

## DSME 6635: Artificial Intelligence for Business Research

# Introduction

Renyu (Philip) Zhang

1

## Who Am I?

- I am a scholar, a teacher, and a practitioner in data science/AI and operations research.
- Research:
  - How to use data analytics and AI to improve business decision making, especially for digitalized online platforms.
- Teaching:
  - Data science/AI for business to undergraduate, master, EMBA and PhD students.
- Data Science Practitioner:
  - Economist and Tech Lead, Kuaishou (快手: <https://www.kwai.com/>).
  - Evaluating and optimizing the ecosystem of Kuaishou.



- CUHK Business School, Associate Professor (with tenure), since 2022
- NYU Shanghai, Assistant Professor, 2016-2022; Visiting Scholar, since 2022
- Washington University in St. Louis, PhD, 2011-2016
- Peking University, BS, 2007-2011

2

## Agenda

- Course Introduction and Logistics
- AI for Business Research Landscape

3

3

## Purpose of this Course

1. Have a basic understanding of the fundamental concepts/methods in machine learning (ML) and artificial intelligence (AI) that are used (or potentially useful) in business research.
2. Understand how business researchers have utilized ML/AI and what managerial questions have been addressed by ML/AI in the recent decade.
3. Nurture a taste of what the state-of-the-art AI/ML technologies can do in the ML/AI community and, potentially, in your own research field.



4

4

## Other Options to Learn AI

- To learn AI, you have a lot of other options:
  - Basic ML Intro by Andrew Ng: <https://www.coursera.org/specializations/machine-learning-introduction>
  - Basic Deep Learning (DL) Intro by Andrew Ng: <https://www.coursera.org/specializations/deep-learning>
  - Natural Language Processing by Chris Manning: <https://web.stanford.edu/class/cs224n/>
  - Computer Vision by Fei-Fei Li: <http://cs231n.stanford.edu/>
  - Deep Reinforcement Learning by Sergey Levine: <https://rail.eecs.berkeley.edu/deeprlcourse/>
  - Deep Learning Theory by Matus Telgarsky: <https://mjt.cs.illinois.edu/courses/dlt-f22/>
  - Machine Learning Fairness by Mortiz Hardt: <https://fairmlbook.org/>
  - Language Language Models by Danqi Chen:  
<https://www.cs.princeton.edu/courses/archive/fall22/cos597G/>
  - Short Courses on Generative AI: <https://www.deeplearning.ai/short-courses/>
  - And a lot more.

5

## Why This Course?

- A fundamental and delegate trade-off: How **much** to cover vs. How **deep** to cover.
- This course provides a **concise introduction** to AI/ML topics relevant to **applied business research**.
- For each topic, we try to cover **enough necessary knowledge** that could:
  - Help you understand the **key trade-offs** and **invent new applied methods** (most likely without any **theoretical guarantee**);
  - Inform you about the **literature development** in the relevant domain;
  - Prepare you with the **necessary sense** to do **rigorous business research** using the relevant methods.
- We aim to cover **conceptually important theories** in AI/ML that can be **applied** in business research.
- We emphasize the **combination of coding and theory** so that you will be able to **implement your ideas**.

Impact of a **CS Paper** = Problem Importance \* Technical Novelty \* Performance Improvement

Impact of a **Business Paper** = Problem Importance \* Identification Rigor \* Insight Novelty

6

6

## Why Not This Course?

- We have some assumptions on your **prior knowledge**:
  - Working knowledge in calculus, linear algebra, and stats;
  - Working knowledge of Python programming;
  - ML, causal inference, and econometrics: Better that you have some basic sense in them.
- We try to **open doors and windows** for you instead of preparing you to be a leading expert in a specific domain.
- Some of the knowledge is outdated/constrained by academia.
  - Some trendy topics, e.g., large language models.

**Warning 0:** At CUHK, we have an Econ course of similar topics (ECON 5180) **without the coding emphasis**.

**Warning 1:** This may be your **MOST time-consuming course** at CUHK by a wide margin.

**Warning 2:** We will mainly talk about the ideas and methods (with demos) in class, but you will need some **coding skills** to finish your homework.

7

## Course Format

- We have a 2-hrs-and-45mins long course each week.
- For each session:
  - 30 mins: Homework discussions;
  - 90 mins: Theories and coding demos;
  - 30 mins: Student presentations.
- All coursework will be done in groups of at most **TWO** students.
  - Email us your group members (and majors) and your group name **by 11:59pm, Jan. 10, 2024**.
  - Otherwise, we will match you with others (based on majors).
- You will need to evaluate **your group mate's contribution** in all the coursework.

8

8

## Coursework and Grading

- Coursework:
  - Lecture notes scribing (each group will scribe the lecture note of one topic)
  - Paper presentation (one paper presentation per group each week)
  - Homework (one coding assignment each week, due two weeks after distribution; **5 assignments count**, but **3 of them are required**)
  - Final Project (one final project based on your own choice).
- Grading:
  - See Syllabus.
- All homework/final project will be done in **Python**.

9

9

## Coursework Materials

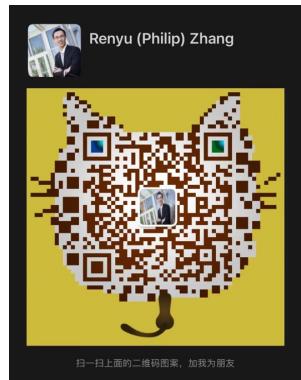
- GitHub: <https://github.com/rphilipzhang/AI-PhD-S24>
  - All course materials will be distributed on this GitHub Repository.
- Google Sheet: [https://docs.google.com/spreadsheets/d/1nOE-saTptG73WMCONDB1Z3pt-jHhmDA\\_1OHpQVHqQ1M/edit?usp=sharing](https://docs.google.com/spreadsheets/d/1nOE-saTptG73WMCONDB1Z3pt-jHhmDA_1OHpQVHqQ1M/edit?usp=sharing)
  - Group Registration
  - Lecture Notes Scribing Sign-up
  - Paper Presentation Sign-up
  - Project Presentation Sign-up
  - Homework Submission (use the link to your Google CoLab and **opensource** your code to your classmates by "Anyone with the link can view")
- Google CoLab:
 [https://drive.google.com/drive/folders/1Th2I26ZUJ4qPosPOJOD3Yoy8o3lr8Q\\_G?usp=sharing](https://drive.google.com/drive/folders/1Th2I26ZUJ4qPosPOJOD3Yoy8o3lr8Q_G?usp=sharing)
  - All code demos will be distributed via Google CoLab.
- Registered students please ask our TA, Leo Cao, to **add your account** to our course Google Sheet.

10

10

## Course Communications

- **Class Meeting:** Tuesday, 12:30AM-3:15PM (@CYT 928A)
- **Office hour:** By appointment, @CYT\_911
- **WeChat group:** Online discussion forum.
- **Instructor contact**
  - Office: CYT\_911
  - Email: [philipzhang@cuhk.edu.hk](mailto:philipzhang@cuhk.edu.hk)
  - Tel: 852-3943-7763
  - WeChat: rphilip\_zhang
- **Teaching Assistant:** Leo Cao
  - Email: [yinglycao@cuhk.edu.hk](mailto:yinglycao@cuhk.edu.hk)



11

11

## Python Tutorial Sessions

- We have two **optional** Python tutorial sessions held **online** at **Friday night, 6:30pm-8:30pm**.
- Tutorial Instructor: Qiansiqi Hu, MSBA Student @CUHK Business School, BS in ECE Alumni & SJTU Michigan Institute, [1155208353@link.cuhk.edu.hk](mailto:1155208353@link.cuhk.edu.hk)
- Check the course GitHub Repo for CoLab and Zoom links.
- Session 1: Friday, Jan 12, 2024
  - Python Basics
- Session 2: Friday, Jan 19, 2024
  - PyTorch Basics
- Other References:
  - [https://colab.research.google.com/drive/1hxWtr98jXqRDs\\_rZLZcEmX\\_hUcpDLq6e?usp=sharing](https://colab.research.google.com/drive/1hxWtr98jXqRDs_rZLZcEmX_hUcpDLq6e?usp=sharing)
  - [https://colab.research.google.com/drive/13HGy3-uIIy1KD\\_WFhG4nVrxJC-3nUUkP?usp=sharing](https://colab.research.google.com/drive/13HGy3-uIIy1KD_WFhG4nVrxJC-3nUUkP?usp=sharing)
  - <https://cs231n.github.io/python-numpy-tutorial/>
  - <https://colab.research.google.com/github/cs231n/cs231n.github.io/blob/master/python-colab.ipynb>

12

12

# Agenda

- Course Introduction and Logistics
- AI for Business Research Landscape

13

13

# What is AI/ML?

- ML is a CS subfield that **automates** computers to learn from **data** without explicitly programmed.
- Different names:
  - Data mining
  - Statistical learning
  - Data science

 Mat Veloso   
@matveloso

Difference between machine learning and AI:

If it is written in Python, it's probably machine learning

If it is written in PowerPoint, it's probably AI

9:25 AM · Nov 23, 2018 · Twitter Web Client

8,368 Retweets 906 Quote Tweets 23.9K Likes



14

14

## Prediction vs. Estimation

### Perspective

### Integrating explanation and prediction in computational social science

<https://doi.org/10.1038/s41586-021-03659-0>

Received: 23 February 2021

Accepted: 20 May 2021

Published online: 30 June 2021

 Check for updates

Jake M. Hofman<sup>1,17</sup>, Duncan J. Watts<sup>2,3,4,17</sup>, Susan Athey<sup>5</sup>, Filiz Garip<sup>6</sup>, Thomas L. Griffiths<sup>18</sup>, Jon Kleinberg<sup>10</sup>, Helen Margetts<sup>11,12</sup>, Sendhil Mullainathan<sup>13</sup>, Matthew J. Salganik<sup>6</sup>, Simine Vazire<sup>14</sup>, Alessandro Vesplignani<sup>15</sup> & Tal Yarkoni<sup>16</sup>

Computational social science is more than just large repositories of digital data and the computational methods needed to construct and analyse them. It also represents a convergence of different fields with different ways of thinking about and doing science. The goal of this Perspective is to provide some clarity around how these approaches differ from one another and to propose how they might be productively integrated. Towards this end we make two contributions. The first is a schema for thinking about research activities along two dimensions—the extent to which work is explanatory, focusing on identifying and estimating causal effects, and the degree of consideration given to testing predictions of outcomes—and how these two priorities can complement, rather than compete with, one another. Our second contribution is to advocate that computational social scientists devote more attention to combining prediction and explanation, which we call integrative modelling, and to outline some practical suggestions for realizing this goal.

15

15

## Landscape of AI/ML for Business Research

- **ML as Data/Data Source**

- Cohen M, Zhang R, Jiao K. (2022) Data aggregation and demand prediction. *Operations Research*, 70(5): 2597-2618.

- **ML for Causal Inference**

- Ye, Z., Zhang, Z., Zhang, D. J., Zhang, H., Zhang, R. (2023) Deep Learning Based Causal Inference for Large-Scale Combinatorial Experiments: Theory and Empirical Evidence, *working paper* and EC'23.

- **ML for Predictive Decision Making and Optimization**

- Ye, Z., Zhang, D. J., Zhang, H., Zhang, R., Chen, X., and Xu, Z. (2023) Cold start to improve market thickness on online advertising platforms: Data-driven algorithms and field experiments. *Management Science*, 69(7), 3838-3860.

- **ML as Subjects**

- Zhao, Z., Zhang, D. J., and Zhang, R. (2023) Algorithmic Self-Preferencing on E-Commerce Platforms: Evidence from JD.COM, *working paper*.

- **ML for Structural Estimation**

16

16

# ML as Data/Data Source

(Almost) 200 Years of News-Based Economic Sentiment\*

J. H. van Binsbergen<sup>†</sup> S. Bryzgalova<sup>†</sup> M. Mukhopadhyay<sup>§</sup> V. Sharma<sup>¶</sup>

March 23, 2023

## Abstract

Using the text of 200 million pages of 13,000 US local newspapers and state-of-the-art machine learning methods, we construct a novel 170-year-long time series measure of economic sentiment at the country and state levels, that expands the existing measures in both the time series (by more than a century) and the cross-section. We show that our measure predicts economic fundamentals such as GDP (both nationally and locally), consumption, and employment growth, even after controlling for commonly-used predictors, and materially predicts monetary policy decisions, particularly during recessions. Our measure is distinct from the information in expert forecasts and leads its consensus value. We use the text to isolate information about current and future events and show that it is the latter that drives our predictability results.

**Keywords:** Business cycle, macroeconomic news, economic sentiment, monetary policy, textual analysis, machine learning, big data, neural networks

**JEL codes:** G1, G4, E2.

## Financial Machine Learning

Bryan Kelly<sup>1</sup> and Dacheng Xiu<sup>2</sup>

<sup>1</sup>Yale School of Management, AQR Capital Management, and NBER; bryan.kelly@yale.edu

<sup>2</sup>University of Chicago Booth School of Business; dacheng.xiu@chicagobooth.edu

## ABSTRACT

We survey the nascent literature on machine learning in the study of financial markets. We highlight the best examples of what this line of research has to offer and recommend promising directions for future research. This survey is designed for both financial economists interested in grasping machine learning tools, as well as for statisticians and machine learners seeking interesting financial contexts where advanced methods may be deployed.

17

17

# ML for Causal Inference

## Mega or Micro? Influencer Selection Using Follower Elasticity

Zijun Tian, Ryan Dew, Raghuram Iyengar\*  
University of Pennsylvania

July 28, 2022

## Abstract

Despite the explosive growth of influencer marketing, wherein companies sponsor social media personalities to promote their brands, there is little research to guide companies' selection of influencer partners. One common criterion is popularity: while some firms sponsor "mega" influencers with millions of followers, other firms partner with "micro" influencers, who may only have several thousands of followers, but may also cost less to sponsor. To quantify this trade-off between reach and cost, we develop a framework for estimating the *follower elasticity of impressions*, or FEI, which measures a video's percentage gain in impressions corresponding to a percentage increase in the follower size of its creator. Computing FEI involves estimating the causal effect of an influencer's popularity on the view counts of their videos, which we achieve through a combination of a unique dataset collected from TikTok, a representation learning model for quantifying video content, and a machine learning-based causal inference method. We find that FEI is always positive, but often nonlinearly related to follower size, suggesting different optimal sponsorship strategies than those observed in practice. We examine the factors that predict variation in these FEI curves, and show how firms can use these results to better determine influencer partnerships.

**Keywords:** influencer marketing, causal inference, deep learning, representation learning, heterogeneous treatment effects, video data



MANAGEMENT SCIENCE  
Articles in Advance, pp. 1–15  
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

## Targeting for Long-Term Outcomes

Jeremy Yang,<sup>a,\*</sup> Dean Eckles,<sup>b,\*</sup> Paramveer Dhillon,<sup>c</sup> Sinan Aral<sup>d</sup>

<sup>a</sup>Harvard Business School, Boston, Massachusetts 02163, <sup>b</sup>Massachusetts Institute of Technology, Cambridge, Massachusetts 02142;

<sup>c</sup>University of Michigan, Ann Arbor, Michigan 48109

\*Corresponding authors

Contact: jeremyyang@hbs.edu, <https://orcid.org/0000-0001-8639-5493> (JY); eckles@mit.edu, <https://orcid.org/0000-0001-8439-442X> (DE); dhillomp@umich.edu, <https://orcid.org/0000-0002-0994-9488> (PD); sinan@mit.edu, <https://orcid.org/0000-0002-2762-058X> (SA)

Received: October 7, 2021

Revised: February 2, 2022

Accepted: February 27, 2022

Published Online in Articles in Advance: August 3, 2023

<https://doi.org/10.1287/mnsc.2023.4881>

Copyright: © 2023 INFORMS

**Abstract:** Decision makers often want to target interventions so as to maximize an outcome that is observed only in the long term. This typically requires delaying decisions until the outcome is observed or relying on simple short-term proxies for the long-term outcome. Here, we build on the statistical surrogate and policy learning literatures to impute the missing long-term outcomes and then approximate the optimal targeting policy on the imputed outcomes via a doubly robust approach. We first show that conditions for the validity of average treatment effect estimation with imputed outcomes are also sufficient for valid policy evaluation and optimization; furthermore, these conditions can be somewhat relaxed for policy optimization. We apply our approach in two large-scale proactive churn management experiments at *The Boston Globe* by targeting optimal discounts to its digital subscribers with the aim of maximizing long-term revenue. Using the first experiment, we evaluate this approach empirically by comparing the policy learned using imputed outcomes with a policy learned on the ground-truth, long-term outcomes. The performance of these two policies is statistically indistinguishable, and we rule out large losses from relying on surrogates. Our approach also outperforms a policy learned on short-term data in the long run. In a second field experiment, we learn the optimal targeting policy with additional randomized exploration, which allows us to update the optimal policy for future subscribers. Over three years, our approach had a net-positive revenue impact in the range of \$4–\$5 million compared with the status quo.

**History:** Accepted by Eric Anderson, marketing.

**Funding:** This work was supported by Boston Globe Media.

**Supplemental Material:** The online appendix and data are available at <https://doi.org/10.1287/mnsc.2023.4881>.

**Keywords:** long-term effect • statistical surrogate • policy learning • targeting • proactive churn management

<https://bookdown.org/stanfordqsbsilab/ml-ci-tutorial/>

18

18

# ML for Predictive Decision-Making & Optimization



OPERATIONS RESEARCH  
Vol. 70, No. 1, January–February 2022, pp. 309–328  
ISSN 0030-364X (print), ISSN 1526-548X (online)



MARKETING SCIENCE

Articles in Advance, pp. 1–22

ISSN 0732-2399 (print), ISSN 1526-548X (online)

## Crosscutting Areas

### Customer Choice Models vs. Machine Learning: Finding Optimal Product Displays on Alibaba

Jacob Feldman,<sup>a</sup> Dennis J. Zhang,<sup>b</sup> Xiaofei Liu,<sup>b</sup> Nannan Zhang<sup>b</sup>

<sup>a</sup>Olin Business School, Washington University in St. Louis, St. Louis, Missouri 63130; <sup>b</sup>Alibaba Group Inc., Hangzhou 311100, China  
Contact: jfeldman@wustl.edu, <https://orcid.org/0000-0002-5576-1953> (JF); denniszhang@wustl.edu (DZ); xiaolei.liu@alibaba.com (XL); nannan.zhang@alibaba.com (NZ)

Received: November 5, 2019  
Revised: September 18, 2019  
Accepted: April 25, 2020  
Published Online in Articles in Advance: October 26, 2021  
Area of Review: OR Practice  
<https://doi.org/10.1287/opre.2021.2158>

Copyright © 2021 INFORMS

**Abstract.** We compare the performance of two approaches for finding the optimal set of products to display. One approach is a traditional choice model, and the other is machine learning. We conducted a large-scale field experiment in which we randomly assigned 10,421,649 customer visits during a one-week-long period to one of the two approaches and measured the revenue generated per customer visit. The first approach we tested was Alibaba's current practice, which embeds product and customer features within a sophisticated machine-learning algorithm to estimate the purchase probabilities of each product for the customer at hand. The products with the highest expected revenue  $\times$  probability were displayed on the front page of the Alibaba shopping platform. Our second approach, which we developed and implemented in collaboration with Alibaba engineers, uses a factorized multinomial logit (MNL) model to predict purchase probabilities for each arriving customer. We used historical sales data to fit the MNL model, and then, for each arriving customer, we solved a cardinality-constrained assortment-optimization problem under the MNL model to find the optimal set of products to display. Our field experiments revealed that the MNL-based approach generates 5.17 million RMB more revenue than the MNL-based approach when both approaches were given access to the same set of the 25 most important features. This improvement represents a 28% gain in revenue per customer visit, which corresponds to a 4 million RMB improvement over the week in which the experiments were conducted. Motivated by the results of our initial field experiment, Alibaba then implemented a well-tailored version of the MNL-based approach, which now serves the majority of customers in that setting. Using another full-scale field experiment, we estimate that our new MNL-based approach that utilizes the full feature set is able to increase Alibaba's annual revenue by 57.26 million RMB (12.42 million U.S. dollars).

**Supplemental Material:** The online appendix is available at <https://doi.org/10.1287/opre.2021.2158>.

**Keywords:** choice models • product assortment • machine learning • field experiment • retail operations

### Dynamic Coupon Targeting Using Batch Deep Reinforcement Learning: An Application to Livestream Shopping

Xiao Liu<sup>a</sup>

<sup>a</sup>Stern School of Business, New York University, New York, New York 10012  
Contact: xl23@stern.nyu.edu, <https://orcid.org/0000-0002-7093-8534> (XL)

Received: September 3, 2020

Revised: September 8, 2021; April 17, 2022

Accepted: June 28, 2022

Published Online in Articles in Advance: October 20, 2022

<https://doi.org/10.1287/mksc.2022.1403>

Copyright: © 2022 INFORMS

**Abstract.** We present an empirical framework for creating dynamic coupon targeting strategies for high-dimensional and high-frequency settings, and we test its performance using a large-scale field experiment. The framework captures consumers' intertemporal tradeoffs associated with dynamic pricing and does not rely on functional form assumptions about consumers' decision-making processes. The model is estimated using batch deep reinforcement learning (BDRL), which relies on Q-learning, a model-free solution that can mitigate model bias. It leverages deep neural networks to represent the high-dimensional state space and alleviate the curse of dimensionality. The empirical application is in a multibillion-dollar livestream shopping context. Our BDRL solution increases the platform's revenue by twice as much as static targeting policies and by 20% more than the model-based solution. The comparative advantage of BDRL comes from more effective and automatic targeting of consumers based on both heterogeneity and dynamics, using exceptionally rich, nuanced differences among consumers and across time. We find that price skimming, reducing discounts for attractive hosts, and increasing the coupon discount level at a faster rate for low spenders are effective strategies based on dynamics, consumer heterogeneity, and the two combined, respectively.

**History:** K. Sudhir served as the senior editor and John Hauser served as associate editor for this article.

**Funding:** Partial financial support was received from the NYU Center for Global Economy and Business.

**Supplemental Material:** The data files and online appendices are available at <https://doi.org/10.1287/mksc.2022.1403>.

**Keywords:** dynamic pricing • coupon • deep reinforcement learning • reference price • livestream shopping • targeting

19

19

# ML as Subject



MANAGEMENT SCIENCE

Vol. 65, No. 7, July 2019, pp. 2966–2981

ISSN 0025-1909 (print), ISSN 1526-5501 (online)

### Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads

Anja Lambrecht,<sup>a</sup> Catherine Tucker<sup>b</sup>

<sup>a</sup>Marketing, London Business School, London NW1 4SA, United Kingdom; <sup>b</sup>Marketing, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139

Contact: alambrecht@london.edu, <https://orcid.org/0000-0001-6766-1602> (AL); ctucker@mit.edu,

<https://doi.org/10.1287/mnsc.2018.3093>

Copyright: © 2019 INFORMS

**Abstract.** We explore data from a field test of how an algorithm delivered ads promoting job opportunities in the science, technology, engineering, and math fields. This ad was explicitly intended to be gender neutral in its delivery. Empirically, however, fewer women saw the ad than men. This happened because younger women are a prized demographic and are more expensive to show ads to. An algorithm that simply optimizes cost-effectiveness in ad delivery will deliver ads that were intended to be gender neutral in an apparently discriminatory way, because of crowding out. We show that this empirical regularity extends to other major digital platforms.

**History:** Accepted by Joshua Gans, business strategy.

**Funding:** Supported by a National Science Foundation Career Award [Grant 6923256].

**Keywords:** algorithmic bias • online advertising • algorithms • artificial intelligence

**AI/ML as subjects:** Machine human collaboration; ML fairness/discrimination; ML and labor market; data privacy; Data and ML in IO; AI as a species, etc.

20

20

Journal of Financial Economics 151 (2024) 103745

Contents lists available at ScienceDirect

Journal of Financial Economics journal homepage: [www.elsevier.com/locate/jfec](http://www.elsevier.com/locate/jfec)

Elsevier

Artificial intelligence, firm growth, and product innovation

Tania Babina<sup>a,b</sup>, Anastassia Fedyk<sup>c,d</sup>, Alex He<sup>d</sup>, James Hodson<sup>e,f</sup>

<sup>a</sup>Columbia University, New York, NY, USA  
<sup>b</sup>NBER, USA  
<sup>c</sup>University of California, Berkeley, Berkeley, CA, USA  
<sup>d</sup>University of Wisconsin, Madison, Madison, WI, USA  
<sup>e</sup>AI for Good Foundation, Berkeley, CA, USA  
<sup>f</sup>Institut Jozef Stefan, Ljubljana, Slovenia

ARTICLE INFO

Dataset link: <https://data.mendeley.com/datasets/c2d4xvsgp07/2>

JEL classification:

- J22
- E22
- J23
- J24
- J31
- J33

Keywords:

- Artificial intelligence
- Intangible capital
- Technological change
- Product innovation
- Superstar firms
- Industry concentration

ABSTRACT

We study the use and economic impact of AI technologies. We propose a new measure of firm-level AI investments using employee resumes. Our measure reveals a stark increase in AI investments across sectors: AI-investing firms experience higher growth in sales, employment, and market valuations. This growth comes primarily through increased product innovation. Our results are robust to instrumenting AI investments using firms' exposure to universities' supply of AI graduates. AI-powered growth concentrates among larger firms and is associated with higher industry concentration. Our results highlight that new technologies like AI can contribute to growth and superstar firms through product innovation.

# ML for Structural Estimation

Estimating Parameters of Structural Models Using Neural Networks

*Econometrica*, Vol. 91, No. 6 (November, 2023), 2041–2063

AN ADVERSARIAL APPROACH TO STRUCTURAL ESTIMATION

TETSUYA KAJI  
University of Chicago Booth School of Business

ELENA MANRESA  
Department of Economics, New York University

GUILLAUME POULIOT  
University of Chicago Harris School of Public Policy

We propose a new simulation-based estimation method, adversarial estimation, for structural models. The estimator is formulated as the solution to a minimax problem between a generator (which generates simulated observations using the structural model) and a discriminator (which classifies whether an observation is simulated). The discriminator maximizes the accuracy of its classification while the generator minimizes it. We show that, with a sufficiently rich discriminator, the adversarial estimator attains parametric efficiency under correct specification and the parametric rate under misspecification. We advocate the use of a neural network as a discriminator that can exploit adaptivity properties and attain fast rates of convergence.

**KEYWORDS:** Structural estimation, generative adversarial networks, neural networks, simulation-based estimation, efficient estimation.

Yanhao 'Max' Wei and Zhenling Jiang\*

December 1, 2023

## Abstract

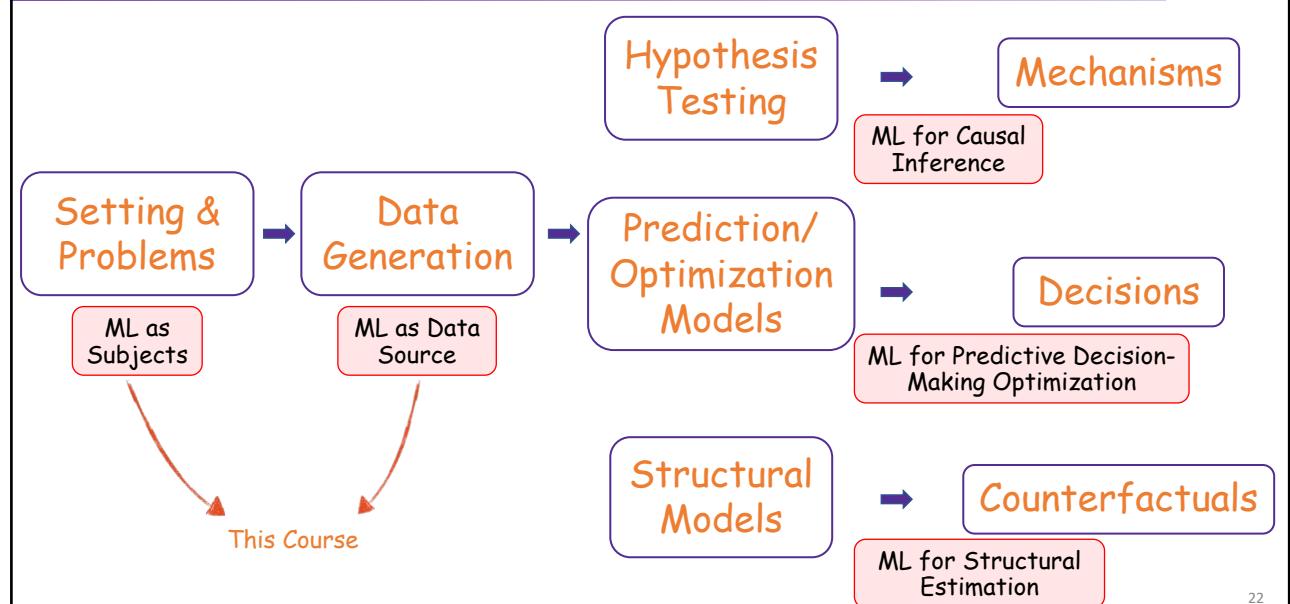
We explore an alternative use of machine learning. We train neural nets to provide the estimate for the parameter of a given (structural) econometric model, e.g., discrete choice, consumer search. The training examples consist of datasets generated by the econometric model under a range of parameter values. The neural net takes the moments of a dataset as input and tries to recognize the parameter value underlying that dataset. In addition to point estimate, the neural net can also be trained to provide statistical accuracy. We establish that this neural net estimator (NNE) converges to limited-information Bayesian posterior when the number of training datasets is sufficiently large. We compare NNE to the prevailing estimation approach in a consumer sequential search application. NNE gives accurate and robust estimates at light computational costs. We discuss more broadly what types of applications are suitable (and unsuitable) for NNE.

**Keywords:** neural networks, machine learning, structural estimation, redundant moments, simulation burden, sequential search.

21

21

# A Typical (Empirical) Insight Paper



22

22

## Course Schedule

- Introduction to Supervised Learning (1)
- Introduction to Deep Learning (1)
- Natural Language Processing (5)
- Computer Vision (2)
- Unsupervised Learning (2)
- Algorithm and Fairness (1)

Note: Tentative schedule subject to changes. See Syllabus and GitHub repo for details.

23

23

## Who Are You?



24

24

## Who Are You?

- What is your name?
- Which department are you from?
- Why are you here?
- What do you expect from this course?
- What else do you want me to cover?

25

25

## ML as Data Source

- Any recordable information that is **not numerical** can be analyzed with ML to answer business questions.
- References:
  - Text - Natural Language Processing (NLP)
  - Image/Video - Computer Vision (CV)
  - Sound - Deep Learning (DL)
  - And many more...

26

26

## ML as Data Source

- Why do we use ML to understand unstructured data?
  - Cost reduction and scalability
  - Objectivity
  - Easy to built into other systems
  
- Issues with using ML to understand unstructured data:
  - Measurement errors
  - Interpretation

27

27

## Issues with ML as Data Source

- Empirical model:  $Y = a + b \cdot D + g(X) + \epsilon$ 
  - Key parameter of interest:  $b$
  
- Outcome
  - $Y$  may be generated through ML with error.
  
- Treatment
  - $D$  may be generated through ML with error.
  
- Controls
  - $X$  may be generated through ML with error.
  - $X$  may be selected by ML with error.

28

28