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Connecting the Dots: A Programmatic Approach to Data Science within Engineering

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Connecting the Dots: A Programmatic Approach to Data Science within Engineering

ABSTRACT

The importance of "data acumen" for STEM students has been well-articulated by scholars and industry professionals—in part because data science infiltrates many areas of engineering and science. Yet within engineering programs, students often have few opportunities to develop expertise in data science or even to explore how data science is relevant to their degree specializations. This paper reports on an NSF-funded study of a program that prepares STEM students to engage with data science in coursework and then mentors them as they secure internships and complete a capstone that demonstrates their application of data science expertise. Drawing on a mixed-methods study, including student reflections, capstone project assessment, and survey reporting, this paper suggests not only that students make deep connections between their existing majors and data science but also that students trained in our data science micro-credential have unique opportunities to improve critical super-skills, including written communication, project management, iterative thinking, and real-world problem-solving.

THE NEED FOR DATA ACUMEN

Engineering disciplines are increasingly adopting and integrating data science into their problem-solving and experimental approaches [1-3]; yet few engineering programs directly integrate data science and visualization into their curriculum. In an effort to address this need and respond to the NASEM report on Data Science for Undergraduates, which calls on institutions to increase "data acumen" through "a range of educational pathways," [REDACTED] School of Engineering and Applied Sciences launched an undergraduate micro-credential in data science. The micro-credential includes two new courses, an internship, and a final capstone project. This paper shares the structure and content of the micro-credential and, using data from the first cohort of students, reports on the successes and struggles of the program.

THE MICRO-CREDENTIAL PROGRAM

Micro-credentials have a long history in both higher education and technical training [4-5]. Olcott defines them as being "shorter duration education and/or training activities" that are "focused on a specific set of skills" [5, p. 4]. In designing a micro-credential for data science, we sought to hone in on concepts and skills central to the work of data science and offer students a meaningful complement to their existing educational programming. In doing so, we designed a data science micro-credential (DSMC) that would fully integrate conceptual learning and the application of skills. The DSMC was developed as part of a National Science Foundation (NSF) grant that aimed to increase the number and diversity of undergraduate students with data science acumen across an array of disciplines. The micro-credential is open to any undergraduate student, although prerequisites exist for the courses, which will be addressed in the next section.

Students enrolled in the DSMC enrolled in two full semester-long courses (not the short courses that have received critique from micro-credential naysayers) with project-based learning at their pedagogical cores. Then, the DSMC research team assisted students in locating data-science-focused internships, through which they applied their data science knowledge. Finally, DSMC students worked to develop a capstone project, through which they reflected on their experiences, shared their knowledge, and explored the next steps for their data-science career.

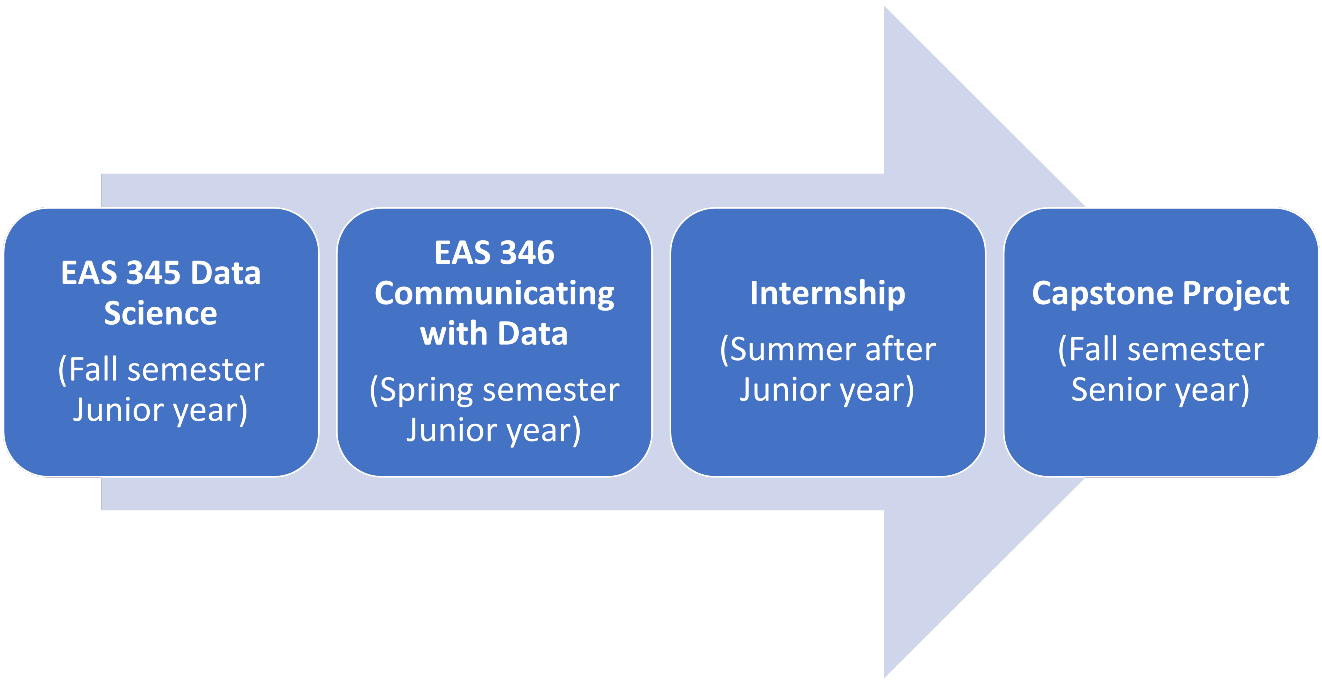

Fig 1. Typical sequence of students in Data Science Micro-Credential program

DSMC Coursework

Two courses comprise the foundation of DSMC: a course on data science and a course on data communications. These two courses provided introductions to data science skills through project-based learning. Project-based learning is an approach to learning that prioritizes learning through action rather than passive learning through lectures. The two new technical elective (TE) courses (IDS and IDCV) to be developed in this project, described below, are each based on project-based learning (PBL) to engage students in solving complex problems via inquiry, research, and ideation [12, 13, 14]. The value of utilizing PBL in this project is two-fold in that (a) it is the vehicle by which participants will engage with real-world data sets to consolidate their classroom learning, and (b) it directly brings 'super-skills' development into the classroom, including through meaningful collaboration, engaging with multiple perspectives, project management skill development, connecting problem-solving to real-world contexts, engaging in development of iterative thinking and design, development of empathy, practice with different communication modes, and increased meta-cognition [15]. We note that such multi-faceted engagement factors align particularly with the findings of Savaria and Monteiro for promoting the involvement of women in STEM [16]. Fortunately, DS instruction is well suited to PBL methods since digital technologies allow for creation, sharing and documentation to be readily accomplished on integrated platforms [13].

Data Science Course: This course is an introductory level course in data science. The prerequisites for the course include a math course (MTH 142) and a computer programing course (several of which are listed as acceptable from the computer science department or engineering and applied science). The course also requires that students are an approved major within the engineering school or have permission of the instructor. It should be noted that the instructor is a co-PI on the grant team and has an extensive background in data science. Students were introduced to fundamental concepts in data science. It focused on three major themes: Data characteristics, data science pipeline, and data-driven applications. Some of the topics discussed in the course include data diversity, data products, data collection methods, data cleaning, and formatting, storing and sharing data, privacy, and confidentiality of data, data security, small data analysis, statistical analysis using R studio, presentation of analytics, and data applications for the society. Data for the projects were obtained from data.gov, Pew research, Kaggle, and other data sources identified by the students. All concepts covered were illustrated using hands-on experiments and problem-based learning activities, analyzing real-world data sets to develop data science skills.

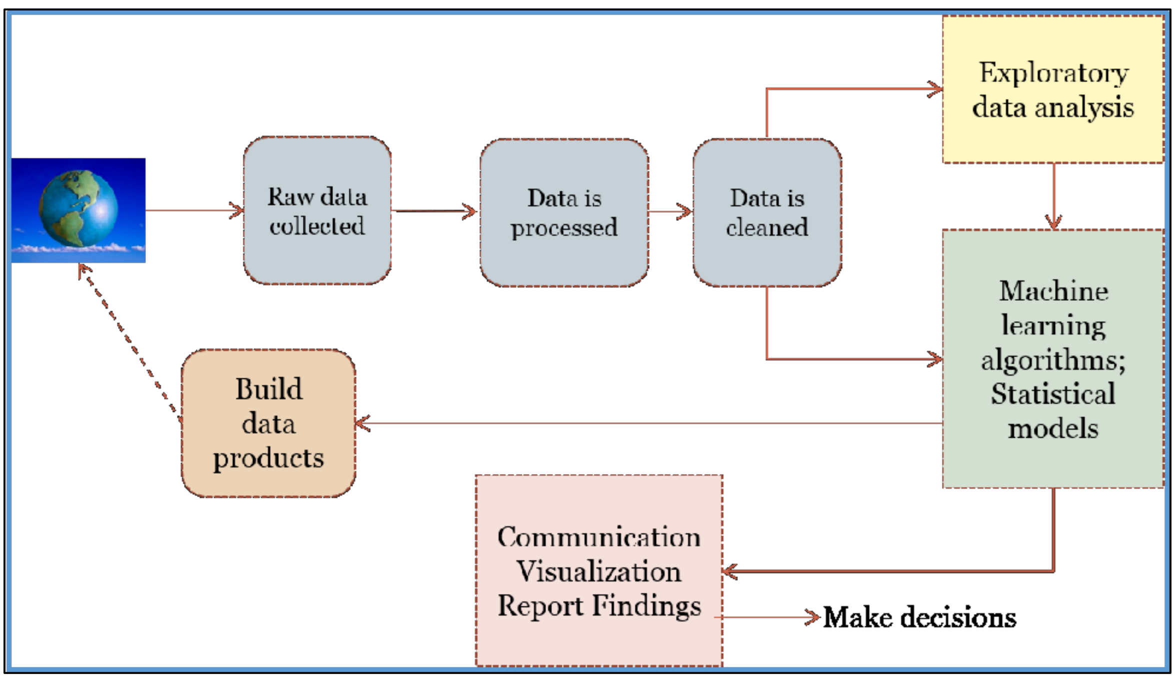

Fig 2. Overview of the concepts taught in EAS 345

Data Communications Course

Driven by case studies and community partner-supplied PBL projects, this course connected students' development of communication skills with real-world DS problems. The only prerequisite for this course is the mandatory STEM communications course (EAS 360) that is required of all school of engineering undergraduate students. Like the data science course, this is also open only to approve school of engineering students or permission of the instruction (who is also a co-PI on the grant team, as well as an expert in technical communication and data visualization). Students designed data displays and visual arguments; engaged in iterative design practices; and worked to solve real-world problems on data communications and visualization. Central to the course's design was that students were trained in key rhetorical principles, including the understanding data visualization as a form of storytelling, information design as responsive to a particular problem or context, and the strategies for developing effective presentations. Students were required to design polished, professional and ethical presentations and reports; they read and write about visual-design best practices; and they used modern data visualization tools such as rShiny to create a range of data visualization. Central to this course's design was its emphasis on user experience and human-centered design. By forefronting the *user* of the data display and communication, the course encouraged students to think about *who* would use the data display, *how* they might use it, and (in turn) what key design elements should be prioritized.

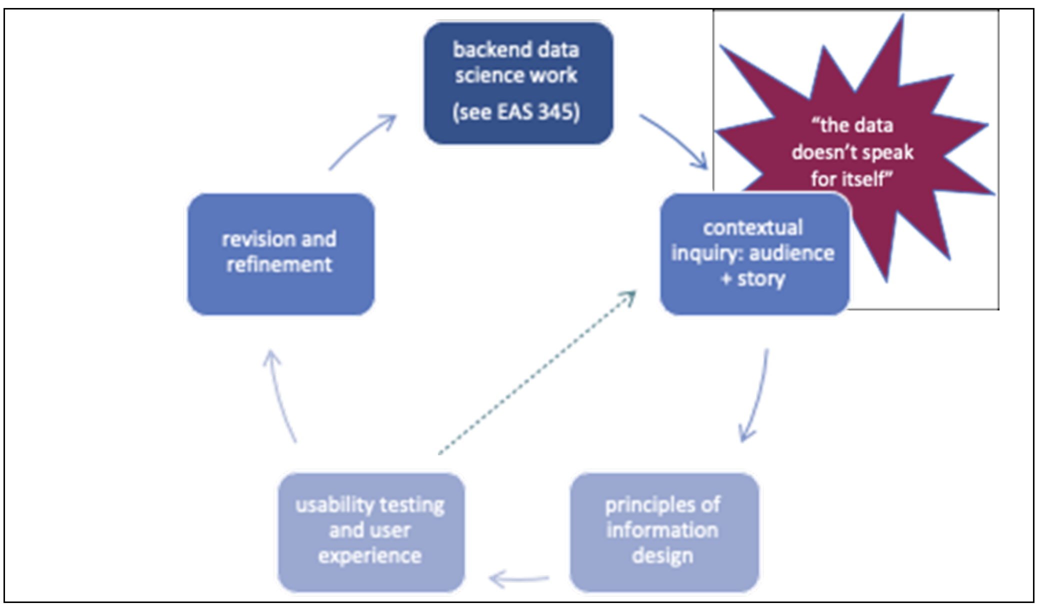

Fig 3. Visualization of the Data Communication course's primary content and process.

DSMC Internship

All students in the DSMC were required to secure an internship that focuses on or integrates data science. Although some students secured traditional internships, others worked with the grant team to secure grant-specific internships located in non-profits or NGOs and funded by the grant project. In designing two types of internships, the program not only educates students but disseminates data science knowledge into the community. In securing their internships, students (in conjunction with their hiring supervisor) proposed a project to the DSMC team, articulating the ways the project engaged data science content.

DSMC Capstone

DSMC students concluded the program by completing a Capstone Activity Project. The Capstone allowed the students an opportunity to reflect on their experiences in the classroom and in their internships. Students were aware of the Capstone from the beginning of the program; however, to ensure they continued to think about their overall experience, information was sent to them via email before they began their internships. The information reminded them the Capstone would require them to create a video or equivalent visual, audio, or written reflection (i.e., a website, Jupyter notebook, etc.) about their experiences as a data scientist. It was stressed the Capstone should illustrate some of the work they did in their internship and focus on the relationship between their internship and key concepts in data science presented in the two courses.

The students were also asked to incorporate appropriate use of data communication and visualization tools. It was stressed the Capstone was meant to be a reflection on how one or more professional competencies were important in their internship work.

Ultimately the Capstone involved three main components:

1. Provide Evidence of Expertise – Providing a brief synopsis of the work they did in the internship
2. Reflection – Asking the students to consider what key concepts of data science were used in their internships, as well as to think about what they needed to know in their internships that they did not learn in their coursework.
3. Drafting and Revision – Working with the Engineering Librarian (and other grant team members, as needed) on the creating and editing their Capstone deliverable; utilizing workshops and other tools where necessary (i.e., recording tools, storyboarding techniques, etc.).

The students met with Author 2 at several points following their internship to ensure they were set up for success with the Capstone. Author 2 discussed what their Capstone should and should not include, reviewed presentations, and set students up with the necessary tools to complete the Capstone (i.e., the video recording studios available in one of [INSTITUTION'S] libraries). The Capstone was not meant to be a full semester-long project; therefore projects were due roughly halfway through the Fall 2021 semester. Final projects were submitted to a shared Box folder. At the students' request, we convened a final meeting of the student cohort and grant team members. Capstone projects were reviewed by the team ahead of time to allow the students to answer questions in a panel-type setting. Students interested in the DSMC were invited to attend the meeting to learn about the program, especially the internship experience.

CHALLENGES AND SUCCESSES WITHIN THE DSMC PROGRAM

These four components, when taken together, provided students with opportunities to engage in the development of content knowledge, application of skills, and reflection on their experiences. Or so we hoped. As the first cohort completed their capstones, we assessed the program using both formal and informal approaches: a) student surveys; b) course evaluations; c) capstone assessments; and d) post-mortem discussion with faculty. The first cohort of students was small (7 students), primarily because the pandemic disrupted so much of the university's operations, so the more formal and quantitative measures provide only a limited perspective on student experiences. As such, our current assessment measures can give only broad stroke reflections on the successes and challenges faced in developing the micro-credential; a more comprehensive assessment will be more feasible once several cohorts have completed the DSMC.

Challenges for Students and Administrators in DSMC

The DSMC endeavored to provide students and the local community with an introduction to data science and its key skills. Both students and faculty/administrators faced several challenges in achieving our goals.

As with many new programs, one of the primary barriers to success was the interruptive nature of COVID and the pandemic, which caused a number of changes to the DSMC plans. In addition to pushing back the first cohort, COVID moved both introductory courses online in their first iterations. Cohorts of students taking introduction to data science, for example, were learning online in a pandemic, and although we didn't study COVID-19's impact expressly, it would be easy to see how outcomes and experiences of students would be much different in on campus learning environments. Additionally, we struggled to recruit students into the data science micro-credential, and although we have a number of plans to address this difficulty, the effects of the pandemic on students' willingness to adopt new lines of study is assumed.

Recruitment of Students & Finding Room in Curriculum

Due to COVID-19, student recruitment was through virtual informational meetings held via Zoom. The Zoom sessions were conducted lived but also recorded in order to reach all interested students. The grant team provided a short presentation on the micro-credential including its goals and requirements. A brief overview of the two courses was provided as well as information on the internship and subsequent capstone project. Students were made aware of these virtual information sessions via recruitment emails. Emails were sent to undergraduates in the School of Engineering and Applied Sciences, but also those in other departments and schools via the affiliated liaison librarians. Student attendance (including views of the recorded webinar) was good considering the timing of these sessions (shortly after the initial COVID-19 lockdown) reaching several dozen students.

The internship component of the micro-credential proved to be an important aspect of recruitment as it offered students access to established relationships between [INSTITUTION NAME] and community partners. These community partners include local companies, not-for-profit agencies, and non-government organizations (NGOs). The micro-credential also offered a streamlined process for applying for internships with qualifying opportunities tagged in the university's job search tool. Internship hosts were vetted by the grant team Principal Investigator (PI) who then guided the hosts through the process of designing a data science internship. The NSF grant funding also allowed for financial support for non-profits and NGOs by providing the pay stipends for the students. This allowed for more diverse internship opportunities, especially for those organizations that might not have the budgets to pay a student intern.

Evidence of Data Science Skills through Reflection or Self-Reporting

One of the primary indicators of content comprehension and skills was that in their capstone projects, students reported the transfer of content to their internship. One important transfer was the students' ability to transfer their skills from the platform used in courses (R) to the platforms required in their internships. As part of their internship, students used both proprietary and mainstream platforms to engage with data science, including:

1. Excel
2. Microsoft Power BI
3. Internal Dashboards (x2)
4. Machine Learning.

Although one student recommended the introduction of python in some of the courses, all students indicated in their post-internship surveys that they felt prepared to engage with data science, despite not using R directly during their internships. The data science skills students deployed in their internships were discussed in their capstone projects, and most students were able to point directly to specific data science skills taught in the two courses. They spoke of these skills during a wrap-up panel discussion held after the final capstone projects were submitted. Cleaning up the data, data exploration, and data analysis were common data-related skills the micro-credential students encountered during their internships.

Cleaning Up Data

A shortage of data was not an issue for any of the micro-credential students. However, cleaning up that data was a skill they all had to employ early on in their internship experiences. This was a skill they were taught in the EAS 345 course. One student noted they felt prepared for the challenge for of cleaning data; they explained,

> "In EAS 345 we were taught how to clean data, and so, especially in real life, [your employer] gives you data and they're just like 'good luck, you got it.' So you have to

> know how to clean it and you have to know how to clean it with a purpose, I feel like he has 345 I got all [of] that information."

Another student explained their own internship experience where their employer "basically wanted a dashboard to tell them the raw data they were getting in a nice format to explain their [redacted] security vulnerabilities." The student elaborated that the skills learned from the EAS 345 and 346 courses they "used the R language and R Shiny and R studio to create... a pie chart and a data table with everything in a nice format."

Being able to navigate through raw data was the first challenge the students faced. In both of the instances detailed above, students demonstrated they were able to pull from their knowledge skillsets to solve the problems presented to them by their internship supervisors.

Data Exploration

Beyond cleaning the data, data exploration was another key concept students centered on during their self-reflection. Data exploration can be viewed as the first step in data analysis, incorporating visualization to reveal insights or identify patterns. All the students detailed this process in their internship experiences even if they did not use the specific term of "exploration."

For example, one student indicated that while working for the risk adjustment department of a major health insurance company, they were concerned with Medicaid claims. The student worked with others as a team to create a prioritization of diagnoses associated with the claims. The went on to explain, "I updated the [internal] dashboard using Microsoft Power BI which is like a big visualization software. Which gave info [sic] on like the amount of money, which diagnoses were being rejected, just all types of data." The student then was able to use this dashboard to present to their supervisor and others on their findings.

Another student detailed their experience with data exploration stating,

> "[m]y job was to take a bill of materials, which is basically a roadmap of how you can go from raw materials to your main products, how would I build that up and I had to visualize how we can save costs for buying extra inventory or surplus, because in your manufacturing process things happen stuff can go wrong So where do you buy extra inventory to fix that stuff. I'm utilizing graph theory and Python specific package network acts were able to visualize that and so using a tabular format which is kind of hard to read and see relationships between parts within a graph you can see all the relationships."

Discovering the patterns in the data allowed this student to be successful in their role and move on to the final common theme from the self-reflection, data analysis.

Data Analysis

"Analysis" was a term the micro-credential students used often in their self-reflection. The students exhibited that they understood the intention of the micro-credential was to ultimately analyze the raw data they cleaned and visualized. Outside of conducting this analysis, several students remarked their astonishment regarding the intersection of their main field of study and data analysis. A student explained that it

> "was interesting this internship ... combined the mechanical engineering side [with] data analysis ... and I was able to combine the two together which worked out pretty well and I'm interested in that kind of intersection so I'm really glad I took this micro-credential because I think it opened me up to a new area a new intersection that I could not go into [before]."

Another student noted their surprise how important data analysis (and visualization) is in their own field of study, something they had not considered before the micro-credential. They said,

> "I'm a math major with a concentration actuarial science. And over the summer I interned at [redacted] a major health insurance company. And I can say it definitely opened my eyes to how much the actuarial field is centered around data analysis and like coding and even visualization."

Data analysis skills were noted by internship supervisors as well. A supervisor replied to a post-internship survey stating that the student "worked well with partnered colleagues. They spoke highly of her. She was willing and able to 'dig deep' in current data sets in order to help inform decisions." These data analysis skills extend beyond the typical "technical skills" and merge into more sophisticated, nuanced skills. Although other programs might subjugate these skills to the "soft skills" that matter less than the technical skills, our micro-credential committed to supporting students in their development of what others have described as superskills. In the next section, we describe the ways data science might appropriately be included in the superskills that many have articulated as skills required for 21st century students. More precisely, we suggest that our program (and our modest assessments) illustrate the relationship between data science and the superskills many have identified.

Superskills as Part of Data Science

One key objective in the DSMC was to engage students in a coherent curriculum that prioritizes superskills like communication and presentation. Rather that subordinate these skills, the courses emphasized the need to communicate using data from the very beginning, and students' capstone projects and post-program debriefing suggest that this priority was sustained through the internship and beyond. According to Ağaoğlu & Demir, the four superskills (or the 4Cs) include critical thinking and problem solving, effective communication, collaboration, and creativity and innovation [6]. Each of these skills comprises a central skill that 21st century students must necessarily engage, and one goal of our micro-credential is to emphasize the importance of these superskills in the development of data science acumen. And, indeed, one of our findings was that students engaged each these in their internships in meaningful ways.

Both communicating and collaborating are articulated as superskills, and both were important for the success of students in class and in their internship and capstone. Both courses included small group work and collaborative learning opportunities, but the import of collaboration and communication was particularly emphasized in the capstone presentations, when students described their key challenges. Students described that beyond the data science work, the communicative challenges (particularly in collaboration with their supervisors) stood out as impactful and important. One student reported,

> So I think a big thing with me was since we were remote like I was on Microsoft teams a lot and the thing with the workplace is you begin when you're in a place for a little while a few months you begin to see the relationships that people have and like, I was in office politics... like, even though they aren't I guess crucial to the work itself, they are crucial, within the space. And you have to know how to navigate them in order to get your work done, because I had to learn, you know what my boss does my bosses behavior how they you know, sometimes my boss was asking for things and never asked for it again and say. I just did like a whole but it's just like I had to keep just being alert because that's how my boss was and like learning to navigate like who you're working with and what you can ask certain people and, like things like that I feel like that's a big life lesson that I learned, even while being remote so.

Here, the student reveals one of the more difficult superskills: learning to navigate power differentials and communicate in complex situations. Although this wasn't fully elaborated upon, the student's discussion draws our attention to realities of workplace communication and the rhetorical work required of data scientists (and all of us) when we enter professional spaces. Students in the data communication course were introduced to fundamentals of rhetoric, including learning to communicate for particular audiences, and this comment demonstrates the need for continued training in supporting students' rhetorical abilities.

The emphasis on superskills also emerged in another student's capstone presentation when she discussed not only the need to communicate but to structure and creatively respond to lack of direction from a supervisor. The student describes the situation this way:

> My internship project was kind of very it was like a side project, it was like the second so um it was kind of very loose, not very structured so for me. They were more of like you know you explore this and then let us know when you're done and then like you know do this. So for me, like the communication was very spotty only because they wanted to give me that freedom, and it was also like a secondary project... I didn't know what I should focus on when I was researching like where how far should I go.

Here, we understand the student to be navigating the freedom and independence their supervisor offered to them. They described the need to develop their own project, creatively exploring the potential of the data set. They also described the need to initiate communication, a part of both collaboration and problem-solving.

> So for me I kind of had to like I would like you know email them like once a week or once every two weeks kind of saying hey. Can we meet, so I can like you know update you on this, what I've discovered so far and then they're like okay cool and they show

> me something new and then I will get back, like the next two weeks, and every kind of repeat like that, but like that was like me initiating that too.

In engineering, it's easy to see problem solving as isolated to the engineering space: how does the solve an engineering design problem? How does the student apply a model to a particular problem to solve it? Here, we see the problem-solving ability move into the workplace, and the student here engages meaningfully in communication problem solving in order to address the lack of oversight.

In the data communication course, course content emphasized the importance of *presenting* data—not just visualizing it. In both the capstone presentations and in internships, these presentation skills emerged as meaningful for our cohort of students. One of the students described one of their greatest challenges in the internship as the application of critical thinking and problem solving to communication challenges. One student shared that they were working primarily alone on a project and was asked to present their work fairly last minute to a group of internal colleagues. They explained, "So the project was really just a translation from going from MATLAB to Python and presenting it, you had to basically take all these really interesting concepts and math and present that the people who don't have that background, so doing that was like a hardcore like, how can you express your ideas in a way that makes sense to people don't have that knowledge, so that was a lot of fun it's really hard, a challenge, but it was something that I didn't really expect."

Some of the communicative work took a more explicit teaching frame for students because they were the only person trained in data science in the organization. These teaching experiences provided an opportunity for students to engage not only in critical thinking and problem-solving but in creativity and problem solving. One student explained that they were the sole person responsible for figuring out how to engage with data science in their organization.

> They really had me like my real job my job is really to figure out their [redacted] program and how to take the data out and then analyze it. I was teaching them how to do it, so they knew how to figure it out when I left.

In articulating it this way, the work of the internship became clear: more than *doing* data science, the intern was responsible for communicating the process and content to others in the organization.

The role of teaching as a form of collaboration and communication was also clear with a student who engaged with decision-making surrounding which platform to use in the internship.

> I worked with two other interns and we…weeks it took us that long to figure out what do we actually want to do like what do we want to use to figure out this problem and we originally were going to do Python but then, by the end of the second week we realized that we don't want to create like an entire [library]. And so I was like well there's R shiny... so then we switched to that, but then I had to teach them like a crash course in it.

This student had to develop a strategy for solving the problem that Python wasn't an effective tool for completing the assigned task. The solution required teaching of a next level: explaining to other novices how rShiny works and how they can use it to engage with the data set. Based upon this, we conclude that the communicative and technological skills required in the internship aligned with our micro-credential goals.

CONCLUSION AND LIMITATIONS

This program is in its infancy: we've only just now begun the second cohort, and the pandemic greatly impacted our ability to secure students. Nonetheless, we think reporting out on this project is worthwhile for a number of reasons. First, data science is an increasingly important part of STEM education, but its locale within academic programs is inconsistent and not necessarily within engineering programs' footprints. We hope this program offers a blueprint for how interdisciplinary and engineering programs might engage engineering students in data science. Second, data science can easily be divorced from the communicative emphases that prepare students for data science; we hope our program provides (limited) evidence that the communicative aspect of data science is both worthwhile and necessary for effective data science application. Finally, our program suggests that data science training that doesn't include an applied, experiential component could miss the opportunity to engage students in *praxis* tied to data science and communication. In the internships, students discovered the relationships among the content and theory they engaged and the actual work of *doing* data science in context. Cambridge describes *praxis* as the application of a theory that a person has studied or learned. In describing data science as a *praxis,* we connect the classroom and the experience, the theory and the practice. In this way, our data science micro-credential offers a practical, praxis-driven approach to engaging students in data science.

Of course, there are limitations to this paper and to our assessment of the program. We have limited data tied to our students because, frankly, we have limited students. We imagined that several years in, we would have more data, but we have struggled to recruit students. The struggle is not because students are disinterested; the struggle emerges from the strict nature of required courses in engineering and from the demands of programs on students' time. An ideal program would be introduced in the first year, with students enrolling in the second year, taking courses in year two, and then completing the internship in the summer after their sophomore year. This hasn't worked for us. Students who want to take our data communication course need to complete a pre-requisite course before the enroll. This course is a high-demand, difficult to enroll in course. This has limited our ability to enroll students in the second year.

Therefore, we recommend that institutions looking to add a similar micro-credential program should examine the timing of courses and prerequisites for those courses. For many engineering students, a typical four-year program does not leave much room for elective courses. Students need to be made aware early and reminded often of the existence of the micro-credential so they can budget their time accordingly. Communication and advertising of the micro-credential is also something to consider early on in the planning process for those interested in building something similar. What are the best methods to make the student population aware at your own institution? Having a plan from the outset will make the process for recruitment easier.

At present, we plan to continue offering the DSMC however we may look to amend certain aspects of it if recruitment issues due to scheduling persist. [INSTITUTION] has a rigorous process for approving micro-credentials, therefore if major changes to the program were recommended, we may have to have the Office of Micro-Credentials provide approval for the DSMC again. Nonetheless, we are hopeful about the potential for engaging more students this year and in the coming years as the micro-credential continues. We look forward to reporting more fully articulated claims and data sets in the coming years.

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