

# Building a Robot Judge: Data Science for Decision-Making

## 9. Algorithms and Decisions I

## Weekly Q&A

[http://bit.ly/BRJ\\_Padlet9](http://bit.ly/BRJ_Padlet9)

## Activity: Review, Four Types of Confounders

<https://twitter.com/ASlavitt/status/1319870491063177216>

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<https://padlet.com/eash44/p4h4614170q4ixzd>

- ▶ last name starts with A-F, answer first column
- ▶ last name starts with G-L, answer second column
- ▶ last name starts with M-R, answer third column
- ▶ last name starts with S-Z, answer fourth column
- ▶ when done, answer fifth column or other columns.

# Outline

AI and Decisions: Overview

Human Decisions and Machine Predictions (Kleinberg et al 2018)

# Learning Objectives

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  - Evaluate proposed policies/systems that use algorithms for decision support – along accuracy, bias, gaming, and other dimensions.
  - Read and critique research papers reporting on these policies/systems.
  - If you are signed up for the project: Implement/analyze such a system and write a paper about it.

# Example: Allocating Inspectors

Athey 2017; Glaeser et al, AER P&P 2016

- ▶ Governments can conserve resources by inspecting establishments that are likely to have violations, e.g.:
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  - ▶ some firms might know they have a low inspection due to a low violation probability (because of their neighborhood, for example), and reduce safety measures.
- ▶ Overall, the inspection policy problem is a causal inference problem:
  - ▶ What is the expected improvement in overall quality of units (e.g., food poisoning rates) in the city under a new inspector allocation regime?

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Athey 2017; Blake et al 2015

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- ▶ The problem with the previous approach: confounding.
  - ▶ many people who clicked on search advertisements would have purchased items from eBay anyway.

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- ▶ Finally, there are considerations of fairness or discrimination.
  - ▶ more on this in week 11

## Zoom Poll: Copyright or Patent Infringement



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# Humans vs. Machines

- ▶ Given the same data/features  $X$ , machines tend to beat humans:
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- ▶ So when should machines make decisions?

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- ▶ Costs of release:
  - ▶ failure to appear at trial
  - ▶ commit more crimes
- ▶ Judge is implicitly making an assessment/prediction about these outcomes, and then making a decision based on that.

# COMPAS

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- ▶ Dress and Farid (Science Advances 2018):
  - ▶ a logistic regression model with two features is just as accurate as COMPAS
  - ▶ majority vote by 20 non-specialist human participants (Amazon Mechanical Turk) predicts recidivism as accurately as COMPAS.

# Kleinberg et al (2018) Data

- ▶ 750,000 individuals arrested in New York City between 2008-2013
- ▶ Same data on prior history that is available to judge (rap sheet, current offense, etc.)
  - ▶ Data on subsequent crimes to develop and evaluate performance of algorithm
  - ▶ Define “crime” as failing to show up at trial; objective is to jail those with highest risk of committing this crime
    - ▶ Other definitions of crime (e.g., repeat offenses) yield similar results

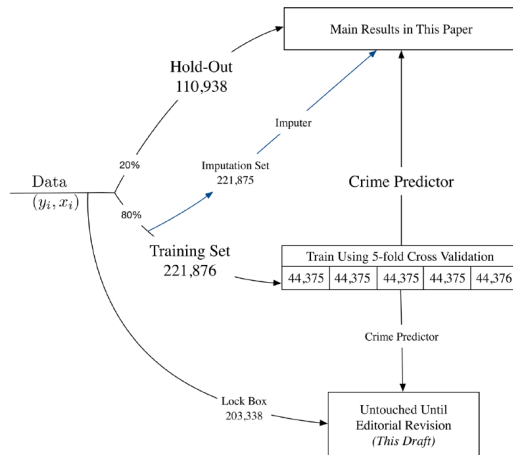


FIGURE I  
Partition of New York City Data (2008–13) into Data Sets Used for Prediction and Evaluation

# Data: Defendant Features

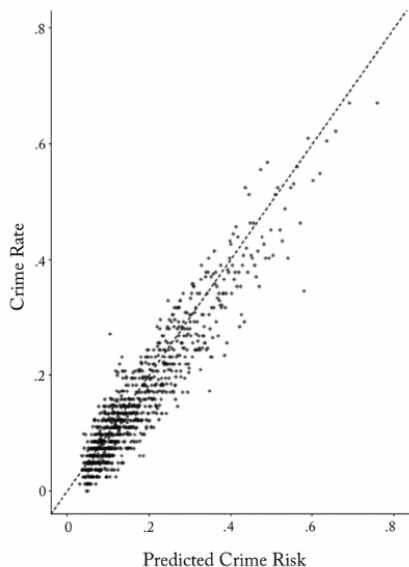
Kleinberg et al (2019)

Age at first arrest, Times sentenced residential correction, Level of charge, Number of active warrants, Number of misdemeanor cases, Number of past revocations, Current charge domestic violence, Is first arrest, Prior jail sentence, Prior prison sentence, Employed at first arrest, Currently on supervision, Had previous revocation, Arrest for new offense while on supervision or bond, Has active warrant, Has active misdemeanor warrant, Has other pending charge, Had previous adult conviction, Had previous adult misdemeanor conviction, Had previous adult felony conviction, Had previous Failure to Appear, Prior supervision within 10 years

- ▶ excludes race, gender, and religion
  - ▶ not legal to include – will come back to this issue

- ▶ Use labeled dataset (released defendants), to predict whether they fail to appear or commit more crimes.
  - ▶ preferred model: gradient boosting (GB): test-set AUC = .71

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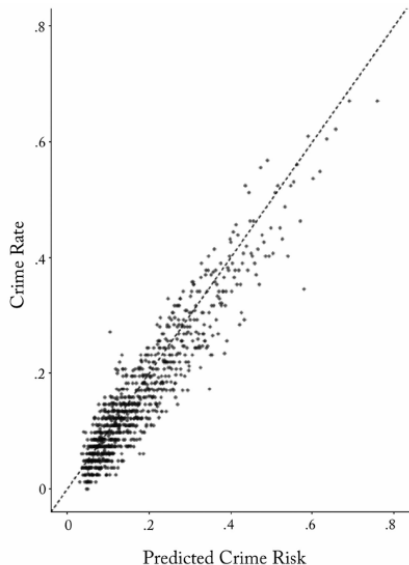
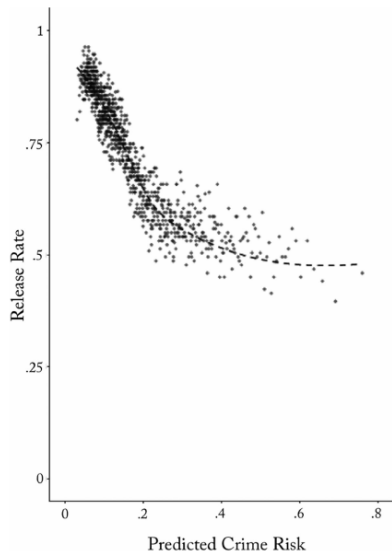


TABLE II  
COMPARING LOGISTIC REGRESSION TO MACHINE-LEARNING PREDICTIONS  
OF CRIME RISK

Predicted risk percentile	ML/ logit overlap	Average observed crime rate for cases identified as high risk by:				
		Both ML and logit	ML only	Logit only	All ML cases	All logit cases
1%	30.6%	0.6080 (0.0309)	0.5440 (0.0209)	0.3996 (0.0206)	0.5636 (0.0173)	0.4633 (0.0174)
5%	59.9%	0.4826 (0.0101)	0.4090 (0.0121)	0.3040 (0.0114)	0.4531 (0.0078)	0.4111 (0.0077)
10%	65.9%	0.4134 (0.0067)	0.3466 (0.0090)	0.2532 (0.0082)	0.3907 (0.0054)	0.3589 (0.0053)
25%	72.9%	0.3271 (0.0038)	0.2445 (0.0058)	0.1608 (0.0049)	0.3048 (0.0032)	0.2821 (0.0031)

**Zoom Private Chat to me:**  
**What do these exhibits tell us?**

# What human judges do



- ▶ Human judges tend to follow what algorithm suggests.
- ▶ But judge sees factors the machine does not
  - ▶ makes decisions based on  $\Pr(Y|X_H)$ 
    - ▶  $X_H$  includes other factors not seen by the machine – e.g., defendant demeanor.
  - ▶ Machine makes decisions based on  $\Pr(Y|X)$ ,  $X \subset X_H$ .

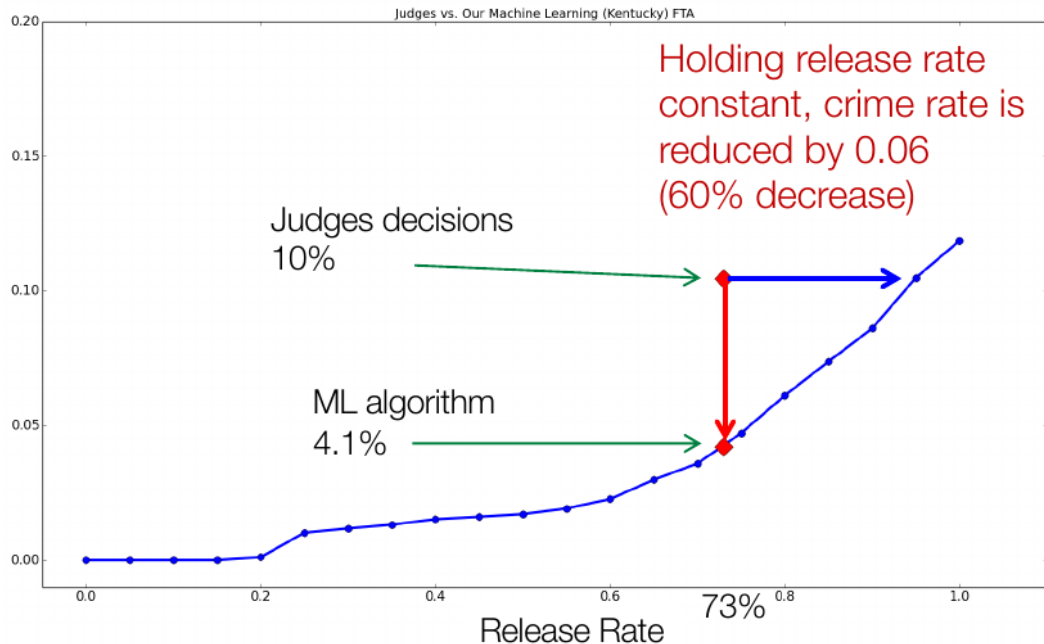
## Prediction $\rightarrow$ Release Rule

- ▶ Kleinberg et al consider the following release rule based on recidivism predictions:
  - ▶ For every defendant predict  $\hat{Y}(X_i)$
  - ▶ Sort by increasing  $\hat{Y}(X_i)$
  - ▶ Release bottom  $N$  defendants, jail the rest.

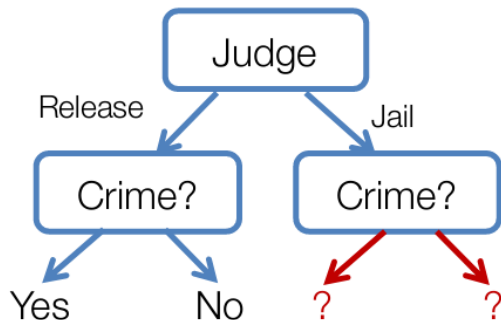
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- ▶ What is the fraction released vs. crime rate tradeoff?

## Compare Judge to ML in predicted crime rate

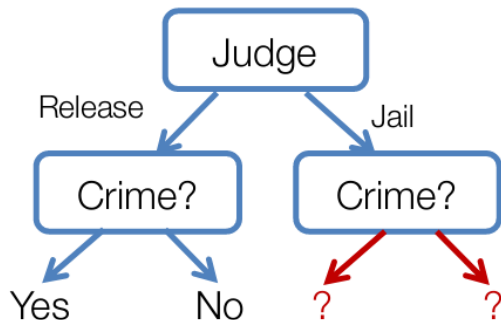


## Problem: Judge is selectively labeling the dataset



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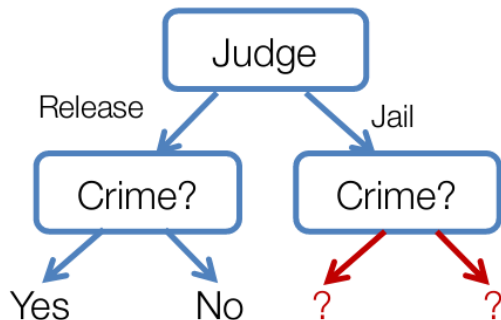


Selective labels introduce bias. Example:

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

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- ▶ 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.
- ▶ We can only train on released people:
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  - ▶ Compare change in crime rate to that observed for stricter judge.

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- ▶ **This approach requires random assignment of cases to judges to work.**
  - ▶ **Zoom Private Chat: Explain why.**

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

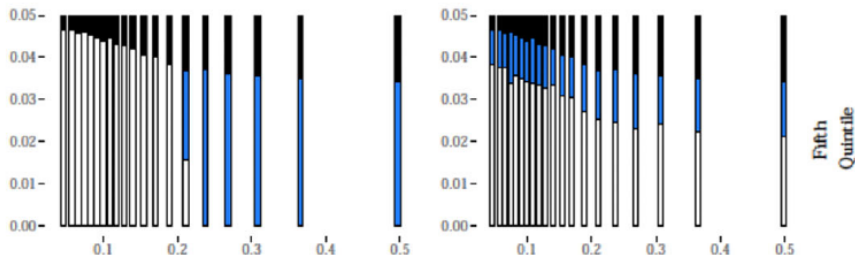


FIGURE VI

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.
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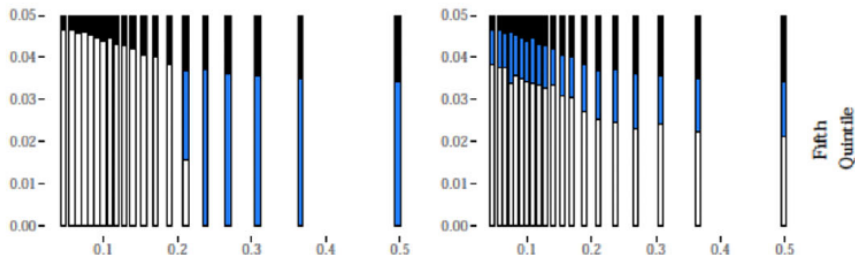


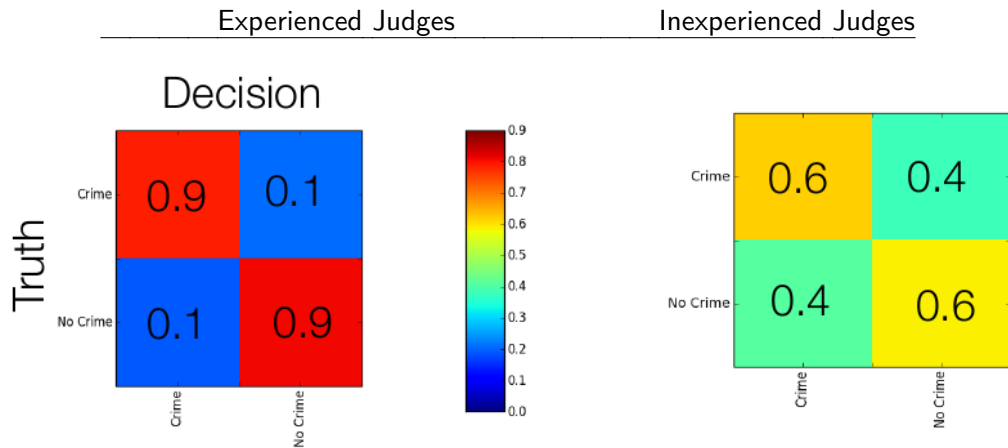
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- ▶ **Zoom Private Chat: What does this graph show?**

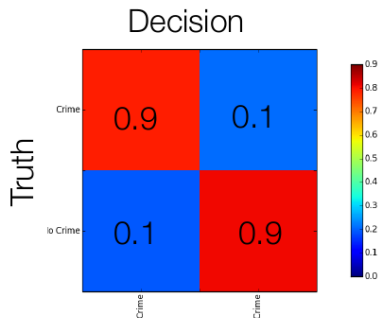
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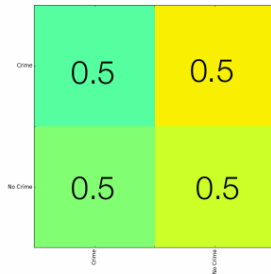


Source: Jure Leskovec slides.

## Analyzing judge mistakes



Defendants who are single, did felonies, and moved a lot are accurately judged



Defendants who have kids are confusing to judges

- Or are judges balancing crime risk against kids' welfare?

Source: Jure Leskovec slides.



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- ▶ Not just about prediction. Key is starting with decision:
  - ▶ Performance benchmark: Current “human” decisions
- ▶ Question: What are we really optimizing?

# 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

## Focusing on re-arrest rates is limited

- ▶ Is minimizing the crime rate really the right goal?
- ▶ There are other important factors
  - ▶ Consequences of jailing on the family
  - ▶ Jobs and the workplace
  - ▶ Future behavior of the defendant
- ▶ How could we measure/model these?

# Lightning Essay

For last minutes of class:

<https://bit.ly/BRJ-W9-Essay>