Building a Robot Judge: Data Science for Decision-Making

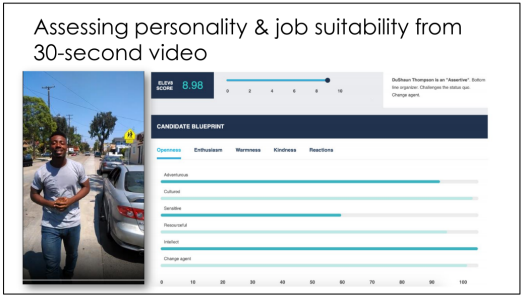
13. Algorithms and Decisions IV

Q&A Page

https://padlet.com/eash44/dn2c5exyl1lx0wnd

https://padlet.com/eash44/of2j80mt3hwnikh4

What are some problems with algorithmic hiring systems? (Raghavan et al, 2019)



Write down an answer privately for sharing in the zoom chat: Identify a problem with algorithmic hiring, explain why, and what would have to change to fix that problem.

Outline

Perspective | Published: 13 May 2019

Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead

Cynthia Rudin

Nature Machine Intelligence **1**, 206–215 (2019) | Cite this article

https://www.nature.com/articles/s42256-019-0048-x

Simple Rules for Complex Decisions (Jung et al 2017)

Table 1: A defendant's flight risk is obtained by adding the scores for age and prior failure to appear (FTA).

Feature	Score	Feature	Score
$18 \leq$ age < 21	8	no prior FTAs	0
$21 \leq$ age < 26	6	1 prior FTA	6
$26 \leq$ age < 31	4	2 prior FTAs	8
$31 \leq$ age < 51	2	3 prior FTAs	9
$51 \leq$ age	0	4 or more prior FTAs	10

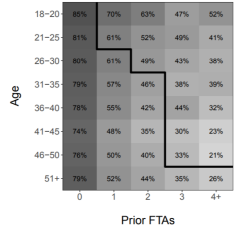


Figure 1: Graphical representation of a simple rule for release decisions, based on setting a release threshold of 10.5 on the risk scores described in Table 1. Groups to the left of the black line are those that would be released under the rule; for comparison, the shading and numbers show the proportion of defendants that are currently RoR'd in each group.

Simple Rules for Complex Decisions (Jung et al 2017)

(1) **Select.** From the full set of features, select k features via forward stepwise regression. For fixed k, we note that standard selection metrics (*e.g.*, AIC or BIC) are theoretically guaranteed to yield the same set of features.
(2) **Regress.** Using only these k selected features, train an L^1-regularized (lasso) logistic regression model to the data, which yields (real-valued) fitted coefficients $\beta_1, \ldots, \beta_k$.
(3) **Round.** Rescale the coefficients to be in the range $[-M, M]$, and then round the rescaled coefficients to the nearest integer. Specifically, set

$$w_j = \text{Round}\left(\frac{M\beta_j}{\max_i |\beta_i|}\right).$$

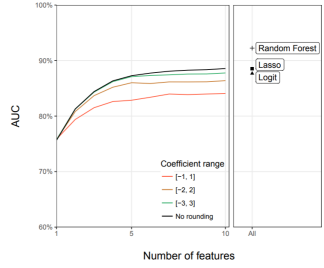


Figure 5: Mean test AUC of decision rules over 22 datasets.

Kleinberg and Mullainathan, "Simplicity Creates Inequity" (2019)

- Individuals have characteristics X and group membership A.
- Algorithm approximates score $f(X, A)$,
  - decide outcome (e.g. admit to college) based on threshold on $f(\cdot)$

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- assume a non-trivial (e.g. real-world) dataset (see paper)
- starting from a simple model, there exists a more complex model (smaller cells) that improves both efficiency *and* equity.
  - Efficiency = average $f(\cdot)$ of admitted candidates.
  - Equity = relative share admitted for the disadvantaged group.

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Result 2:

- with a simple model (relative to a complex model), info on group membership is more likely to help the decision-maker select candidates with higher $f(\cdot)$.

"Predictive power at what cost? Economic and racial justice of data-driven algorithms" (Jabri 2019)

This paper studies how algorithms use variables to maximize predictive power at the cost of group equity. Group inequity arises if variables enlarge disparities in risk scores across groups. I develop a framework to examine a recidivism risk assessment tool **using risk score and novel pretrial defendant case data from 2013-2016 in Broward County, Florida**. **I find that defendants' neighborhood data only negligibly improve predictive power, but substantially widen disparities in defendant risk scores and false positive rates across race and economic status**.
. . .

(good paper for RE03 or RE04)

Outline

- Algorithms influence various aspects of life:
  - selecting tax payers for audits
  - granting or denying immigration visas
  - security screening at airports
- Benefits many and growing:
  - efficiency, accuracy, scalability
  - increase consistency and reduce bias
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  - economic/innovation
- But AI has risks and harms.
  - Public interest requires governance to reinforce benefits and minimize risks.

Tradeoffs

- accuracy vs
  - equity
  - explainability
  - data privacy
- innovation vs
  - safety
  - transparency
  - data privacy
  - consumer rights

Challenges to developing standards

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  - tradeoffs among various stakeholders
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Challenges to developing standards

- Collective decision processes
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  - technical issues $\rightarrow$ politicians and voters have low information
- Global coordination needed for digital tech
  - accounting for different cultures and contexts
- How to assign responsibility for risks/harms
  - creator / owner / operator/ user?
  - how to understand / determine intentions
  - balance accountability with innovation and growth

Governance Strategies

- Industry-driven approach;
  - Reduces regulatory red tape, could help innovation
  - No central authority to enforce best-practices;
  - Expands the power of large corporations.
  - Significant externalities, tendency to concentration

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  - Reduces regulatory red tape, could help innovation
  - No central authority to enforce best-practices;
  - Expands the power of large corporations.
  - Significant externalities, tendency to concentration
- Regulator-driven approach:
  - significant technical knowledge/skills needed to be effective
  - bad actors always a step ahead.
  - limits innovation and expansion of digital economy.
  - could collude with industry leaders

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- How can we make sure that the decision maker is not merely claiming to follow the rules?
  - Disclose the trained model? training data? training code?
- Policy challenges
  - ML processes not understandable by non-experts
  - Sometimes even experts don't understand the model
  - Understanding the code/model not the same as understanding behavior/responses

"An Economic Approach to Regulating Algorithms"

Rambachan, Kleinberg, Ludwig, and Mullainathan (2020)

- Apply welfare economics to the design and regulation of algorithmic decision processes.
- Algorithmic decision-making has two components:
  - (1) training a prediction function, and (2) a decision rule based on the predictions.

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- without disclosure, algorithms will be just as biased as humans.
- with disclosure, discrimination decreases relative to humans, and government should impose no constraints on the use of sensitive attributes as predictors.
  - caveat: disclosure must include the data and ML training process, not just the decision rule.

"Algorithmic Social Engineering" (Cowgill and Stevenson 2020)

We examine the microeconomics of using algorithms to nudge decision-makers towards particular social outcomes. . . . **Manipulating predictions to express policy preferences strips the predictions of informational content and can lead decision-makers to ignore them.** When social problems stem from decision-makers' objectives (rather than their information sets), algorithmic social engineering exhibits clear limitations. **Our framework emphasizes separating preferences and predictions in designing algorithmic interventions**. . . .

(another good paper for RE03 or RE04)

Application: Content/Ad Targeting

- Should social media content/ad targeting algorithms (eg Facebook) be able to use sensitive attributes as features?
  - gender, age, race, etc.

Write down an answer privately for sharing in the zoom chat:

1. **Give at least one reason that gender/race targeting should be allowed.**
2. **Give at least one reason it should not be allowed.**
3. **Propose a restriction/regulation that addreses your problem without banning the targeting.**

Outline

Perception Tasks

- Content identification (Shazam, reverse image search)
- Face recognition
- Medical diagnosis from scans
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Overall, problems seem straightforward to solve.

Human Judgment Annotation Tasks

- Spam detection
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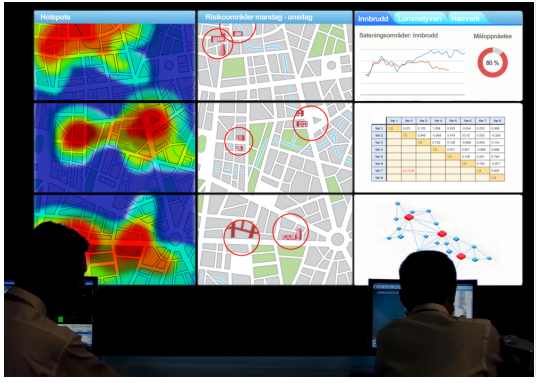
Labels are past behavior, so model is stable and incentive responses are constrained.

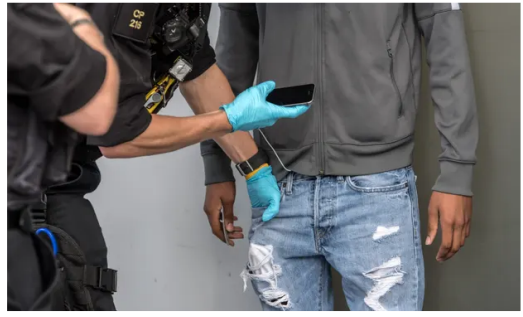
- compare: predicting how someone will score on these predictions in the future.

Predictive Policing



Predictive policing poses discrimination risk, thinktank warns

Machine-learning algorithms could replicate or amplify bias on race, sexuality and age



▲ One officer said human biases including more stop and searches of black men were likely to be introduced into algorithm data sets. Photograph: Carl Court/Getty Images

https://www.theregister.com/2020/12/08/texas_compsci_phd_ai/

{* ARTIFICIAL INTELLIGENCE *}

Uni revealed it killed off its PhD-applicant screening AI – just as its inventors gave a lecture about the tech

Fears of bias put compsci dept into damage-limitation mode after years of using it to analyze applications

Katyanna Quach Tue 8 Dec 2020 // 12:04 UTC SHARE

A university announced it had ditched its machine-learning tool, used to filter thousands of PhD applications, right as the software's creators were giving a talk about the code and drawing public criticism.

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Facebook and Google on
privacy, pledges fight

Predicting future choices and social outcomes

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These systems are risky and can have unintended consequences:

- **Predictions influence availability of labels and subsequent behavior.**
- **Outcomes are in future so models lack external validity.**
- **Strong incentive responses by decision subjects and decision-makers.**
- **Errors are costly.**

Overview of ML policy problems

- Accuracy issues:
  - model stability
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- Behavioral responses by subjects:
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- Behavioral responses by decision-makers:
  - decision-makers ignore model because it is a black box
  - or they rely too much on it and don't do their own diligence

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- Why? With recidivism:
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  - the factors that judges are supposed to use are also measured: factors that predict recidivism.
- In contrast, for the liability decision (guilty or not):
  - the label is not observed directly, we just have a human judge's decision to go on.
  - the factors are part of a specific circumstance, and not part of a standard data set.

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  - ↑ *would require a lot of (sophisticated) NLP tools*

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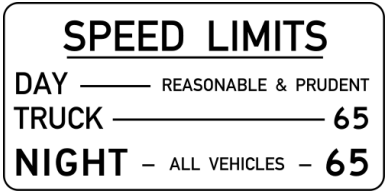
- Would not work on new types of cases.
  - In particular, would not account for new laws/legislation.
- Teaching the algorithm to understand rare evidence, discount suspicious evidence, and to understand new laws, would require something much closer to **legal artificial intelligence**.

Legal Vagueness and Value Judgments



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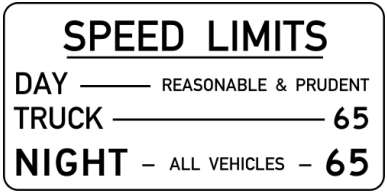
Legal Vagueness and Value Judgments



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- Making choices in the presence of vagueness or indeterminacy requires value judgements.

What counts as a "good" outcome? Is it even measurable?

- at a minimum, would require an unrealistic number of empirical policy analysis studies.

Philosophical Issues

- What does it mean to surrender the implementation of law enforcement and judicial decision making to machines?
- What are the long-term implications for the system and its adaptiveness to change?
  - what are the political and cultural impacts?
  - how does it affect motivation to appeal?

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Thoughts? What else?

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- Policy goals:
  - Understand how (not) to use data science tools (machine learning and causal inference) to support expert decision-making.

Final Assignment

`https://bit.ly/BRJ-exam-guide`

- If you haven't done so yet, sign up for a final assignment cohort by 5pm, otherwise you are in Cohort 2.

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- Not a lot of overlap, and in many ways it builds on the content in this course.
  - i.e., focus on sequence data, and on transformer architectures (e.g. BERT, GPT-3)
- Similar setup in terms of course credits:
  - 3 credits for the lectures/assignments, 2 additional credits for a project.

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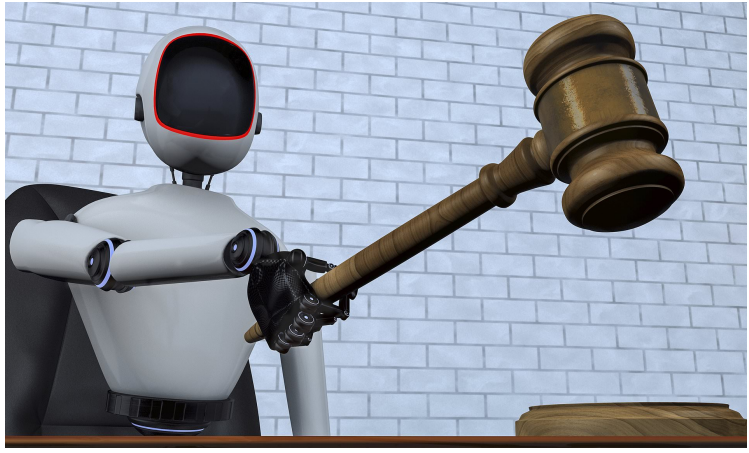

Meeting Adjourned!