Building a Robot Judge: Data Science for Decision-Making

10. Algorithms and Decisions I

Weekly Q&A

https://padlet.com/eash44/rdfswr8dzcxhka0z

Outline

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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:

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- Exogeneity assumption: $\mathrm{Cov}[s_i, \epsilon_i] = 0$
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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 othe samples from the same data generating process.

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  - recividism risk prediction model trained in 2020, is it valid for 2021?
- In general **estimates/metrics are not valid for other populations**.
  - other populations are different. so treatment effects and predictions might be different.

Practice Quiz, Weeks 2-9

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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.

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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- Suppose there is a prediction technology where the decision-maker observes $\hat{Y}(X) \in [0,1]$.
  - choice function becomes

$$\hat{Y}R + (1 - \hat{Y})r < S$$

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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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.**

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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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- 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 ignore the algorithm?
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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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- Main Lesson: inspection policy is not just a machine prediction problem
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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?

Example 2: eBay advertising

Athey 2017; Blake et al 2015

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- The problem with the previous approach: confounding.
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  - again: AI-suppported decision-making is both a machine learning and causal inference problem.

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  - Games: Chess, AlphaGo, Poker
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- So when should machines make decisions?

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  - Costs to taxpayers of jails
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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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- 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

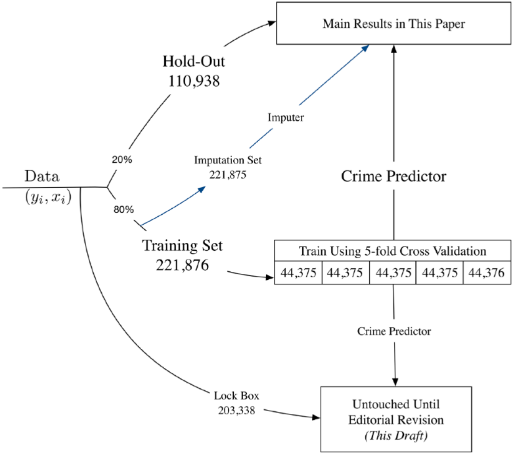


FIGURE I

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

Data: Defendant Features

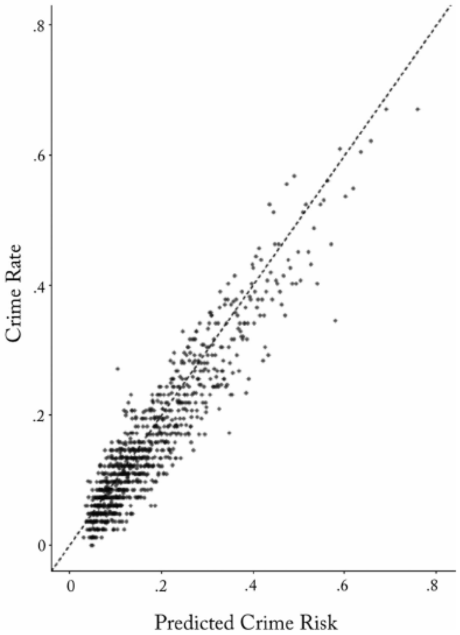
Kleinberg et al (2019)

`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`

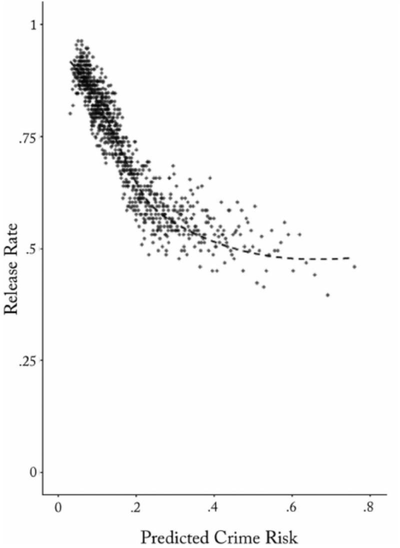
- excludes race, gender, and religion
  - not legal to include – will come back to this issue

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

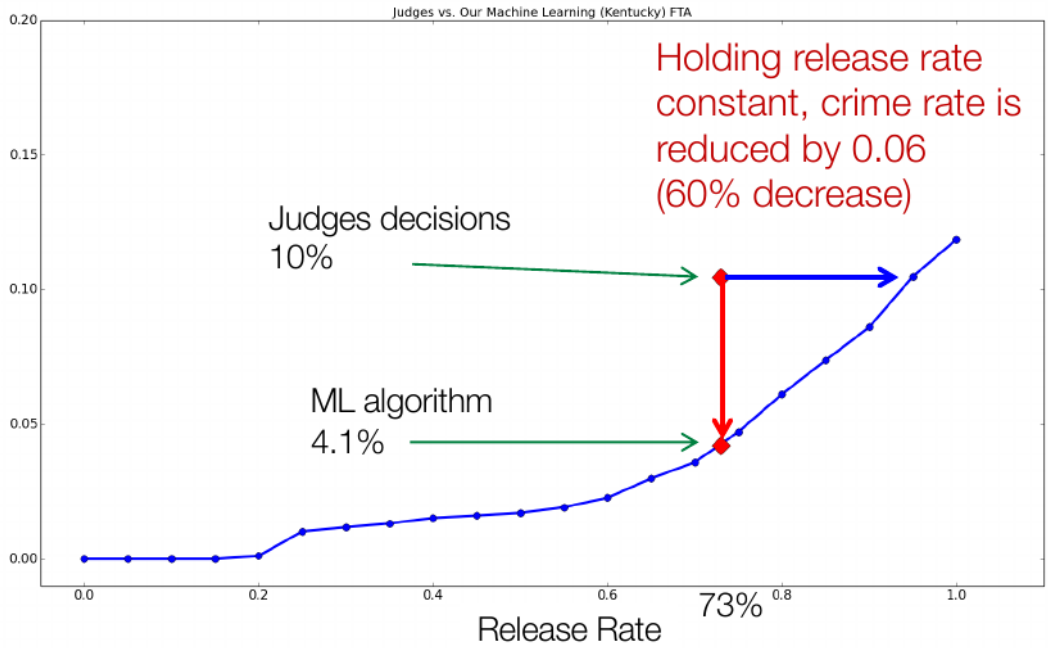


- Human judges tend to follow what algorithm suggests.
- But judge sees factors the machine does not
  - makes decisions based on $\Pr(Y|X_H)$
    - X_H includes other factors not seen by the machine – e.g., defendant demeanor.
  - Machine makes decisions based on $\Pr(Y|X)$, $X \subset X_H$.

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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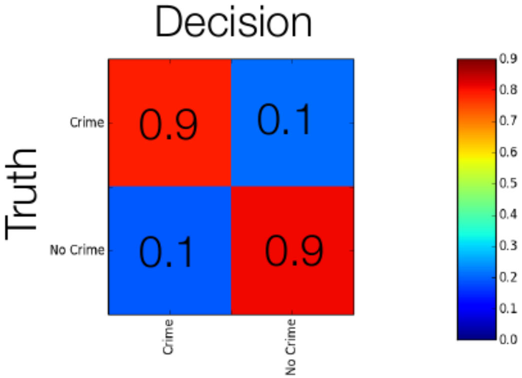
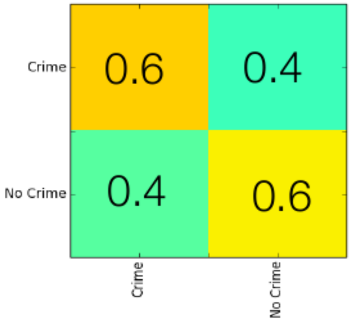
Experienced Judges	Inexperienced Judges





Source: Jure Leskovec slides.

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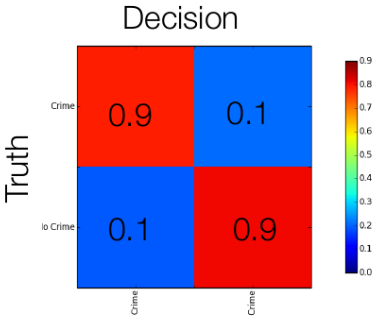

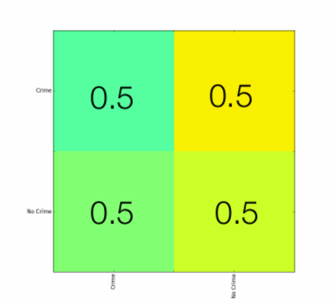

Defendants who are single, did felonies, and moved a lot are accurately judged

Defendants who have kids are confusing to judges

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

Activity

- **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.
- **In 5 minutes, paste your answer into a padlet post here:** `https://padlet.com/eash44/u4rfjxc8mbgjd587`