Building a Robot Judge: Data Science for Decision-Making

13. AI Regulation and Policy

Q&A Page

https://bitly.com/BRJ_Padlet13

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- Why not just use simple models?
- Kleinberg and Mullainathan, "Simplicity Creates Inequity" (2019):
  - simple models are strictly suboptimal in terms of equity and efficiency.

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- Individuals have characteristics X and group membership A.
- Algorithm approximates score $f(X, A)$,
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- 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.
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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 $f(\cdot)$.

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Outline

Summary

- **Internal validity**: the statistical inferences about causal effects are valid for the population and setting being studied.
- **External validity**: the statistical inferences can be generalized from the population and setting studied to other populations and settings

Internal Validity (from week 3)

Linear regression model:

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

- 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 (ML)

- In machine learning, we gauge internal validity by proper train/test splits, and avoidance of data leakage.
- then performance metrics are valid to that population.

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- External validity is an issue for both causal inference and machine learning.

Outline

- Algorithms influence various aspects of life:
    - selecting tax payers for audits
    - granting or denying immigration visas
    - security screening at airports
- Besides benefits, can have risks and harms.
- Public interest requires governance to reinforce benefits and minimize risks.

Benefits

- Efficiency, accuracy, scalability
- Algorithms can be a boon to due process
  - Consistent decision making
  - Making bias evident
- Growing digital economy

Principles and Objectives

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- Privacy, surveillance
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- Auditability, transparency
- Responsibility, accountability

Challenges to developing standards

- Collective decision processes
  - tradeoffs among various stakeholders
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- Global coordination needed for digital tech
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- 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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- 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

Transparency

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- Closed-source algorithms result in “black box justice” and could be abused by insiders.
- But open-source algorithms are prone to gaming: savvy attorneys could “trick” the algorithm.
- Understanding the code/model not the same as understanding behavior
  - ML processes not understandable by non-experts
  - Sometimes even experts don’t understand the model

Enforcement

- How can we make sure that the decision maker is not merely claiming to follow the rules?
  - Disclose the code?
  - Disclose the logs?
- Idea:
  - technical tools for verifying correctness
  - ensure that appropriate evidence exists for later oversight.
  - can be decentralized on blockchain

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  - caveat: disclosure must include the data and ML training process, not just the decision rule.

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Incentive Responses

- Decisions today change features tomorrow.
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- Milli et al, "The Social Cost of Strategic Classification" (2019)
  - model sequential decision of modeler and subject as Stackelberg Competition, a classic model from game theory on the interaction between duopolists.

Strategic Classification (Milli et al 2019)

- Each individual has features X and a label $Y \in \{0,1\}$.
- Institution gets utility from a classifier $f : X \to Y$ equal to $\Pr(f(X) = Y)$.
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- Social costs:
  - the costs $c(\cdot)$ are socially wasteful, but responses to manipulation increase them.
  - $c(\cdot)$ could be different across groups, causing inequity

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Internal vs External Validity

AI Governance

Incentive Responses to AI Decisions

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AI for legal decisions

Recap and Conclusion

Perception Tasks

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

Human Judgment Annotation Tasks

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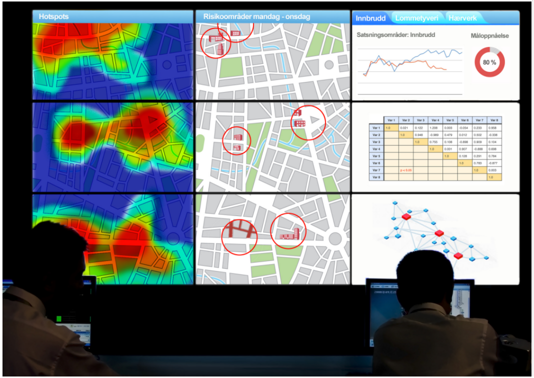
Labels are past behavior, so model is stable and incentive responses are constrained.

- 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.

// MOST READ

Apple fires warning shot at Facebook and Google on privacy, pledges fight

Predicting future choices and social outcomes

- Predicting criminal recidivism
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Errors are costly. Strong incentive responses.

Overview of problems relevant to ML fairness

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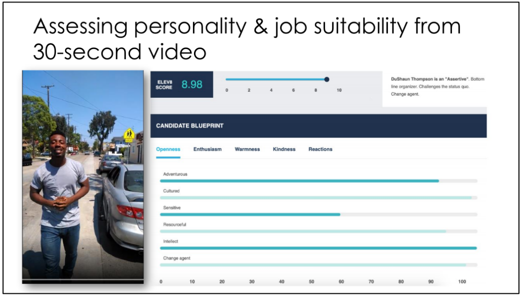
  - asymmetric information (AI company knows your preferences (price point)$\rightarrow$ they have information advantage and can capture more surplus).
- Incentive responses:
  - subjects try to manipulate features to game system
  - systems (e.g. essay grading) perceived as biased/unfair are discouraging.

Why don't algorithmic hiring systems work? (Raghavan et al, 2019)



Zoom private chat: Identify a problem with algorithmic hiring, explain why, and what would have to change to fix that problem.

Additional issues with using AI for predicting social outcomes

Narayanan slides

- Hunger for personal data
- Transfer of power from domain experts & workers to unaccountable tech companies
- Veneer of objectivity
- Lack of explainability
- ...

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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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  $\uparrow$ *would require a lot of (sophisticated) NLP tools*

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- Algorithm has severe evidence constraints:
  - can only use evidence that appears in a lot of cases; it ignores special/mitigating circumstances.
  - cannot (easily) contextualize evidence that is more or less trustworthy
- Would not work in many types of cases:
  - murder cases, where only evidence is witness testimony
  - antitrust violations
  - tax avoidance through accounting tricks

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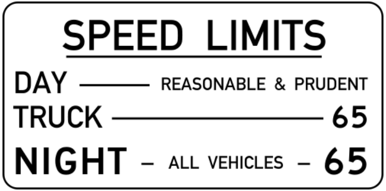
- Teaching the algorithm to understand rare evidence, discount suspicious evidence, and to understand new laws, would require something much closer to **legal artificial intelligence**.

Legal Vagueness and Value Judgments



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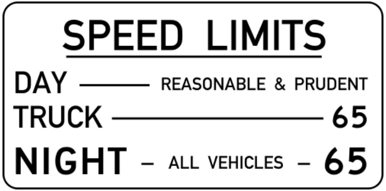

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- Making choices in the presence of vagueness or indeterminacy requires value judgements.

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

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?

Outline

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  - Understand the factors underlying decisions of judges.
  - Assess the real-world impacts of decisions on society – e.g. defendants, patients.

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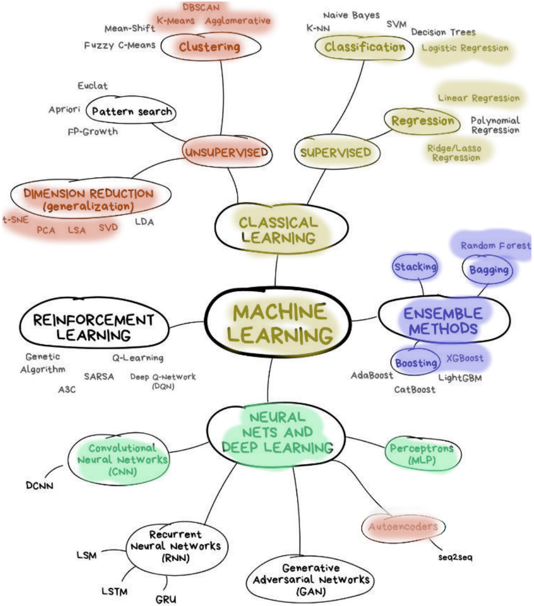
3. **Understand how (not) to use data science tools (ML and CI) to support expert decision-making.**


MACHINE LEARNING
CLASSICAL LEARNING
UNSUPERVISED
SUPERVISED
Clustering
DBSCAN
K-Means
Agglomerative
Mean-Shift
Fuzzy C-Means
Pattern search
Euclat
Apriori
FP-Growth
DIMENSION REDUCTION (generalization)
t-SNE
PCA
LSA
SVD
LDA
Classification
Naive Bayes
K-NN
SVM
Decision Trees
Logistic Regression
Regression
Linear Regression
Polynomial Regression
Ridge/Lasso Regression
ENSEMBLE METHODS
Stacking
Bagging
Random Forest
Boosting
XGBoost
AdaBoost
LightGBM
CatBoost
REINFORCEMENT LEARNING
Genetic Algorithm
Q-Learning
SARSA
Deep Q-Network (DQN)
A3C
NEURAL NETS AND DEEP LEARNING
Convolutional Neural Networks (CNN)
DCNN
Perceptrons (MLP)
Autoencoders
seq2seq
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)

Review Questions

https://bit.ly/BRJ-A13-Qs

Exam

- I will provide more detail in the coming weeks, and we will have a review session in early January.
- Please post questions here and we will try to answer them regularly, or post links to answers:

`https://padlet.com/eash44/1gunge0ijdx2bc0c`

Next Term: NLP Course

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  - "Sequencing Legal DNA: NLP for Law and Political Economy" (851-0739-01L)

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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.

Stay in touch

- e.g. add me on LinkedIn
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