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Teaching Artificial Intelligence and Machine Learning to Everyone Else

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Abstract

Artificial intelligence (AI) and machine learning (ML) have become essential technologies in modern organizations, but there currently is a lack of AI/ML literacy across workforces. To help alleviate this problem, universities should offer courses providing a basic understanding of AI and ML. To date, mainly (or only) Computer Science departments offer such courses. In this paper, we discuss the importance of offering introductory courses on AI/ML to undergraduate business students. We focus on business students to keep the paper length manageable but note that the paper applies to most university majors. We first offer a rationale for these courses and follow with a brief course design for a three-course introductory sequence in AI and ML.

Keywords: Artificial intelligence, machine learning, teaching.

1. Rationale for Learning about AI and ML

Modern organizations must successfully operate in real time or near real time, data-intensive, global environments. To do so, they are increasingly employing artificial intelligence and machine learning (AI/ML) systems that enable them to quickly capture, store, and analyze vast amounts of data to make informed decisions. We emphasize to our students that they will have their first jobs and probably entire careers with companies operating in such environments.

AI/ML systems are significantly changing the way that businesses, customers, and industries operate by displacing or replacing established business processes, products, services, and operations. These technologies are creating new markets, modifying existing ones, and leading to the obsolescence of old technologies, products, and services.

Udacity (www.udacity.com), the for-profit educational organization offering massive open online courses, states that the #1 in-demand technical skill for 2023 is AI and Machine Learning. It is interesting that Udacity noted that AI and ML are technical skills. We contend that a basic understanding of AI and ML is *not* only for technical professionals, such as computer scientists. Rather, such an understanding is essential for *all* students because AI/ML applications apply to such a large number of disciplines. For example, Martins et al. [2] proposed teaching machine learning to middle- and high-school students! Clearly, AI/ML literacy will be extremely useful to university students.

It is noteworthy that leading influencers in the field regard machine learning as not being an engineering discipline. Professor Michael Jordan [3], a computer scientist who researches Artificial Intelligence at Berkeley, observed that as humans built bridges and buildings before those practices developed engineering standards, early efforts often collapsed. We are in a similar stage on development in AI progression as it is replete with various combinations of inference-and-decision- making systems that do not meet the types of standards found in engineering fields.

With the unprecedented growth of AI/ML technologies, it is imperative that business schools, as well as other schools in universities, train those who will ultimately decide when, where, and how these new systems will be deployed. It will be the managers and leaders of organizations who confront and decide the difficult issues of bias, appropriate use, context, privacy, and the myriad of ethical challenges that will grow as AI/ML increasingly permeate products and services. It will be managers who need to be trained to consider both organizational decision making and ethical choices in a decision timeframe that is

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becoming more compressed with the advancement of the very technologies being deployed.

Today, a lack of AI literacy among the existing workforce of companies is hindering the development and implementation of AI/ML applications. That is, very few employees have a basic grasp of AI/ML technologies. Working with AI and ML applications is no longer the exclusive responsibility of technical professionals. Rather, business users now play key roles in developing and using AI and ML applications.

In his article, Jordan also notes that while industry will drive AI developments, academia must play a role of innovation and leadership in bringing together researchers from the computational and statistical disciplines with those from the other sorely needed perspectives—notably the social sciences, the cognitive sciences and the humanities [3].

For these reasons, we feel that all students should learn about AI and ML. Our three-course sequence is designed to equip students to identify opportunities for developing, implementing, and integrating AI/ML solutions into business strategies and decision-making processes. To accomplish this, courses have been designed to convey understanding about what sources of competitive advantage enabled by AI/ML technologies look like and how to shape them for particular organizational needs.

We recognize that technical expertise will be a strong component of any AI program based in a business school. Thus, the class series will need to include analysis techniques for large datasets to include pattern extraction for structured and unstructured data. To assure that students can independently plan, implement, and manage AI/ML assets, coursework will need to ensure a thorough grounding in communications excellence for planning as well as in the use of software tools and platforms for implementation of models.

This paper reviews our rationale for designing coursework to address learning deficiencies in the fields of ML/AI, presents our three-course sequence content as it has evolved over the three years these topics have been taught, and provides our initial impressions and results on this effort.

2. Organizational Roles in AI Projects

There are many different organizational roles in the AI/ML space and different organizations have different job titles. To simplify, we place these roles into three main groups: business users, business analysts, and technical professionals, who work together to design, develop, implement, maintain, oversee, and work alongside any AI/ML app that the organization deploys. We make sure that our students pay particular attention to this section because they will be in one of these three roles. Further, they will be involved with AI and ML technologies *regardless of their major*. For example, if they do not take even the first introductory AI/ML course, they will still be consumers of the outputs of AI/ML systems.

Business users are responsible for identifying business opportunities that can be addressed with AI applications and use those applications in performing their jobs. Business users can come from any university major. The vast majority of undergraduate courses taught in universities today are in Computer Science departments. Other university majors typically do not take any undergraduate courses on AI and ML. Business users should take at least the first course in the three-course sequence.

Business analysts focus on deriving insights from data using AI as a tool. Their primary role is to perform data analyses and present the results in a way that is easy for all stakeholders to understand. On one hand, business analysts work with business users to identify and define the business requirements for new products, services, or processes. On the other hand, they work with technical professionals to develop AI models to ensure that business requirements are met. Business analysts can come from any major and will take the entire three-course sequence in AI and ML.

Technical professionals encompass several different roles. We discuss three of the most prominent roles here. Technical professionals will major in Computer Science, mathematics, and statistics.

Specifically, *machine learning engineers* are responsible for building and deploying AI/ML systems that can learn and improve over time with additional data. They often employ well-documented, easy to use ML applications and libraries. *Data engineers* collect, aggregate, clean, and transform the data into inputs for the AI/ML algorithms. *Data scientists* are responsible for designing and implementing AI/ML models that can analyze large data sets to make predictions. They use statistical and mathematics procedures to build predictive models to derive meaningful insights from the data.

Business users and business analysts can have difficulties working with technical professionals because technical professionals may lack business expertise. This deficit means that they may not understand what the organizational goals or what each business function or unit does. As a result, business analysts act as "translators" between the other two groups, helping to ensure that AI/ML project prioritize the right initiatives, ask the right questions, and align around a common and informed set of expectations. Acting together, the three groups must find a common language which can be the most important determinant of successful AI projects.

Let's take a closer look at how the three groups collaborate. Business users have domain expertise, which is deep knowledge, skills, and experience in a particular area of endeavor. Note that domain experts prioritize the *why* rather than the *how* of AI/ML model development.

Business users are the experts on their organizations. They provide relevant background information and play a key role in defining worthwhile and actionable use cases, along with relevant organizational objectives, for AI/ML applications. Business users communicate with business analysts to provide technical professionals with the business context to help them derive the correct approach to a potential AI/ML application.

At each step of AI/ML model development, business users can pre-emptively anticipate biases, ethical concerns, risks, and potential regulatory problems. These potential problems can have serious consequences for your customers, your organization, and society as a whole.

Business users' domain knowledge enables them to critically interpret the outputs of AI/ML models. They can conduct "sanity checks" because they have an understanding for what is plausible and what is not. Further, they can provide insights into which results are important and which are trivial.

Business analysts also have domain expertise and organizational knowledge, overlaid with a deeper understanding of AI/ML technologies. They know how to work with (or use) AI/ML applications, interpret their recommendations, rely on system outputs (or question those outputs), and oversee their functioning.

For example, business analysts collaborate with business users to help technical professionals select, prepare, and analyze data that will provide inputs to the AI/ML applications. Technical professionals are trained to understand data in general, but not specifically the organization's data, systems, and business processes. Business analysts can provide insights about what kinds of data the organization has and what data it can access, what data might be relevant to a given project, how the organization's data has been maintained (e.g., how the data has been cleaned and documented with metadata), how the organization's data has changed over time, and if the data could have potential errors, inaccuracies, caveats, missing data, and other problems.

A particularly daunting problem for every organization will be data preparation for AI/ML. Throughout the history of information systems management databases have evolved from flat files, to binary retrieval systems to sophisticated relational databases. These have increased in performance and reliability to manage data in a particular way: to combine data for producing information. AI/ML increases the connectedness of data to improve understanding by discovering patterns in information [3]. This paradigm shift is resulting in increasing volumes of unstructured relative to structured data. Too, the processing requirements for structured data requires a tedious reformatting for ordinal, qualitative, and categorical data. A rule-of-thumb is to allow for about eighty-percent of the time required to build and deploy an AI/ML model to be devoted to data cleaning and preparation. These best practices—which continue to evolve—must be a part of any competent machine learning education.

Business analysts work with business users and technical professionals in selecting input features (variables), which is critical to AI/ML application development. Feature selection is how technical professionals choose and refine data will contribute to the model.

Business analysts have an important role in the maintenance of AI applications. By design, AI/ML models tend to change over time. Unless these models are closely and continuously monitored, they may drift or deteriorate. Their domain knowledge helps them ensure that the model remains relevant.

3. The Three-Course Sequence

Our overall goal in teaching the AI/ML three-course sequence is to provide our students with the necessary information and skills to work independently across a wide range of functional areas, perform hands-on model building, and provide leadership to teams tasked with deploying AI/ML technologies. Students will be required to identify the business problem and determine if this problem can or should be addressed with AI or ML applications [1].

Generally, the courses are sequenced to start with problem identification and proceed to acquiring and preparing the needed data [2], select and train the appropriate algorithm, evaluate the model's performance using testing data, improve the results, and operationalize the model into a production environment. This sequence is reinforced over several models and problem sets over the three-course sequence. Additionally, students are taught to recognize bias and perform ethically while exploring new technological ground, often with highly sensitive data revealing new and unsuspected insights.

3.1. Introductory Course

Students begin with learning the AI/ML environment that will be used throughout the three-course sequence. The Anaconda suite is installed on the computers to be used. Note that while AI and ML in production settings routinely run on computers with Graphical Processing Units (GPU), these courses are designed to work effectively on more common CPU-based laptops and desktops.

Anaconda contains Jupyter Notebook capability, which is commonly used in AI/ML production environments and provides an intuitive and easily learned interface for running the Python models. Along with Anaconda, additional libraries and routines are installed to enable data manipulation, simplify functions, and provide the foundations for AI modeling.

In our classes we use prebuilt Jupyter Notebooks so students concentrate on loading and preparing data along with choosing parameters and adjusting hyperparameters to learn effective modeling. The focus is on the AI, not on coding. To wit, students are encouraged to use Generative AI such as ChatGPT to help them perfect any Python code tweaks they may need to accomplish the data and parameter tasks.

The introductory course also covers fundamentals such as how the strong pattern recognition of AI has resulted in the paradigm shift from legacy information systems to using data for increasing knowledge. Too, the differences between general programming and machine learning is covered, along with key historical events, and narrow versus general AI.

So that students develop an ability to recognize opportunities, the many and constantly growing sources of data are covered with many being used in the course. When considering such pervasive data, students consider possible sources of bias from incomplete, historically inaccurate, intentionally biased, or faked data.

The fundamentals students acquired in previous elementary statistics courses are reinforced and used when measuring Type I and Type II errors, bias, overfitting, and underfitting. Various algorithms for regression and categorical problems are introduced and compared for best use. Generally, the models introduced in the first course include classification trees, regression, random forests, support vector machines, clustering, Naïve Bayes, and simple neural networks. These allow students to gain experience with supervised, unsupervised, and semi-supervised learning.

3.2. Deep Learning, the Second Course

In their second course students are introduced to simple feed-forward networks through studying topologies comprised of the input, hidden, and output layers of a neural network, learning the effects of weights and biases, how activation functions ensure learning, and how the backpropagation process adjusts parameters to allow artificial learning. Students use data sets from the first course to gain insights into how the more sophisticated neural network models impact learning and predictive power and also work with larger and more complex data sets to learn how adjusting the topology and density can be used to fine-tune artificial learning.

In addition to the fundamental neural network, students are introduced to Convolution Neural Networks (CNN) for image processing, Recurrent Neural Networks, Probabilistic Neural Networks (Bayesian), and Generative AI such as that used to create images and Large Language Model technologies such as ChatGPT models.

3.3. The Third Course, Data Visualization

Moving from the easily contextualized sphere of legacy data processing to massive amounts of multiple sources of data being processed in a "black box," it is imperative for students to develop skills for visualizing the nuanced and important relationships among data. To be effective team members and influencers in organizations, students use common visualization platforms such as Microsoft's PowerBI to delve into the numerous relationships between units of data and learn to tease out and convey visually insights that would be challenging to grasp by reviewing numeric or descriptive narratives.

Students learn how data imaging can be used to mislead or convey false insights and how to ethically create presentations as well as dynamic dashboards fed by AI/ML algorithms for continuous monitoring and management that is data informed.

7. Our Experiences to Date

The first author has been teaching the introductory course for two years. While a doctoral student, he began teaching the introductory course to a group of volunteers who met one evening per week. He found that his students were increasingly in demand for internships and jobs and had success finding both.

He is now at another university, where he has established an AI/ML curriculum. He is teaching the second course, Deep Learning, and his students are contributing to complex, real-world projects. Other faculty members at his current university have learned from him and are teaching the introductory course and the data visualization course. They feel that the data visualization course can be taught concurrently with either of the other two courses.

The second author, learning from the first author, is teaching the introductory course at his university. We should note that when both the first and second author initially taught the introductory course, it was the first time that their universities had ever had such a course taught outside the Computer Science departments.

We have had questions about the courses from various faculty members. One of the most common comments is that "we already teach this material." Indeed, some faculty members teach some ML applications in their courses; e.g., predictive modeling to analytics majors. However, it is difficult for students to understand isolated AI/ML applications without an overarching paradigm.

Our introductory course, by itself, provides the paradigm that we feel is essential to our students. Namely, that we want our students to be able to progress from identifying a business problem to effectively communicating actionable business decisions to decision makers. Our next two courses serve to strengthen that paradigm.

As just one example, let's take a closer look at predictive analytics. We feel that there are significant differences between predictive analytics and ML. These differences include:

- Predictive analytics models involve a human-centered process of selecting and tuning models, where ML algorithms are designed to learn automatically from data and improve with more data.
- ML algorithms are typically more flexible than predictive analytics models as ML algorithms can learn from many data types and adjust to changing circumstances.
- ML algorithms can be more accurate than predictive analytics models, particularly when ingesting large, complex data sets.

9. Limitations and Contributions

The paper is a review of establishing a nascent machine learning and artificial intelligence teaching program at the graduate and undergraduate level. There are no other business schools teaching this curriculum so the paper is limited by the lack of multiple examples for study. Too, measuring the effectiveness of the courses cannot be conducted using common pedagogical methods; rather, the authors had to reply on effectiveness of the curriculum in providing internships, jobs, and research projects in where ML/AI was central to the engagements.

The knowledge base, given that the coursework is a combination of technical skills, business decision making, team leadership, and ethical reasoning, is forming as students complete the courses.

Designing course content was influenced by how ML/AI projects are conducted in firms, which is exploratory at best, and by the profound social needs to address concerns of bias and fairness of use. These concerns place a serious demand on business schools—where leaders are educated—to step to the forefront and establish education in these areas, which is growing exponentially.

The contribution of this paper is that it will stimulate discussion and future research by the academy in the domains of effectively teaching ML/AI to those students whose careers will include answering the hard questions of where and when it is appropriate to us ML/AI, and when it is not, and how to influence and lead in appropriate directions.

9. Conclusion

There is a widening gap between industry and academia in the ML/AI field. Most relevant research is being conducted at companies, not universities. Given the exponential growth of computing power the field is growing faster than the academy can provide research and guidance and education. It is imperative that MIS department at universities join the authors in exploring how to best prepare students to be prepared to manage and evaluate these information technologies.

10. References

[1] E. Brynjolfsson, E., & Mitchell, T. (2017). What Can Machine Learning Do? Workforce Implications. Science, 358 (6370). 1530-1534.

[2] Martins, R. et. al. (2023). Machine Learning for All! – Introducing Machine Learning in Middle and High School. International Journal of Artificial Intelligence in Education.

[3] Jordan, M. (2018). Artificial Intelligence—The Revolution Hasn't Happened Yet. Medium. https://medium.com/@mijordan3/artificial- intelligence-the-revolution-hasnt-happened-yet- 5e1d5812e1

11. Appendix

Course outlines. Topics covered over multiple days have been combined for brevity, as have review and exam days.

1st Course: Introductory

DIK(W) model, ML and AI vs Programming, Strong vs Weak AI
ML vs AI vs Deep Learning, Supervised vs unsupervised
Reinforcement learning, Hao's flowchart with examples
Data sources, databases, textual data, IoT, streams
Structured vs unstructured data, SQL vs noSQL
Classification tree
Classification tree exercises - Iris
Random forests
Classification tree exercises - Sports
Classification tree exercises – Iris and Sports
Random forests and ensemble
One hot encoding, imputation
K-means Clustering
Neural Networks
NN algorithms and applications
NN exercises
Case discussion: Moderna, Watson, as appropriate

2nd Course: Deep Learning

DIK(W) model, ML and AI vs Programming, Strong vs Weak AI
Linear vs. multivariate vs. neural network modeling
NN topology and the feed-forward process
Activation functions
Neural network exercise
Data preparation
Imputation
One-hot encoding
Backpropagation
Backpropagation match
Neural network exercise - MNIST
Neural network exercise - FashionMNIST
Convolutional Neural Networks (CNN) and applications
CNN Neural network exercise
Recurrent Neural Networks (RNN) and applications
RNN Neural network exercise
Generative AI - ChatGPT
Probabilistic Neural Networks (Bayesian)

3rd Course: Data Visualization

Data sourcing
Raw versus combined data techniques
Traditional visualization tools; MS Excel
Misrepresenting data and ethical considerations
Introduction to PowerBI
Data preparation
Visualizing modeled data
Combined data sources
Dynamic versus static modeling
Static model exercise
Dynamic model exercise
Production versus ad hoc modeling
Production visualization modeling exercise