

TEACHING AI IN BUSINESS SCHOOLS: BEYOND PREDICTIONS

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A bit about me

- Research: Mostly use-inspired AI research
- Publish in ML, AI, and business
- Co-founded Sweetch (AI-based platform for chronic disease prevention)
- Insights through consulting

Teaching

Developed MBA ML course in 2002-3

Full time MBA elective

Executive/Working professional MBA

Masters in Business Analytics (MSBA)

Executive education (non-degree)

Undergraduate elective

Ph.D. course (CS, Engineering, and Business Ph.D. students)

Objectives for teaching AI in MBA and Executive-MBA courses

Empower business leaders

- lead in an AI-abundant future that they do not yet fully appreciate.
- be agents of progress
- Identify opportunities to use AI for progress
- Make well-informed decisions about the use of and innovations with AI: Meaningfully evaluate the risks and value from AI-based solutions.

In doing so, we can continue to be somewhat market-driven, but we must also lead

- Business schools tend to be conservative, and market driven
- When possible, offer the fundamentals of what you anticipate students would need, not only what they or their immediate employers think they need.
 - In some areas, we have a responsibility to push what we know is important.

Business leaders have an important role in facilitating progress with AI

AI will have a significant impact on our lives

Business leaders play an important role and we have a responsibility to prepare them:

Key to facilitate progress with ML & AI or otherwise miss/delay opportunities to do so

Business leaders may also oversee less thoughtful use of ML & AI, that can lead to a backlash and missed opportunities for progress

Our responsibility: Prepare leaders to facilitate progress with ML & AI and help materialize the opportunities waiting to happen

Overview

- The landscape & fundamentals of ML/AI methods
- **Understanding the complete cycle: Context is key!**
 - Careful problem formulation. What are useful to measures?
 - Data understanding/preparation & construction, ML, evaluation, & deployment.
- **AI : Beyond ML Predictions**
 - Automation of traditionally human tasks (subtask performed exclusively by machine) is not the only form of AI's integration in practice (now and in the future). For example,
 - **Deferral Model:** Decisions are routed to either an AI or a human to maximize benefits
 - **Human-in-the-loop:** AI advises a human decision maker
 - Understand what is an appropriate framework in a given context, and why?
 - These understandings are key to identify meaningful, context-relevant evaluation of the systemExample: In high-stake decisions: A human-in-the-loop is preferred. For instance, because this allows avoid disastrous outcomes in some settings.
Hence, relevant performance is not expected error, but maximum regret.

When AI-informed decisions apply to humans: Societal and ethical issues for responsible AI

First, offer background and context: Human and AI decision-making

- The key for evaluating and advancing any technology is whether it advances the state-of-the-art using meaningful measures (achieving what we want).
 - When AI automates (or inform) decisions, are we alarmed more by AI's bias (say against a minority group) than we were when human performed these tasks?

(Do we respond similarly to errors done by humans as to errors done by autonomous cars?)

Why so?
 - Is there a difference between the impact of AI vs. a human bias? Scale!
- Q. What can be done about human bias? What about AI bias?

When AI-informed decisions apply to humans: Societal and ethical issues for responsible AI

Review of the different sources for bias arise in ML predictions

When formulating a problem into a predictive task relies on proxies (that may reflect historical or human bias):

- Prioritizing high-risk patients for early care: transformed into estimating which patients are most likely to incur high costs (Obermeyer et al. 2019).
- The goal of hiring the most qualified candidates translates into: hiring candidates based on their predicted performance reviews (Raghavan et al. 2020)

Bias ingrained in assumptions: Inferring a person's character from their appearance (physiognomy: a debunked theory that was used as a basis for scientific racism, Gould 1996).

Sample bias: Clinical trials for learning personalized treatment rules involve primarily white patients (cf. Warren et al. 2020)

The covariates used to represent individuals. Some predictors can be less predictive for a minority/under-represented group, yield poorer predictions for these groups.

Bias estimation and detection

Bias can be sometimes detected and mitigated

Need to be able to judge what's fair. Not a universal notion across contexts.

Position and Evaluation of AI In Context

Evaluation should aim to assess the value a ML/AI solution produces towards relevant (business/organization) goals

In some contexts, a “highly accurate” predictive model (when measured via general-purpose measures of predictive performance) do not add value at all, while a “marginally better” model may yield tremendous value.

Predictive Analytics with ML and AI: A core subject for business education

There is no business discipline in which Machine Learning & AI are not already informing key decisions.

- **Marketing:** E.g., Direct targeting, CRM, personalization and recommender systems
- **Finance:** E.g., Trading and investment, credit or other type of risk prediction/assessment
- **Management:** E.g., Recruiting, employee satisfaction, retention,
- **Operations and Supply Chain:** Inventory management, scheduling, etc.
- **Accounting, audits and compliance:** E.g., fraud and non compliance detection, etc.

Impacts not only how things are done, but what is being done: meaningfully impact and transform disciplines and industries

Business leaders ought to be competent about the nature of these technologies to critically evaluate opportunities and risks in the use of ML/AI to inform decisions and create value

Machine Learning's significance to all business disciplines is already reflected in a growing number MBA electives:

Analytics is a pillar of a growing number of business schools' branding:

ML & AI are by far the most impactful data analytics developments of recent decades

A fast-growing number of the courses across disciplines increasingly rely on or introduce machine learning methods to reflect state-of-the-art practices.

Fintech (focus on financial services and practices)

Operations: supply chain analytics,

Marketing Analytics

Social media/ User-generated content analytics

Health care analytics

People / HR analytics...

Our responsibility

- We must push our schools to be forward looking: teach what students should know, not focus only on their immediate experience
- What business leaders must know (today) about AI requires more than common core MBA courses offer
- In the immediate course of their career, our students will face decisions that demand good knowledge of business data science and of AI, and its interface with business practices
- We have a responsibility to educate future leaders who will be well prepared to do so

Putin: Leader in artificial intelligence will rule world

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KEY POINTS

- Putin says that whoever reaches a breakthrough in developing artificial intelligence will come to dominate the world.
- Putin warned that “it would be strongly undesirable if someone wins a monopolist position”.

Besides,
Putin said
SO



New data science/computing colleges, divisions, institutes: What are the implications for business education?

- Data science is an interdisciplinary domain
 - Breakthroughs are expected through domain-specific advances
- Teaching: Degree programs and courses will be developed to target domain-specific challenges
 - Much of core methods/algorithms are the same. Yet, challenges vary
- We need to prepare our students for this future