Near-peer mentoring in data science: Two experiences at Stanford University

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Abstract

Universities have been expanding the data science programs for undergraduate students, with the simultaneous goal of reaching and retaining students from under-represented groups in the data science workforce. The set of new programs also offer opportunities to involve graduate students, fostering their growth as future leaders in data science education. We describe two programs that use the near peer mentoring structure to provide pathways for graduate students to develop teaching and mentoring skills, while providing research and learning opportunities for undergraduate students from diverse backgrounds. In the Data Science for Social Good Summer program, graduate students mentor a group of undergraduate fellows as they tackle a data science project with positive social impact. In the Inclusive Mentoring in Data Science course, graduate students participate in workshops on effective and inclusive mentorship strategies. In an experiential learning framework, they are paired with undergraduate students from non-R1 schools, who they mentor through weekly one-on-one on-line meetings. These initiatives offer a prototype of future programs that serve the dual goal of providing both hands-on mentoring experience for graduate students and research opportunities for undergraduate students, in a high-touch inclusive and encouraging environment.

Keywords: Data science education, inclusive mentoring, project-based learning, experiential learning
1 Introduction

The education literature documents multiple advantages of training opportunities where graduate students work with undergraduates in mentoring capacities. First, involving graduate students can help decrease the student to instructor ratio in many courses (Sorte et al., 2020). Second, the access to mentors increases retention of first generation and underrepresented minorities (URM) in Science, Technology, Engineering and Medicine (STEM) disciplines (Wilson et al., 2012). Near-peer mentoring in particular has been shown to be an effective mechanism with which to foster a sense of belonging and self-identity as a scientist (Zaniewski and Reinholz, 2016; Wilson and Grigorian, 2019). Third, acting as mentors positively influences the personal, cognitive, and professional growth of graduates students (Dolan and Johnson, 2009; Tenenbaum et al., 2014). Opportunities that value interdependence and recognize communal goals may increase some students’ cultural alignment with the research institution (Stephens et al., 2012; Boucher et al., 2017; Anderson et al., 2019; Belanger et al., 2020).

The possible benefits of near-peer mentoring resonate particularly well with challenges we encounter in data science education. We focus on two. First, as a vibrant new field, data science requires specifically tailored instruction (National Academy of Sciences, Engineering, and Medicine, 2018). This often involves “experience-centered” training, where students actively engage with the support of more experienced practitioners (Rodolfa et al., 2019). These “high touch” educational opportunities require a low mentor-to-student ratio, which is in many cases challenging to achieve. Second, it is vital to increase the diversity of the data science workforce. As in many fields of science and engineering, increasing diversity expands the talent pool, enhances innovation and improves the nation’s global leadership (National Academy of Sciences, Engineering, and Medicine, 2011). Furthermore, given the sensitive applications of data science, it is “important to support research into mitigating algorithmic discrimination, building systems that support fairness and accountability, and developing strong data ethics frameworks” (Executive Office of the President, 2014)—all of which benefits from a diverse and representative community of practitioners.

Finally, the strong job market in data science (Davenport and Patil, 2012) assures that outreach and retention efforts towards URM positively impact social mobility.
Data science, then, experiences strongly both the need to create more immersive opportunities for students and the need for outreach and retention activities, building an environment where groups currently underrepresented feel they belong. We here report on two programs developed at Stanford University during the last few years, designed to address these needs leveraging the documented advantages of near-peer mentoring both for mentees (Wilson et al. 2012; Zaniewski and Reinholz 2016; Wilson and Grigorian 2019; Sorte et al. 2020) and mentors (Dolan and Johnson 2009; Stephens et al. 2012; Tenenbaum et al. 2014; Boucher et al. 2017; Anderson et al. 2019; Belanger et al. 2020). Specifically, we built on two observations from this literature. First, graduate students mentors are particularly effective in “experience-centered” training: they can provide some guidance while still being perceived as peers and therefore not being automatically vested with leadership roles that diminish undergraduate students’ engagement. Second, engaging students on projects with “social good” goals can contribute to develop a stronger sense of purpose and belonging.

Our goal with this article is to share modalities in which near-pear mentoring experiences can be built specifically for data science and the lessons we have learned in the process. We have collected feedback from the stakeholders involved, used it to retune our programs and to develop guidelines for future iterations. Importantly, we have not conducted a case-control study to demonstrate the efficacy of our programs. We are sharing our experiences in the spirit of a “case study,” hoping that reading about them will generate discussions in other institutions about the opportunities and challenges that similar programs might offer for their students. We provide the context for two programs in Section 2. We describe the Data Science for Social Good summer fellowship in Section 3 and the Inclusive Mentoring in Data Science program in Section 4. For each program, we discuss the program goals, participants, structures, curriculum development and impact on the participants.

2 The context

Stanford University is both the home of some well-established programs of study in domains that overlap with that of “data science”. For over 50 years, the department of Mathematics, Statistics, Computer Science, and Management Science and Engineering have run an
interdisciplinary undergraduate program for students interested in the application of quantitative and inferential reasoning to science and engineering. The number of average yearly graduates has increased in the last ten years from about 25 to about 40. At the same time, Stanford University has been identifying gaps in undergraduate and graduate education and supplementing with new offerings. For example, since September 2022, students can join two new majors — Bachelor of Arts and a Bachelor of Science in Data Science. In concert with the overall university requirement of capstone experiences, these new programs both need to provide opportunities for students to “integrate knowledge and skills developed in the major and learn to think independently with the tools of the discipline”.

A number of these recent efforts have been supported by Stanford Data Science (SDS), an initiative that aims to foster research collaborations and novel opportunities for students to be involved in the practice of data science. Part of the activities of SDS have been supported by an NSF grant NSF 1934578 (2019), with a major goal to support in graduate students the mindset and habit of interdisciplinary team work.

Aside from the specificities of the Stanford context, we experience challenges that are common to many data science programs: how to support graduate students’ grow not only in the knowledge of their discipline, but in their ability to work in groups with diverse cultural and intellectual backgrounds? how to increase the diversity of students applying and enrolling in graduate programs? how to make sure that students from underrepresented backgrounds feel that they belong and thrive? how to provide undergraduates with the opportunity to participate to the design and realization of a data science project? In this article, we describe two programs, the Data Science for Social Good summer fellowship and Inclusive Mentoring in Data Science, that were introduced to make progress in these directions in the context of our university, and contingent circumstances.

The impetus for both programs came from requests and expression of interests of graduate students. In the first case, a graduate student in education that was being partially supported by SDS had participated in the Data Science for Social Good (DSSG) fellowship organized by Rayid Ghani in Chicago and, having found the experience transformative, was determined to have some version of it at Stanford. The student’s testimony and willingness to work towards this goal was crucial in garnering the SDS leadership’s support that al-
lowed us to put together a team to first run a pilot experience, and then develop it over four years. Our second program was launched during academic year 2020-21, when instruction was entirely remote, and the US society had experienced a number of dramatic events. In particular, the protests and reckoning with racism following the murder of George Floyd had engaged the graduate students population, who self-organized in many forms of activism. A program aimed at increasing the diversity of the data science workforce aligned well with their interests and offered them an opportunity to channel their desire for action.

In both programs, graduate students have been involved in the program design and have participated with great creativity. At the same time, the faculty and institutional leadership worked to develop “learning goals” and program structures that creates learning opportunities for both graduate and undergraduates students.

3 Stanford Data Science for Social Good

The Stanford Data Science for Social Good (DSSG) is a summer fellowship program where undergraduate participants, mentored by graduate students, tackle a data science project with positive social impact over the course of eight weeks. Faculty advisors provide additional guidance on individual projects as well as program design. While sharing features with other Data for Good fellowships developed in academic settings [Dailey et al. 2021], our DSSG was developed primarily as an educational opportunity for both the participants and mentors. We describe the program goals in Section 3.1 and illustrate how the program supports participants and mentors’ growth through an example in Section 3.2.

3.1 Program goals

The Stanford DSSG serves three groups: undergraduate participants, graduate student mentors in training, and project partners.

Our participants are “beginner data scientists,” who have sufficient technical competences, but without experience applying data science to a real world problem, and indeed, possibly not entirely committed to a career in this space. These are typically upper level undergraduate students or beginner master students. We set four broad goals for this
group: (1) Engage in an authentic data science project that addresses a societal need; (2) Receive training, mentorship, and practice in aspects of data science life cycle least reflected in a typical educational curriculum. These skills, e.g. data science ethics, communication, workflow, correspond to multiple aspects of “data acumen” identified by National Academy of Sciences, Engineering, and Medicine (2018); (3) Feel that data scientists are “people like me”; (4) Strengthen professional skills and increase self-efficacy of making career choices with a sense of purpose and service.

The DSSG program has been offered five times, and fellows have been recruited openly in 2021 and 2022, and limited to Stanford students in the other years. To encourage students from a diverse background to apply, we distributed calls for applications in multiple channels: SDS website, social media platforms, student-led groups for social good, non-R1 institutions and HBCUs. We focus on the following questions when selecting participants: do they have adequate foundations in data science, statistics and programming? are they excited to apply data science for social good? what research areas and society issues are they passionate about? what are their experiences with working in a diverse team? what are their commitment to diversity and inclusion?

Our mentors are graduate students and postdocs, who have strong technical expertise and some training in teaching, e.g., through serving as teaching assistants or course instructors. On the other hand, they typically have limited training on mentoring, managing a research group, or navigating the challenges of interdisciplinary work. By engaging in DSSG, the mentors build competence in the following areas: (1) Mentoring undergraduate participants in an “active learning” environment; (2) Lead a data science team project; (3) Engage with project partners of different competences and background without the scaffolding typically provided from a senior principal investigator.

Our project partners are often non-profit organizations who have a research question that the DSSG team can address through data analysis. The complementary skill sets — technical skills of the DSSG team, domain knowledge and ethical values of the project partners — foster a natural collaboration. Months before the program, faculties from across the university are invited to contribute project ideas and potential partners. Faculty advisor and the lead mentors scope the projects to ensure that undergraduate participants can
make progress during the summer. We communicate to the project partner that scope and impact may be limited by the fact that we include undergraduate students as participants and give mentorship and coordination roles to PhD students.

3.2 Description of roles of graduate mentors

At the DSSG program, participants’ learning is mostly facilitated by graduate student mentors. In turn, mentors strengthen their teaching, mentoring, project management, and leadership skills. In this section, we illustrate how student-mentor interaction support mentors’ learning goals through the activities mentors engage in during the program.

3.2.1 Identifying project objectives and milestones

A few months prior to the program, faculty advisors and mentors meet with the project partner to understand the status of their project as well as their needs. After the meeting, mentors outline concrete project goals, weekly milestones, available data set and resources. They develop onboarding materials for the participants, which include project information, technical resources, and relevant reading. Together with the project partner, mentors scope the project in terms of its societal impact, the learning it provides to participants, feasibility given the time frame, and the ease with which it can be communicated. While the project partner typically provide data sets for the participants, mentors do not curate the data beforehand, in order to expose participants to real world data and encourage them to investigate which aspect of the data set can be used to answer the question.

3.2.2 Project onboarding

At the start of the program, the participants study the onboarding materials and meet with the project partner to clarify their problem. After the meeting, the project team frames their overarching goal for the summer and identify their first set of tasks, which often involve identifying appropriate data sets, processing the data into a convenient format, and performing exploratory data analysis. Here and below, we use one project in 2022 (“Identifying behavioral health conditions from police records”) as a concrete example. In the example, the goal was to classify whether documents pertaining to a use-of-force case
mentions behavioral health conditions or not, and the first task was to compile a training data set where the labels and features are extracted from a case data base and documents respectively.

### 3.2.3 Providing technical training

During the project, participants often need to learn new skills they have not encountered in previous courses. The training are often provided by mentors, in the form of technical training for the all the DSSG participants, or just-in-time teaching during meetings. Mentors determine which information needs to be provided, how to teach in an active learning framework, how to encourage explorations and integrate learning into project work. In the example, participants needed to learn how to work with a SQL database in order to compile the training data. The mentor provided tutorials, designed exercises, and invited a graduate student to give a lecture and answer questions. The participants then applied the newly acquired skill to examine raw data, select and transform raw data to curate a data set to work with.

Mentors may also facilitate students’ self-directed learning by guiding them to find resources and tutorials to support their learning. In the example, participants learned how to compile a Python package that they can distributed to future users. For participants, this hands-on experience strengthened their skill and commitment to robust and reproducible data analysis. As for the mentors, by facilitating self-directed learning, they learn to support a growth mindset and help students develop confidence and self-efficacy.

### 3.2.4 Facilitating team meetings

Throughout the program, mentors meet with the project team daily to brainstorm ideas and provide feedback. The topics evolve as the project progresses, e.g., brainstorming potential approaches, evaluating different approaches, selecting an appropriate method, presenting to a non-technical audience. This regular mentor-participant interaction provides an opportunity for the mentor to facilitate successful team work, monitor discussions, manage a team project, and foster a sense of belonging.
3.2.5 Leading interdisciplinary collaboration

During the program, the project team meet with faculty advisors and project partner weekly to share progress, obtain feedback, clarify project directions, and identify additional areas where they need support. This provides an opportunity for both participants and the mentor to collaborate with domain experts who do not have strong data science competence, but can articulate the goal, relevance, and implications of the project.

3.2.6 Building a data science community

Besides leading project work, mentors also organize other activities to introduce participants to the diverse range of data science topics and career paths, and to cultivate a sense of community. For example, they invite members of the data science community to discuss their projects or career trajectory in a weekly presentation. They also organize social activities such as improvisation and trivia challenge. We provide examples of other activities in the DSSG program in the Supplementary Material.

3.3 Program outcomes

We have run the DSSG program for five summers, between 2019 and 2023. The average number of people involved has been 8 participants, 3 mentors and two faculty members. In response to the COVID pandemic the programs for the year 2020-2022 have been in virtual format. The partner and project details can be gathered from the program web-pages. Support for the program was provided by the Stanford Data Science initiative and by a grant from the grant NSF 1934578 (2019), which allowed us to extend participation to non Stanford students.

Demographics details on participants and mentors from 2019–2022 are available in Figure 1. We achieved our goal of involving in this experience a larger number of underrepresented minorities: about 50% of participants and 70% of mentors identify as females or other gender identity. More than 70% of participants and 60% of mentors are from a minority group by the definition of National Center for Science and Engineering Statistics.

We have surveyed DSSG mentors on their experience. Mentors who responded to the survey (n = 9) reported gain in their capacity in multiple dimensions (Appendix A). For
instance, a vast majority are more confident in their ability to employ different teaching strategies, working with students to set academic and professional goals, setting goals and milestones of a data science project, and communicating progress with participants and project partners.

3.4 Curriculum development and shared resources

Our experience at DSSG has led us to identify areas for which we needed structured educational material in addition to the one we were already familiar with. We describe two areas: data science communication and mentor onboarding.

Communicating data science  During the program, we noticed the fellows often find it challenging to draft the final report. Most of their extensive writing has been argumentative, possibly including reference to facts or findings, but substantially “data free”. This experience provided the starting point to develop the materials for what is now a class offered to Stanford undergraduates and called “Data Narratives.” In an active learning framework, students analyze a dataset to address a question of choice, write weekly on this data, and produce a final report. The course covers one topic each week, e.g., selecting the data and formulating interesting questions, documenting each step, making the important observations stand out, crafting a compelling narrative, considering alternative explanations, evaluating the uncertainty and generalizability of the conclusions in an intelligible way. As students reflect on these topics as a group, they weekly carry out a corresponding
analysis/writing assignment on the data they have identified, gradually building material for a “data story” that they write as their final paper. Students are paired at the beginning of the course: each member reads the weekly writing of the partner and provides feedback, in addition to the one coming from the teaching team.

The pilot version of this class was offered in academic year 2021-22 and it is now one option to fulfill the writing requirements in the new Data Science major, as well as a prerequisite for major sponsored summer research experience.

**Engaging graduate students as mentors**  As we develop courses that are centered around undergraduate research projects, we are working to meaningfully engage graduate students as mentors, and provide them with the support they need for this. It is also with this broader goal in mind, that we have developed a set of onboarding materials for DSSG mentors, included in the Supplementary Material. Grounded in the growth mindset and with the purpose of facilitating growth of mentors, participants and the project, this onboarding guide covers three broad areas: (1) What are the characteristics of a good mentor and how to develop them; (2) How to facilitate the progress of a team working on an interdisciplinary data science project; (3) How set individualized learning goals and useful approaches to help students reach them. Organized around these themes, the guide introduces concepts with wide applicability: from the value of goal setting to belonging, from facilitating discussions to peer and active learning. Each idea is made concrete with an “activity”: by completing all of these, mentors-in-training will carry out most of the tasks they need to prepare for a successful DSSG experience. An extensive bibliography offers an easy connection to further resources. We plan to use this material as a starting point of a series of onboarding workshops for future DSSG mentors.

**4  Inclusive Mentoring in Data Science**

Inclusive Mentoring in Data Science (IMDS) is both a class offered to Stanford graduate students and an outreach initiative. Graduate students enrolled in the class participate in both weekly in-class meetings and a mentorship practicum. We describe the program goals for both graduate students and undergraduate mentees in Section 4.1 and outline program
4.1 Program goals

The ultimate goal of this program is to assure that the data science workforce is well connected to society and reflects its diversity. Inclusive Mentoring in Data Science (IMDS) works towards this goal with a dual strategy. On the one hand, IMDS strives to recruit students from currently underrepresented groups in data science, reaching them early enough to make an impact on their undergraduate education and equip them for successful graduate studies. On the other hand, it aims to educate graduate students on the status and value of diversity in a research environment, equipping them with practical techniques to mentor and engage individuals from diverse backgrounds. We now outline the goals of both the undergraduate participants and graduate students.

The undergraduate participants are at the initial stages of their interaction with data science: they might have taken an introductory statistics course or have some programming experience. They might be more advanced in a degree program in disciplines related to data science, but in need of a more personal and direct connection to the field. Our overarching goal is to recruit and retain these participants into data science. We aim to motivate, support and nurture their interest in data science, through individualized mentoring tailored to their interests, and introducing possible career paths and research topics associated with data science in diverse domains. We collect simple information from applicants on demographics, current school, courses completed in math/computer science/statistics, areas of interest, plans for the future. When selecting participants, we looked at questions like: did they have enough background to engage in some data exploration? Was there room in their plans to increase and sustain an interest in data science? Did they appear to be in need of mentorship?

Graduate students working in the data science space can enroll into a class (BIODS360 “Inclusive mentoring in data science”), offered for credit. This course trains them to (1) Develop a set of tailored goals for the mentoring relationship based on the needs and aspirations of their mentees; (2) Recognize stereotypes and implicit biases that might shape our behavior, learn and utilize strategies to overcome these to create and maintain an
inclusive environment; (3) Articulate the value of a diverse and inclusive team to tackle a
data science problem, be informed about current composition of data science workforce,
put this into historical context and use this information to devise future goals for our field.

At the beginning of the class, we allowed graduate students to self-match to the admitted
participants on the basis of some of the information collected in the application. We
found that this increased their sense of agency, without creating specific biases (some
students were interested in mentoring a person of their same sex, other of the opposite; some
preferred a mentee in their same ethnic group, other desired the opposite experience, etc...).
In truth, the information shared with mentors was minimal enough that the encounter with
each mentee was effectively a surprise.

4.2 Description of the program

Graduate students enrolled in BIODS360 participate in both weekly in-class meetings
and weekly one-on-one meetings with their undergraduate mentees. The in-class meet-
ings consists of (1) formal workshops about strategies to create an inclusive environment,
approaches to effective mentoring and coaching, and techniques to develop a personal-
ized curriculum, (2) reflection on and informal sharing of successes and challenges in the
mentoring, and (3) community building where all participants meet each other and share
experiences. In this section, we first provide a detailed description of the class meetings,
and then briefly describe activities students participate in during one-on-one meetings.

During the first in class meeting, after an introduction of the structure of the course,
graduate students are divided in pairs and go through the wallet exercise developed by
Stanford d.school, where they are tasked to design an “ideal wallet” for their partner.
After interviewing their partner, students brainstorm an initial design, which they refine
after iterations of feedback, and eventually come up with a prototype. This activity serves
multiple purposes: it acts as an ice breaker, helping to establish a climate for safe ex-
ploration and sharing; it underscores the importance of listening and empathy during the
upcoming first meeting with participants; it frees mentors from the idea of guiding their
mentees through the “ideal” research project and encourages them to jointly develop one
experience that fulfilled individual needs; and it introduces the idea that false starts are
possible and sometimes necessary to find the right path. The first class concludes with the assignment for each graduate student to identify their mentee, respond to the e-mail that the course organizer would send to the pair establishing contact, scheduling a first meeting during the current week. During the first meeting graduate students are tasked to learn as much as possible about their mentee, share some information about themselves to start developing a relationship, and find a mutually agreeable set time each week to devote to these online meetings for the coming quarter.

During the second in class meeting, all participants are invited to join in on zoom. Everyone briefly introduced themselves, with the aid of ice-breaker questions (ex. “if I were an animal I would be a..., because ...”). The instructors of the class then share examples of directions that the mentee and mentors could take in their work together: preparing for internship applications, learning the basics of a data analysis software, exploring possible careers in data science, taking a close look at a dataset on a topic of interest etc.. While we try to underscore that each pair had total autonomy in deciding their “curriculum,” we have found that being presented with a list of possibilities helped them to articulate needs and interests.

We have created a collection of central resources to support graduate students as they develop activities with their mentees: pointers to outreach programs and internships at Stanford; articles on data science careers; suggestions on resume and cover letters; tutorials on relevant math/stats topics and software; and a collection of datasets and basic analysis scripts in R and Python that can be used as a starting point for exploration of data science concepts, software, and analysis. These include projects centered on movies, global mortality causes over time, corn yields, NBA Basketball, multispectral satellite imagery, Stock data. These resources help to take the pressure off mentors to identify and create resources, allowing them to focus on mentoring.

The assignment for the second one-on-one meeting was for the mentor and participant to do a first round of brainstorming on activities that they might engage in during the quarter. We suggested keeping this brief, leaving time to re-evaluate during the coming weeks. During the rest of the meeting, we invited mentors to share a bit more on their experience as data scientists, describing the course of study they are involved in and the
topic of their dissertation.

In the following weeks’ in class meetings, we invite a number of campus experts in the area of diversity, equity and inclusion to facilitate workshops. They introduced and discussed concepts as belonging, “identity interference,” “stereotype threat”, “imposter syndrome,” “mindset,” offering pointers to literature (Leslie et al. 2015; Stephens et al. 2012) as well as personal experiences. For example, workshops in Spring, 2021 include “Bridges and barriers to belonging” by Marcella Anthony, “Diversity and the challenge to academic culture” by Joseph Brown, and “Navigating mentor-mentee dynamics” by Miranda Stratton. We found these workshops particularly useful. Engaging with experts provided a strong signal of the importance of these topics, the need to design educational practices that reduce barriers of engagement, and the amount of scholarly work that has been carried out in this space. Speakers also brought to the table years of personal experience which grounded the concepts and solutions presented and established warmth and acceptance as the dimensions of the in class discussion. Finally, connecting with campus resources substantially enlarged the reach of the program: both students and faculty ended up leveraging these in other contexts, making further progress towards the goal of increasing the diversity of the data science workforce.

After a few workshops, we devote a number of in-class meetings to mutual sharing of how the mentor-mentee relationships are evolving, and brainstorming around possible roadblocks. The instructor also meet one-on-one with undergraduate participants and bring to the meeting common feedback from participants. We notice that, through hearing from each other, mentors are better able to notice their own growth and identify successes and challenges in their own mentoring. They are more motivated to develop solutions knowing that they will benefit others. Sharing and discussing as a group also fosters a sense of community among graduate students from different academic backgrounds.

Towards the end of the program, we invite all participants to join a synchronous class meeting once more. We use this as an opportunity for participants to share a bit about their growth during this program, reinforce possible connections between peers, and present further possibilities to continue engagement—for example through other programs at Stanford that might be of interest. We have also organized a career panel during one of the classes,
inviting professionals who had attended the same schools as our participants and are currently working in the data science space. Due to the pandemic and available resources, our participants’ experience has been entirely online. We are working to organize an in-person gathering for the conclusion of the program: we are hoping that this would help to establish peer-relationships and create a closer connection with the university environment and learning and research opportunities in similar spaces.

Having described the in class meetings, we now briefly turn our attention to the one-on-one meetings between graduate student mentors and undergraduate participants. These meetings provide participants with individualized mentorship and expose them to work and research in data science. During meetings, participants engage in a mixture of activities: participants and mentors get to know each other and share experiences; participants engage in mini-research projects, often working on-line with the direct support of the mentor; they receive coaching in planning courses of study and advice on navigating internship opportunities and preparing applications; they learn specific data science skills, and the mentors provide support in terms of choosing topics, appropriate materials and some tutoring. We have asked undergraduate participants to estimate the proportion of time they spend on each activity throughout the program. Among the 34 participants who responded to the survey, on average they spent 59% (std. dev of the average is 4%) meeting time on learning specific data science skills, 30% (std. dev is 5%) time on career counseling such as selecting classes, preparing for interviews and applications, 29% time (std. dev is 4%) working on a data science project.

4.3 Program Outcomes

We offered IMDS three times during 2021–2023. A summary of the demographic and education information for participants and mentors during is provided in Figure 2. End of program survey results show that participants are more interested in data science at the end of the program, and mentors are more interested in mentoring and engaging in activities to enhance diversity (Appendix B). For instance, on a Likert scale of -2 to 2 (-2 indicating definitely less interested and 2 indicating definitely more interested), mentees reported an average score of 1.6 in terms of how the program changed their interest in data
science. Mentors reported an average score 1.5 in terms of how the program changed their willingness to engage in activities to enhance diversity in their working environment.

(a) Demographics of IMDS participants. (b) Home programs of IMDS mentors.

Figure 2: Demographic information of Inclusive Mentoring in Data Science participants and degree program of mentors. We use the definition of underrepresented minority groups in science and engineering professions (Blacks or African Americans, Hispanics or Latinos, and American Indians or Alaska Natives) by NCSES. Other minority groups are defined as minority groups defined by NCSES that are not one of the underrepresented minority groups (Native Hawaiians or Other Pacific Islanders, Asians, and individuals reporting more than one race). Mentors come from a wide range of academic programs, including (but not limited to) civil and environmental engineering, economics, computer science, management science and engineering, and earth system science. A mentor is counted once for each time they participated in the program.

5 Discussions

In exit surveys, participants and mentors alike report an overwhelming positive experience in DSSG or IMDS. While we have collected feedback from participants and mentors, we have not run a case-control study, and analysis of the outcomes is additionally complicated by the fact that we are here reporting results of pilot programs, whose structure has evolved over time, in response to the feedback received. In addition, our main goals of long-term involvement in data science and education is impossible to measure in this short time frame. As these programs take a more permanent place in the offerings in our university, it will be possible to engage in more systematic outcome measurements. For the time being, we
offer the following personal reflections on the impact of these programs on our experiences as a faculty member and as a graduate student.

By design, DSSG and IMDS had graduate students and faculty members working side-by-side in the organization and execution of programs in the educational space. This was an energizing and enriching experience, with both groups engaging differently than in the more common roles of instructor and teaching assistant. Graduate students brought to the table a better fluency in the language and expectations of the participants: they enabled us to make more appropriate choices with respect to electronic communication methods, feedback, software, “fun” activities. They also contributed a lot of energy and fearlessness in pursuing projects and opportunities. Faculty made sure that there was a fertile ground to sustain this growth: they were able to estimate and garner the resources needed, to provide a referential framework with which to evaluate efforts and progress, to place the activities in a broader educational context, bring in experts and pointing to methods and research areas. Faculty and graduate students learned together what hardware/software solutions work for collaborative analysis of sensitive datasets, how to use improvisation activities, how to facilitate group dynamics... This enhanced collaboration improved the cohesion between faculty and students in the same department, and increased the agency and confidence of graduate students.

Both DSSG and IMDS augmented the opportunities offered to undergraduates to engage in projects, understand what a career in data science looks like and receive mentorship in this space. While the number of participants has so far been fairly low, there is a considerable ripple effect. Both these programs have served as models for other activities, aiming to reach a larger number of students. The experience in DSSG fueled the introduction of a data science writing class and is serving as a template for research-project base classes. What we have learned with IMDS is being used to design broad mentoring opportunities, supporting in particular first-generation or under represented minority students.

The two programs have also had a spillover effect in the training of graduate students in teaching and inclusivity. Both the Statistics and Biomedical Data Science department have offered additional opportunities for TA training, and developed new outreach initiatives. We are planning to share broadly the materials that we have developed to support
DSSG and IMDS. The Supplementary Material to this report contains the first example: a self-paced training program for DSSG mentors. We plan to provide the guide to DSSG mentors as a resource for onboarding workshops, and work with DSSG mentors to continue developing the guide and expand topics covered.

Working in a university, and having only a finite amount of time and resources, we experience occasionally tensions between what appear to be different goals: educate a new generation, transmitting the knowledge we have and cultivating in them the aspiration to keep increasing it; engage in research, pushing the boundaries of our understanding; deploy this knowledge in practical applications, impacting the society around us. Being involved in these programs was so enjoyable partly because multiple of these goals aligned: we had the opportunity to connect with many different reality on campus, learn, educate, and make an impact—university at its best.

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A  DSSG mentor growth

We surveyed DSSG mentors who participated in the years 2019–2022, asking them how DSSG impacted their skills in teaching, mentoring, project management, leadership and community building. Each question is framed as following: “How does DSSG change your confidence in the following aspects of teaching data science (mentoring/project management/leadership and community building)?” Mentors are asked to rate on a Likert scale (“Much less confidence”, “Somewhat less confident”, “No change”, “Much more confident”, “Somewhat more confident”) with an additional option of “Prefer not to respond”. We code the five options using numeric values (−2, −1, 0, 1, 2). Nine mentors took the survey, and almost all of them responded to all of the questions in the range from 0 to 2. We report the mean and standard deviation of the responses to each aspect in Table 1. We note that the survey was first conducted in June, 2022, which may be a long time away from when some of the mentors participated in DSSG. Nevertheless, the results suggest that DSSG positively impacted mentors’ skills in several dimensions.

B  IMDS program feedback

We surveyed both participants and mentors who participated in IMDS at the end of the program, and we report some survey results in this section. Altogether, 34 out of 57 undergraduate participants in 2021–2023 have responded to the survey. We received 26 survey responses from the graduate student mentors (because the survey is anonymous, if a mentor participated in the program multiple times, then their responses in each year are counted as separate responses). Participants and mentors are asked to rate on a Likert scale (“Definitely less interested”, “Slightly less interested”, “No change”, “Slightly more interested”, “Definitely more interested”) and we code these five options using numeric values (-2, -1, 0, 1, 2). All of participants and mentors rated all of the questions in the range from 0 to 2. We report the mean and standard deviation of the responses to each
Table 1: Mentors’ self-identified growth in various aspects of teaching, mentoring, project management, leadership through the DSSG program. Mentors rated their change of confidence in each category on a Likert scale, where -2 indicates “much less confident”, 0 indicates “No change”, and +2 indicates “Much more confident”. We report the average of mentors’ responses and its standard deviation within the parenthesis.

| Aspects                           | Average |
|-----------------------------------|---------|
| **Teaching Data Science**         |         |
| T1. Assessing my mentee’s prior knowledge and skills in data science. | 1.1 (0.2) |
| T2. Communicating data science topics effectively. | 1.2 (0.3) |
| T3. Employing different teaching strategies (e.g. worked example, peer feedback). | 1.3 (0.2) |
| T4. Encouraging students to reflect on their work. | 0.9 (0.3) |
| **Mentoring**                     |         |
| M1. Connecting with students from diverse backgrounds. | 1.1 (0.3) |
| M2. Cultivating a growth mindset. | 0.9 (0.2) |
| M3. Working with mentees to set academic and professional goals. | 1.3 (0.2) |
| M4. Providing constructive feedback. | 1.0 (0.2) |
| M5. Actively listening to mentees’ feedback and concerns, and incorporating them into my mentoring. | 1.3 (0.3) |
| **Project Management**            |         |
| P1. Gauging the impact of a project. | 1.2 (0.1) |
| P2. Setting goals and milestones for a data science project. | 1.4 (0.2) |
| P3. Communicating progress with participants and community partners. | 1.1 (0.3) |
| **Leadership and community building** |         |
| L1. Facilitating group collaboration. | 1.2 (0.1) |
| L2. Motivating and engaging participants. | 1.0 (0.2) |
| L3. Building a community of data scientists. | 0.8 (0.3) |
aspect in Table 2.

Table 2: Participants and mentors’ feedback at the end of IMDS program. Participants and mentors rated their change of interest in each question on a Likert scale, where -2 indicates “Definitely less interested”, 0 indicates “No change”, and +2 indicates “Definitely more interested”. We report the average of responses and its standard deviation within the parenthesis.

|                        | Questions                                                                 | Participants | Mentors |
|------------------------|---------------------------------------------------------------------------|--------------|---------|
| **Participants**       | P1. How has participating in this experience changed your interest in Data Science? | 1.6 (0.1)    |         |
|                        | P2. How has your experience in this program changed how likely you are to apply for other internships/mentorships? | 1.7 (0.1)    |         |
| **Mentors**            | M1. How has participating in this class changed your interest in mentoring? | 1.4 (0.1)    |         |
|                        | M2. How has participating in this class changed your willingness to engage in activities aimed at increasing diversity in the groups of people with whom you work? | 1.5 (0.1)    |         |

**SUPPLEMENTARY MATERIAL**

**DSSG Activities** Descriptions of activities in the Data Science for Social Good summer program.

“Growing by mentoring: A guide for Data Science for Social Good mentors”

Onboarding material for DSSG mentors about inclusive mentoring, leading an interdisciplinary project team and using active learning strategies.
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