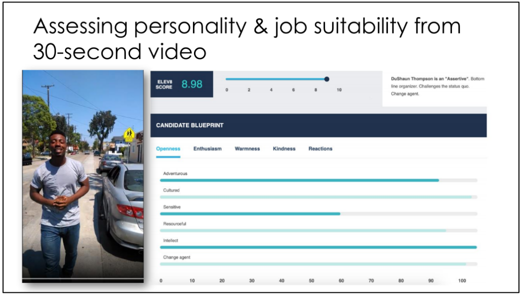
Building a Robot Judge:
Data Science for Decision-Making

13. Algorithms and Decisions IV

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



Write down an answer privately for sharing with the group:

- **[Last name starts with A-M] Give an example situation where algorithmic hiring should be allowed and explain.**
- **[Last name starts with N-Z] Give an example situation where algorithmic hiring should not be allowed and explain.**
- **What are some restriction/regulations that address problems without banning algorithmic hiring?**

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
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- Benefits many and growing:
  - efficiency, accuracy, scalability
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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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- 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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  - 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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- 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.
- Focus on **post-processing approach** to fairness:
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Caveats:

- disclosure must include the data (including sensitive attribute) and ML training process, not just the decision rule.
- how to decide on 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**. . . .

Application: Content/Ad Targeting

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

Write down an answer privately for sharing with the class:

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AI Governance

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AI for legal decisions

Recap and Conclusion

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These types of problems cannot be fixed by ML.
But ML can help diagnose them.

Perception Tasks

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

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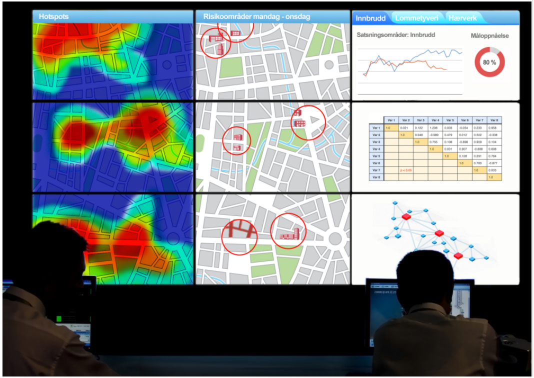
Labels are past behavior, so model is stable and incentive responses are constrained.

- 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.

// MOST READ

Apple fires warning shot at 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

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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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  - $\uparrow$ *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.

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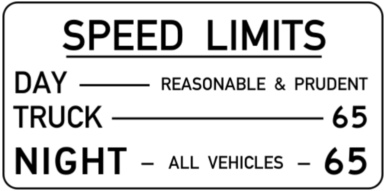
- Teaching an algorithm to understand rare evidence, discount suspicious evidence, and to understand new laws, would require something much closer to **legal artificial intelligence**.
- The most recent generation of large language models, like GPT 3.5 and chatGPT, are much much closer to this than what we had even a year or two ago.

Legal Vagueness and Value Judgments



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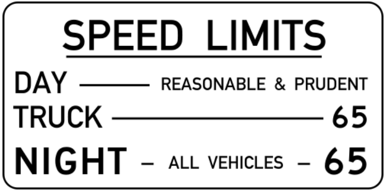

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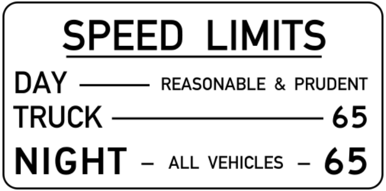

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- GPT-type models will give the likely response based on the training corpus. But that is backward-looking by construction and won't take into account information that is not in the corpus.

Philosophical Issues

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Thoughts? What else?

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- Scientific goals:
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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

- If you haven't done so yet, **you must sign up for a final assignment cohort by 7pm**. Otherwise you are assigned to Cohort 1.

Next Term: NLP Course

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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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- let me know if anything in this course helps you later on!
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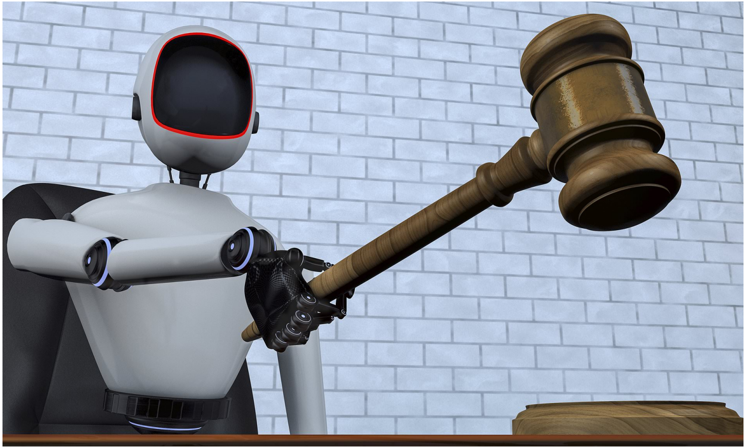

Meeting Adjourned!