Establishing a Data Science 101 Pedagogy

Reimagining the MOOC Learning Experience Through a Case-Based Learning Methodology

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ABSTRACT

This work involved a comparative analysis of randomly selected Data Science Massive Open Online Courses (MOOCs) and master's degree programs in investigating how effectively interdisciplinary curricula approaches were being utilized in the course design. It also involved a second study, in the form of a qualitative survey, that asked students to share their perspective, satisfaction, and sentiment from MOOC experiences. These findings were combined, analyzed and utilized to support the foundation of the proposed case-based learning methodology. This approach provides a more real-world and project simulated approach that challenges students to solve problems analytically which is seen as a more effective framework for delivering data science offerings.

KEYWORDS

Data science, MOOC, Case-Based learning, Online, Machine learning, Artificial Intelligence, Sentiment analysis, Ethics.

CCS CONCEPTS

Social and professional topics → Professional topics → Computing education → Computing education programs.

1 INTRODUCTION

Big data is influencing how we make intelligent decisions and perceive the world around us. It is updated continuously by users from websites, social media posts, digital images, IoT sensors, satellites, and videos. Current approximations show that more than 2.5 quintillion bytes of structured and instructed data are generated around the world in a single day [32]. Once generated, the raw data must be mined, processed, modeled, analyzed and visualized by specialists referred to as data scientists who are responsible for extrapolating a meaningful story from the information provided. To perform these detailed analyses requires the data scientist to also have experience with quantitative and qualitative methods, interdisciplinary problem-solving abilities and strong communication skills. Historically, these skills were acquired during the pursuit of an advanced academic degree such as a master's or doctorate in a scientific field where statistical analysis is the norm. For example, in a 2018 study of 4,000 Data Science professionals, Burtch reported that 91% had an advanced degree with 43% holding a Master's, and 48% with a Ph.D. [9]. Consequently, marketplace supply and demand problems have developed. This means that the number of skilled data professionals in the labor pool are unable to proportionally scale to meet the demand of existing Data Science jobs which results in large percentages of jobs unfilled.

In order to address this problem, academic institutions and industry have responded with a new learning paradigm known as Massive Open Online Courses (MOOCs). These offerings provide students with new learning opportunities without having to enroll in a full-fledged academic degree program. These offerings provide accelerated learning formats, global availability, and emphasis on a specific area within a discipline such as Data Science. The curriculum modules are commonly asynchronous, hands-on versus theoretical and self-paced which is appealing to many working professionals. As a result, online delivery of MOOC offerings have disrupted the traditional classroom delivery model [16, 30, 19]. This alternative model also enables students to apply different learning strategies and provides them with unique opportunities to prepare themselves for the workforce or career advancement. On the edX MOOC platform alone, more than 4.2 million students have enrolled in Data Science related courses from 56 universities and industry partners since its inception [10].

However, due to open formats, limited standards and governing bodies, many of these programs are developed without curriculum alignment which ultimately impacts student preparedness, readiness and competency levels upon completion. Furthermore, graduates enter the workforce underprepared for the demanding role. The remainder of this paper analyzes these pedagogical imbalances between traditional academic degree programs and existing MOOC curriculums. It describes the results from the two-pronged study and proposes adopting a case-based methodology to overcome the imbalances through macro and micro learning strategies.

2 BACKGROUND

To understand the problem space at a more in-depth level, a two-part qualitative research study was conducted over the course of 8 weeks. The first component consisted of a 12 question survey from a diverse global demographic of 100 respondents including graduate students at the Georgia Institute of Technology, industry professionals and Data Science practitioners. The second component focused on the deconstruction of existing curricula between master's degree programs and MOOCs to identify imbalances. During the study, each of the offerings was analyzed based on a set of standard keyword criteria that was used to assess how well they prepare graduates for the workforce.

3 RELATED WORK

Data Science curricula shifts are underway at several top master's degree programs; however, no such work was found that addresses MOOC shortcomings. For example, at Vanderbilt University's Data Science Institute a practical interdisciplinary approach is being applied [21]. Students in this graduate program take courses in areas of computation, data analysis and practice which offer an interdisciplinary selection of courses in programming, ethics, data analysis, modeling, and machine learning with an emphasis on team-based projects [15]. Additional work is also underway at Duke University where a similar interdisciplinary approach is being applied to cultivate student engagement and collaboration on real-world analytical problems. The University of California at Berkeley, Division of Data Sciences, has taken a slightly different approach and begun offering a "Foundations of Data Science" course to undergraduates. Their foundational approach aligns perfectly with this research effort to establish a reusable pedagogy. Furthermore, they are offering the entire course and related materials on GitHub (http://data8.org/) which can be leveraged by other course designers.

4 SURVEY

The primary goals of the survey were three-fold. First, to understand the student's perspective of Data Science related MOOCs. Second, to evaluate their familiarity with current Artificial Intelligence (AI) principles. Third, to analyze sentiment around online course experiences. Finally, each of these observations and takeaways was also used to isolate commonality for areas of improvement is the course design.

The demographics of the survey participants ranged in age from 18 to 64 with 83% identifying as male, and 17% as female. Also, similarly to the education data from the Burtch study, 66% reported having a bachelor's, and 33% earned a master's or Ph.D. Additionally, 88% reported that their degree was in a Science, Technology, Engineering or Math (STEM) areas of study.

Experience with Data Science Related MOOCs

Each participant was asked a series of questions that were designed to evaluate the reasons why they opted to enroll in MOOCs. In total, 87% reported they had previously enrolled in a MOOC offering from edX, Coursera, Udacity or another MOOC platform. Collectively, they enrolled in more than 10 different focus areas related to the field of Data Science with an emphasis on programming as the top category as shown in **Figure 1**. One key observation is that 77% reported being enrolled in a program while working full-time with 41% seeking professional development followed closely by 30% who wanted to explore new areas for personal growth.

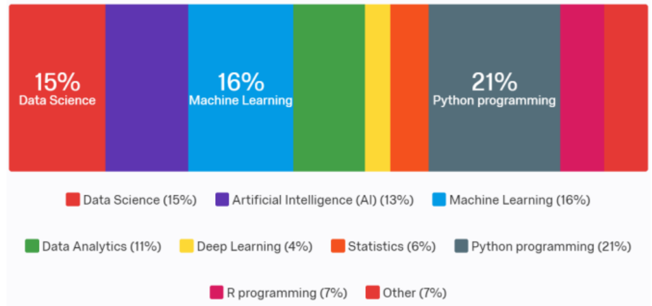

Figure 1 – Primary MOOC focus area by participants.

Another question explored whether the enrolled Data Science MOOCs included interdisciplinary modules that covered topics such as ethics, privacy, data wrangling, and storytelling. The results are shown in **Figure 2** highlight an example of the curricula imbalances and illustrate the limited inclusion of interdisciplinary modules. For example, ethics was only included in 11%, and communications or storytelling was only present in 9%. Therefore, a key takeaway is that students who enrolled in these MOOC offerings may have received a limited educational experience and were required to augment their learning elsewhere.

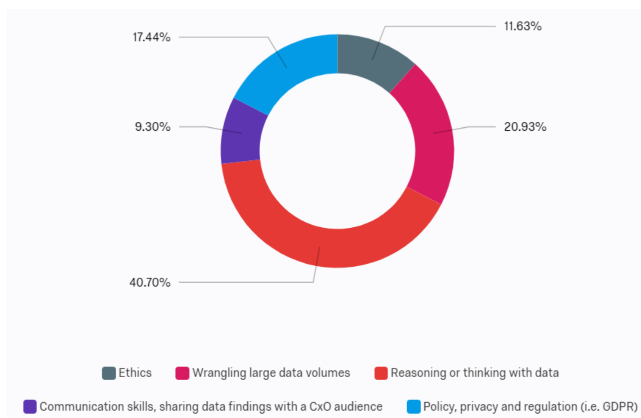

Figure 2 – Interdisciplinary elements in MOOC curricula.

Familiarity with Asilomar AI principles

Participants were also asked about their familiarity with the Asilomar AI principles that were a result of the 2017 Asilomar Conference [3]. An astonishingly low number of 87% reported they had no previous knowledge of the principles. This observation further highlights the fundamental argument outlined in this research which calls on academia and industry to align on core AI standards [14]. It also highlights the need for more evangelism of these foundational principles.

Sentiment Analysis

The final elements of the survey focused on the participant's perception and sentiment around their MOOC experience.

Overall, 54% reported having a moderately satisfying experience while only 6% were extremely satisfied. More importantly, however, is that 40% reported they were slightly satisfied or less. Next, 35 different keywords were analyzed from the open-ended answers provided by participants. These answers provided insight into the reasons why students felt the experience was less than optimal. The results can be seen in the word cloud visualization shown in **Figure 3**. A critical observation is that the students felt that MOOCs lacked real-world projects, peer interactions, relevant content and community engagement.

Figure 3 - Sentiment of what was missing from MOOCs.

5 COMPARATIVE ANALYSIS BETWEEN MOOCS AND DEGREE PROGRAM CURRICULA

The fourth industrial revolution is fundamentally changing how workers must be adequately prepared to understand, process, and analyze data in order to use and build intelligent solutions [39]. In fact, workers at all levels within an organization are interacting with data-driven solutions that leverage AI, machine learning and advanced analytics which is fueling the demand for highly skilled Data Science specialists [4]. To help meet this demand, academic institutions and instructors are turning to MOOCs and online degree programs which are popping up frequently and disrupting the traditional classroom model [16]. However, many of these programs lack consistency or alignment between curricula and learning objectives. Therefore, graduates often find themselves entering the workforce without foundational skills.

The second part of this study sought to understand program variances of program curricula between MOOCs and master's degree programs. The analysis focused on similarities, differences and structural imbalances that could be included in a proposed case-based learning alternative.

MOOCs

First, a random sampling method was applied to collect curricula, syllabus and program data from 10 Data Science MOOC offerings hosted on the top three platforms consisting of edX, Coursera, and Udacity. Offerings categorized as MicroMasters, Nanodegrees, Master's Degree or equivalent were considered in the analysis. Additionally, a combination of keyword searches was performed against the curricula for the inclusion of values such as ethics, policy, privacy, security, law, storytelling, capstone, case studies, communications, and visualization. The results are shown in **Table 1** where only Harvard, Microsoft and Udacity included interdisciplinary curricula items that met the criteria for each category out the 10 programs.

Institution	Includes Introduction to Data Science	Includes Ethics, Privacy, or Security	Includes Real-World Cases Studies, or Capstone Projects	Includes Storytelling, Communications, or Visualization
The University of California, San Diego	No	No	No	No
Massachusetts Institute of Technology	No	No	Yes	No
Harvard	Yes	Yes	Yes	Yes
Microsoft Professional Program	Yes	Yes	Yes	Yes
University of Michigan	Yes	No	Yes	No
IBM	Yes	No	Yes	Yes
Johns Hopkins University	Yes	No	Yes	Yes
Imperial College London	No	No	No	No
Data Science Nanodegree	Yes	Yes	Yes	Yes
University of Adelaide	No	No	No	Yes

Table 1 - Listing of 10 randomly selected MOOCs.

Institution	Includes Introduction to Data Science	Includes Ethics, Privacy, or Security	Includes Real-World Cases Studies, or Capstone Projects	Includes Storytelling, Communications or Visualization
University of Michigan	Yes	Yes	Yes	Yes
New York University	Yes	No	No	Yes
The University of Illinois at Urbana-Champaign	No	No	No	No
Vanderbilt University	Yes	Yes	Yes	Yes
Rochester Institute of Technology	Yes	No	No	Yes
University of Notre Dame	Yes	Yes	Yes	Yes
Duke University	Yes	Yes	Yes	Yes
Johns Hopkins University	Yes	No	No	No
Columbia University	No	Yes	Yes	Yes
University of California, Berkeley	Yes	Yes	Yes	Yes

Table 2 - Listing of 10 randomly selected master's degree programs.

Master's Degree Programs

For comparison, a separate random data sampling was taken from 10 Data Science graduate degree programs listed in the North Carolina State University Institute for Advanced Analytics comprehensive website catalog (https://analytics.ncsu.edu/). These offerings were then analyzed against the same set of criteria. The results from this analysis are displayed in **Table 2** and highlight the curriculum imbalances. First, the analysis showed that 50% of degree programs have shifted to interdisciplinary approaches which met all criteria. Second, 80% contained 2 or more modules that met the criteria as opposed to 60% of the MOOCs. Finally, 60% of the degree offerings included an ethics, privacy or security module as opposed to only 30% of MOOCs.

Study Conclusion

The observations and takeaways demonstrate that imbalances exist between program offerings. Additionally, student engagement, perception, satisfaction levels, and learning experiences are frequently less than optimal. Therefore, the remainder of this paper shifts its focus to an alternative case-based methodology that is designed to bridge the gaps and provide a better learning experience.

6 CASE-BASED LEARNING

Research has shown that Data Science professionals are in high demand and can expect to earn median base salaries between $95,000 for $165,000 [9] for individual roles and from $145,000 to $250,000 for managers [9]. These figures assume students are well-educated, experienced and prepared. When a student graduates from his or her respective MOOC or online program in Data Science, they are expected to be prepared for new challenges in the workforce. However, are they truly ready? What if the student completed a self-paced MOOC with limited modules shown in **Table 1** that only covered Python frameworks? Did they learn about loss functions, regression, gradient descent, plotting, visualizations, privacy, and data cleansing? What about techniques to address bias and ethics in massive Big data datasets? This wide disparity in program offering standards is a fundamental Data Science pedagogy problem in large part due to keeping up with demands from the marketplace. For instance, degree programs alone have quadrupled in size since 2013 in the United States as illustrated in **Figure 4**. Furthermore, online programs such as MOOCs have shifted to a global student population that spans multiple generations including millennials, baby boomers and Gen Z which requires new strategies for student engagement [36]. To address these pedagogical imbalances and primary student reported concerns, a case-based learning approach that aligns with academia and industry AI principles is henceforward proposed.

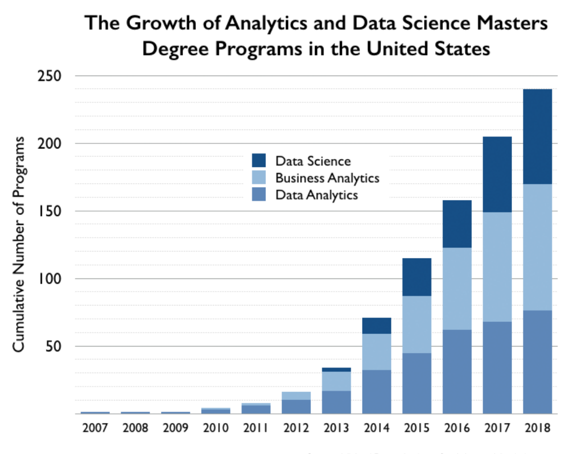

Figure 4 - Image from Michael Rappa, Institute for Advanced Analytics at North Carolina State University.

Methodology

For decades, professional schools in academia including business, law and medical schools have leveraged real-world case studies to educate their students [48]. These cases are designed to simulate real-world situations and comprised of interdisciplinary methods that challenge students to solve real-life problems analytically from multiple dimensions. Research from Stanford also shows that Case-Based Learning (CBL) approaches force students to think "outside the box" about abstract situations [4, 8, 17, 48, 49] For example, a Data Science student might be presented with a case that includes privacy and ethical issues for patient medical records that arise during the analysis of cancer disease prediction and modeling. The case-based methodology also lends itself to role-playing for group projects which promote different student perspectives.

The CBL approach being proposed in this research varies from traditional professional school approaches and aligns most closely with existing curricula structure used by Udacity. It strives to meet the following learning strategies and objectives.

1. Establish a Data Science 101 pedagogy with consistent modules that educate students with the fundamentals that can be delivered reliably and repeatably in a MOOC format.
2. Establish alignment with academic and industry AI principles such as the work underway at the Future of Life Institute with Asilomar AI Principles [3].
3. Establish a standard, free, open and community-driven repository of cases with relevant datasets.
4. It is comprised of 4 or more micro-learning modules based on real-world cases depending on the learning objectives and duration.
5. Culminate with a single macro-learning capstone that measures student comprehension, achievement, and engagement.

In order to achieve these objectives, each case would be developed from a set of predefined standards that include a foundational problem that needs to be solved, a dataset that corresponds to with least 4 micro-learning modules and a macro-learning capstone that measures the student's comprehension. Each module would align with a set of challenges outlined in the case and include an interactive component requiring students to communicate their findings or solution to classmates. Also, each module would include a corresponding quiz that would be used to be combined with the interactive component and capstone for a final grade.

Table 3 below illustrates an example of an Introduction to Data Science module.

Introduction Module: Introduction to the field of Data Science
Learning Goals: Examine the role of a data scientist and expose the student to terminology, tooling, trends and case-based methodology.
Duration: 2 weeks
Case: Patient Medical Records
Level: 1
Topics Covered: • Introduction to the field of Data Science • Overview of the Case and Terminology • Understanding Big data and Statistical Modeling

Table 3 - CBL Case example module.

Each additional micro-learning module would, therefore, be aligned to case sections and simulate real-world scenarios to challenge students and promote critical problem-solving skills. The total number of modules, length of the program and learning goals would remain flexible at the instructor's discretion. For example, Module 1 shown in **Table 3**

Module 1 – Ethics, privacy, governance, and security
Learning Goals: Examine complexities and challenges associated with designing a solution that uses patient medical records. Core focus areas include ethics, security, and privacy from various roles within a project team.
Duration: 4 weeks
Case: Patient Medical Records
Level: 2
Topics Covered in Case: • Ethics, privacy, governance and legal • Security • Storytelling

Table 4 - Example of CBL module.

The capstone module as shown in **Table 5** is an example of how students can showcase their understanding of the material. It can also serve as an opportunity for them to share their portfolio with potential employers. Students will be challenged on a macro-level and be required to approach the case holistically by implementing techniques they learned during the micro-learning modules.

Capstone
Learning Goals: Comprehensive case review that assesses the student's ability to combine learnings from all the modules into a final project that showcases their work.
Duration: 4 weeks
Case: Patient Medical Records
Level: 5
Topics Covered in Case: • Ethics, privacy, governance, and security • Reasoning with large datasets • Modeling • Programming • Visualization • Presentation

Table 5 - Example of Capstone CBL module.

Community

Finally, a community atmosphere should be established to address the feedback elements related to lack of interactions in MOOCs from the survey participants. The CBL platform should include a forum mechanism where classmates can interact, share ideas and project artifacts. Most existing MOOC modern platforms such as edX, Udacity and Coursera already support this capability. Therefore, the attention should be focused on the establishment of a Data Science mentoring community whereby working professionals already in the field can earn Continuing Education Units (CEU) as a reward.

7 FUTURE WORK

Additional work needs to be performed to develop a set of pedagogical standards and establish ownership. One option could be to align the with Artificial Intelligence efforts that are part of the Asilomar AI Principles [3]. This approach could extend the existing principles to include learning standards which will help to address new categories such as bias and algorithmic transparency. Other areas that need significant attention are around the measurement of student success. For example, survey participants described real-world projects a current MOOC shortcoming. This new CBL approach starts to address that problem, but this research falls short of establishing how to measure success.

Another area that requires new thinking is around the CBL structure itself. For example, each module could be representative of a case which would allow for more agility and flexibility. However, there may considerable overlap between cases if this approach is undertaken. Regardless, there needs to be a central repository for cases similar to the Harvard Business Publishing engine. Finally, there also exists an opportunity for the marketplace to monetize this case-based approach which is also worthwhile pursuing in future work.

8 CONCLUSION

This research work has highlighted many of the shortcomings and curricula imbalances that exist between current Data Science MOOC and master's degree program offerings. Survey respondents provided their feedback and sentiment on the current landscape and offered suggestions for areas of improvement. Their suggestions and feedback consistently aligned with the gaps and differences identified from the subsequent detailed offering analysis. As a result, a new paradigm based on case-based learning was proposed to help address the problems and provide a better way forward. This new learning pathway will help systematically ensure that students are well-rounded and educated on equal ground. It will also ensure graduates of Data Science programs enter the workforce prepared and on the same footing.

ACKNOWLEDGMENTS

Thanks to all the of the survey study participants, my faculty advisor Mr. Ken Brooks from Georgia Tech, my wonderful wife and supportive family. I am very fortunate to have had such an excellent support system, and without them, this research would have not been possible.

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