DOTE 6635: Artificial Intelligence for Business Research

Introduction

Renyu (Philip) Zhang

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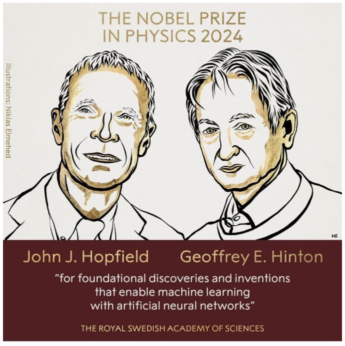
AI: Future of Human Civilization



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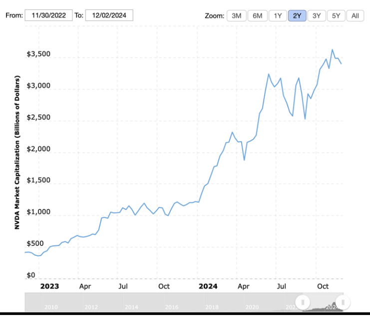
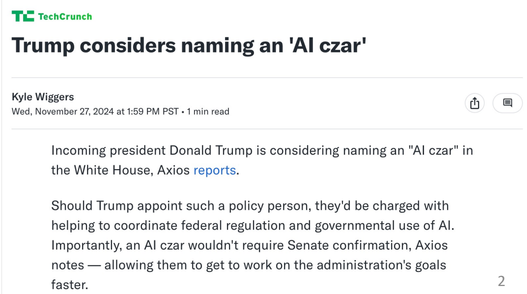
OpenAI完成最新一轮66亿美元融资 警告投资者不准支持马斯克xAI等劲敌

赵雨荷 10-03 00:07

摘要：

本轮融资也是史上规模最大的私人投资之一，由Thrive Capital领投，参与者还包括微软、英伟达、软银等，其中微软投资约7.5亿美元。本轮融资过后，OpenAI的估值达到1570亿美元，跻身全球前三大初创公司的行列。同时，OpenAI希望与投资者达成独家协议，防止马斯克的xAI和Anthropic等竞争对手获得战略合作机会和资本支持。





TechCrunch

Trump considers naming an 'AI czar'

Kyle Wiggers
Wed, November 27, 2024 at 1:59 PM PST • 1 min read

Incoming president Donald Trump is considering naming an "AI czar" in the White House, Axios reports.

Should Trump appoint such a policy person, they'd be charged with helping to coordinate federal regulation and governmental use of AI. Importantly, an AI czar wouldn't require Senate confirmation, Axios notes — allowing them to get to work on the administration's goals faster.

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Who Am I?

- I am a scholar, a teacher, and a practitioner in data science/AI and operations research.

- Research:
  - How to use data science 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.
  - 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

The Bitter Lesson

- References: http://www.incompleteideas.net/IncIdeas/BitterLesson.html https://www.youtube.com/watch?v=vbVfAqPI8ng

- The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin.

- Leveraging domain knowledge (short-term & specific) vs. Leveraging computation (long-term & general).

- Bitter lesson: Leveraging domain knowledge is self-satisfying and intellectually inspiring, but plateaus in the long-run or even inhibits further progress.

Prof. Richard Sutton

Agenda

- Course Introduction and Logistics
- AI for Business Research Landscape

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.

What's New Beyond Last Year?

- Roughly 80%+ new content compared with last year.
  - Only the first two sessions (ML and DL introductions) are similar to those of last year.
- Topics: Large language models and AI-powered causal inference.
- I have learned more and deeper about AI as well ☺

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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/
- See https://github.com/rphilipzhang/AI-PhD-S25 **for** more resources.

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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

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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 (but we have Cursor now…);
  - 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.
- I am trying my best to stay at the frontier, but some of the knowledge is outdated/constrained by academia.

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 and replication project.

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Course Format

- We have a 2-hrs-and-45mins long course each week.
- For each session:
  - 15 mins: Homework discussions and review of previous content;
  - 105 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.

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Coursework and Grading

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

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Coursework Materials

- GitHub: https://github.com/rphilipzhang/AI-PhD-S25
  - All course materials will be distributed on this GitHub Repository.
- Google Sheet: https://docs.google.com/spreadsheets/d/1ffRNlSFqki4vomz5UN0OseFNEoEXBY5kptS79wmgWs4/edit?usp=sharing
  - Group Registration
  - Lecture Notes Scribing Sign-up
  - Paper Replication and 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/1lYO4ni5B5AVkYZ3qVrVs2LoWxHProsxM
  - 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.

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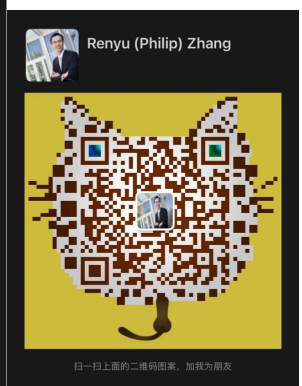
Course Communications

- Class Meeting: Tuesday, 12:30AM-3:15PM (@WMY 504)
- Office hour: By appointment, @CYT_911
- WeChat group: Online discussion forum.
- Instructor contact
  - Office: CYT_911
  - Email: philipzhang@cuhk.edu.hk
  - Tel: 852-3943-7763
  - WeChat: rphilip_zhang
- Teaching Assistant: Leo Cao
  - Email: yinglyucao@cuhk.edu.hk



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Python Tutorial Sessions

- We have two optional Python tutorial sessions held online at Friday night, 7:00pm-9:00pm.
- Tutorial Instructor: Xinyu Li, MIS PhD Candidate @CUHK Business School, xinyu.li@link.cuhk.edu.hk
- Check the course GitHub Repo for CoLab and Zoom links.
- Session 1: Friday, Jan 17, 2024
  - Python Basics
- Session 2: Friday, Jan 24, 2024
  - PyTorch Basics & DOT Server
- Other References:
  - https://colab.research.google.com/drive/1hxWtr98jXqRDs_rZLZcEmX_hUcpDLq6e?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

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Agenda

- Course Introduction and Logistics
- **AI for Business Research Landscape**

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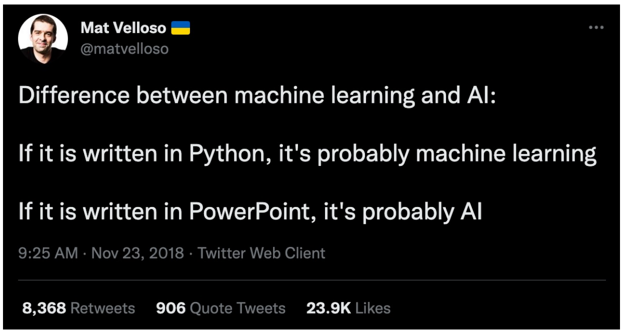
What is AI/ML?

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



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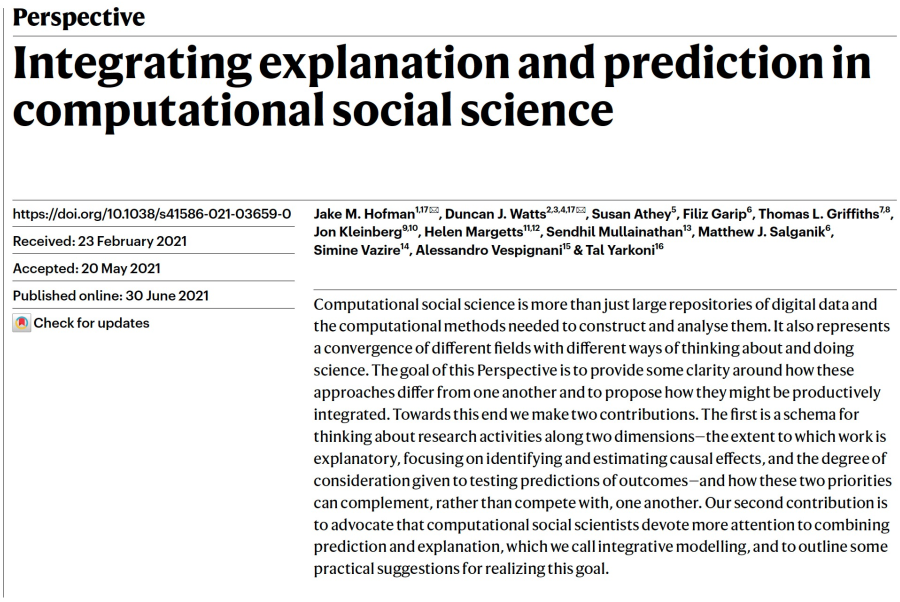
Prediction vs. Estimation



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[1,17]✉, Duncan J. Watts[2,3,4,17]✉, Susan Athey[5], Filiz Garip[6], Thomas L. Griffiths[7,8], Jon Kleinberg[9,10], Helen Margetts[11,12], Sendhil Mullainathan[13], Matthew J. Salganik[6], Simine Vazire[14], Alessandro Vespignani[15] & Tal Yarkoni[16]

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.

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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
  - Zhang, X., Sun, C., Zhang, R., and Goh, K-Y (2024) The Value of AI-Generated Metadata for UGC Platforms: Evidence from a Large-scale Field Experiment, *working paper* and *CIST 2024*.
- ML for Structural Estimation

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ML as Data/Data Source

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

J. H. van Binsbergen† S. Bryzgalova‡ M. Mukhopadhyay§ V. Sharma¶

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[1] and Dacheng Xiu[2]

[1] *Yale School of Management, AQR Capital Management, and NBER; bryan.kelly@yale.edu*
[2] *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.

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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

informs
https://pubsonline.informs.org/journal/mnsc

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

Targeting for Long-Term Outcomes

Jeremy Yang,[a,*] Dean Eckles,[b,*] Paramveer Dhillon,[c] Sinan Aral[b]

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Published Online in Articles in Advance: August 3, 2023

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

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 surrogacy 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 proxies for the long-term outcome. In a second field experiment, we implement 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://causalml-book.org/

https://bookdown.org/stanfordgsbsilab/ml-ci-tutorial/

ML for Predictive Decision-Making &Optimization

informs
http://pubsonline.informs.org/journal/opre

OPERATIONS RESEARCH
Vol. 70, No. 1, January–February 2022, pp. 309–328
ISSN 0030-364X (print), ISSN 1526-5463 (online)

Crosscutting Areas

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

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Accepted: April 6, 2021
Published Online in Articles in Advance: October 26, 2021

Area of Review: OR Practice

https://doi.org/10.1287/opre.2021.2158

Abstract. We compare the performance of two approaches for finding the optimal set of products to display to customers landing on Alibaba's two online marketplaces, Tmall and Taobao. 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 largest expected revenue (revenue × predicted purchase probability) are then made available for purchase. Our second approach, which we developed and implemented in collaboration with Alibaba engineers, uses a featurized 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 generated 5.17 renminbi (RMB) per customer visit, compared with the 4.04 RMB per customer visit generated by the machine-learning-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 full-featured version of our MNL-based approach, which now serves the majority of customers in this setting. Using another small-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 87.26 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

informs
https://pubsonline.informs.org/journal/mksc

MARKETING SCIENCE
Articles in Advance, pp. 1–22
ISSN 0732-2399 (print), ISSN 1526-548X (online)

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

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Received: September 3, 2020
Revised: September 5, 2021; April 17, 2022
Accepted: June 23, 2022
Published Online in Articles in Advance: October 20, 2022

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

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

ML as Subject

Journal of Financial Economics 151 (2024) 103745

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Artificial intelligence, firm growth, and product innovation

Tania Babina [a,b], Anastassia Fedyk [c,*], Alex He [d], James Hodson [e,f]

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[b] NBER, USA
[c] University of California, Berkeley, Berkeley, CA, USA
[d] University of Maryland, College Park, MD, USA
[e] AI for Good Foundation, Berkeley, CA, USA
[f] Institut Jožef Stefan, Ljubljana, Slovenia

ARTICLE INFO

Dataset link: https://data.mendeley.com/datasets/s26kxvspn7/2

JEL classification:
D22
E22
J23
J24
L11
O33

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.

informs.
http://pubsonline.informs.org/journal/mnsc/

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,[a] Catherine Tucker[b]

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Contact: alambrecht@london.edu, http://orcid.org/0000-0001-6766-1602 (AL); cetucker@mit.edu, http://orcid.org/0000-0002-1847-4832 (CT)

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Revised: March 2, 2018
Accepted: March 13, 2018
Published Online in Articles in Advance: April 10, 2019

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

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

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ML for Structural Estimation

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

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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.

Estimating Parameters of Structural Models Using Neural Networks

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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 simulation 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.

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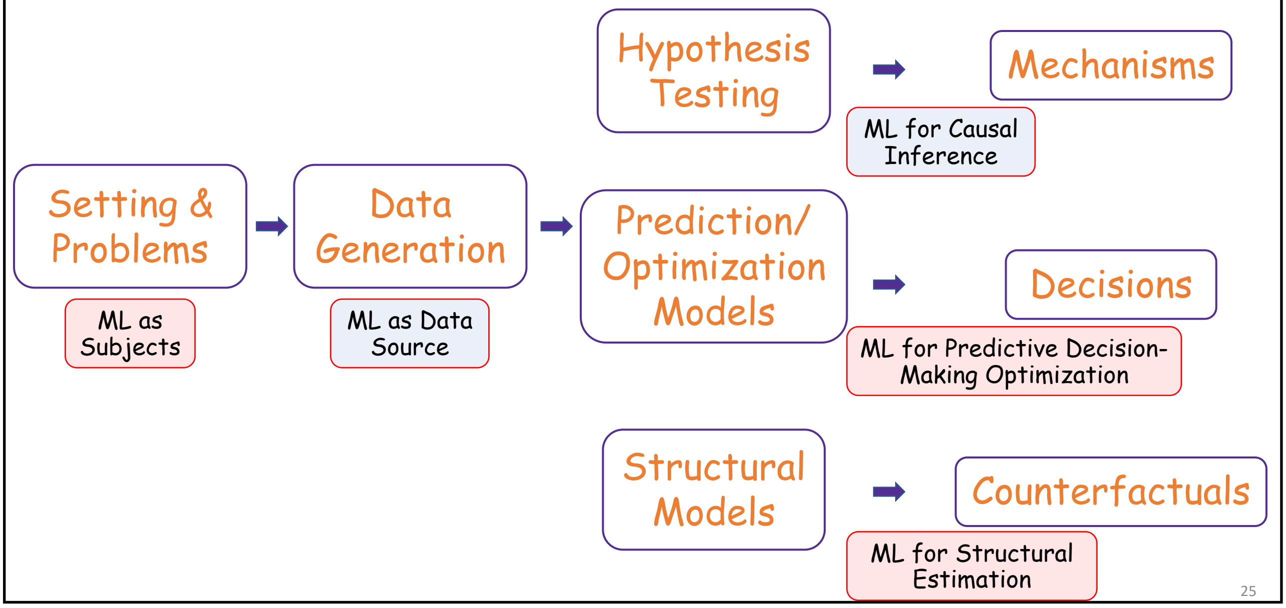
A Typical Applied Business Research Paper



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Tentative Course Schedule

- Introduction to Supervised Learning (1)
- Introduction to Deep Learning (1)
- Large Language Models (4)
- Causal Inference (4)
- Economics and Ethics of AI (1)

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

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Who Are You?

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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?

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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)
  - Genetic information - Bioinformatics
  - And many more…

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

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. (Less of a concern)
- Treatment
  - D may be generated through ML with error which is correlated with ϵ
  - https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4480696; https://arxiv.org/abs/2402.15585
- Controls
  - X may be generated through ML with error.
  - X may be selected by ML with error.
  - Double machine learning can be applied for effective debias.

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