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.
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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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  - other populations are different. so treatment effects and predictions might be different.
  - e.g., medical trials are often run with men, but medicines are then used to treat both men and women.
- 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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- Responsibility, accountability

Challenges to developing standards

- Collective decision processes
  - tradeoffs among various stakeholders
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  - tradeoffs among various stakeholders
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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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  - 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

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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- 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.

Outline

Incentive Responses

- Decisions today change features tomorrow.
- Take the case of ML-based credit scoring.
- Some strategic responses are benign/helpful:
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- Decisions today change features tomorrow.
- Take the case of ML-based credit scoring.
- Some strategic responses are benign/helpful:
  - e.g., pay back existing debts to improve score
- Others could be costly manipulation
  - e.g., open more credit accounts to increase score, but at some risk
  - more generally, ML subjects can pay some cost and manipulate their features to improve their predicted label.

Stackelberg Competition

1. The institution (leader) chooses the decision making model to
   - maximize its utility,
   - knowing that the follower is strategic.
2. The subject (follower) responds by manipulating their features to get a better label at the low cost.
   - knowing the decision making model.

Equilibrium

- At equilibrium, the designer chooses
  - a more conservative decision boundary
  - to increase robustness to the effects of strategic manipulation.

Social Costs of Manipulations

- Social burden: the cost of changing one's predicted label.
- Robustness to strategic manipulation leads to a increase in social burden.
- Social gap: the disparity in social burden across groups

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Perception Tasks

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

Human Judgment Annotation Tasks

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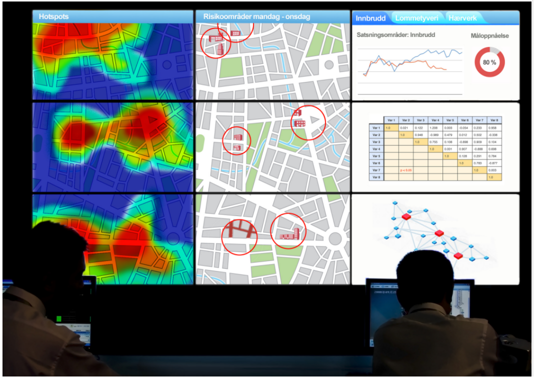
Labels are past behavior, so model is stable and incentive responses are constrained.

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

Predictive Policing

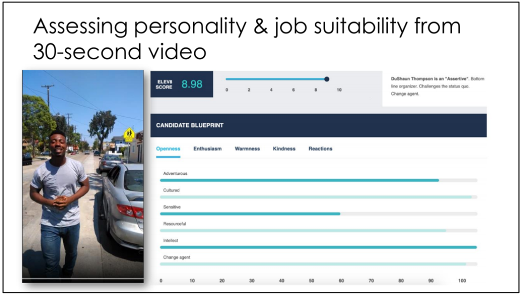


Predictive policing poses discrimination risk, thinktank warns

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

Why don't algorithmic hiring systems work?



Source: Raghavan et al, 2019.

Predicting future choices and social outcomes

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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.

Additional harms of using AI for predicting social outcomes

Narayanan slides

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

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- Would not work on new types of cases.
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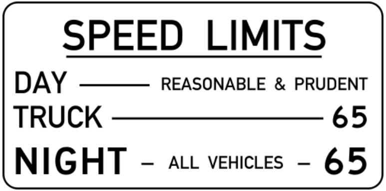
- Teaching the algorithm to understand rare evidence, and to understand new laws, would require something much closer to **legal artificial intelligence**.

Legal Vagueness and Value Judgments



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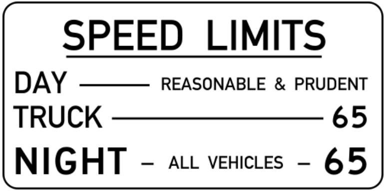

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- Making choices in the presence of vagueness or indeterminacy requires value judgements.

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 concept/motivation to appeal?

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

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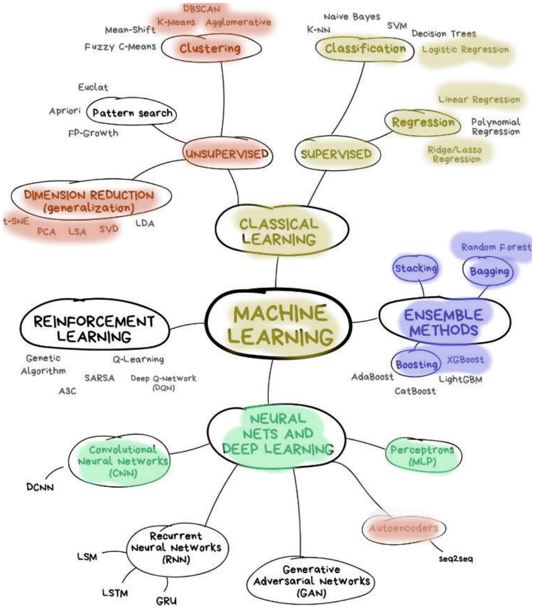
   - Implement these research designs using Stata regressions.
3. **Understand how (not) to use data science tools (ML and CI) to support expert decision-making.**
   - Explore the connections/distinctions between **prediction**, **inference**, and **decisions**.
   - Evaluate proposed policies/systems that use algorithms for decision support – along accuracy, bias, gaming, and other dimensions.
   - Read and critique research papers reporting on these policies/systems.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Polynomial Regression
Ridge/Lasso Regression
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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)
Recurrent Neural Networks (RNN)
LSM
LSTM
GRU
Generative Adversarial Networks (GAN)
Autoencoders
seq2seq

Evaluate (find problems in) machine learning pipelines

- .

Design a pipeline to solve a given ML problem

- .

Implement some standard ML pipelines in Python

- .

Evaluate (find problems in) causal claims

- .

Apply the standard research designs to produce causal evidence for a given empirical setting – or articulate why it is not possible.

- .

Implement causal inference designs using Stata regressions.

- .

Explore 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.

- .

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

- In the spring term, I teach a complementary course in natural language processing:
  - "Sequencing Legal DNA: NLP for Law and Political Economy" (851-0739-01L)

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  - "Sequencing Legal DNA: NLP for Law and Political Economy" (851-0739-01L)
- 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
- let me know if anything in this course helps you later on!
- can provide references for your work in the course.

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Thanks!