

Building a Robot Judge

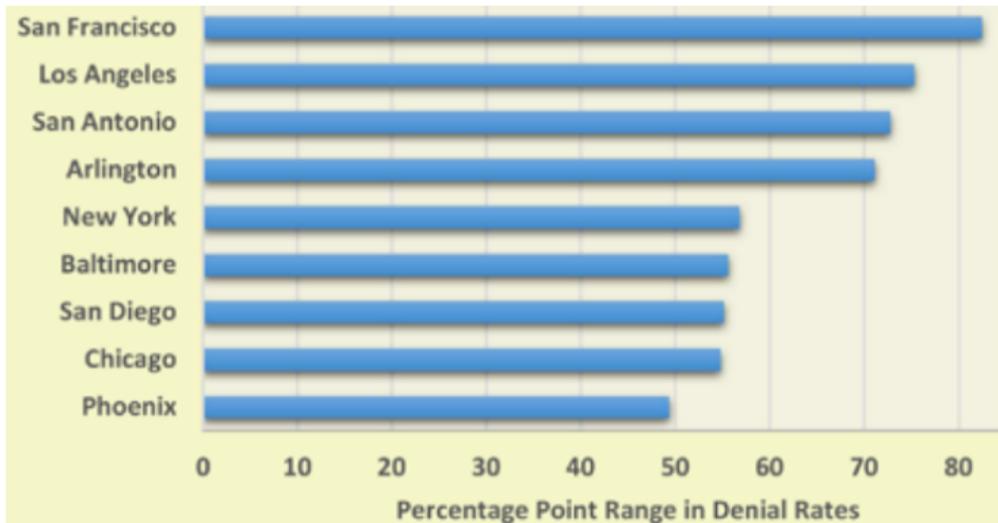
Data Science for Decision-Making

ETH Zurich, Fall 2022

1. Course Overview and Introduction

What's the matter with human decision-making?

U.S. Asylum Courts: Disparities in Grant Rates



- ▶ In San Francisco, one judge grants 90.6% of asylum requests, while another judge grants just 2.9%!

Jailing Decisions Before/After Lunch Breaks

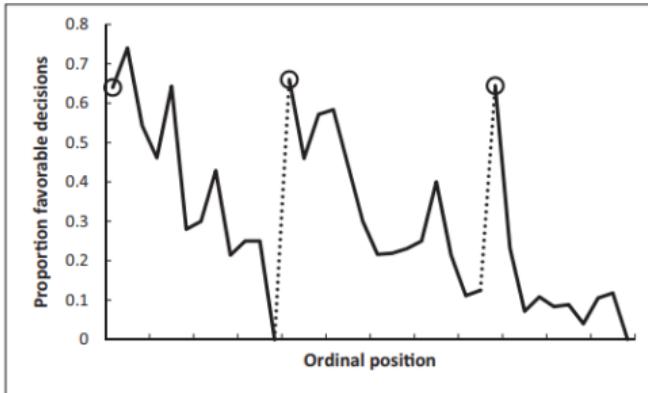


Fig. 1. Proportion of rulings in favor of the prisoners by ordinal position. Circled points indicate the first decision in each of the three decision sessions; tick marks on x axis denote every third case; dotted line denotes food break. Because unequal session lengths resulted in a low number of cases for some of the later ordinal positions, the graph is based on the first 95% of the data from each session.

Source: Danziger et al, PNAS 2011, Israel judges deciding on parole.

How about robot decision-making?

The World's First Robot Lawyer

The DoNotPay app is the home of the world's first robot lawyer. Fight corporations, beat bureaucracy, and sue anyone at the press of a button.

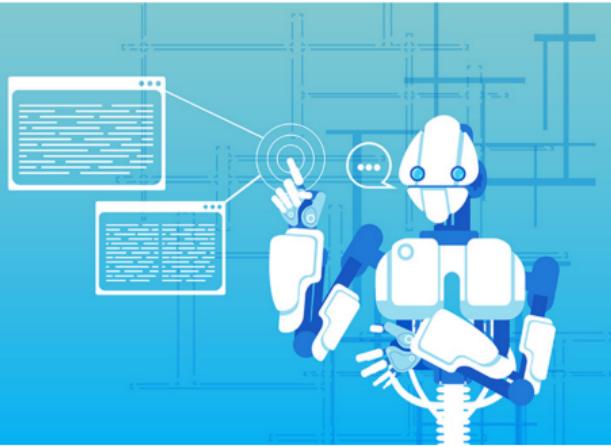
[Sign Up/Login](#)

THINGS YOU CAN DO WITH DONOTPAY

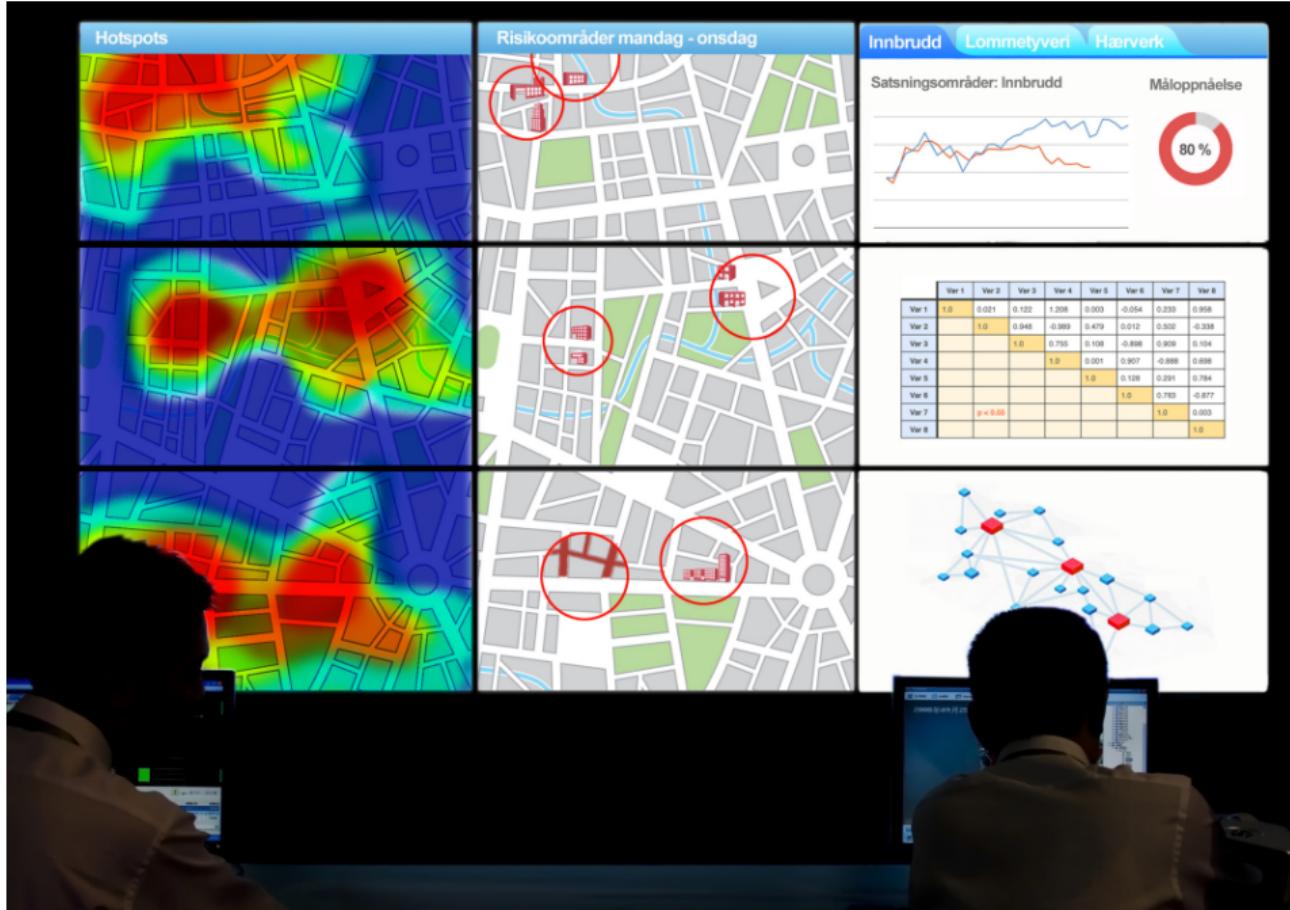
- Fight Corporations
- Beat Bureaucracy
- Find Hidden Money
- Sue Anyone
- Automatically Cancel Your Free Trials



Your Court-Appointed Chatbot – Is Artificial Intelligence Threatening the Legal Profession?



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



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 - ▶ **expert** decision-making requiring **judgment** – not just legal but also medical, political, etc.

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

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 - 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 these research designs using regressions.

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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.
- If you are signed up for the project: Implement/analyze such a system and write a paper about it.

Outline

Logistics

Course Outline

Lecture Times

- ▶ Mondays, 1615h-18h
 - ▶ ML E12
- ▶ ~10 minute break, 17h-1710h

Online Course Materials

- ▶ Course Syllabus:
 - ▶ link sent by email
- ▶ Course Repo (slides, notebooks, and assignments):
 - ▶ https://github.com/elliottash/robot_judge_2022

Teaching Assistant Claudia Marangon

Claudia Marangon (claudia.marangon@gess.ethz.ch)

- ▶ weekly TA sessions are provided as video recording
- ▶ TA office hours: can answer questions about lectures, notebooks, assignments, and projects.

Course Communication

- ▶ Course communication will be done through Moodle.
- ▶ Questions welcome via email, to me or to the TA's.
- ▶ Also feel welcome to ask questions before lecture, during the break, or after lecture.
- ▶ Will schedule meetings with students doing projects.

Reading List

- ▶ There are a handful of required readings (on the syllabus).
 - ▶ for use in classroom activities
 - ▶ could ask about them in final assignment
 - ▶ first one, for today, is a short news article, can read it during the break.
- ▶ Other readings can be used as reference:
 - ▶ to complement the slides
 - ▶ to be used for reading response essays (more next week)
 - ▶ lit review for projects

O'REILLY®

Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow

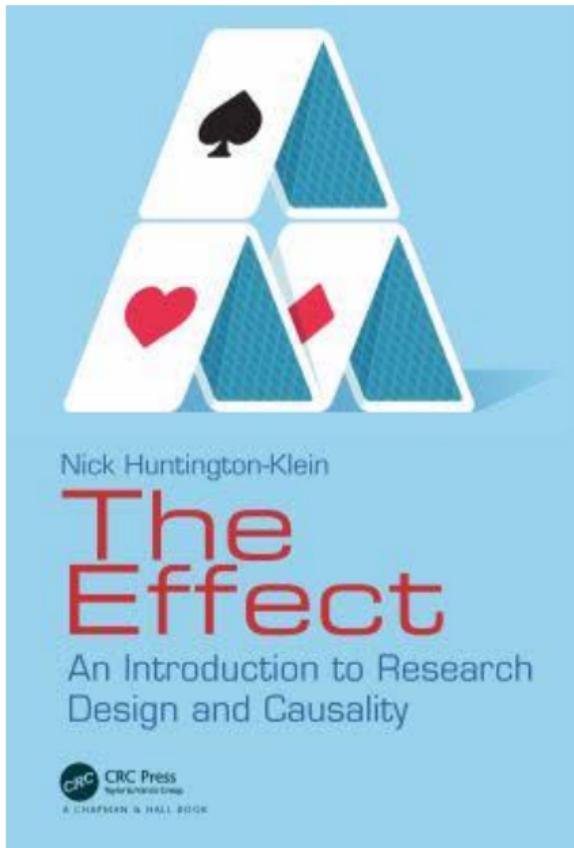
Concepts, Tools, and Techniques
to Build Intelligent Systems

powered by



Aurélien Géron

2nd Edition
Updated for
Tensorflow 2



Programming Material is Python-Oriented

- ▶ Python 3 is ideal for machine learning.
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- ▶ Econometrics:
 - ▶ applied economists use stata, which is closed-source statistical software
 - ▶ but we will have python versions of everything
- ▶ See the syllabus for lists of packages.
- ▶ you can use a different programming language for the assignment if you want – if so, email me about it.

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3 ECTS credits \approx 90 hours of work

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- ▶ 13 lectures, 1.75 hours each = 23 hours
- ▶ 10 ungraded programming assignments, ~1 hour each \approx 10 hours
- ▶ Required readings (three papers and a few short articles/snippets) \approx 9 hours
- ▶ 2 response essays, ~6 hours each \approx 12 hours
- ▶ Final assignment / take-home test, 4 hours
- ▶ **\approx 58 required hours.**

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- ▶ **\approx 58 required hours.**
- ▶ \approx 32 hours at student discretion:
 - ▶ 12 optional TA sessions, 1 hour each \approx 12 hours
 - ▶ leaves ~20 hours for additional study time

Course Projects

2 additional ECTS credits \approx 60 additional hours of work

- ▶ About twice as much out-of-class work expected
 - ▶ previous course projects have turned into conference/journal publications.
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- ▶ Information session after Oct 10th lecture (~10 minutes)
 - ▶ we have a list of potential topic ideas.

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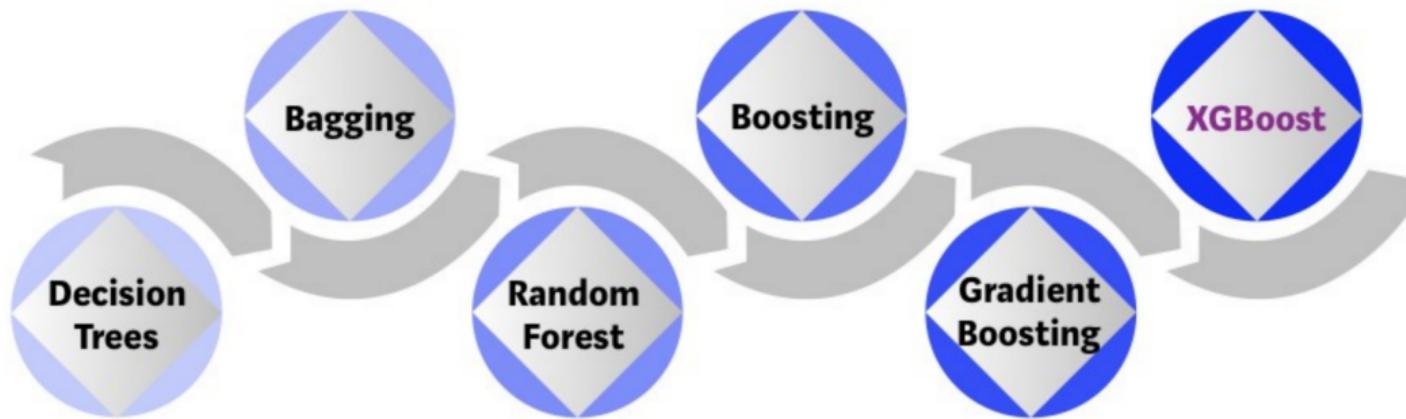
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- ▶ Week 03 Machine Learning Essentials
- ▶ Week 05 Classification
- ▶ Week 07 Deep Learning Essentials
- ▶ Week 09: Encoders and Explanation

"Extreme Gradient Boosting": Ingredients



Complicated in theory, easy in practice

```
from xgboost import XGBClassifier
model = XGBClassifier()

model.fit(X_train, y_train,
           early_stopping_rounds=10,
           eval_metric="logloss",
           eval_set=[(X_eval, y_eval)])
)

y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
```

Predicting U.S. Asylum Court Decisions

Predicting U.S. Asylum Court Decisions

		Predicted	
		Denied	Granted
True	Denied	195,223	65,798
	Granted	73,269	104,406

Accuracy = 68.3%, F1 = 0.60

- ▶ Prediction App (Beta): <https://floating-lake-11821.herokuapp.com/>

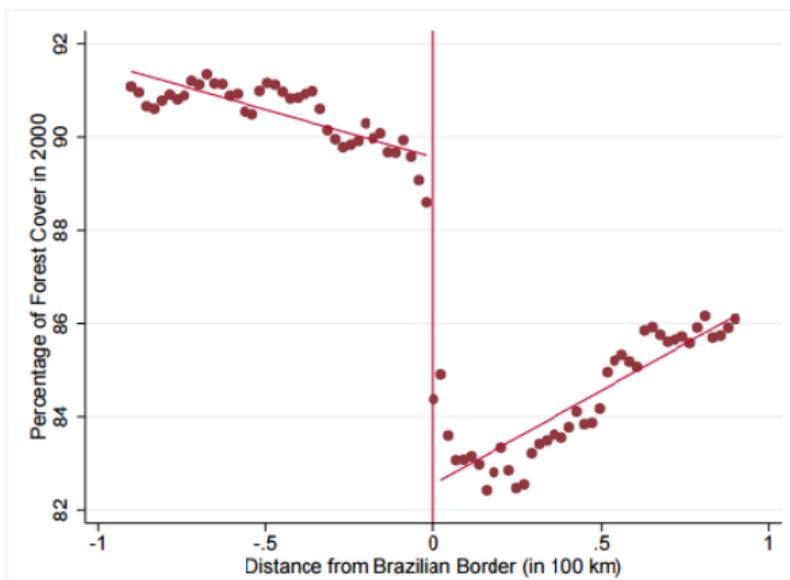
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- ▶ Evaluate (find problems in) causal claims.
- ▶ Apply the standard research designs to produce causal evidence for a given empirical setting – or articulate why it is not possible.
- ▶ Implement these research designs using Python or Stata.
- ▶ Week 02 Causal Inference Essentials
- ▶ Week 04 Panel Data Models
- ▶ Week 06 Machine Learning and Causal Inference
- ▶ Week 08 Instrumental Variables

<http://www.tylervigen.com/spurious-correlations>

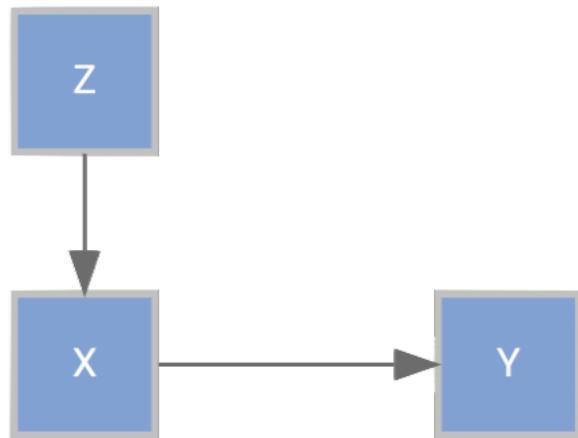
Burgess, Costa, and Olken, “The Brazilian Amazon’s Double Reversal of Fortune”



Source: <https://economics.mit.edu/files/12732>

Instrumental Variables

Before reading the course syllabus, had you ever heard of instrumental variables?



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 - ▶ Read and critique research papers reporting on these policies/systems.
-
- ▶ Weeks 10-13
 - ▶ AI-supported decisions
 - ▶ AI fairness
 - ▶ Explanations
 - ▶ AI policy

The standard learning problem

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- ▶ The label is a probabilistic function of the features:

$$Y = h(X)$$

A decision problem

Now consider a decision-maker who has to make a decision W , that will produce some value or benefit, conditional on the value of Y :

$$u(W; Y)$$

- ▶ e.g., whether to grant bail.
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if X includes a defendant's choices – eg education, criminal record, hiring an attorney
– then X becomes a function of $W^*(X)$:
- ▶ interactive decision problem → have to consider equilibria.

Examples

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 - ▶ assign refugees to locations using an algorithm that predicts higher employment.
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 - ▶ decide on bail/parole using an algorithm that predicts recidivism (whether defendant commits another crime)
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 - ▶ decide on bail/parole using an algorithm that predicts recidivism (whether defendant commits another crime)
 - ▶ algorithm could reduce both incarceration rates and recidivism.
- ▶ **Ash, Galletta, and Giommoni (2021):**
 - ▶ algorithm can predict fiscal corruption from budget data
 - ▶ could be used to double the detection rate of corruption relative to randomly assigned audits.

Can AI decisions be biased?

20 JAN 2017 | Insight

Kevin Petrasic | Benjamin Seal

Algorithms and bias: What lenders need to know

The algorithms that power fintech may be difficult to anticipate—and financial institutions are accountable even when alleged discrimination is unintentional.

A beauty contest was judged by AI and the robots didn't like dark skin

The first international beauty contest decided by an algorithm has sparked controversy after the results revealed one glaring factor linking the winners

The Switch
Wanted: The ‘perfect babysitter.’ Must pass AI scan for respect and attitude.

MENTAL HEALTH
If you’re not a white male, artificial intelligence’s use in healthcare could be dangerous



Women less likely to be shown ads for high-paid jobs on Google, study shows

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



How Facebook Is Giving Sex Discrimination In Employment Ads a New Life

By Gillian Sheehan, ACLU Women's Rights Project
www.aclu.org/women-rights



Source: Hoda Heidari slides.

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- ▶ Active research area on addressing these issues
 - ▶ methods for diagnosing bias / data problems
 - ▶ modal explanation methods to open the blackbox
- ▶ Further: algorithms can also be used to **detect** systematic bias, to **understand** it – and therefore to help **reduce** it.

Pairs Activity: Response on Mullainathan Article

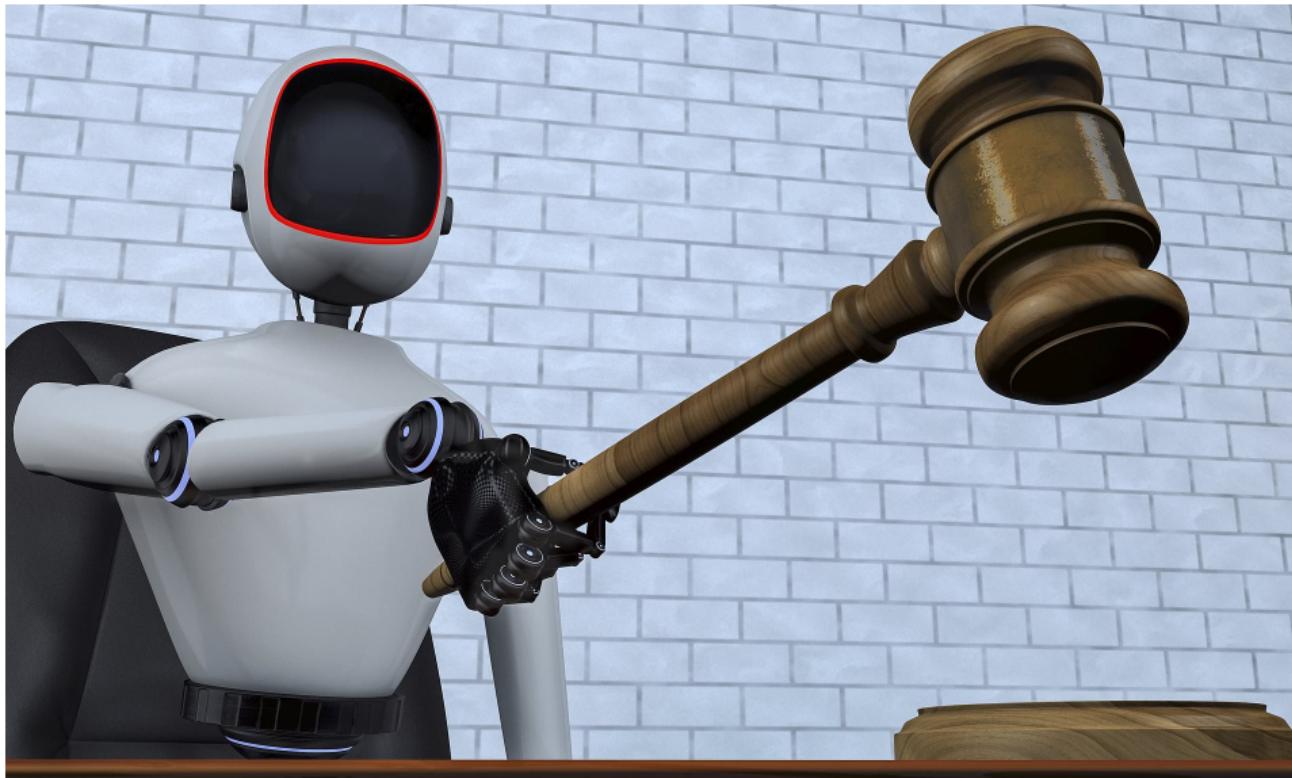
“Biased algorithms are easier to fix than biased people” by Sendhil Mullainathan in *New York Times* (bit.ly/nyt-bias).

- ▶ Pair up with a classmate, or with a group of 3
- ▶ Discuss and write down a short response with your group:
 - ▶ 1. Think of a task where fixing biases in an algorithm is probably easier than fixing it in humans. Why?
 - ▶ 2. Can you think of the opposite case — a task where fixing biases in humans is easier than fixing biases in algorithms? Why?
- ▶ Put your answers in a shared doc and paste a link here (or type answer directly into the padlet): <https://eash.cc/brj-w1a>

First Homework Assignment

see syllabus

- ▶ Write a short fake news article (~300 words) about a fake AI technology supporting/replacing expert decisions, such as by doctors or judges.
 - ▶ This is a completion grade – have fun with it!
 - ▶ See EduFlow page for submission instructions.



Meeting Adjourned!