Building a Robot Judge: Data Science for Decision-Making

9. Algorithms and Decisions I

Recap: Explanations for Decision Support

1. a judge making a decision on bail/parole — what differences should there be for an explanation for judges, vs an explanation for defendants?
2. a doctor making a decision about treatment — what differences should there be for an explanation for doctors, vs an explanation for patients?
3. an appraiser evaluating the value of a work of art – what differences should there be for an explanation for the appraiser, vs an explanation for the buyer/seller?

Outline

Review: Internal vs External Validity

AI and Decisions: Overview

Recidivism Risk Scores for Bail Decisions

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  - when we say "bias" or "endogeneity", that is talking about internal validity
- **External validity**: the statistical inferences can be generalized from the population and setting studied to other populations and settings.
  - this is usually much more speculative.

Internal Validity (from week 3)

Linear regression model:

$$Y_i = \alpha + \beta s_i + \epsilon_i$$

- Exogeneity assumption: $\text{Cov}[s_i, \epsilon_i] = 0$
  - no omitted variable bias (unobserved confounders), no joint causality.

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Under these conditions, causal inferences (statistical estimates on treatment effects) are valid for the population studied.

Internal validity (machine learning)

- In machine learning, we would gauge "internal validity" by proper train/test splits, and avoidance of data leakage.
  - $\rightarrow$ then performance metrics are valid to that dataset, or other samples from the same data generating process.

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  - medical trials are often run with men, but medicines are then used to treat both men and women.
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- In general **estimates/metrics are not valid for other populations**.
  - other populations are different. so treatment effects and predictions might be different.

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2. Implement and evaluate causal inference designs.
3. **Understand how (not) to use data science tools (ML and CI) to support expert decision-making.**
   - Appreciate the connections/distinctions between **prediction**, **inference**, and **decisions**.
   - 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.

Prediction vs Judgment

- **Prediction** is about guessing the state of the world
  - parameters θ from $\hat{Y}(X;\theta)$.
- **Judgment** is about knowing the utility or benefit function
  - parameters β from $W(X, Y; \beta)$.

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  - choice function becomes: jail if

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else release.

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- Note, this simplifies **a lot.**
  - e.g., S is constant; no behavioral responses by defendants; judge always optimizes.

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- One is a prediction problem, and one is a causation problem.
  - which is which?

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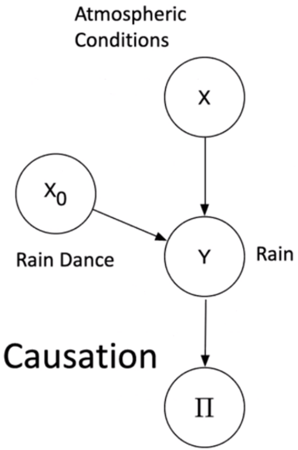
- Umbrella:
  - farmer 2 is walking to work, should she bring an umbrella?
  - $\rightarrow$ **prediction problem (like doctor testing): Will it rain?**

Rain Dances and Umbrellas



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Source: Sendhil Mullainathan Slides.

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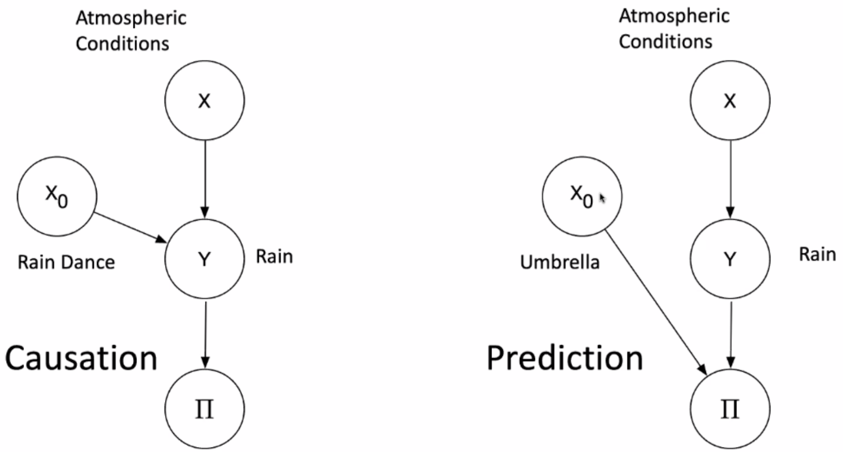

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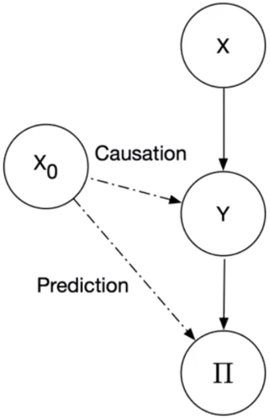
X
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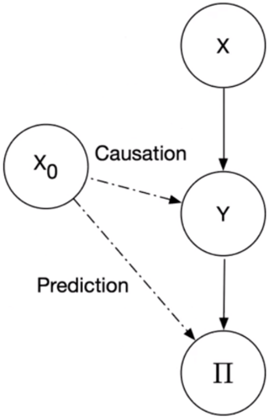

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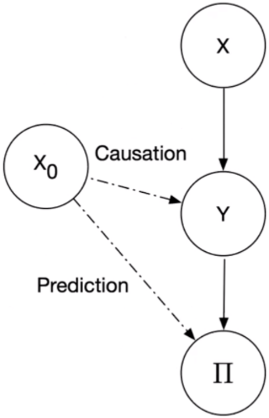

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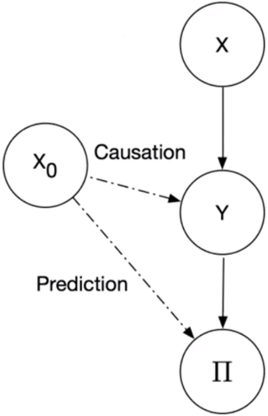

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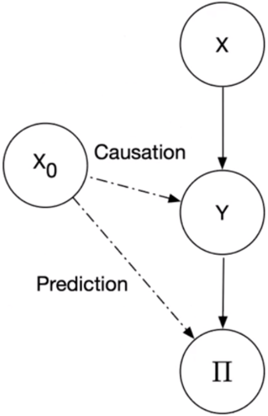

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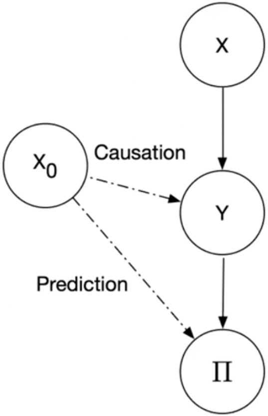

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- Rules for good decision-making:
  - good predictions require machine learning
  - consistent causal effect estimates require causal inference and experiments.

Aside: Praying for Rain

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Praying for Rain
José-Antonio Espín-Sánchez, Salvador Gil-Guirado, and Nicholas Ryan
NBER Working Paper No. 31411
June 2023
JEL No. N3,N5,O13,P48,Z12

ABSTRACT

We study the climate as a determinant of religious belief. People believe in the divine when religious authorities (the "church") can credibly intervene in nature on their behalf. We present a model in which nature sets the pattern of rainfall over time and the church chooses when optimally to pray in order to persuade people that it has caused the rain. We present evidence from prayers for rain in Murcia, Spain that the church follows such an optimal policy and that its prayers therefore predict rainfall. In our model, praying for rain can only persuade people to believe if the hazard of rainfall during a dry spell is increasing over time, so that the probability of rainfall is highest when people most want rain. We test this prediction in an original data set of whether ethnic groups around the world traditionally prayed for rain. We find that prayer for rain is more likely among ethnic groups dependent on intensive agriculture for subsistence and that ethnic groups facing an increasing rainfall hazard are 53% more likely to pray for rain, consistent with our model. We interpret these findings as evidence for the instrumentality of religious belief.

Example: Allocating fire/health 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.:
  - NYC's Firecast algorithm predicts fire risk and code violation
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1. **Benefits of fixing problems are mostly homogeneous.**
2. **Establishments do not change behavior in response to the algorithm.**
3. **Inspectors respond predictably to the algorithm.**
4. **Inspectors get feedback on (changes in) prediction accuracy.**

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- restaurants with high health risk might not have many customers $\rightarrow$ could be better to inspect the more popular restaurants.

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  - but it is also a **domain shift** $\rightarrow$ predictions using pre-reform data are no longer externally valid.
- Responses could be heterogeneous:
  - some firms may be more sensitive to penalties than others,
  - it may be easier for some firms to game the predictors.
  - 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.

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- What if inspectors rely too heavily on the algorithm?
  - e.g., they ignore some obvious special circumstances or variables that aren't in the dataset (e.g. a building being next door to a fire house; a restaurant serving only pre-packaged food).

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- but in some cases, outcomes are not directly observed
  - eg, if you close down a restaurant, you don't observe improvements.

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- Framed differently: What is the expected improvement in overall quality of units (e.g., fire damage, food poisoning rates) in the city under a new AI-powered inspector allocation regime?

Another Example: eBay advertising

Athey 2017; Blake et al 2015

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  - again: AI-suppported decision-making is both a machine learning and causal inference problem.

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- So when should machines make decisions?

Bail Decision: Detain or Release

- Costs of detention (avg. 2-3 months):
  - Consequential for jobs, families
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  - 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.

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  - judges see a risk assessment of how likely a defendant is to commit more crimes if released on bail.

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- Dressel and Farid (Science Advances 2018):
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  - 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

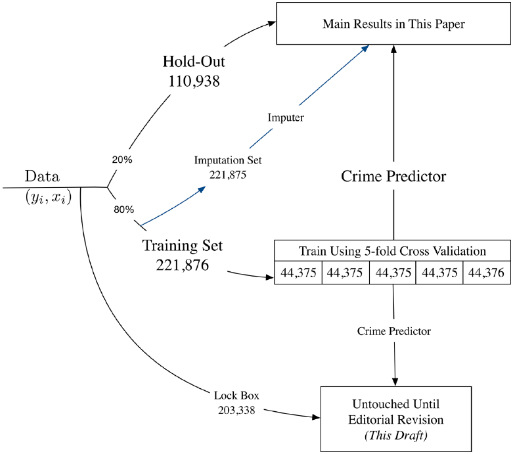


FIGURE I

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

Data: Defendant Features

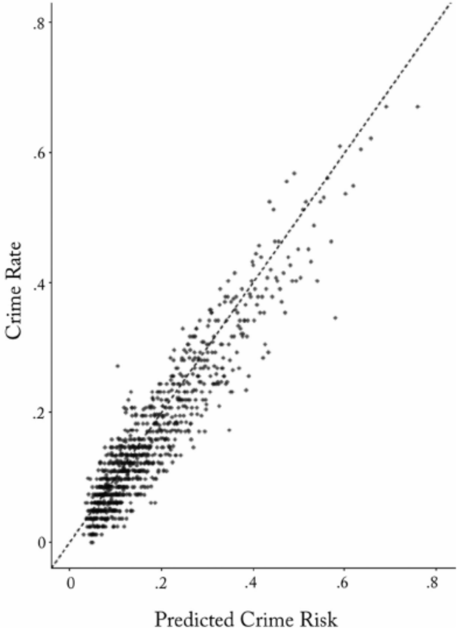
Kleinberg et al (2019)

`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`

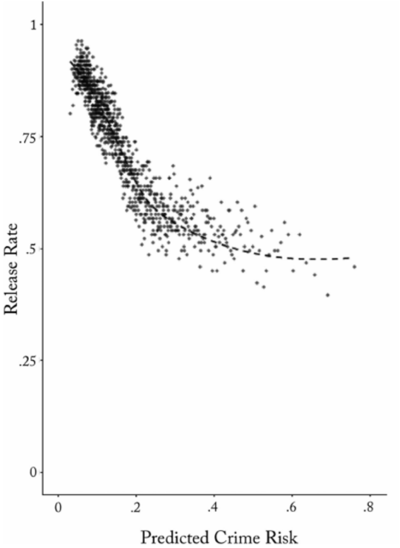
- excludes race, gender, and religion
  - not legal to include – will come back to this issue

Model Performance

- 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



What human judges do

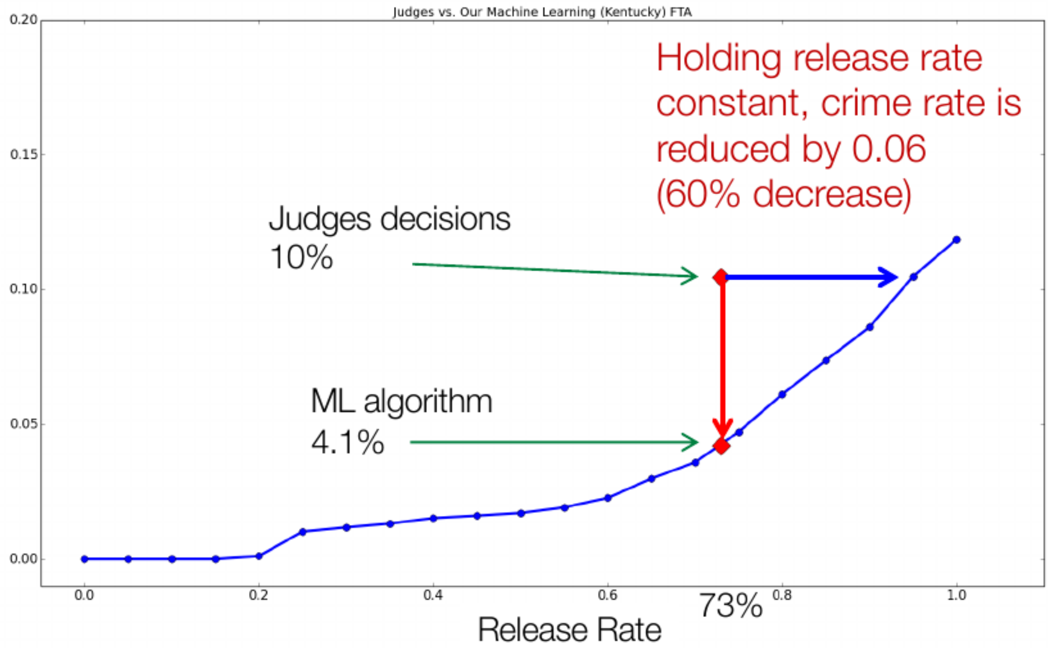


- Human judges tend to follow what algorithm suggests.
- But judge sees factors the machine does not
  - makes decisions based on $\Pr(Y|X_H)$
    - X_H includes other factors not seen by the machine – e.g., defendant demeanor.
  - Machine makes decisions based on $\Pr(Y|X)$, $X \subset X_H$.

Prediction $\rightarrow$ Release Rule

- Kleinberg et al consider the following release rule based on recidivism predictions:
  - For every defendant predict $\hat{Y}(X_i)$, probability of recidivism.
  - Sort by increasing $\hat{Y}(X_i)$
  - Release bottom N defendants, jail the rest.
- Kleinberg et al (2018) use this rule to analyze the tradeoff between fraction released and crime rate.

Compare Judge to ML in predicted crime rate



Analyzing judge “mistakes”

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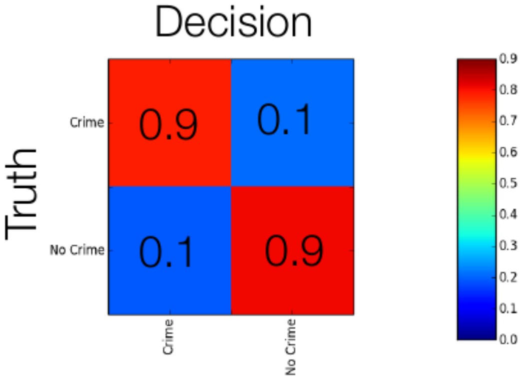
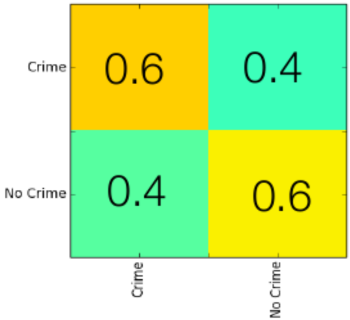
Experienced Judges	Inexperienced Judges





Source: Jure Leskovec slides.

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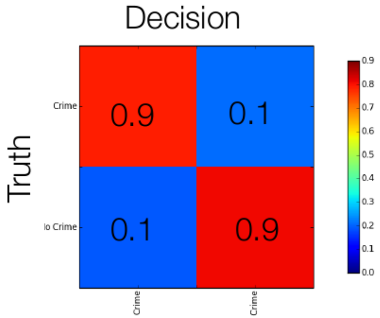
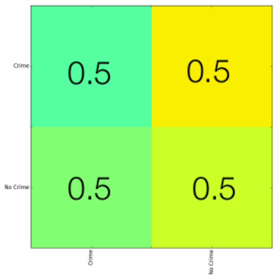


Defendants who are single, did felonies, and moved a lot are accurately judged



Defendants who have kids are confusing to judges

- Or are judges balancing crime risk against kids’ welfare?
  Source: Jure Leskovec slides.

Activity on 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 respond predictably to the algorithm.
  (4) Inspectors get feedback on prediction accuracy.
- When done, compare answers with a partner (or group of 3)

Video Presentation: Ash et al, A machine learning approach to anti-corruption policy