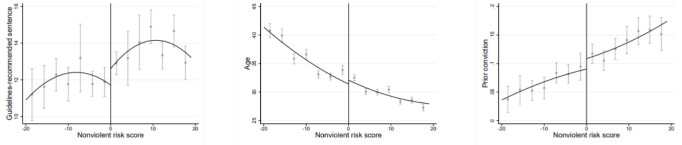
- RD using a continuous risk score – above a discrete cutoff, defendant is labeled "risky".
- Identification check: Other predetermined characteristics are flat around the cutoff (covariate balance):

Figure 2: Covariate balance across risk score cutoffs

(a) Nonviolent risk score and the guidelines-recommended sentence

(b) Nonviolent risk score and age

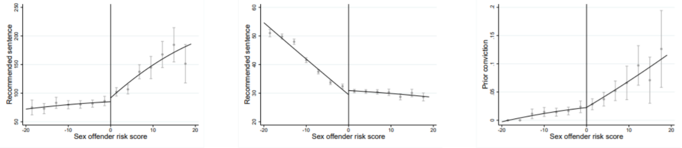
(c) Nonviolent risk score and prior convictions



(d) Sex offender risk score and the guidelines-recommended sentence

(e) Sex offender risk score and age

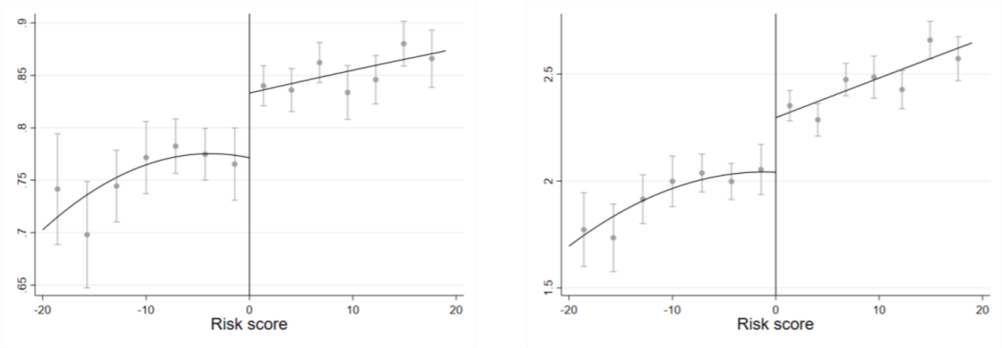
(f) Sex offender risk score and prior convictions



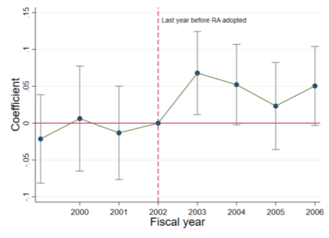
Stevenson and Doleac: Result (RDD)

Figure 3: Does the risk classification affect defendants' sentences at the margin?

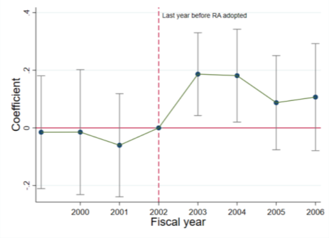
(a) Probability of incarceration (b) The sentence length



(c) Predicted risk score event study (outcome = pr(incarceration))



(d) Predicted risk score event-study (outcome = sentence length)



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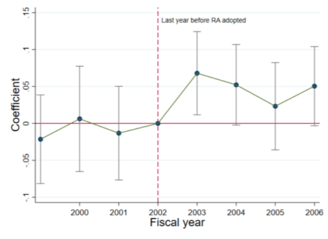
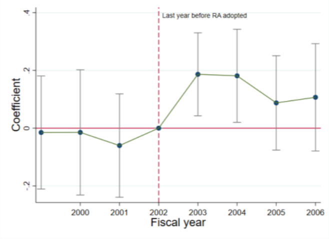
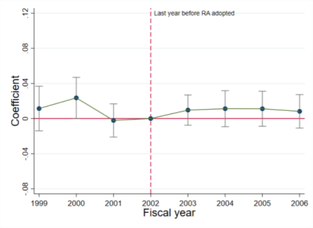


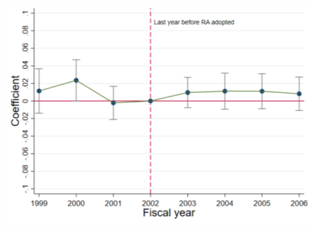
(d) Predicted risk score event-study (outcome = sentence length)



(a) Risk assessment's impact on pr(incarceration)



(b) Risk assessment's impact on sentence length (arcsinh)



"...despite explicit instructions that risk assessment was supposed to lower prison populations, there was no net reduction in incarceration. Nor do we detect any public safety benefits from its use..."

Outline

Prediction / Causation / Decisions

Behavioral Responses to Algorithms
- Responses by Subjects
- Responses by Decision-Makers

Selective Labeling

Checking for Domain Shift

- Under what conditions are predictions $\hat{Y}(X)$ sufficient for making the optimal decision D^*?

1. Payoff of the decision does not depend on other factors besides $\hat{Y}$
2. Environment factors (i.e. decision subjects) do not respond to the algorithm.
3. Decision-makers respond predictably to the algorithm.
4. **Decision-maker gets continuous feedback on model accuracy.**

- What if decision-maker does not get this feedback?

Bail decision: Judge is ***selectively labeling*** the dataset

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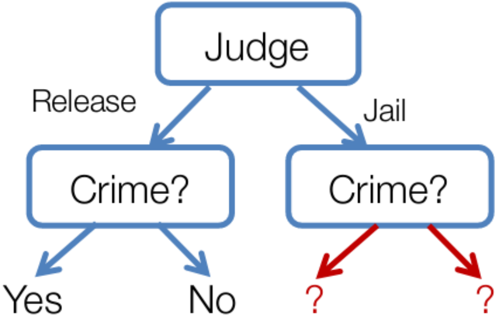
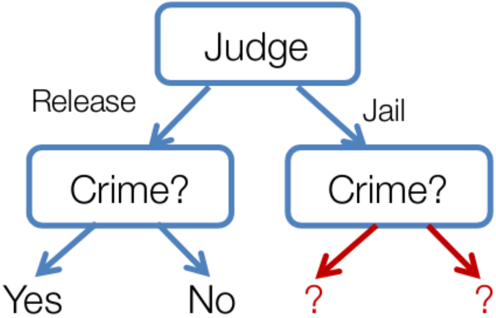


- We can only train on released people:
  - By jailing, judge is selectively hiding labels!

Bail decision: Judge is ***selectively labeling*** the dataset



Selective labels introduce bias. Example:

- Say young people with no tattoos have no risk for crime. Judge releases them.
- Machine observes age, but does not observe tattoos.

- We can only train on released people:
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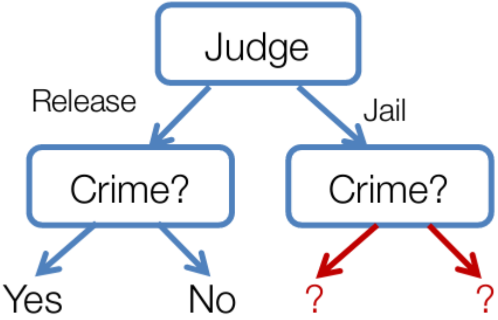

- We can only train on released people:
  - By jailing, judge is selectively hiding labels!

Selective labels introduce bias. Example:

- Say young people with no tattoos have no risk for crime. Judge releases them.
- Machine observes age, but does not observe tattoos.
- Machine would falsely conclude that all young people do no crime, and release all young people.

Solution from Kleinberg et al: Contraction

- Selection problem is one-sided: We observe counterfactual (crime rate) for released defendants, but not jailed defendants.

Solution from Kleinberg et al: Contraction

- Selection problem is one-sided: We observe counterfactual (crime rate) for released defendants, but not jailed defendants.

- **Contraction**:
  - Take released population of a lenient judge.
  - Then ask which additional defendant we would jail to minimize crime rate.
  - Compare change in crime rate to that observed for stricter judge.
- **Why does this approach require random assignment of cases to judges to work?**

Comparing Machine Judges (Left Panel) to Human Judges (Right Panel)

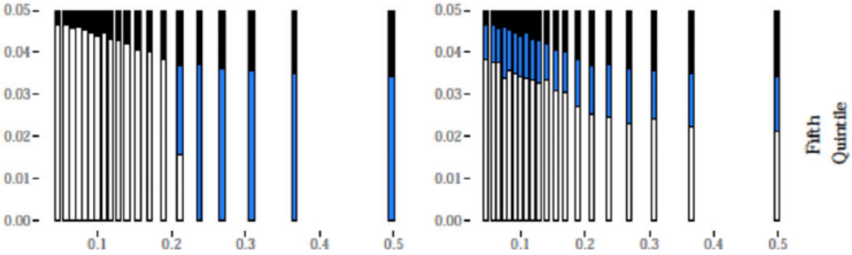

FIGURE VI

Who Do Stricter Judges Jail and Who Would the Algorithm Jail? Comparing Predicted Risk Distributions across Leniency Quintiles

- black = even most lenient judges (bottom quintile) would jail this defendant.
- blue = additional jailed by the strictest judges (top quintile). left panel = algorithm, right panel = human judges.
- white = who is released by all judges

Labels are Driven by Decisions

- We don't see labels of people that are jailed
- This is a broader problem in policymaking systems:
  - Prediction $\rightarrow$ Decision $\rightarrow$ Outcome
- Which outcomes we see depends on our decisions.
  - Kleinberg et al could fix it because of random assignment of judges. But usually that is not possible either.

Activity: ML Detection of Corruption