ASEE 2022 ANNUAL CONFERENCE
Excellence Through Diversity
MINNEAPOLIS, MINNESOTA, JUNE 26TH-29TH, 2022
Paper ID #37027

An Overview of the Multi-Disciplinary Data Science (MDaS) S-STEM Scholarship Program

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Abstract

This paper provides an overview of the MDaS S-STEM scholarship program. With the growing need for professionals with technology and critical thinking skills related to data analysis, the MDaS program employs established recruitment and retention activities for undergraduates in STEM fields, to encourage consideration of careers in data science related fields. The purpose of the program is to provide financial and professional support to low-income and underrepresented STEM students to improve their chances of completing degrees related to data science. This paper presents the motivation for the program, its goals, structure, research questions, and the design and implementation of its bootcamp cohort building component for engaging students. The results and experiences related to its first year of operation are presented.

Introduction

The primary goal of the MDaS program is to help low-income students be better prepared and excel in multidisciplinary STEM degrees in emerging data science and other related areas, which can equip them with highly marketable data science skills that can increase both their market competitiveness, chance of employability and their starting salary potential. While MDaS will be open to all STEM-related majors, preference will be given to students majoring in Data Science, Industrial Engineering, Computer Science and Computer Engineering, and Mathematics with a specialization in Statistics.

The demand for STEM-trained professionals with data science skills is booming. STEM-related companies recognize that firms with effective data science capabilities have a significant market advantage. The ability to draw insight from enormous volumes of data helps these companies make effective, time-critical decisions. STEM graduates who can independently apply their critical content knowledge using data analytic models can better identify developmental efficiencies or market advantages. Such insight is fueling a growing demand for STEM graduates with data science training, regardless of their primary discipline. Recently, data science, considered to be a multidisciplinary STEM-related field, was identified by the Association for Computing Machinery (ACM), the Institute of Electrical and Electronics Engineers (IEEE), and the Institute for Operations Research and the Management Sciences (INFORMS) as one of the top degrees needed for the next decade. As STEM innovation is increasingly driven by data science, training STEM students in data science is critical to keeping our nation's STEM industries globally competitive. For example, in the field of industrial engineering the capture and processing of data from operational processes has become a key differentiator for industries employing industrial engineers. Sackey and Bester [1] indicate that standard industrial engineering functions are being reduced or transformed by the emphasis on data within the Industry 4.0 initiative and that there is a shift to analytics and cyber-physical systems (e.g. digital twin technologies). Thus, industrial engineers need to be better prepared within this changing landscape.

In the next section, we present some background on data science and other similar scholarship programs to inform the reader of prior work in this area and show similarities and contrasts between other approaches and the program discussed within this paper. Then, we provide an overview of the background that motivated the development of the program and a description of the program as it now exists. Then, because the program is in its first year of operation, we summarize the current state of the program and make some suggestions about the future of the program.

Background and Literature Review

The current literature suggests that there is a gap between the STEM persistence of underrepresented and low-income students and their counterparts [2], [3]. There are multiple factors that may contribute to this existing gap. College academic preparation, family income level and socioeconomic resources, sociological factors related to race and ethnicity, and integration into formal and informal academic/social environments present some of the challenges to achieving higher persistence in STEM fields [3], [4]. In terms of socioeconomic status, students increase their probability of earning a STEM degree by 4.12% per one standard deviation increase in their socioeconomic status [3]. Conditioned on students who did not receive Pell grants, low-income students have a higher probability of dropping out than middle-income students [5]. Inadequacy of aid also contributes to student drop-out rates [5], [6], [7]. Although loans and work-study aid are associated with lowering drop-out rates, grant and scholarship funds were found to have the most positive effect on student retention [8]. The current research also suggests that academic preparations, and specifically, enrollment in calculus during a student's first year of college showed a higher persistence in STEM [5], [9].

MDaS is categorized as a STEM intervention program. As such, it is important to also survey existing literature conducting research on the effectiveness of STEM intervention programs. A common characteristic of STEM intervention programs is that it provides financial support, research experience, and faculty and/or peer-to-peer mentorship to participating students. Mentorship (faculty and/or peer-to-peer) was cited as contributing positively to URM undergraduates' "self-efficacy, identity, and values." Specifically, science identity and values uniquely predicted persistence in STEM careers "up to four years after graduation [10]." Furthermore, there is a precedent of successful STEM intervention programs demonstrating an increase in persistence in STEM for URM and low-income students. These programs [9], [11], [12], [13] showed that students who have participated in STEM intervention programs had a higher probability of completing STEM programs than non-participants.

Program Overview and Description

In this section, we present some background on the development of the program and the key components of the program. In the following section, we discuss in detail the main educational component of the program.

The four main objectives of the MDaS program include:

- Provide *scholarships* to STEM students interested in careers that utilize data science, especially students in low-income and underrepresented groups;

- Expand STEM majors' *appreciation and awareness* for the necessity of data science to their fields and how these skills can provide a competitive edge in STEM careers and advanced study;
- Collaborate with local companies to integrate industry *mentoring and career development* opportunities (industry-based in-residence research, internships) into the data science curricular training/experience; and
- Develop a STEM-based multidisciplinary *data science training/experience* for undergraduates constructed using a collaborative and integrated learning community designed to support the specific needs of low-income and underrepresented student groups.

First and foremost, MDaS is a scholarship program. *Scholarships* have a well-known impact on student retention and secondary impacts on creating interest and awareness. Even with financial aid and scholarships, many low-income students cannot attend college because the remaining 'uncovered' college costs are too great. Insufficient financial aid has been shown to be the primary factor contributing to attrition. Research finds that among financial aid options, grant and scholarship funds have the most positive effect on student retention relative to loans or work- study. Comprehensive financial support is critical as these financially vulnerable students will not have to work external jobs or accept counterproductive financial aid for their college expenses and therefore can focus on their studies. The MDaS team carefully weighed two conflicting concerns: should the program maximize the number of students aided (although scholarship amount would be reduced), or should the program maximize the scholarship amount (although fewer students would be assisted)? It was decided that targeting 29 students for MDaS scholarships would maximize the program's benefits because it maximizes the number of students who receive data analytic training while providing sufficient support to cover the total student educational costs, not already covered by other non- MDaS scholarships and/or federal grants.

MDaS covers 29 students up to a maximum of $7,400 per year for up to 6 semesters. All MDaS scholars must have financial needs as determined by the FAFSA and must apply for all scholarships and aid available to them to minimize the size of individual MDaS scholarships. While the actual MDaS scholarship amount will vary depending on each student's non-MDaS funding, the total financial package for almost all students should fully cover tuition, fees, room, and board. Students must remain in good academic (and MDaS) standing to receive funding. MDaS assumes relatively high retention rates given that MDaS students will be engaged in all program activities and the small cohort sizes will allow for peer-to-peer and student-to-faculty interaction. The MDaS program assumes a 2nd to 3rd year retention rate of 78%, and a 3rd to 4th year retention rate of 92%. If attrition exceeds this predicted rate, MDaS funds will be used to support additional students in the last cohort of the program. Students that receive MDaS scholarship funds are required to participate in program enrichment activities that are designed to achieve the other, previously mentioned, programmatic objectives.

To increase student *appreciation and awareness* of the role and necessity of data science skills, the MDaS program has developed enrichment activities. First, the data science bootcamp experience immerses students in the methods used within data science. Further details of this enrichment activity are provided in the next section. Secondly, students will interact with likeminded industry and academic scholars, through a data science speaker series. The data science speaker series is hosted during the academic year. The series provides students and faculty with a better understanding of data science, especially from an industry perspective. Business and industry leaders share their experiences, concerns, and future analytics objectives, while also sharing insight regarding the future job market within their industries. The speaker series provides MDAS students an important opportunity to develop industry contacts, critical to their professional development.

The MDaS program also fosters *mentoring and career development* through its enrichment activities. This program has developed a mentoring program between students, faculty, and industry partners. Mentoring activities include engagement with data science faculty on career and research opportunities. In addition, peer mentoring circles have been established to engage students with industry partners. Finally, student-to-student peer interaction is fostered between the cohorts within social settings.

The MDaS program enrichment activities, many adapted from current campus activities, are based firmly on empirical evidence, having been shown to increase retention and graduation rates for low-income and other underrepresented students. Key areas that inform the MDaS design include: peer bonding (e.g., social support systems, inclusion activities), academic support systems (e.g., learning communities, tutoring, mentoring), professional advising, and financial support (to decrease the need for concurrent employment and to increase participation in unpaid internships, research opportunities, and study abroad programs). The MDaS program incorporates many of these components into an academic and professional program housed within a collaborative learning community, which coordinates academic support, social learning support systems, professional development, and mentoring. In the next section, we discuss the key element used to build the data science learning community between the MDaS scholars: the MDAS Data Science Bootcamp.

The MDaS Data Science Bootcamp

A key component of the MDaS project is the exposure of the student participants to the field of data science and the methods/techniques used within data science. To fulfill this goal, the project has a bootcamp that constitutes a series of units on data science related materials.

The purpose of the MDaS Bootcamp is to provide instruction on data science concepts to students within the MDaS program and to form a cohort of students that share the same experiences, understand each other's goals, and form a learning community during the project. The intention of the peer-to-peer interaction is to form social cohesion between the students and develop a shared purpose. In addition, the bootcamp provides for engagement between the students and the faculty that execute the bootcamp units. The faculty-student engagement has been shown to be a key factor in retention.

The expected outcomes from the MDaS Bootcamp include:

- Students recognize each other and form long-term peer connections.
- Students recognize and become comfortable with project faculty.

- Students can explain the types of work data scientists perform and their potential impact.
- Students can write scripts within Python that enable them to solve basic problems using data science methods.
- Students understand the basics of the relational model and can perform standard SQL DML queries for extracting and manipulating data for future analysis.
- Students can explain the basic principles of regression analysis and apply the principles within the context of a data science problem.
- Students can explain the basic principles of classification and apply the principles within the context of a data science problem.
- Students can explain the basic principles of cluster analysis and apply the principles within the context of a data science problem.

Traditionally computer programming bootcamps are designed as intensive, short-term camps that cover concepts in computing, to prepare participants in new knowledge for job seeking and training[14,15]. However, because the participants in the MDaS program are STEM degree seeking students, who will eventually graduate with a STEM degree, the traditional design of a computer programming bootcamp was changed to a longer-term interaction (over two semesters) of a series of data science workshops. This facilitated two components of the program. First, it provides sustaining, interaction between the program participants, and sustained contact throughout the year between faculty and students. A longer-term interaction was felt to be beneficial in developing a longer-term cohort interaction. As a secondary benefit, short workshops throughout the semester make it easier to schedule the workshops, avoids cost outlays for housing/food for pre-semester activities, and allow for less stress on the participants. Finally, as an added advantage, due to the uncertainty of the COVID pandemic, smaller interactions, over longer periods of time, relieve some of the difficulties of running a bootcamp during challenging and changing COVID educational protocols.

The bootcamp is organized into units. The purpose of each unit is to meet the outcomes of the camp that provides contact between the participants and the project faculty and to provide the students with exposure to common tools used within data science. Flath and Stein [16] suggest such topics as machine learning, unsupervised learning, supervised learning, for a common application toolbox applied to industrial manufacturing contexts. Each unit has a feedback mechanism to gather information from students and allow for improvement. The units have the following topical coverage:

1. Unit 1: Cohort Building and Introduction to Data Science
    a. Group ice breaker
    b. Overview of data science careers and methods
    c. Industry speaker
2. Unit 2: The Role of Databases, Data Extraction and Transformation within Data Science
    a. Database technology and relational modeling
    b. Hands-on building small databases
    c. Introduction to SQL
    d. SQL constructs for data science work
3. Unit 3: A Primer on the use of Python within Data Science

    a. Editing and running python code
    b. Files, reading, and writing
    c. Data frame concepts in Pandas
    d. Visualization and exploratory data analysis
4. Unit 4: A Primer on the use of Regression Analysis within Data Science
    a. What is regression and where does it fit with other data science methods
    b. Mathematical basis for regression analysis
    c. Simple linear regression
    d. Multivariate regression
    e. Applications of regression analysis
5. Unit 5: A Primer on the use of Classification Methods within Data Science
    a. What is classification and where does it fit with other data science methods
    b. Mathematical basis for classification
    c. Simple classification models – decision tree, naïve Bayesian classifier, logistic regression
    d. Advanced classification models – support vector machine and neural networks
    e. Applications of classification
6. Unit 6: A Primer on the use of Cluster Analysis within Data Science
    a. What is cluster analysis and how does it fit with other data science methods?
    b. Mathematical and statistical basis for clustering analysis
    c. Techniques for cluster analysis
    d. Applications of cluster analysis

The purpose of Unit 1 is primarily to build cohesion between the cohort participants. Unit 1 is executed the week before the start of the fall semester. All other units are executed during the semester. Units 2 through Unit 6 of the bootcamp are more traditional in nature, designed as short hands-on workshops, on the topics noted in the list. Units 2 and 3 are executed in the fall semester, and Units 4, 5, and 6 are executed in the spring semester. The time scheduled for each unit is approximately 5 hours. Units 2 and 3 were executed by scheduling two, 2-hour sessions, during the evenings to facilitate student attendance. The units are designed as self-contained learning modules and are led by the faculty involved in the S-STEM grant.

Unit 1 was scheduled prior to the fall semester and consisted of a six-hour event, with learning and socializing, as its key outcomes. At the event, new program participants are informed about how to access the scholarship funds and participation rules are discussed. The main rules include maintaining academic eligibility and attendance at program events. In addition, the participants have the opportunity to meet each other, as well as faculty involved in the program, through a social/lunch setting. Ice breakers and team-building exercises are performed to foster interactions within the group. Finally, an industry speaker discussed their career path involving data science to becoming a senior vice-president at a major retail company. The speaker is also a representative of an underrepresented minority group. The speaker not only informed the participants of innovative applications of data science within their corporation, but also talked about the importance of making a difference in society using the platform obtained from one's work experiences and networking connections. The importance of serving others and making a difference was emphasized in addition to recommendations for progressing in one's career.

Experiences During Year 1

The recruiting of students for the first cohort of the program occurred during the Fall of 2020 and Spring of 2021 semesters. Emails with information about the availability of the program were sent to targeted STEM majors, including first-year engineering students, math/statistics majors, computer science, data science, and business majors interested in data analytics. An information session was held to explain the program to interested students. Applications were accepted from January 1 through February 15 and will reoccur each year of the program. The application process includes an optional letter of recommendation, the student's current resume, and an essay describing 1) why the student is interested in participating, 2) the student's short and long term career goals, and 3) what data science means to them and how it will help them advance in their career.

The first cohort of the MDaS program was recruited during the Spring 2021 semester. In general, the participants' genders were close to being equally split with five males and four females. In terms of races and ethnicities, the majority group is Hispanic and the second highest is White. For their academic majors, three students are in computer science, and one is in computer engineering. The detailed demographic information lists are in Table 1.

Table 1 Demographic for Participants (N = 9)

Measure	Count	%
Gender		
Male	5	55.56
Female	4	44.44
Race		
Asian/Asian American	1	11.11
Black or African American	1	11.11
Hispanic/Latino	4	44.44
White	3	33.33
Major		
Computer Engineering	1	11.11
Computer Science	3	33.33
Data Science & Accounting	1	11.11
Data Science & Computer Science	2	22.22
Mathematics	2	22.22

The remaining five students only have a minor or special concentration in data science: two of them are in computer science and data science, one is in data science and accounting, and two are in mathematics with a statistics concentration and a minor in data analytics. For other personal characteristics, five out of nine MDaS students indicated they are first-generation college students. Six of them are bilingual and seven students live locally with two commuting. There is only one MDaS student who indicated a family member with a job in the data science field.

The first data collection was carried out by an online entrance survey consisting of measures of perceptions about data analytics and psychological attributes. After recruiting the first cohort of MDAS students, they received an invitation email that welcomed them to join this program and were asked to fill out the online survey through the university Qualtrics service. The online survey included instructions to complete the questionnaires, an informed consent form, and 55 items included from eight scales plus 13 items to collect demographic information. Each construct was developed, modified, or adapted from an existing validated scale. All items were on a 5-point Likert-type scale (from 1 = Strongly disagree to 5 = Strongly agree), except the academic self-efficacy scale labeled from 1 = Not at all confidence to 5 = Extremely confidence. This entrance survey for the MDaS student takes 10-15 minutes to complete.

In Table 2, we provide a brief definition for each construct, the number of items associated with the construct, and citations.

Table 2 Entrance Survey Measure Definitions

Construct	**Definition**	**# of Item**
Intrinsic Value	Intrinsic value often results from the enjoyment that a student obtains from an activity [17], [18], [19].	5
Attainment Value	Attainment value is the importance students attach to the task as it relates to the conception of their identity and ideals or their competence in a given domain [20].	5
Utility	Utility value is a measure of perceived usefulness and how the task relates to future goals. While students may not enjoy an activity, they may value a later reward or outcome it produces [20].	4
Expectancy of Success	Expectancy of success refers to the individual's expectation that he or she can succeed at a challenging task, such as majoring in engineering [21].	10
Cost	Cost refers to how the decision to engage in one activity (e.g., doing schoolwork) limits access to other activities (e.g., calling friends), assessments of how much effort will be taken to accomplish the activity, and its emotional cost [19].	6
Ability Beliefs	"Ability beliefs refer to students' perceptions of their ability as a fixed trait that is beyond their control, or as something that can change and grow. When the ability is viewed as fixed, the effort may be seen as futile, and failure as due to a lack of ability." [22]	5
Growth Mindset	One's belief that their basic abilities can be developed [23], [24].	6
Academic Self-Efficacy	Self-evaluation of one's ability and/or chances for success in the academic environment [25].	12

Table 3 provides the preliminary results of the application of the entrance survey to the initial nine participants. While the sample size is clearly low, we can see that there is a slight indication that the participants provided positive and enthusiastic attitudes on learning and gaining more knowledge about data science. Notably, all nine students perceived data science as having great utility (highest mean of 4.56 on 5-point scale; score range of 4.0 to 5.0), with attainment value also presenting with a high average of 4.07. Their expectations at the beginning of the program that data science is important and will be useful to their future success, combined with a belief that they have the ability to attain their goals in this area, provides a promising foundation for their success. Further responses are being collected about each workshop of the bootcamp.

Table 3 Descriptive Statistics for Entrance Survey (N=9)

Scale	**Min**	**Max**	**Mean**	***SD***	**Skewness**	**Kurtosis**
Intrinsic Value	3.40	4.00	3.56	.22	1.289	.770
Attainment Value	3.40	4.40	4.07	.37	-.916	-.636
Utility	4.00	5.00	4.56	.35	-.146	-1.060
Expectancy of Success	3.00	4.30	3.73	.41	-.434	-.019
Cost	2.33	3.67	3.00	.46	-.282	-.514
Ability Beliefs	2.80	4.00	3.51	.35	-.760	1.408
Growth Mindset	2.83	3.67	3.20	.32	.683	-1.385
Academic Self-Efficacy	3.17	5.00	4.07	.59	-.015	-.742

Summary

This paper reports on the initial development of an S-STEM project that prepares STEM (Science, Technology, Engineering, & Mathematics) graduates entering data analytics careers. By targeting low-income and underrepresented students, one of the project goals is to help students develop highly marketable data analytic skills that can increase their market competitiveness as well as starting salary potential. In addition, the project adapts and utilizes several protocols from previous successful recruitment-to-graduation programs that increase students' chances of succeeding in both academics and their careers.

An interesting aspect of this program is the development and use of a data science bootcamp to introduce students with little or no background in the field of data science to important topics in data science and how those topics may be used within their careers. The design of the bootcamp fosters a low-stress, cohort-building approach that includes self-contained learning modules and techniques within data science. A side benefit of this approach is that the learning modules can be used outside of the MDaS program to introduce data science concepts to other disciplines.

The hope is that the MDaS program will improve the likelihood that low-income, underrepresented students will complete their STEM degrees and become competitive in the job market. MDaS will help low-income students from underrepresented populations overcome traditional barriers to entering STEM professions, while building the STEM-based data science talent pool in the State of Arkansas and nearby regions to strengthen the technological and economic development in the region.

Challenges and Lessons Learned in Year One

We have had a number of successes in Year One, including active student engagement in all MDaS activities. However, we have also identified challenges and areas for improvement for the second half of year one and successive years. First, although we have a small cohort of students, their STEM fields and prior data science and programming experience is diverse. This increases the complexity of creating MDaS workshops and selecting content that is applicable to all students. Second, although we have completed six out of approximately twelve activities in year one, the development of an interactive learning community that reaches beyond the MDaS activities is not yet well established. Third, the development of an effective mentoring system that includes both campus and professional community members has been difficult to develop.

The next step planned for addressing the first and second challenges is the integration of more collaborative work on problem-based activities in our spring workshops. Students are currently assisting each other in the learning process during our workshop activities, however we plan to capitalize more on their variation in skill levels by increasing the time spent in co-constructed problem-solving. We believe this additional time in collaborative problem-solving can also facilitate the collaborative learning community we are trying to develop.

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