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Journal of Research in STEM Education

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EDITORIAL

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In this issue of Journal of Research in STEM Education, we present eight articles that came out of an NSF-funded conference that explored three themes in STEM. These themes include: problem solving, equity and computational thinking. This issue was co-edited by Drs. Anna Bargagliotti, Dorothea Herreiner and Jeffrey A. Phillips, the co-organizers of the NSF funded Breaking the Boundaries in STEM Education conference.

In the first article, Bargagliotti and colleagues (2018) present the overall goal of the conference and contributions of the conference to the emerging field of STEM, particularly at the college level. In the second article Berude and colleagues (2018) describe two programs, ACCESS (A Community Committed to Excellence in Scientific Scholarship) and The McNair Scholars Program designed to support underrepresented students in STEM disciplines at Loyola Marymount University (LMU). They provide an overview of each program and detail about components of the programs that have led to success. The third article in this issue is authored by Dekhtyar and Schaffner. Dekhtyar and Schaffner (2018) describe the design of a Cross Disciplinary Minor Program in STEAM that has been implemented at California Polytechnic University.

Consistent with the third theme of the conference, the fourth article by Reinholz et al (2018) focuses on the question of what makes a good disciplinary or interdisciplinary problem. They draw from literature across the STEM disciplines and two conference sessions to provide insight into what makes a good problem within a specific STEM discipline and across the disciplines. The fifth article by Reinholz (2018) explores an important issue, equity during peer conferences. Reinholz provides an analysis of students peer assessment conversations in introductory college calculus using equity as a framework for his analyses. More specifically, it "explores the participation of students in peer assessment conversations , by focusing on the types of feedback and word choices used by different groups of students , by race and gender". In the piece "Reflective Apprenticeship for Teaching and Learning Mathematical Proof", the sixth article of this issue, Reinholz (2018) explores teacher learning in a graduate-level analysis course designed for teachers by drawing from the frameworks of extreme apprenticeship and Peer-Assisted Reflection (PAR). The paper describes how the teachers developed across the four dimensions of extreme apprenticeship. While this paper is grounded in mathematics, implications for teaching and learning in other STEM disciplines are also discussed. Dahlquist et al (2018) make contributions to the ongoing dialogue about integrating computational thinking (CT) into undergraduate curricula in the seventh article of this issue. They provide descriptions of three CT integrated undergraduate courses that have been developed and taught at Harvey Mudd College and Loyola Marymount University. The authors describe the course objectives, implementation challenges, and assessments for each course. In the final article of this issue, Fuqua and colleagues (2018) make an attempt to identify antecedents, processes, and outcomes of an interdisciplinary, collaborative conference and ongoing collaboration that stemmed from the conference by conducting a comparative study of three working groups from the conference using a triangulation of qualitative and quantitative methods.

Collectively, these articles present unique insights into the field of STEM Education and Integration specifically. We hope these articles will engage our community in ongoing discussion around STEM integration at the college level.

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RESEARCH REPORT

Breaking Boundaries: Pressing Issues in Equity, Computing, and Problem-Solving in STEM Undergraduate Education

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Abstract: *The April 2017 National Science Foundation-funded Breaking the Boundaries in STEM Education conference brought together Southern California science, technology, engineering and mathematics (STEM) faculty to explore equity, problem-solving, and computing in an interdisciplinary manner. Two main research questions guided the overall scope of the conference: (1) What are the common threads across disciplines to approach the teaching and learning of skills that are relevant in STEM? (2) What are the challenges and barriers that need to be overcome in order to foster collaboration across disciplines to impact the teaching and learning of skills relevant in STEM? We describe the background of the conference and provide an overview of the questions addressed.*

Keywords: Equity, computing, problem-Solving, STEM

Introduction

On April 7th, 2017 the National Science Foundation-funded Breaking the Boundaries in STEM Education conference (referred to as Breaking Boundaries throughout this paper) was held at Loyola Marymount University (LMU) in Los Angeles, California (NSF grant #1644470). The conference brought together approximately 100 faculty members from the Southern California region interested in transforming classroom practice with Discipline-Based Education Research (DBER) and through the Scholarship of Teaching and Learning (SoTL), with a particular focus on equity, problem-solving, and computing – all pressing issues in STEM education. This special issue of J-STEM is dedicated to presenting results from the conference. We provide a picture of the conference and its organization as well as the themes focused on. We also discuss lessons learned and open questions. This special issue includes papers from some conference attendees related to issues that highlight particular aspects of the themes discussed at Breaking Boundaries.

An important feature of Breaking Boundaries was close attention paid to interdisciplinary collaboration. DBER is fundamentally interdisciplinary in nature as it builds on Education, Cognitive Psychology, and various STEM disciplines (SoTL is often more disciplinary, based on an instructor's own teaching). However, these connections are often within a single STEM discipline, which has resulted in the 2012 National Research Council call for more interdisciplinary studies. Rather than focusing on a topic that is only relevant to a single STEM discipline, researchers can have a greater impact by learning from each other and examining cross-cutting concepts and cognitive processes. Breaking Boundaries aimed to identify similarities and differences of teaching challenges through DBER and SoTL across disciplines for each of the three themes--equity, problem-solving and computing in STEM. All sessions were attended by and had contributions from faculty in a wide variety of STEM disciplines.

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Two main research questions guided the overall scope of the conference:

1. What are the common threads across disciplines to approach the teaching and learning of skills that are relevant in STEM?
2. What are the challenges and barriers that need to be overcome in order to foster collaboration across disciplines to impact the teaching and learning of skills relevant in STEM?

Background: State of DBER and SoTL Research

Discipline-Based Education Research (DBER) integrates the disciplinary knowledge and practices employed by scientists and engineers with research on human learning and cognition to address the needs of STEM education. In the Scholarship of Teaching and Learning (SoTL), instructors systematically investigate student learning and teaching strategies in their own classes in the context of the relevant pedagogical and disciplinary literature. Both, DBER and SoTL investigate instructional strategies, methods, pedagogies, and assessments in the various STEM disciplines with the goal of improving student learning. This improved learning can lead to greater recruitment and retention of students, increased diversity within STEM disciplines, and better preparation of students for STEM careers.

While DBER and SoTL have been effective at improving the learning experiences for many students, much work remains to be done. First, results of past DBER and SoTL projects have yet to be discovered by many STEM faculty so that they can influence the classroom. Adopting and adapting the research findings into widely used classroom practices occurs slowly. If progress is to be made on increasing students' participation, retention, and success in STEM, the number and diversity of institutions and faculty conducting SoTL and DBER research needs to increase.

In the past, widespread dissemination of DBER findings has been challenging. While many DBER-based curricula have been developed and shown to be effective, they are often not widely adopted or, if adopted, they are not implemented with fidelity. Dancy, Henderson, and Turpen (2016) have reported that one of the main challenges in disseminating DBER-based curricula is the desire of faculty to modify the materials. While adaptations are often driven by the desire to tailor the materials to a specific student population, teaching style, or curricular demands, faculty sometimes alter the materials in a manner or to the point of being ineffective since they are often unaware of the essential features of a teaching strategy. On the other hand, teaching strategies are generally only successful if adapted to an instructor's teaching style and well integrated into a course's context. The tension between the narrow implementation of successful teaching strategies and the adaptability to different contexts within and across disciplines is worth further investigation.

A main goal of Breaking Boundaries was to address these challenges of dissemination by having a conference structure that encouraged dialogue and focused on a geographically proximal population of researchers and instructors in order to maximize collaboration and impact (see Fuqua et al., in this special issue for discussion of the conference results). In addition, with the targeted focus on the three themes of equity, computing, and problem-solving, Breaking Boundaries sought to impact timely issues in STEM through DBER and SoTL work.

Many disciplinary conferences either focus entirely on DBER and SoTL, such as the Physics Education Research Conference (PERC) or Research in Undergraduate Mathematics Education (RUME), or include some sessions within a broader conference, such as meetings of the American Association of Physics Teachers or American Society for Engineering Education. While these conferences and sessions offer numerous opportunities for researchers and teachers to communicate, they do not include a diverse set of perspectives and typically only focus on key disciplinary approaches and questions. Researchers from different disciplines, and those within STEM, can add new ideas, experiences, and interpretations of research. Without this interdisciplinary perspective, research projects may not reach their potential or impact a larger community.

Many discipline-based DBER and SoTL research projects focus on or are limited by content

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knowledge. When groups of researchers and teachers from multiple disciplines exchange ideas they can explore commonalities and find common ground on broader issues such as equity, social factors, and skills that are employed by all STEM fields. While disciplinary conferences do sometimes focus on, for instance, affect or cultural aspects of learning (such as PERC 2013 and PERC 2014), the lack of multiple disciplines limits the possible insights and impact of the research.

Multidisciplinary SoTL conferences such as those organized by the International Society for the Scholarship of Teaching & Learning (ISSOTL) or the Lilly Conferences on College Teaching offer the promise of multiple perspectives, however, these often do not include the STEM disciplines to a significant degree. For example, at the 2013 ISSOTL conference, approximately 5% of the presentations were on projects based largely on a STEM discipline. While other presentations, such as those on online learning and writing across the disciplines could have been applicable to STEM researchers and teachers, they generally came from non-STEM disciplines relying on knowledge bases and assumptions that are very different from STEM fields. A clear understanding of the relevance for STEM fields and deep roots in the respective STEM fields are essential for a long-run impact on teaching and learning. Differences in disciplinary backgrounds can open perspectives and inspire new approaches; differences that are too large can inhibit collaboration due a lack of a common language and experiences. By targeting interdisciplinary collaboration in STEM fields, we capitalize on the benefits of differences without making the differences so large that common ground is difficult or impossible to establish.

Similar to the Southern California Project Kaleidoscope (PKAL) Regional Network Annual Meetings, Breaking Boundaries aimed to improve teaching practices in STEM fields through dissemination of existing and generation of new knowledge. The Breaking Boundaries conference purposefully pushed beyond these goals by focusing on interdisciplinary inspiration and collaboration as driving and sustaining forces for the generation of new research projects. By rooting the conference in challenges experienced and approaches used by participants in their classrooms, supplemented with key presentations about methods, results, and opportunities for research and development, the conference created an environment where participants could explore options of learning from each other. The goal of the conference was to create an experience that would plant and develop the seeds for future explorations and collaborations.

Background: Three Important Areas in STEM Education

The three themes of equity, problem-solving, and computing served as the guiding framework for the conference. All three are pressing issues in STEM education that can be and have been studied through DBER and SoTL research.

Equity in STEM Education

The public and expert debate about education and also, specifically, higher education has been dominated by the concern about underrepresentation of minorities and women in STEM fields (worse in certain disciplines than others; NSF 2015) and the need for more graduates in those fields (or with those skills). Such underrepresentation has been shown to often be self-perpetuating due to the absence of role models and frequent explicit and implicit biases resulting in the so-called leaky pipeline in academia (Allen-Ramdial & Campbell, 2014). The issue of diversity in the STEM classroom has garnered much attention due to the recent US Supreme Court discussion and subsequent statement by the President of the American Physical Society (https://www.aps.org/about/governance/letters/scotus.cfm); nevertheless, it remains an open question for some why diversity would be needed in STEM classes. In addition, the lack of diversity has also been a topic within the Black Lives Matter and other social movements. Not only is diversity generally seen as having educational value in itself (although this is controversial in several ways), enrolling, supporting, and retaining students from underrepresented groups in STEM fields is a key mandate of fairness and also efficiency.

Evidence from learning theory and psychological studies has shown that small interventions in areas such as stereotype threat (Spencer, Logel, & Davies, 2016) or mindset (Dweck 2006) can often make a significant difference in self-image, sense of belonging, study strategies, success, and therefore retention in

STEM fields with particular relevance for underrepresented students. Much evidence also exists that effective teaching strategies, such as active learning (Freeman et al., 2014), or regular testing (Roediger & Karpicke, 2006) can significantly affect student learning, success, and retention. So far, there is little wider-scale evidence of successful implementation of these and other strategies that enhance student learning for STEM fields. Additionally, there is even less systematic and cross-disciplinary evidence about which teaching strategies support underrepresented students and create more equity of learning conditions. Under the theme of Equity in STEM Education, the field must open the window to implementation studies across different disciplines, courses, and institutions and facilitate a deep exploration of equity dimensions in teaching. The Equity in STEM Education sessions at Breaking Boundaries focused on better understanding of equity issues and integration of promising strategies into teaching across the STEM disciplines.

Problem-Solving in STEM Education

In the workplace, employees often are asked to solve problems in the midst of changing conditions and goals. Because of this need for independent thinking, problem-solving skills are seen as essential learning outcomes for all college graduates (AAC&U, 2007). In the STEM disciplines, problem-solving is one of the most widely used workplace skills and listed by many professional societies as a desired student proficiency (ABET, 2014; ACS Committee on Professional Training; AIP, 2015; Zorn, 2015). In some STEM fields (such as Physics), problem-solving strategies have been heavily investigated, whereas in others (such as Economics) little work has been done, although the quantitative and qualitative nature of the course content often is similar. This allows for many opportunities to learn from each other and to further explore nuances of problems and problem-solving skills.

While employers rate problem-solving and critical thinking among the top five “very important” skills for job success, only 28% classify college graduates’ problem-solving skills as excellent (Casner-Lotto & Barrington, 2006). Another recent survey among 400 employers told a similar story, indicating that only 24% of recent college graduates were well-prepared to engage in analyzing and solving complex problems (Hart Research Associates, 2015). Other surveys similarly describe the need for improved problem-solving instruction, reporting that 64% and 82% of employers desire a greater emphasis on complex problem-solving in college (AAC&U, 2007; Hart, 2013).

From this environment of a weaker-than-desired-problem-solving proficiency emerges the need for curricula that foster improved problem-solving skills among STEM students. To develop them, researchers will need a better understanding of the problem-solving process itself as well as tools to assess it. The Problem-Solving in STEM Education sessions at Breaking Boundaries focused on better understanding of problem-solving across the STEM disciplines.

Computing in STEM Education

The International Society for Technology in Education (ISTE) and the Computer Science Teachers Association (CSTA) define computational thinking as a problem-solving process that includes (but is not limited to) the following characteristics:

1. Formulating problems in a way that enables us to use a computer and other tools to help solve them;
2. Logically organizing and analyzing data;
3. Representing data through abstractions such as models and simulations;
4. Automating solutions through algorithmic thinking (a series of ordered steps);
5. Identifying, analyzing, and implementing possible solutions with the goal of achieving the most efficient and effective combination of steps and resources;
6. Generalizing and transferring this problem-solving process to a wide variety of problems. (CSTA & ISTE, 2011)

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The characteristics described in this definition of computational thinking resonate with modern societal needs for STEM graduates. Wing (2006) and the National Academies Workshops on Computational Thinking reports (National Academies 2010, National Academies 2011) provide strong arguments for viewing computational thinking as essential to STEM. They describe how computational thinking allows one to choose appropriate modeling processes for a problem and use relevant aspects of a problem in order to make it tractable. Through the National Academies workshops, the collective work of over two dozen researchers in computer, information, and cognitive science supports that computational thinking skills enhance human problem-solving abilities. This occurs by extending the complexity and informational detail that can be identified when well-trained scientists employ methods of computation to solve problems involving rich and detailed data representations. The necessity for computational thinking has garnered national attention. For example, then President Obama set a goal to bring computer science to all students (https://www.whitehouse.gov/blog/2016/01/30/computer-science-all) and introduced an initiative aimed at increasing computational-thinking skills in schools (e.g., CS 10 Initiative at https://cs10kcommunity.org/).

While there has been a push to increase computational thinking, particularly for STEM students, many open questions exist about how to promote and integrate this type of thinking into the undergraduate curriculum, especially when introducing novice students to computational thinking. Of particular interest at Breaking Boundaries, was the differing degree to which computational approaches have been integrated into the curriculum of different disciplines allowing for interesting comparative approaches. The focus of this theme of the conference was to understand what role computing, coding, and general computational thinking as a problem-solving process plays in the STEM classroom across disciplines.

Breaking Boundaries Conference Structure

For each theme, a parallel schedule was created which included a contributed paper session, a working group breakout session, and a workshop for each. In addition, plenary speakers were scheduled for the entire group to start off the conference, after lunch, and at the end of the day. The following sections focus on reporting what happened in each theme throughout the day.

Theme 1: Equity in STEM Education

The conference started with Dr. Susan Singer from Rollins College giving a plenary presentation in which she described the inequities in access, persistence, and graduation in STEM education. Although there have been gains across all groups, young people with low socioeconomic status have had the smallest gains in degree attainment over the last fifty years. While more education leads to higher salaries, women need a much higher degree to make what a man with a lower education level achieves (see Carnevale and coauthors in different studies, such as the 2011 Georgetown University report). Minorities are also typically less enrolled in majors that yield high-paying jobs. Ample opportunity exists in the STEM fields and it will increase in the coming years. Although, interest in STEM fields has also been increasing, success rates are very uneven, leaving much talent out. This has consequences for economic growth and is a key question of social justice. Dr. Singer shared data that show the stark racial differences for STEM completion rates. Understanding the causes and providing appropriate support structure to address differing needs is key. According to Dr. Singer, if we want all of our students to be able to succeed, we need to address these issues.

As Dr. Singer made clear, what we can influence, and where our responsibilities lie, is the quality of our teaching as this attracts students into the STEM fields and allows them to succeed. She made reference to the 1997 study by Elaine Seymore and Nancy Hewitt, Talking about Leaving: Why Undergraduates Leave the Sciences, that showed that the overarching reason for students leaving STEM fields is poor instruction. Relying on Freeman et al.'s 2014 meta-study on active learning, Dr. Singer discussed the ample evidence that active learning is generally much more effective in increasing student learning and providing students with a better gauge of their understanding. Yet, we lack a robust understanding of high-quality learning environments and a consistent awareness of such resources and findings. Based on Bryk et al.'s 2015 study Learning to Improve: How America's Schools Can Get Better at Getting Better, Dr. Singer mentioned the need to change the research paradigm that supports teaching practices by bringing researchers and practitioners together. She also spoke to the need and some recent conferences that are bringing neuroscientists and STEM instructors together, so that they can jointly explore how to apply cognitive principles to courses in STEM fields at different levels. Such collaborations are essential for a better understanding of effective teaching practices as implementation details can make a significant difference in their success.

Dr. Singer mentioned the recent emergence of the student success movement that often is somewhat disconnected from the academic experience and would need to be more systematically integrated with research on classroom practices. For work in this and other areas to be successful, reliable, and meaningful metrics and a broadening of the criteria considered are needed. We have to understand how apparently teaching-unrelated aspects such as financial, cultural and emotional issues influence classroom performance and degree completion. We need to extend our analysis and the implementation to the systemic level, in particular, at the institutional level and within professional societies. (See Eubanks-Turner et al. in this special issue for a discussion about successful institutional programs that promote equity.) We need to work on all these levels, from the individual classroom to the larger disciplinary and institutional levels, from research to practice, to achieve the changes and improvements that are needed for equitable access to educational opportunities and achievements.

The Breaking Boundaries conference focused specifically on what makes an equitable classroom in the STEM disciplines and how equity can be fostered through access, diversity, learning, and content in the class. Dr. Coleen Lewis from Harvey Mudd Computer Science Department opened up the equity sessions with a two-hour workshop discussing teaching tips for creating equitable classrooms. In one activity, Dr. Lewis provided participants common teaching problems and asked groups to come up with solutions. Results from that activity indicated that helpful tips for creating equity in a STEM classroom might include strategies such as: making learning goals explicit; emailing students with low grades to let them know the instructor cares and believes in them; scheduling breaks in class; embracing instructor mistakes; giving worked examples that unpack the thought process; and being explicit about teaching and student expectations. During another activity, workshop participants were given typical equity-related comments, such as: "Women are great collaborators" or "We want diversity, but don't want to water down the content." Participants noted the emotional impact of such comments and came up with responses and considered their effectiveness. Overall, the workshop provided an opportunity for faculty to think through some of their own biases and gave space for participants to suggest solutions that could be effective.

The lunchtime plenary speaker, Dr. John Brooks Slaughter, spoke about STEM education needs to bridge ideas, disciplines, and societal issues. He stated: "Those of us engaged in STEM must be today's Medici, thinking at the junction of ideas, concepts, and cultures—historically an uncomfortable place to reside."

Dr. Slaughter shared his experiences of relating STEM and equity in an ever more connected world. Alluding to the globalized society we live in, Slaughter made a plea that STEM education should focus on teaching the habits of mind of creativity, teamwork, optimism in problem-solving and design, systems thinking, and ethical considerations. These skills certainly reach across many subjects and grade levels. Slaughter's focus offered a broad approach to inclusiveness; when discussing the disciplines, he emphasized breaking down the barriers between the different silos and when discussing student learning, he emphasized the importance of being exposed to different cultures, different interests, and different points of view. In particular, he discussed bridging the humanities and the sciences. In STEM fields, we often focus too much on skills that are typical for our fields. Instead, Slaughter said: "Simply stated, our graduates should not only achieve mastery of the skills and techniques of the math, science, or engineering courses they study but they must also obtain an appreciation for accompanying human concerns and societal issues." Dr. Slaughter strongly promoted convergence (collaboration) as a way to increase access into STEM fields.

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As the contributions to the equity theme illustrated, STEM faculty want to create equitable classrooms. At the undergraduate level, it is important for faculty to understand the key role they play in making their classrooms and the learning that occurs there inclusive. This topic is often easy to ignore when focusing on learning abstract and technical concepts. Inclusivity is typically not addressed in PhD programs and other faculty development programs. The "burden" of achieving equitable classrooms typically is on individual faculty members who often are ill-prepared for the task. Continuous reflection on teaching practices and outcomes and the willingness to adapt teaching strategies are necessary to advance a more equitable learning experience.

Theme 2: Problem Solving in STEM Education

To start the problem-solving theme conversation, Dr. David Quarfoot (Department of Mathematics at UC San Diego) led a workshop that guided participants through the analysis of what constitutes a problem. He discussed the components that make up the problems we consider and assign in STEM fields, how different aspects of problems facilitate learning problem-solving skills, what educators value in problems, and how that differs across disciplines. By focusing on problem features, Dr. Quarfoot suggested that instructors can move from "What are the good problems?" to the more productive and specific question "What features do I want problems to have so as to further my goals?" Dr. Quarfoot defined problem features as "some dimension along which a problem may be analyzed to better understand the process of problem-solving," i.e. for him, features of problems are directly tied to the problem-solving process. He distinguished between cognitive/metacognitive and affective/belief-/society-based features, such as number of entry and exit points or cognitive engagement in the former case and such as degree of encouragement and elegance in the latter case. During the discussion among participants, it became apparent that disciplines put different weights on the problem features suggested, some being closely tied to the nature of the discipline whereas others seemed to be more tied to disciplinary convention – both offering opportunities to learn across disciplines. Dr. Quarfoot also presented results of a project in which he is measuring the presence of various problem features, the relationship between them, and the extent to which experts agree on problem features.

The presentations and discussion throughout the day built on the above understanding of problem features by looking at how students, and instructors, interact with problems (see Reinholz et al. in this special issue for a discussion of good problems across disciplines). One common topic was the role of feedback for learning problem-solving skills – the internal or metacognitive feedback by solvers themselves and external feedback provided by computer systems, coaches, and peers (see Reinholz's discussions in this Special Issue about peer review for students and future instructors). Coaches (instructors) need to provide not only feedback during the problem-solving process, but also scaffolding prior to the attempted solution. An underlying common thread of all presentations, including those on different kinds of active learning strategies related to problem-solving, was the need for careful and purposeful design, sequencing, and scaffolding of problems and problem-solving activities in a course. Not only do we need a more metacognitive approach for students to help them learn problem-solving skills, we need a more metacognitive approach for instructors designing courses and problems. This starts with choosing problems that have features that support good problem-solving practices and then includes providing structured environments in which students receive the necessary heuristics.

With participants from very different disciplines, it was interesting to see that there are many commonalities among the problems we use and, yet, there are also many differences. The problem-solving theme provided much input for a more in-depth conversation about the nature, function, and use of problems in different STEM fields. Quarfoot's list of problem features provides a framework for such a conversation; for an interdisciplinary approach, consider the role of the four dimensions suggested in the Reinholz et al paper in this Special Issue about good problems. The interdisciplinary conversation was productive and inspiring and made clear how much need there is for a continuation of the interdisciplinary conversation and hands-on development of problems.

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Theme 3: Computational Thinking in STEM Education

The morning workshop was delivered by Dr. Leo Porter from the Computer Science Department at UC San Diego. Dr. Porter's workshop touched on what it means to have "CS for all," how student misconceptions can be utilized when analyzing others' code, and how we can focus on communication in coding. Computer science is experiencing an increasing demand in most universities, so much so, that students' access to the major is restricted due to resource issues. These days, some students are entering their undergraduate work with coding experience from high school. With limited available spots in computer science majors, Dr. Porter pointed out that we need to be thoughtful about ensuring access for all, in particular, if some students are fortunate enough to come with prior knowledge and experience in coding.

In all STEM majors, some degree of coding has become required. This means that faculty in the various STEM disciplines are employing computing in many of their own classrooms. This could be simply in a point-and-click software platform, often as a means to an end (as, for instance, in many statistics packages) or it could be as complex as actually teaching some aspects of coding (see Libeskind-Hadas et al. in this special issue for presentation of different disciplinary courses that integrate computing into the course in a seamless fashion). Although STEM faculty are often sufficiently proficient coders (or users of a specific software package), in general, they do not have the depth of knowledge needed to teach students coding and computational thinking. To illustrate this shortcoming, Dr. Porter provided slightly different lines of Python code and had the participants decipher what each did. Deciphering the code proved challenging to all faculty in the room. This was because each of the lines of code targeted a particularly common misconception known in the CS education literature. This workshop highlighted the need for STEM faculty to work collaboratively with CS education faculty in order to effectively include coding and computational thinking in non-CS STEM classes.

The dinner plenary speaker, Dr. Rob Gould from the UCLA Department of Statistics, gave a thought-provoking presentation on data science. The premise was that in our current society we are surrounded by data and that instructors and institutions need to do more to develop a data-literate society. All citizens need the necessary skills to identify, collect, evaluate, analyze, present, and protect data. These are skills that can and should be integrated in the entire K-16 curriculum. Modern data is often comprised of a number of variable types (numerical as well as text or images, etc.), "big" data, and a complex structure with nested variables that require a database, rather than flat spreadsheet, structure. These realities of real-world data are often not reflected in curricular structures and assessments. The examples used in classroom teaching are often rather simplified applications that can easily be distilled down to a single spreadsheet rather than the more complex real-world data that students and citizens encounter in their lives. While it is difficult, it is important for our students to learn how to ask the right questions about data and draw valid conclusions from complex data.

While real data can be complex and difficult to work with, there are an increasing number of sources and tools that are available to teachers and students. Dr. Gould presented several examples of projects that are rooted in real data. One is the Mobilize Project, in which LAUSD and UCLA are collaborating to use students as sensors. Unlike "citizen science" efforts, this "participatory sensing" project is one where those collecting the data also do the analysis. In addition to collecting and analyzing the data, students and teachers engage in conversations about privacy and ownership. DataFest is an annual competition hosted by UCLA and sponsored by the American Statistical Association. In this multi-day competition, or data hackathon, undergraduate students analyze real datasets that have been provided by large corporations.

Dr. Gould pointed out that there is more work to be done. For example, researchers still have much to learn about how students perceive "data," what heuristics they use when making predictions, and the misconceptions they have when working with data. There is a need for more tools that allow students to find and analyze complex data. Most importantly, given the changes that CCSS has brought to the K12 classroom, there is a need for data literate teachers, who can also address the social issues often found within real world data.

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Overall, the computing sessions had several main ideas that consistently surfaced throughout the day. The main points that was that in order to fully integrate computing into STEM education there must be a real commitment from faculty and institutions to do so. In a sense, many STEM faculty are teaching outside their discipline when they are teaching coding and computational thinking. To approach this in a healthy way, faculty can make clear what they are trying to accomplish with code and illustrate how we would sift through code in attempting to get it to work. This process in itself would help students see the struggle. Ultimately to integrate computational thinking, however, it was proposed that team-teaching with CS education faculty would help other STEM faculty incorporate computing into their own courses. This would help STEM faculty be aware of potential student pitfalls and misconceptions. CS education faculty is greatly needed at institutions to lead efforts in integrating computational thinking through coding in STEM classes (see Schaffner & Dekhtyar article in this special issue for discussion on garnering institutional support for computational thinking).

Conclusions

In all of the theme sessions it was apparent that for STEM education to improve, it will take an interdisciplinary, if not transdisciplinary approach. Most faculty are not sufficiently trained to address the complex issues of equity, problem-solving, and computational thinking in the STEM classroom; much has entered the different disciplines in a piecemeal and almost ad-hoc fashion and is overdue for a more systematic exploration within and across disciplines. Equity and inclusivity are generally not components of a graduate student's education. STEM faculty are experts in their disciplinary content and methods, but rarely in the sociology of their scientific community. Similarly, while STEM faculty are generally very good problem-solvers or coders, they have not been educated in how to unpack these large skill sets for students as much of their own learning happened by doing and in an unstructured fashion. Studying the role of metacognition in problem-solving or common misconceptions in computational thinking is key for aiding students, in particular, those that come equipped with fewer skills, support, or confidence but no less ability. By having conversations across the disciplines, especially the social sciences, STEM faculty may be able to make advances in research on equity, problem-solving and computational thinking. Such progress can help to increase the number and diversity of students in STEM pathways and improve students' skill sets that can be utilized in all STEM disciplines and careers.

Such conversations between individuals in different fields have to be slow and in-depth as there are many challenges to productive interdisciplinary or transdisciplinary collaborations. At the conference, we barely managed to touch upon issues and be inspired to ask more questions and follow up. While the atmosphere for the day provided ample opportunity for participation, it still was challenging to promote interaction of faculty beyond the day of the conference. Our finding was that the workshops and the working groups were perhaps the most important in stimulating conversation, while the paper sessions offered a good way to present a variety of ideas. Because of the variety, however, it was challenging to solidify emerging themes. In addition, the teaching, research, and administrative realities on the ground make such conversations difficult, if not impossible, to sustain beyond the Breaking Boundaries conference, unless there are solid institutional structures that provide time, support, and recognition within and beyond institution. We encourage those embarking on DBER and SoTL work to foster their interdisciplinary connections both within and outside their own institution (see Fuqua's discussion in this Special Issue on how to achieve this).

The questions raised and the opportunities that emerged did provide an incentive to pursue the emerging collaborations further. Having excellent speakers and a program that provided a variety of opportunities for people to engage and interact was essential for the success of the conference. To push the three themes and STEM faculty engagement in them will require conferences like Breaking Boundaries, where instructors from different fields and with different backgrounds get together and are intrigued and inspired by what they hear from others, but it will also take hands-on workshops where participants can engage in more in-depth conversations and the comparison, learning, and development of new pedagogical approaches.

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In the meantime, we rely on faculty who are "change agents" to be catalysts for DBER and SoTL collaborations and to analyze and disseminate new results about effective teaching strategies. We also rely on conferences such as Breaking Boundaries, to bring faculty together and expose them to key ideas and kindle the flame of interest in such questions. Having a truly interdisciplinary organizing team of individuals familiar with research-based instructional strategies is an important consideration when planning conferences of this type. The emergence of the DBER Alliance, https://www.aau.edu/sites/default/files/STEM%20Initiative%20Images/STEM%20PDFS/17-043%20AAAS%20STEMDBERAllianceflyer_rnd3.pdf, an interdisciplinary group focused on promoting DBER work across the disciplines, for example, can provide a platform for further work in this area. From a regional perspective, a conference like Breaking Boundaries offered an effective way to identify nearby people who are interested in similar work. Such a conference connects faculty across the disciplines who would not regularly communicate as they tend to do within their own disciplinary silos.

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RESEARCH REPORT

A Tale of Two Programs: Broadening Participation of Underrepresented Students in STEM at Loyola Marymount University

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Abstract: *This paper highlights two programs that successfully support underrepresented students in STEM disciplines at Loyola Marymount University (LMU). ACCESS (A Community Committed to Excellence in Scientific Scholarship) is a program that focuses on academics and critical thinking skills, which provides a three-week residential component for incoming students and continued mentoring during their first year in college. The LMU McNair Scholars Program is one of over 150 McNair Scholars Program sites federally-funded by the U.S. Department of Education and has the overarching goal of increasing number of graduate degrees awarded to students from underrepresented segments of society. For both ACCESS and McNair, we give an overview of each program and detail about components of the programs that have led to success. In addition, we specifically address the rewards and challenges when providing mentorship at multiple levels.*

Keywords: Underrepresented students, mentoring, broadening participation, undergraduate research, first-generation students

Introduction

A number of studies have focused on the pipeline into the sciences, as well as factors related to attrition and persistence of students from traditionally underrepresented groups in STEM fields (NAP, 2011; Chubin et al. 2009; Herzig, 2004). Some research suggests that non-cognitive or social-psychological factors impact selection of and persistence in STEM majors along with other demographic factors, particularly for students from underrepresented groups, that is, students of color, first-generation, and low-income students. The first year of college is critical to student success because it sets the stage for the remaining undergraduate experiences (Nora, 2001). Furthermore, underrepresented students may experience differing racial dynamics within college environments (Chang et al., 2006; Steele and Aronson, 1998). Chang et al. (2006) found that Black students at predominantly white dominant institutions often feel anxiety and fear at being the only one or one of a few African Americans in a particular environment. This anxiety can lead African Americans to seek support through increased contact with other African Americans. The first level of help students use is their peers, and students may be without an appropriate peer community due to a lack of critical mass. Research on school cultures has identified school belonging or connectedness as an important factor in students' achievement motivation (Anderman & Freeman, 2004). Students need to feel that they are cared about and meaningfully connected to a group; lack of such a sense of belonging has been linked with dropout (Ianni & Orr, 1996). Tinto (1997) studied the influence of a learning community on student persistence and determined that a small support community of peers can have a positive effect on students.

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Individuals with high self-efficacy have been shown to exert more effort in the face of difficulty and to persist longer. Huang et al. (2000) found that high self-confidence and high aspirations for degree attainment were significant in predicting degree completion. Furthermore, high self-confidence and degree aspiration decreased the effect of family financial support and level of parental education on degree completion (Huang et al., 2000).

In this article we feature two programs that have been successful at supporting students from underrepresented groups at Loyola Marymount University (LMU): The ACCESS (A Community Committed to Excellence in Scientific Scholarship) program, which is a program for underrepresented first-year STEM majors who enter LMU's College of Science and Engineering and the LMU McNair Scholars Program, which is a mentoring program for continuing LMU students who are underrepresented in STEM. We will give pertinent background about these programs and discuss components of both programs that have led to successful implementation. We will also mention evidence of successes in each of the programs.

The ACCESS Program

The ACCESS program is a year-long experience for first-year students in the Seaver College of Science and Engineering at LMU. Selected students participate in an intense three-week summer program before the beginning of the fall semester and receive continued advising and mentoring throughout their freshman year at LMU. The program aims to prepare students for academic excellence through collaborative engagement in scientific scholarship. Through participation in the summer program and activities throughout their freshman year, ACCESS students live by the program motto "You are no longer responsible solely for your own success, but for the success of your peers as well."

The intent is to help students (1) increase confidence in math and science, (2) increase college preparedness and a sense of belonging, (3) demonstrate pro-social skills in scientific scholarship, and (4) remain and (5) excel in the sciences and potential ways to better support students throughout the college year in hopes of encouraging them to persist in STEM careers.

The goals and objectives of ACCESS include the following:

- 95% of ACCESS Scholars will be retained into their sophomore year
- ACCESS Scholars will achieve an overall first term GPA of 3.2 or higher
- 50% of ACCESS Scholars will participate in funded research opportunities during their time at LMU
- 85% of ACCESS Scholars will complete a bachelor's degree in a STEM discipline
- 60% of ACCESS Scholars will apply to graduate or health professions programs upon graduation, and the remainder of those who graduate will immediately enter the STEM workforce

Each year, a summer community-committed transition program enrolls 18 incoming freshman students who are from low socio-economic backgrounds and are often either first-generation college students or under-represented minorities in the sciences. We invite approximately 50 to 100 students from the incoming class of the college of science and engineering to apply to the program. Each student invited to apply must be of low socio-economic status. Of these 50 to 100 students, about 35-40 apply to the program. One-on-one interviews are conducted with all applicants and 18 participants each year are selected to participate.

Components of the ACCESS program

Each activity in the ACCESS Summer Program has been carefully designed to meet the program goals. Activities fall into one or more of the following areas: academic and professional development, personal development, and community building.

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Academic and professional development activities

The academic activities of the summer program reflect the diversity in majors of the program participants. However, we focus on two main areas: communication skills and mathematical modeling. The art of and skills necessary for communication are integral to any discipline. We offer learning experiences that result in the students becoming well-versed in communicating their ideas orally and through writing. Virtually all the academic activities culminate with individual or group presentations or written papers. ACCESS is focused on mathematical modeling because the ability to analyze data, identify trends, and draw conclusions are crucial skills needed in any discipline, and most students do not have any experience in these areas before entering college.

Personal development

We have two main activities aimed at having the students reflect on who they are and want to be. The first activity is a two-part reflection exercise. In the first part, the students are asked to reflect on their current lives (good and bad habits, things they would like to improve about themselves, things they want to learn in the short and long term, etc.) and their ideal future. In the second part, the students are asked to write about concrete goals (academic, personal, and social). They write about the things they need to do each day, month, and year to achieve those goals. The students really enjoy this exercise, and many of them remark that they never actually sat down to think about what kind of person they want to be over the long term. Studies have also shown that setting, elaborating, and reflecting on personal goals improves academic performance (Morisano et al. 2010).

The students also have one "day of service" during the three-week summer program. On that day, we visit Homeboy Industries in downtown Los Angeles to see how former gang members turn their lives around to become productive members of society. We then walk through Skid Row in downtown Los Angeles to The Midnight Mission, where the students prepare and serve dinner to hundreds of homeless people.

Community building

Perhaps the most important aspect of the ACCESS summer program is the formation of a tightly-knit community of scholars who are dedicated to one another's success. A key to retaining students during and beyond their freshman year is to instill in them a sense of belonging at the University. Over the course of the three weeks, the students engage in a variety of activities meant to make them feel at home with one another, with the LMU campus, and in the city of Los Angeles. These include fields trips (Santa Monica Pier, Dodger game, bowling, museums, etc.), scavenger hunts on campus, shared meals, and soccer games.

Overall, the program provides an opportunity for freshman to participate in an all-expense paid, three-week residential program that focuses on academics and critical thinking in the sciences. Students are introduced to key faculty, staff, and administrators before the first day of classes and are engaged with scientific projects that encourage them to work collaboratively. Students also produce technical reports of their work and give formal presentations to a variety of audiences during the program.

The Ronald E. McNair Program at LMU

In general, McNair programs have a general philosophy of creating a community of academic excellence that provides intense experiences through research and faculty mentoring to help students find their passion and prepare them for graduate school, where all of our scholars are either first-generation and low-income students or from underrepresented groups in STEM fields. The goals of the McNair program are for the scholars to possess the knowledge, ambition and confidence to pursue and complete the doctoral career path, carry out research and other scholarly activities, communicate effectively, possess leadership skills, and exhibit prosocial skills in an academic setting.

The McNair Scholars Program at LMU was designed to sustain a cohesive support system for first-generation, low-income and underrepresented participants. LMU's local enrollment area encompasses the

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densely-populated urban metropolis of Los Angeles, where public high schools and one of the largest community college systems in the country serve a significant population of first-generation, low-income students. Within this population there are many students classified as high-achieving, but who are underrepresented in both STEM fields and Ph.D. programs. According to data collected from a series of interviews conducted with LMU faculty in the 2011- 2012 academic year, the LMU target population of participants in LMU's McNair Scholars Program experience specific academic, social, financial, and other challenges.

During the McNair selection process, we focus on students who have some interest in research, but also accept students who may be undecided in terms of their long-term objectives. Our goal is to help such students overcome anxiety, self-doubt, and familial pressure to enter the work force immediately upon graduation. We often encountered first-generation college students whose families thought that graduate school was a foolish choice, and we work directly with those families to help them better understand the graduate school process and the career options that would become possible with post-baccalaureate studies. Academic and social challenges encountered by first generation, low-income, and underrepresented students are often reinforced by financial hardships, which are particularly pronounced at LMU because of the high cost of tuition. In particular, many of these students often feel responsible for taking care of other family members and have minimum wage jobs to provide financial assistance to their families. Being able to afford LMU's tuition is a constant concern, leaving the students feeling more isolated, and set up for failure. This is particularly problematic for students starting at an academic disadvantage, who are more likely to need an extra year to graduate due to the sequential nature of the courses in STEM disciplines.

The LMU McNair Program Components

The LMU McNair Program offers scholars rigorous research experiences including an on-campus summer research program, guidance and strong support to secure off-campus research and internship opportunities, faculty mentoring, guidance and financial support for research projects during the academic year, support and encouragement for McNair Scholars and alumni to attend and present their work at academic and professional conferences.

Undergraduate Research Experience

The Program provides high quality research experiences for LMU McNair Scholars by integrating them into the LMU undergraduate research environment in several ways. The director of the program invites all newly-selected McNair scholars before their junior year to participate in an existing LMU summer research program. In the fall of their junior year, scholars join the research teams of LMU McNair Research Advisors. Mentoring and guidance by the McNair Team ensures that McNair Scholars have a summer research opportunity after their junior year, either at LMU or in an off-campus program.

In addition to these activities, all McNair students participate in at least two LMU Undergraduate Research Symposia during junior and senior year. Scholars also travel with Faculty Mentors and Research Advisors to academic regional and national conferences in their field and are responsible for reporting to their fellow McNair Scholars on their experiences. Through all of these activities, McNair Scholars learn to give and receive helpful feedback to develop the necessary confidence and public speaking skills for success on the road to the Ph.D.

Research Advisors and McNair Mentors

After consultation with the scholars, the McNair Team matches students with qualified LMU Research Advisors who have proven records of success in fostering the research excellence of talented first-generation and underrepresented students. Multiple LMU faculty, who serve as Research Advisors, are first in their family to attend college and are underrepresented minorities in STEM. Research Advisors facilitate the engagement of McNair Scholars in a research project suitable for presentation at venues such as the Southern California Conference for Undergraduate Research (SCCUR), Society for the Advancement of Chicanos and Native

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Americans in Science (SACNAS), National Society for Black Engineers (NSBE), Society of Women Engineers (SWE), and at discipline-specific conferences. Research Advisors ensure that the scholars disseminate their findings in the form of a paper or a poster, with the intent of submitting it to a peer-reviewed journal. These activities introduce scholars to the procedures involved in scientific inquiry and the importance of academic research, thereby motivating them pursue graduate education in STEM.

To ensure scholars receive adequate mentoring, the director of the McNair program assigns a full-time LMU faculty member as a mentor to each of the scholars admitted to the program. Faculty Mentors meet with the scholars at least once a month and monitor their progress in achieving short-term and intermediate goals using various measures and report back to the director regularly. LMU has a significant number of faculty members from groups traditionally underrepresented in STEM fields, including women, underrepresented minorities and individuals who are the first in their family to attend college, and former McNair Scholars. Faculty Mentors periodically attend student academic presentations that take place during the McNair class and provide helpful feedback to students regarding the quality of their work and presentation styles. Assigned Faculty Mentors and Research Advisors work with students to create their initial research question. They also coach students in the designing, implementing, analyzing, writing and presenting of their research papers throughout the academic year. When possible, mentors also assist students in publishing their research sometimes as co-authors. One of the most critical roles that faculty mentors play is that of introducing and recommending McNair Scholars to their national network and advocating on behalf of their mentee for coveted graduate school slots and fellowships. Since 2012, approximately 56 LMU faculty members (20 from the Bellarmine College of Liberal Arts and 36 form the Seaver College of Science and Engineering) have contributed to the program as mentors, research advisors, and/or summer faculty associates.

Success and Challenges

Advantages of Faculty Driven Programs

Both the ACCESS Program and the McNair Scholars Program are faculty-driven, which adds to their strength. Each program is directed by faculty members, which brings about a host of challenges and advantages. Because each program has a director overseeing all components, the workload is very demanding. For the ACCESS program, the director must coordinate items ranging from food and housing to curriculum development, teaching, and mentoring.

For the McNair Scholars Program, the advantages of a faculty-driven program are manifold. Due to their background and first-hand experience, faculty are in a unique position to mentor students as they navigate through the graduate admission process. Since faculty had previously gone through the same process as the scholars, they are able to provide guidance and feedback that comes from direct experience. In addition, the faculty are often part of a closely knit group of academic researchers. During the application process, students are often given the opportunity to connect directly into that network through introductions made by their faculty mentors.

When a McNair site is faculty driven, students are able to see how the faculty member engages in research herself or himself. Such faculty members often have direct knowledge of other researchers on campus whose research closely aligns with the interests of their scholars. Moreover, since faculty members frequently deliver presentations at conferences, they are also capable of providing guidance for the scholars who are about to head off and give their own research presentations for the first time.

Individualized Care

One of the primary advantages of hosting programs like McNair and ACCESS at LMU is the comparatively small size of the institution. It is much easier for faculty and staff to gain an understanding of the landscape of the university and interact with multiple segments at both administrative and academic levels. This allows faculty and staff to support students in an individualized manner. Regardless of whether a student is excelling or struggling, most faculty are aware of various sources of support and can draw upon multiple people to work directly with the student. This helps to provide students with targeted support that addresses their immediate needs. Specifically, for the McNair program, whenever a student is seeking opportunities to promote his or her success, it is fairly common for a faculty mentor to initiate contact with the student and hold conversations with other faculty members that ultimately lead to a network of mentors. As a case in point, it is not uncommon for faculty to help students identify research opportunities on campus while simultaneously replacing off-campus minimum wage jobs with meaningful work on campus such as grading or tutoring.

The smaller size of the university can also lead to the development of intersecting, supportive communities. Most faculty in the College of Science and Engineering at LMU are aware of both the ACCESS and McNair program, and, often, when they learn about one of our scholars facing specific challenges, they will pick up the phone or send an email in order to begin a dialog about how to best support that student. This sense of community makes it much easier to strengthen certain aspects of both programs. Faculty regularly come to events showcasing our scholars' research, and they often provide valuable feedback. In turn, students come to recognize a good number of these faculty members as allies. From the student perspective, this expands the network of individuals that can provide both tangible and emotional support.

Community Building

As previously mentioned, community is an very important aspect of the success of the scholars in the ACCESS program. At the end of the summer portion of the program, the students have bonded socially and academically. Consequently, at the start of their first semester in college, they feel like they belong at the university not just because they have a built-in group of friends, but also because those friends understand how to navigate the university. When these scholars encounter either academic or general life challenges, which are typically experienced by all first-year undergraduates, they not only turn to their individual families for encouragement, but also recognize the value of the support network provided by ACCESS. If a student in the program is giving a presentation on campus, for example, the ACCESS faculty leaders and other ACCESS scholars will often attend to demonstrate their support.

In the McNair program community is fostered in a myriad of ways. Throughout students' time in McNair they engage consistently with their peers in their specific cohort as well as their peers in other cohorts. One way community is built is through the one-credit-hour seminar classes scholars attend during the academic year where they discuss topics that include successful study habits, preparing and planning for undergraduate research, preparing for the GRE and applying to graduate school. A unique feature of the LMU McNair Scholars program is the summer seminars for scholars. Each summer a scholar participates in McNair they attend seminars to help "fine tune" their research presentations. During these sessions faculty from various fields and other McNair scholars listen to scholars' research presentations and critique their presentations. As scholars present multiple times throughout the summer, scholars adapt and improve their presentations based on faculty and peer input. This helps to further acclimate scholars into the academic community and give targeted professional development, which many scholars have noted as invaluable.

Another unique feature of the LMU McNair Program is its deliberate, multi-pronged engagement with scholars' families, as the project team believes familial support is crucial in ensuring scholars' academic success. At regular McNair events, including an annual banquet, the program celebrates the scholars' accomplishments, and engages their families in discussions about their children's academic progress, graduate school plans, and their trajectory to the doctoral degree.

A common goal to both programs is the promotion of self-efficacy in participants. In the ACCESS program self-efficacy and student confidence is promoted as soon as students step foot on campus. In particular, as soon as students enter the program one of their initial exercises is to have them describe themselves as scientists ten years in the future, and then share their story in multiple contexts: once with an assigned partner who is instructed to engage with an attentive ear and ask questions, and another time with the entire cohort

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of 18 students. Similarly, with McNair, we have students give multiple presentations to their peers and a select group of faculty members. Those presentations often take the form of polished research talks, which helps the scholars build confidence. The presentations are sometimes also about the professional and academic goals. Typically, First-generation college students do not have the opportunity to voice their career and educational goals, and this provides them with a unique opportunity.

Challenges

One of the biggest challenges faced when directing programs such as ACCESS and McNair is the steep learning curve during the initial implementation stage. At a small-to-medium-sized institution, it is easier to get to know the key players on a personal level who can provide logistical support. For both programs, one must focus on numerous details that do not directly connect to the students' academic success. These can range from housing and food for summer programs to identifying the correct paperwork in order to disburse stipends. For a program such as McNair, which has federal funds that support the infrastructure of the program, one can hire staff to take care of such details. For programs such as ACCESS, where the funding is comparatively small, the director must personally make connections with all the appropriate people from various divisions on campus. Because of the relatively small size of the university, many of those people work in concert with one another and are often willing to go the extra distance to make things run smoothly. Without such personal connections, navigating through bureaucratic red tape would be much more challenging.

Success in the ACCESS Program

Overall, ACCESS has had 164 student participants since its start in 2009, with roughly equal numbers of males and females; 27% identify as African-American, 7% Asian, 62% Latino, and 4% White.

ACCESS runs on a yearly budget of about $80,000, where about 39% goes directly to support participant costs like food, housing, field trips, transportation, textbooks, etc. The ultimate measure of the effectiveness of the ACCESS Program will be the long-term success of the students. We can measure their success in terms of grade point average, retention, and ultimately career paths after college. For the first four cohorts (2009, 2010, 2011, 2012), the overall 6-year graduation rate from LMU for students with any degree is 88.9% (64/72 students). The pre- and post-summer data show that ACCESS participants feel that the program helps them to get acclimated to LMU and helps nurture a positive sense of belonging and community. ACCESS participants have also had success after their time at LMU. Many have gone on to STEM careers and graduate school. Data from participants in the 2009-2012 cohorts show that at least 18 of the participants went on to graduate or medical school or have begun careers in STEM fields.

Success in the LMU McNair Program

The LMU McNair Scholars Program provides the structure necessary to sustain a support system for a qualified group of first generation, low-income, and underrepresented undergraduate students. Each academic year, we identify and address the higher education needs of 26 first generation, low-income and underrepresented undergraduates who are interested in attending graduate school to earn a doctoral degree. This target population is recruited from the College of Science and Engineering, which has 100% STEM majors, and students majoring in Economics, Political Science, Psychology, and Sociology in the College of Liberal Arts. A deliberate effort is made to ensure that the McNair Scholars are a gender-balanced group so as to also address the challenge of women underrepresentation in STEM. A significant component of the program is its emphasis on undergraduate research that allows students to collaborate with faculty and become involved in ongoing undergraduate research. It exposes them to an environment in which they can be supported as they experiment in STEM and perhaps struggle without negative repercussions and which provides them opportunities to write up and present research findings. Other components of the program include providing GRE preparation courses, educating students about academic/professional supply and demand trends in STEM fields, and establishing bridges for students transitioning from college to graduate school to STEM careers. The table below presents details about the program since its start in 2012 to 2017.

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Table 1.
LMU McNair Program Data

Students accepted into the McNair program (2012 –2017)	86
Scholars completed the program (until spring 2017)	61
Scholars currently enrolled in the program (AY 2017 – 2018)	25
Average cumulative GPA of scholars graduated (until 2016)	3.5
LMU McNair Scholars who went to graduate school between (2012 – 2017)	34
Conferences where LMU McNair scholars presented their research (2012 – 2017)	30
Conference research presentations by LMU juniors and seniors (AY 2016 – 2017)	81

Notes: n=86

The LMU McNair program continues to achieve the overarching goal of McNair programs, which is, increasing graduate degree awards for students from underrepresented segments of society. Since 2012, 34 of the 86 LMU McNair scholars have enrolled in graduate programs in the fields of math, engineering, life sciences, and social science and have also enrolled in medical school, MD/PhD programs and JD programs. Students attend graduate programs at national and international institutions, such as, MIT, Tufts, UC Berkeley, Claremont Graduate University, University of Southern California, Emory, École Polytechnique Federale de Lausanne (EPFL) and London School of Economics, just to name a few. In 2017, the first LMU McNair program alum received her PHD in the biological sciences.

Over the past 5 summers (2013, 2014, 2015, 2016, 2017), 66 McNair scholars have participated in LMU's summer research program. In addition, 13 McNair scholars have participated in summer research opportunities away from the LMU campus at the following universities:

- Arizona State University
- Carnegie Mellon
- Duke University
- Harvard University
- Louisiana State
- Ohio State
- UC Berkeley
- UCLA
- University of Connecticut
- University of Iowa
- USC
- University of Wisconsin at Madison
- Wake Forest School of Medicine

Scholars have also participated in summer internship opportunities at several sites, such as, Space X, Moog Inc., and Northrop Grumman. LMU McNair has sent student scholars to over 30 different conferences to present their research and expand their discipline specific network. For 2016 -2017 academic year, over 81 research presentations were given by the junior and senior cohorts. LMU McNair scholars have received awards and recognition including one Amgen scholar, one NCAA Graduate School scholarship, and two GEM Fellowships.

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Conclusion

We attribute much of the success of both ACCESS and McNair at LMU to the dedication and support received from faculty, staff, and administration at LMU. Studies have shown that support systems that include many of the components in both ACCESS and LMU McNair, such as student community-building efforts, undergraduate research programs, academic enrichment programs, tutoring and mentoring are essential in broadening URM participation in STEM (Rodriguez et al., 2012). While both programs have had success, directors still have additional goals they would like to achieve. As the number of applicants increase in both programs, the project team is looking for ways the programs can be expanded to include more student participants. The ACCESS leadership team has applied for funding from the NSF to provide scholarships to ACCESS students over the next 5 years. The LMU McNair program was recently approved for another five-year funding cycle. Future plans for the McNair program involve incorporating new initiatives and methodologies that would further increase the number and proportion of underrepresented students prepared for graduate study in STEM.

Overall, the contributions made by both programs have greatly impacted the Seaver College of Science and Engineering at LMU. While both programs have individualized, peer and community mentoring at both levels, the data mentioned above shows that these various mentoring structures have contributed to success of its participants. Moreover, the mere existence of such programs contributes to a culture that engages in dialog about how best to support a diverse student body. Synergistic relationships between ACCESS, McNair and other on-campus programs with similar missions have evolved over the past 5-10 years, and this has led to new individuals becoming involved in the support of our cause.

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RESEARCH REPORT

Cross-Disciplinary Studies Minors as a New Vehicle to Enhance STEAM Programs

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Abstract: *This paper describes the motivation and organization of Cal Poly's new type of academic subprogram: the Cross-Disciplinary Studies Minor (CDSM). CDSMs are an appropriate educational vehicle for providing both depth in one's own field and breadth in a companion field for students who want to excel in studying topics that straddle the boundaries of traditional BS degrees. The design of CDSMs is illustrated using the example of Cal Poly's Cross-Disciplinary Studies Minor in Data Science, which has been in place since 2015-2016 academic year.*

Keywords: STEAM, Cross-Disciplinary Studies, Cal Poly

Introduction

In September 2015, two brand-new programs opened their doors at Cal Poly, San Luis Obispo: the Cross-Disciplinary Studies Minor in Data Science[1] and the Cross-Disciplinary Studies Minor in Computational Interactive Art[2]. The common denominator connecting these nascent programs is a new type of academic subprogram: The Cross-Disciplinary Studies Minor (CDSM). We designed it to specifically address a number of challenges that traditional academic programs and subprograms face when dealing with cross-disciplinary education. In particular, the CDSM provides an academic policy to structure and coordinate an in-depth curriculum in partnered related disciplines with the aim of satisfying the changing needs of industry for employees to have strong skill sets integrated across multiple domains. The introduction of CDSMs at Cal Poly led to immediate development of the current programs in Data Science and Computational Interactive Arts. Another program, the Cross-Disciplinary Studies Minor in Bioinformatics, is currently under development for anticipated enrollment in Fall 2019.

In this paper, we describe the motivation, challenges, and process behind developing Cross-Disciplinary Studies Minors and describe their structure. Using Cal Poly's CDSM in Data Science as a case study for implementation, we show how specific curricula for CDSMs can be developed. We concentrate our discussion on how the Data Science CDSM addresses the challenges faced by Cal Poly, while leveraging the strengths of existing BS programs in statistics and computer science, and on how this experience can be replicated by other institutions of higher learning to spearhead quality cross-disciplinary educational efforts.

The rest of this paper is organized as follows. We first discuss the emerging need for cross-disciplinary education programs at institutions of higher learning, and outline the challenges to successful design and implementation of such programs. We then introduce the key part of our solution: the Cross-Disciplinary Studies Minors. After that we discuss our implementation case study, the curriculum for the CDSM in Data Science. We conclude with a few observations and lessons learned.

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[1]http://catalog.calpoly.edu/collegesandprograms/collegeofsciencemathematics/statistics/ crossdisciplinarystudiesminordatascience
[2]http://catalog.calpoly.edu/collegesandprograms/collegeofengineering/computersciencesoftwareengineering/computingforinteractiveartsminor

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Motivation

Background

California Polytechnic State University (a.k.a. Cal Poly, San Luis Obispo) is a comprehensive public university of about 20,000 students and is one of the 23 campuses of the California State University system. Cal Poly is classified as a regional Masters-level institution and is consistently ranked as the best public university in the West in its category[3]. Cal Poly consists of six academic colleges operating on the quarter system. Our institutional motto is "learn by doing," and this motto is incorporated at all levels of curricula across campus, promoting hands-on, laboratory-based and project-based learning experiences.

The curriculum development process at Cal Poly traditionally originates within a single department and subsequent review running through the department's college followed by the Academic Senate Curriculum Committee. Final recommendation for approval is granted by the Academic Senate with final approval granted by the Provost. Prior to 2015, when Cross-Disciplinary Studies Minors were introduced, Cal Poly had a limited track record of development and support of cross-disciplinary programs. In fact, some past administrative actions actually made cooperation among related disciplines more difficult. For example, at the undergraduate level, the establishment of a BS degree in Computer Engineering in 1984 lead to a split of the Department of Statistics and Computer Science into its constituent parts, with the subsequent move of the Department of Computer Science from the College of Science and Mathematics to the College of Engineering, where the Department of Electrical Engineering, the other collaborator in the Computer Engineering program resided. Other administrative practices only carry the illusion of being cross-disciplinary. Consider the graduate level cross-college dual-degree offered at Cal Poly: a combined MBA and MS in Engineering Management. This dual-degree program essentially pairs two existing 45-unit[4] MS degrees into a single 90-unit course of study without any significant coordination of the partnering degree curriculum.

Emergence of the Need for Cross-Disciplinary Educational Experiences

Today cross-disciplinary knowledge is either outright required or is in high demand for some college graduates. Examples include the applied fields of data science, bioinformatics, and a variety of management and entrepreneurial occupations that must pair business knowledge and experience with a specific domain (Kim & Lee, 2016; Finzer, 2013; Lafferty-White, 2017; Levine, 2014; Davenport, 2012; Dymond et al.; 2015; Luke et al., 2015).

We define a cross-disciplinary program as one that combines in-depth knowledge in two or more related fields with additional advanced study at the intersection of the fields. For example, our data science cross-disciplinary curriculum combines in-depth coursework from the fields of computer science and statistics; our computing and interactive arts cross-disciplinary program – from computer science and art; and currently under development at Cal Poly, bioinformatics – from computer science, statistics, and biology. Other examples of cross-disciplinary studies include health management – from business and pre-med/biology; public health – from social science, nutrition, and biology; and bio-innovation – from business and biology. The term "cross-disciplinary" is chosen to emphasize the need for a single person (a student, in case of an academic cross-disciplinary program) to master the advanced knowledge in multiple disciplines. This is in contrast to other common -disciplinary terms such "multidisciplinary" or "interdisciplinary", which we take to describe team compositions comprised of expert individuals from multiple fields with possibly only rudimentary understanding in partner fields[5] (Knight et al., 2012; Razzaq et al., 2013).

[3]See http://colleges.usnews.rankingsandreviews.com/best-colleges/rankings/regional-universities-west. Cal Poly is ranked #11 overall and is the top-ranked public university.

[4]All units mentioned in this paper are quarter units. Thus a 45-unit MS degree at Cal Poly is equivalent to a standard 30-unit degree at university that uses the semester system.

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When considering the need for new curricular programs, an important first question is who the students to be trained in the new field are. With cross-disciplinary studies, universities have an existing built-in population of students who can be engaged. These are the students majoring in one of the partnered disciplines associated with the cross-disciplinary study. For example, a target population of students to study bioinformatics can come from Biology, Computer Science, and Statistics majors mutually interested in focused study (beyond a traditional minor) in the complementary disciplines in addition to their own. We note, that this actually leads to a certain diversity of experience and expertise among the students trained in cross-disciplinary studies: a student with a BS in Biology trained in bioinformatics will have more in-depth knowledge of biology and less in-depth knowledge of Computer Science than a CS major trained in bioinformatics. However, both will have a greater depth of knowledge in the partner area compared to those students who simply minor in the partner disciplines. Additionally, unlike those who complete traditional minors, they will have completed advanced studies at the intersection of the disciplines and greater experience working on diverse teams.

Industry wants trained professionals with cross-disciplinary skills; multidisciplinary teams are also important, but not sufficient in many cases. Universities have a limited number of options on how to respond. Some universities can afford to establish new BS programs run by brand new departments with new tenure lines. This is expensive, may create duplication of experience and coursework, and incite turf wars.

Another common option is post-baccalaureate degree education through certificates. As an example, a BS in Biology can take a certificate in CS-centric bioinformatics (Parthasarathy, 2015; Ranganathan, 2005). The drawbacks here stem from the fact that there are essentially two completely independent paths to bioinformatics proficiency - one for those with BS in Biology, and the other - for those with BS in Computer Science (not to mention a third path for BS in Statistics degree holders). These varied paths, and hence student preparedness, limit the depth of coursework in the intersection. Additionally, certificates are constrained by the limited amount of coursework they can have.

A third option is an MS degree in a cross-disciplinary subject. This, for example, is a popular emerging path with Data Science (Tate, 2017). While BS in Data Science degrees are still fairly rare, many universities have created MS in Data Science (or similar) programs hoping to attract applicants with a wide range of undergraduate degrees. A cursory look at these programs though reveals their key disadvantage. While MS in Computer Science and MS in Statistics programs are true in-depth advanced degree programs in their respective fields, MS in Data Science education often starts with remedial subjects, such as Linear Algebra, Numerical Analysis, Introduction of Computing and Introduction to Statistics, in order to accommodate the wide variety of educational backgrounds and skills of the incoming class. This leaves precious little time for actual in-depth preparation in the core field of study.

Impediments to Cross-Disciplinary Learning Using Traditional Undergraduate Programs

There are several core obstacles preventing successful deployment of full-scale "ideal world" cross-disciplinary studies curricula at modern US universities. In particular, they are fueled by the non-trivial desiderata for such curricula.

In-depth education in multiple fields of study. Industry needs are not properly addressed by BS degree holders with only rudimentary command of one of the partner disciplines (Pournaras, 2017; Kim and Lee, 2016; Van der Alst; 2014). A college graduate hoping to continue their career in the field of bioinformatics would need to have in-depth knowledge of biology – perhaps not of the entire field, but certainly of cell and molecular biology, genetics and evolution. The same graduate needs to be a competent software developer, with CS expertise that is above and beyond the introductory CS course sequence (e.g., databases, algorithms,

[5] We understand that the use of "-disciplinary" terms such as "interdisciplinary" or "cross-disciplinary" in other work may differ from ours, since these terms are not fully codified. Rather than attempting to instill our readings as general definitions, we simply clarify the use of these terms in this paper. When referring to prior work, we use the term (usually "interdisciplinary") used in the work itself, but elsewhere, we stick to our interpretation of "cross-disciplinary" vs. other similar terms.

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machine learning techniques, advanced data structures, etc.). This need for depth in multiple disciplines is a challenge because at present, most existing BS programs provide for in-depth study in only a single field.

Budget. Ideally, a university can hire qualified faculty in a new emerging cross-disciplinary area, create a new department (if necessary), and a create a new program of study from scratch. Realistically, however, universities are guided by the same return-on-investment principles that guide business decision-making. A cross-disciplinary program has a higher chance of being approved by administration and a higher chance of having institutional support if it relies on existing resources and strengths, and requires only modest additional investment from the administration. This typically means, that new BS degree programs are often not achievable in the contexts of US universities. This is doubly so for resource-constrained universities, such as those with a focus on teaching and those without Ph.D. programs.

Filling the Gaps. There is a modest scope of literature that defines interdisciplinary studies as a means to explore these gaps or intersections. An entire journal dedicated to this topic: Issues in Interdisciplinary Studies. We note, however that much of the interdisciplinary literature emphasizes partnerships among experts from multiple disciplines to solve interdisciplinary problems as opposed to experts in the intersection between disciplines. "Interdisciplinary research is pluralistic in its methods and involves researchers working in tandem with each other in an integrated way to create new and unpredictable patterns, referred to as a 'kaleidoscope'" (Razzaq et al. (2013)). In contrast trans- or cross-disciplinary research refers to the intersection of disciplines to be a new discipline in its own right: "collaboration and mutual learning among people from practice and society are a salient and necessary part of transdisciplinarity." (Razzaq et al. (2013)).

While there is often confusion, misuse, and exchangeability using the terms inter, multi, cross, and trans-disciplinary as synonymous gradations, we aim to directly train students towards becoming an expert in the new intersection domains – the gap.

Augsburg and Henry (2009) and Klein (2009) define the notions of strong and weak interdisciplinary programs touching on one of the most important issues with building cross-disciplinary studies programs: they characterize strong programs by the existence of special-purpose coursework that "bridges the gap" between the partnered fields of study, while weak interdisciplinary programs are characterized by the absence of such coursework. It is insufficient for a cross-disciplinary study program to merely bring together the knowledge from two related fields by offering curriculum in only the partnered fields. Coursework to facilitate the synthesis of knowledge and skills from both fields, not taught in existing coursework in either field, must be provided. This synthesis coursework represents "the gap" between the two disciplines that a Cross-Disciplinary studies program needs to bridge. As examples of coursework indicative of a strong program, Augsburg and Henry (2009) identify (1) the presence of an introduction into the cross-disciplinary area courses (such as Introduction to Data Science for a Data Science program), and (2) capstone coursework that synthesizes the knowledge and applies it to specific project-oriented work. The ability to offer such book-end coursework is essential; it strengthens the students' command of the respective subject matter, allows them hands-on experience within the actual cross-disciplinary field, and teaches them how to apply discipline-specific knowledge and skills in problem-solving in the cross-disciplinary field. These "bridging the gap" synthesis classes would typically only be accessible to the students pursuing the cross-disciplinary studies, as they would require drawing heavily on the prior in-depth multi-field knowledge that only those students gain.

Integration of cross-disciplinary study throughout the entire program. Many possible ways of offering cross-disciplinary educational experiences assume that students already have received a degree, or have been exposed in-depth to one of the fields related to the cross-disciplinary study, and thus concentrate on remediating their lack of knowledge and skills in the other related field or fields. In contrast, a well-designed cross-disciplinary study program can provide the exposure to the coursework in all related fields in an integrated way. For example, statistics students studying Data Science progress through the introductory coursework in both Statistics and Computer Science during their first two years in college, rather than learning how to proficiently program in Python after they have received a BS in Statistics (as an example). Similarly, because of their early experience

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in multiple fields, during their third and fourth years of study, both computer science and statistics students in data science can be exposed to advanced coursework relevant to data science (e.g., Regression Analysis from the Statistics Curriculum, and Distributed Computing from the CS curriculum) in parallel. This creates a balanced "leveling-up" of students, and allows for appropriate "bridge-the-gap" coursework to complete the program of study. Further, because students begin taking partner work early in their academic year, students will be able to achieve the cross disciplinary objectives and graduate in a timely manner.

Limitations of traditional programs and subprograms

Cal Poly offers two types of primary degree experiences: an undergraduate (B.S.) degree and a graduate (M.S.) degree. Prior to the development of the CDSM, Cal Poly offered three non-degree granting subprograms: undergraduate minors and concentrations, and graduate specializations.

Budget constraints make it difficult to offer cross-disciplinary experiences such as Data Science, Computational Interactive Art, or Bioinformatics as independent BS or MS degree programs. Cross-disciplinary education delivered in a form of subprogram is potentially more flexible, nimble, and cost-effective in the context of a school like Cal Poly.

As noted above, we argue that three important components comprise the cross disciplinary curriculum: (1) an introduction to the cross-disciplinary study, (2) in-depth coursework in each of the partner domains, and (3) synergistic courses and/or capstone experience. Minors and concentrations cannot meet these demands with limited units (a maximum of 30 additional quarter-units for minors and a maximum of 180 units for BS degrees with a concentration). Because of minor or degree unit limits, traditional subprograms either provide (1) a lack of depth in the partner discipline (minors), or (2) a lack of exposure to the partner discipline altogether (concentrations).

Unit limits aren't the only inadequacies of concentrations and minors for cross-disciplinary studies. Because concentrations are limited to subprograms within a single major, it is not possible to maintain a common curriculum for all students in a cross-disciplinary study across multiple (independently managed) BS degrees. And, because a core principle of most minors is exposure and breadth with an "everyone is welcome" philosophy, minor programs lack the needed depth to prepare students for the advanced synergistic capstone coursework in the cross-disciplinary study.

A new subprogram: the cross-disciplinary studies minor

To administratively address the requirements for cross-disciplinary studies we developed the cross-disciplinary studies minor. The new subprogram was adopted by the Cal Poly Academic Senate and approved by the University President in the 2013-2014 academic year as permitted by CSU Executive Order 1071, which grants each CSU campus the responsibility for defining the rules and restrictions for subprograms. While many universities have provisions for students to individually create programs of interdisciplinary studies, to our knowledge, the structure, goals, and requirements of our CDSM subprogram is unique among US academic institutions as a formal subprogram to address cross-disciplinary domains. The definition and key requirements of the CDSM as adopted at Cal Poly are as follows.

Definition. A cross-disciplinary studies minor (CDSM) is the result of a partnership between two or more target major programs. It is defined as a set of curricular requirements comprised of coherent groups of courses tailored for each partner program such that all students from target majors develop (1) depth in the partner discipline, (2) focused study in their own discipline, as well as (3) focused study in the mutual domain of the minor.

[5] Now officially known as the Department of Computer Science and Software Engineering.

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Key Requirements

1. The curricular requirements are the same for all students in the CDSM.
2. The total number of units in the CDSM that cannot be covered by the requirements of the student's major shall not exceed 24 quarter-units.
3. The CDSM curriculum shall require at least 12 quarter-units of coursework that cannot be covered by the requirements of the student's major.
4. At least half of the units must be from upper division courses.

Each key requirement is readily justified.

Identical curricular requirements regardless of student's major. This follows from the principle that all students pursuing a CDSM, regardless of their major are to acquire the same knowledge and skills. The intent is for the CDSM creators to identify the list of courses in both partner disciplines which provide the appropriate background, skills, and knowledge, and require these classes of all students. The additional new coursework developed specifically for the minor is also required for all students. At the same time, while students from all target majors have the same curricular requirements, some requirements may be met by more than one course.

Limited total units. As an undergraduate degree enhancement, only a reasonable number of units may be required without fully impeding a timely graduation or turning the program into a full dual-degree. Cal Poly's traditional minor policy requires between 24 and 30 units of coursework.

Minimum required units beyond the major. As a cross-disciplinary study, the coursework should not be entirely subsumed by courses already in the major BS curriculum. As a degree enhancement, we require that students take coursework beyond the minimum requirements for the BS degree.

Upper division coursework. Similar to the traditional minor, advanced coursework is required to ensure discipline depth. In the traditional minor this coursework is often chosen from a menu of courses, whereas the cross-disciplinary minor will usually explicitly require certain upper division courses that support the cross-discipline.

Steps for developing partnerships and curriculum for a CSDM

In the development of curriculum for new CDSM we suggest following the following steps: (1) identify stakeholders, (2) generate learning objectives, (3) identify existing curriculum and curricular gaps to support the learning objectives, and (4) streamline and map the curriculum to partner programs.

Identify stakeholders. There are three primary stakeholder groups to consider when developing the new CDSM: students, faculty, and industry. The natural student and faculty populations stem from the partner disciplines in the cross-disciplinary studies. We recommend limiting the number of partner programs in order to preserve the ability to maintain sufficient depth in each of the partner fields and to better facilitate curricular maintenance as programs evolve.

Generate learning objectives based on understanding of the cross-disciplinary needs and industry needs. The essential questions to ask at this stage are "what do we want our students to learn in the CDSM?" and "what do we want them to be able to do upon completion?" Understanding the demands of today's workplace, the work the professionals who complete the CDSM will be asked to perform, can help formulate the answers to these questions. We developed CDSMs to produce career-ready employable graduates with practical experience. CDSM students will also be well prepared to pursue graduate coursework, but the curriculum emphasizes career readiness within the curricular limits of an undergraduate program.

Identify existing curriculum and curricular gaps. The next step is to map the high-level learning objectives produced in the previous stage to specific knowledge and skills that are to be taught in the CDSM. In this step, each item from the list of objectives is mapped to courses in the curricula of the partner disciplines in

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which it is taught, or is labeled as "unmet" by the existing curricula. Any learning objectives, skills, or knowledge that are not sufficiently addressed with existing curricula will highlight gap needs that can be addressed both an in introductory course in the CDSM, as well as in the synthesis coursework.

Streamline and map curriculum to partner programs. The reason why CDSMs are useful is their unique ability to map courses required by the CDSM to the curricula requirements of the partner programs in ways that drastically reduce the course load above and beyond the major requirements. This needs to be done separately for each partner discipline. Because close to half (or, perhaps, close to 40%) of the CDSM may consist of courses coming from a specific partner discipline, students majoring in this discipline will have some of the courses already required in their major program while other courses may count as electives. Sometimes, it may also be possible for students to count the coursework offered by the other partner program as electives in their major: for example the CDSM in Data Science (see below) takes full advantage of the flexibility of both the CS and Statistics curricula to incorporate 4-5 courses from the partner discipline as electives of different kinds.

The process of mapping the courses in the CDSM to each partner discipline, while pruning the list of courses as needed to be able to meet the "no more than 24 units above and beyond the major" requirement is, in our experience, the most complex part of the CDSM development process. The initial list of potential coursework to address the objectives from each of the partners can be quite large and must be pruned. In the mapping and pruning process we strive to balance coursework from each of the partners, as the resulting pruned curriculum will have to be mapped to each partner BS degree program. We shape the curriculum to have an equitable balance of extra-discipline (beyond credit for the major) coursework for each partner program as well as equitable unit double-counting for degree progress. In some cases, in order to be able to map courses in CDSM to the BS degree requirements in desired ways, changes to BS degree requirements, such as adding certain courses from one discipline to the list of electives of another discipline, or changing course prerequisites, may be proposed. In such cases, CDSM designers have to confer with the appropriate curriculum committees to ensure that the proposed changes will not have adverse effect on the BS degree itself.

Our Data Science case study demonstrates how the final list courses for the CDSM was selected and mapped to the BS in CS and BS in Statistics requirements, and how the CS and Statistics curricula was updated to accommodate the CDSM.

Case Study: Cross-Disciplinary Studies Minor in Data Science

The notion of Cross-Disciplinary Studies Minors appeared during the two-year long process of developing a Data Science program at Cal Poly undertaken by the authors of this paper. In this Section we briefly introduce the stakeholders in the minor, give the short history of its development, and discuss the CDSM in Data Science as currently deployed at Cal Poly, paying close attention to the aspects of the minor discussed in the previous section.

The Stakeholders

Early in the development of the Data Science program (and before it became the CDSM in Data Science), the Departments of Computer Science[6] and Statistics emerged as two key stakeholders in bringing Data Science education to Cal Poly.

The Department of Computer Science oversees the B.S. in Computer Science, B.S. in Software Engineering, M.S. in Computer Science, Computer Science Minor program, and jointly with the Department of Electrical Engineering houses the B.S. in Computer Engineering program. Between the three majors and the M.S. program (and not including the hard-to-count students minoring in CS) the department serves around 1200-1300 students every given year.

The Department of Statistics runs a B.S. in Statistics program with the total enrollment of about 120-140 students as well as a Statistics minor serving approximately 90-100 students. It also hosts an Actuarial Sciences Minor. In addition to teaching its own majors, the department offers a wide range of Statistics coursework to

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students from other disciplines: the vast majority of Cal Poly majors require at least one course in Statistics.

Brief History

In Spring of 2012, a conversation around the subject of Data Science took place on the Cal Poly campus, featuring interested parties from all colleges, and from many departments. This conversation gave birth to numerous initiatives, chief among which was the emergence and approval of the Cross-Disciplinary Studies Minors at Cal Poly, and the establishment of the CDSM in Data Science.

As part of the initial conversation about the Data Science education at Cal Poly, we asked the question of who, among the current body of our students, are most ready for Data Science education. After some conversation about the definition of Data Science, and the skills and knowledge associated with professionals trained in this area it became clear that two existing student populations: Computer Science majors and Statistics majors already take much of the coursework that was deemed necessary for a proper Data Science education.

A preliminary survey conducted in 2012-2013 suggested that around 35% of Statistics majors, and 13% of CS majors may be interested in a Data Science curriculum. Taking the respective sizes of the programs into account, we estimated that an undergraduate Data Science program that relies on CS and Statistics students as primary target populations can realistically have 20-30 students per year/cohort roughly evenly split between the two majors. Our program design used this estimate throughout the process, and, at present, it appears that our estimate was correct: the 2017-2018 (our second) cohort is 24 students.

With CS and Statistics majors in mind we approached the development of our Data Science curriculum in the following way. At the outset, we put together an overarching list of skills that we wanted Cal Poly graduates of a Data Science program to have. The list ranged from relatively generic skills, such as "able to work with databases to store, organize, and retrieve data" to some very specific ones, such as "able to apply Principal Components Analysis to reduce the dimensionality of complex data". We then mapped the desired skills to the existing CS and Statistics coursework, tracked all course prerequisites (e.g., databases are covered in Introduction to Databases course, its prerequisite is a Data Structures course), and identified "gap skills", i.e. skills and experiences that the students were not getting from the CS and Statistics courses. We determined that at a bare minimum the "gap skills" could be covered in four courses (totaling 12 quarter units): an Introduction to Data Science course, a senior-level Data Science course, and a two-quarter capstone sequence. The total number of quarter units in the coursework we earmarked for a Data Science curriculum (including the new coursework) was 80 – far exceeding the unit requirements for a minor.

This was discouraging. But we did not stop there.

We asked ourselves, if a B.S. student majoring in Computer Science (Statistics) were to take all of these courses, how many extra units would it cost them? Our mapping of the 80 units of proposed coursework (see below) to the B.S. in CS and B.S. in Statistics degree requirements surprised even us:

- with minor alterations in the Statistics curriculum, a Statistics major could take all the courses with only 12 extra units above and beyond the 180 major units.
- with minor alterations in the Computer Science curriculum, a Computer Science major could take all the courses with only 16 extra units above and beyond the 180 major units.

This feat is possible because much of the coursework in one's own major is either required in one's own degree, or counts as a technical elective, and because both the B.S. in Statistics and B.S. in Computer Science are flexible enough to allow counting upper-division courses taken in the other major as technical electives.

At this point we made use of CSU Executive Order 1071 which grants the responsibility for subprogram development to individual campuses to propose a new subprogram type that would allow us to offer the Data Science curriculum the way we envisioned it without having to compromise. The proposal for Cross-Disciplinary Studies Minors was created in consultation with a number of other possible stakeholders on

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campus (faculty from departments who could partner for additional CDSMs), and was shepherded through the Academic Senate.

The Curriculum

Matching and enhancing the target majors, the Data Science curriculum consists of coursework in three areas: traditional Statistics (with some prerequisite math), traditional Computer Science, and newly developed Data Science Courses. The courses range from full introductions to both disciplines through upper-division technical electives. All students studying for the Data Science CDSM will take the courses described below, plus two elective courses of their choosing in computer science, statistics, or data science.

Statistics and Math Coursework

Two mathematics courses were included in the official description of the Data Science curriculum: Calculus III (as a required prerequisite to Linear Algebra), and Linear Algebra. Knowledge of Linear Algebra was deemed a core requirement for a properly educated Data Scientist.

The Statistics coursework consists of five courses. Two are introductory in nature: an Introduction to Statistics course, an Introduction to Probability Theory. Three other courses are Applied Linear Regression, Multivariate Regression, and Statistical Computing in R. These classes from the Statistics curriculum address several of the statistical objectives deemed necessary for the Data Science CDSM: linear regression, knowledge of modern tools for statistical analysis (R), and dimensionality reduction techniques using Principal Component Analysis.

Computer Science Coursework

Four courses from the introductory CS curriculum became part of the Data Science curriculum: Fundamentals of Computer Science I, Fundamentals of Computer Science II (Object-Oriented Programming), Fundamentals of Computer Science III (Data Structures), and a Discrete Mathematics course. In addition, four upper-division courses were added to the curriculum to cover the requirements for Data Scientists to be familiar with algorithm development, databases, distributed computing, and machine learning techniques. The four courses are Design and Analysis of Algorithms, Introduction to Databases, Distributed Computing, and Knowledge Discovery in Data (the CS department's undergraduate Data Mining and Machine learning course).

Data Science Coursework

The remaining four required courses in the CDSM are specially developed for it to address gaps in the cross-disciplinary curriculum.

Introduction to Data Science. This sophomore level gateway course is intended to be accessible to students after completing only an introductory statistics course and two-quarters of introductory programming. Primarily using Python, students get their first exposure to working with non-standard data types including raw machine, text, geospatial, images, and audio. The data science workflow is introduced in small scale settings. Based on interest and success in this course, students decide whether or not to continue (or be accepted into) the CDSM.

Data Science. This senior level course (team-taught by CS and Statistics faculty) is taken during the Fall quarter of the senior year after completing the majority of the CS and Statistics courses in the CDSM. This course aims to synthesize the statistics and CS skills acquired in the prerequisite coursework and to present a holistic picture of Machine Learning not seen elsewhere in the curriculum. The course introduces core material from the fields of applied mathematics, statistics, and computer science. Students receive a brief introduction into numerical analysis and optimization, including gradient descent and Lagrangian optimization. Drawing from the statistics discipline, the course presents parametric and nonparametric models of data, and the principle of maximum likelihood to derive a number of machine learning techniques such as linear and logistic regression. Advanced machine learning techniques not covered in the Knowledge Discovery from Data course,

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such as Support Vector Machines and Neural Networks, are also studied with emphasis on the mathematics behind the methods and their optimization techniques to discover solutions. Throughout the course students work in small teams on a number of data science projects to practice applying the material covered in the class culminating in class presentations.

Data Science Capstone I and II. This 6-month long capstone sequence follows the Data Science course (above) and completes the senior year. This capstone is meant to give students real-world experience so that they can be ready for industrial and scientific applications. Working with real clients, student teams manage all aspects of the data science workflow. In collaboration with their clients, they specify and design project requirements, implement data gathering methods leading to the deployment and delivery of a system or analytical methodology that involves working with, analyzing, and visualizing large quantities of data. Projects include technical documentation, quality assurance, integration and systems testing. Other non-technical skills include project planning, time and budget estimating, project team organization, ethics, and professionalism. The inaugural capstone was taught in Winter and Spring of 2017 to a cohort of nine students. The course had three outside customers: a government agency (USAID; students working on this project analyzed household surveys from a number of African countries), an academic customer (a Political Science professor interested in the problem of redistricting), and an industry customer (a San Francisco startup OpenDoors, which asked the students to learn a variety of features for evaluating the price of real estate).

Making it Work

The full CDSM in Data Science proposal, as described above constituted 21 required courses totalling 80 quarter units, including four new courses developed specifically for the Data Science curriculum (12 units). This is a very ambitious curriculum: by way of comparison, BS in Computer Science major requires 15 CS courses, seven more technical electives and a two-quarter senior project for a total of 24 courses in the major. The key behind the ability to offer an ambitious cross-disciplinary Data Science curriculum to Computer Science and Statistics majors lies in the ability to map the CDSM coursework to the respective BS requirements in CS and Statistics. Table 1 shows how each course was mapped to both the Computer Science and Statistics curricula.

As seen from Table 1, both mappings take significant advantage of the fact that many courses in the curriculum are required for each respective major, and that there is reasonable flexibility in the elective coursework in both majors. Eight courses from the list above are accounted for via major requirements in one or more programs (five mutually required). Additionally, BS in CS students can count six more courses as various types of electives, including all but one upper-division Statistics courses. BS in Statistics students can count seven courses as various types of electives, including all upper division CS coursework. Only the four special purpose Data Science courses (and the Multivariate Analysis course for CS majors) comprise the coursework above and beyond the major.

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Table 1.

Mapping of Data Science curriculum classes to CS and Statistics majors.

Course	BS in CS	CS: extra units	BS in Statistics	Statistics: extra units
Calculus III	required	0	required	0
Linear Algebra	required	0	required	0
Intro to Statistics	required	0	required	0
Intro to Probability	math elective	0	required	0
Applied Linear Regression	upper div elective	0	required	0
Multivariate Analysis	minor	**4**	tech elective	0
Statistical Computing in R	tech elective	0	required	0
Fundamentals of CS I	required	0	required	0
Object-Oriented Programming	required	0	support elective	0
Data Structures	required	0	support elective	0
Discrete Math	required	0	required	0
Algorithms	required	0	tech elective	0
Intro to Databases	tech elective	0	tech elective	0
Distributed Computing	tech elective	0	tech elective	0
Knowledge Discovery in Data	tech elective	0	free elective	0
Intro to Data Science	minor	**4**	minor	**4**
Data Science	minor	**4**	minor	**4**
Data Science Capstone I	minor	**2**	minor	**2**
Data Science Capstone II	minor	**2**	minor	**2**

Lessons Learned

The Data Science CDSM opened its doors in Fall 2015. Due to the structure of the minor, it was possible to engage rising sophomores and juniors, thus allowing us to produce our first graduating class of nine students representing four majors (Statistics, CS, Computer Engineering and Mathematics) in Spring of 2017. Another 24 students will receive the Data Science minor in Spring 2018. It will take several more years for us to be able to appropriately assess the actual impact the program has had on its participants. At the same time, we believe that our experience and discoveries on the way to designing the CDSM may offer valuable insight to other campuses in how to proceed in building a healthy cross-disciplinary programs in ways that leverage the existing knowledge and expertise to a maximum. Throughout our experience, the following core lessons and conclusions have emerged.

When everything else fails, create your own rules. To create a successful data science program, we had to build a brand-new unique academic subprogram: the Cross-Disciplinary Studies Minor. The CDSM is a perfect vehicle for programs that want to combine a concentration in a student's major, with an in-depth minor in another, related and relevant area: the key feature of CDSM is to make such opportunities reciprocal for participating programs. The authors are grateful to all their colleagues among the faculty and administration who have participated in the past five years in discussions and the approval process for this vehicle.

The CDSM is a degree enhancement. The initial development of the Data Science curriculum followed a path similar to the development of a full-blown degree program, but to achieve all of the learning objectives (and general education requirements of all degree programs) the total unit demand would exceed 180 units, the maximum permitted by Cal Poly policy. For example, using the CDSM as a vehicle to offer a curriculum to meet the full set of objectives yields a "super-degree" in Data Science – the BS enhanced by the CDSM. In general, a

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key feature of a CDSM is that it produces two (or more) "flavors" of specialists: one for each participating degree program. For example, the CDSM in Data Science produces Data Scientists with BS degrees in Computer Science and Statistics, each with their own, unique to their core discipline additional knowledge and skills.

CDSMs allow for bigger subprograms. The immediate consequence of a definition of a CDSM is that with a pair of participating programs, it provides an immediate ability to build either a 12-course cross-disciplinary curriculum with little additional synthesis coursework, or a 10-course one including more synthesis coursework for universities operating on the quarter system. For universities operating on semester system, a CDSM that does not exceed the units above and beyond those of a regular minor would allow for an 8-course "weak" curriculum, or a 6-course "strong" curriculum.

We illustrate this on the example of the other CDSM at Cal Poly, the Computing for Interactive Arts (CIA) minor. The participating programs in this CDSM are Art and Computer Science. These programs have no ability to count courses taken in the partner discipline towards their own own BS degree. As such, the CIA minor incorporates three required Art courses, three required CS courses, two approved tech electives in each field, and a two quarter capstone course (totaling 4 units) for a total of 12 courses. Each major counts the five courses (20 units) in its field as part of the BS degree, and leaves the remaining seven courses worth 24 units as above and beyond the major. The CIA CDSM does not have an introductory course in the field of Computational Interactive Art, but it does include a two-quarter project-based capstone.

Widespread campus interest. Our development of the CDSM in Data Science was an attempt to directly address the growing demand for formally trained ready-to-deploy data scientists by developing a rigorous curriculum with focus on foundational and generalizable concepts in computer science and statistics. This approach excludes any training for the more casual analyst who might use a commercial visualization tool on a processed or structured dataset. As a result, colleagues in Business and Journalism, for example, have felt alienated and have developed curriculum of their own to address niche analytics (e.g., in Business, an M.S. in Business Analytics; in Journalism a course in "Data Journalism"). We have been challenged to find a "one-size fits all" solution. At the same time, consistent with the core demands in the tech industry for properly trained data scientists, we believe that a curriculum that emphasizes the technical depths in CS and statistics and targets students in these majors needs to be offered. Note that access to the CDSM in Data Science is not exclusive, it is merely optimized for the statistics and computer science programs. Some of the students who have already received the Data Science CDSM, or have been admitted into the minor are students in mathematics, computer engineering, software engineering, and political science majors. Their participation in the program has a higher unit cost, but a cost these individual students are willing to bear.

Collaborative nature of the process. To put it simply, this achievement would not have been possible without two critical components: the ability of the representatives of the two departments to work together in a trusting manner on the development of the CDSM proposal. Additionally, each specific CDSM requires strong support from the participating departments, including the willingness of the departments to admit additional students into their classes, collaboration between the CDSM creators and the department curricula committees and department chairs.

Unique Educators. If it's difficult for industry to find competent young data scientists, it is even harder to find data scientist educators. As a still emerging field, there are still very few new PhDs who are comprehensively trained, and those that are have many opportunities for financial reward that greatly exceeds what most universities can pay faculty. This situation likely exists for other cross-disciplinary areas as well. It is expected that individuals with specialized knowledge in multiple domains are in high demand and have many lucrative and rewarding opportunities. Our solution at Cal Poly has been to leverage the expertise of interested and engaged faculty and to encourage "on-the-job training". Such an approach may not be appropriate for graduate programs, but an undergraduate program allows for faculty growth alongside the student growth.

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RESEARCH REPORT

Good Problems within and Across Disciplines

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Abstract: *This paper focuses on the question of what makes a good disciplinary or interdisciplinary problem. We draw from literature across the STEM disciplines and two conference sessions to provide insight into what makes a good problem within a specific discipline and across the disciplines. We use various frameworks to analyze a variety of problems that were nominated as exemplars by STEM education research experts. Common features identified include real-world connections, reinforcement of conceptual understanding, a low floor and high ceiling, multiple solutions paths, and building dispositions of professionals in the discipline. While a good problem need not have all of these features, in general, good problems have more of these features. We also recognize that these problems are context-specific, as what may be considered a problem for one learner could be a trivial exercise for another. We discuss some of the challenges of designing good interdisciplinary problems and identify some features that can make a problem interdisciplinary, including use of cross-cutting concepts and drawing on the specific expertise of each discipline.*

Keywords: Problem solving, interdisciplinary activities, problem choice, disciplinary tasks

Introduction

STEM professionals are problem solvers. Engineers design solutions – bridges, airplanes, computers – that transform the way we live and work. Computer scientists develop applications that take our productivity to new levels. Physicists use fundamental laws to build models of increasingly complex real-world phenomena. Biologists develop new techniques for taming microscopic hazards that attack the human body. Chemists transform and analyze matter, from drug therapies to designer materials, to better our quality of life. All of these solutions arise from addressing basic problems of human existence, and these solutions transform our society.

Given the fundamental role of problem solving across the STEM disciplines, problem solving is a highly-valued practice in STEM education. But what types of problems should students solve? Which problems will help them develop the relevant skills that later allow them to solve problems like minimizing the effects of climate change, treatments for diseases, or engineering solutions? How do instructors support students to engage with such problems?

This paper addresses the question: what makes a problem good? Thinking beyond problems generally, what makes a problem good for biology, physics, math, engineering, computer science, or chemistry? What are the implications for interdisciplinary problems? In this paper, we discuss a variety of frameworks for thinking about good problems, both within and across disciplines. Drawing from two conference sessions focused on

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good problems, we analyze a variety of problems nominated by Discipline Based Education Research (DBER) scholars as exemplars. The authors of this paper span a variety of disciplines, so the individuals analyzing each of the problems given have expertise in that particular discipline. We close by discussing the challenges and opportunities for interdisciplinary problems.

Theoretical Background

What makes a problem?

We take the view that problem solving is relative. In this way, what constitutes a problem is a relationship between a problem solver and the task itself, not an inherent property of the task (Schoenfeld, 1985). Thus, a problem is something that is difficult for someone who is engaging with it. A good problem is typically more than just a technical or computational challenge, but something that poses an impasse in conceptualizing or implementing a solution. We recognize that some great unsolved problems in the STEM disciplines are also computational challenges, like image recognition, but this is different from a computational challenge such as multiplying two four-digit numbers mentally. In other words, if someone has a readily available solution schema, that they could in principle implement, it is an exercise, not a problem (Schoenfeld, 1985). Further, problems can be conceptualized as seeds to disciplinary thinking (Schoenfeld, 1991). This means that problems serve as a platform for students to engage in the practices of a discipline. For our own work, we focus on tasks that are likely to serve as problems for students in our courses, recognizing that they would not be problems in this sense for disciplinary experts.

How do problems support learning?

Educators have developed a variety of metaphors for learning. Two prominent models are learning as knowledge acquisition and learning by apprenticeship (Sfard, 1998). From the knowledge acquisition perspective, we can think of learning in the STEM disciplines as a process of developing more normative conceptions of scientific (and mathematical) phenomena (Linn, Clark, & Slotta, 2003; Smith, diSessa, & Roschelle, 1993). From the apprenticeship perspective, learning is about being able to "do" the same things that STEM professionals do, in increasingly sophisticated ways (Lave, 1996). Taken together, we can think about learning as a process of changing what it means to "know and do" within the STEM disciplines (Lampert, 2003).

Across the STEM disciplines, scholars have paid great attention to features of problems that can support learning. We consider these as the pedagogical aspects of good problems. Our goal here is not to provide an exhaustive list of such features. Indeed, a recent dissertation focused on good problems analyzed a number of problems along over 20 dimensions, or mathematical problem features (Quarfoot, 2015). Aggregating these dimensions across disciplines, the list soon becomes intractable. Rather, we provide a brief look at some of these literatures simply to make the case that problems are good both because of what they help students learn, and how they help them learn it (i.e., the pedagogical features).

In mathematics, Schoenfeld (1991) describes a problem aesthetic, favoring problems that have some or all of the following four features: (a) accessibility, (b) multiple solution paths, (c) insight into mathematical concepts or practices, and (d) generalizability (to promote future exploration). Principles (a) and (d) are often described as having a "low floor and high ceiling," meaning that a problem is easy for any student to start, but allows for a great deal of challenge and exploration. The emphasis on multiple solution paths is pervasive in mathematics education (e.g., National Council of Teachers of Mathematics, 2000), because it allows students to compare and contrast their solutions to develop deeper knowledge. Taken together, these problem features are valuable because they support learning across a variety of students in heterogeneous environments (Cohen & Lotan, 1997), which is a real pedagogical challenge.

In computer science, the notion of "nifty" problems adds some other aspects of good problems (Layman, Williams, & Slaten, 2007). Such problems also meet four criteria, they are: (a) playful, fun, or interesting; (b) topical (fitting into standard curricula); (c) scalable (i.e. with a low floor and high ceiling); and (d) easily

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adoptable (by other instructors). This work emphasizes that good problems should be enjoyable for students, having some sort of fun factor that motivates students to want to work on the problem. Also, fitting in with standard curricula and having materials (e.g., handouts, source code) that can be easily used by others means that they are problems that can have utility to instructors in a variety of situations. Like the problem aesthetic described above, much of this niftiness is that the problems are designed in a way that they can work well for a variety of students in a variety of situations.

In physics, several novel problem formats have been developed: context-rich problems (Heller & Hollabaugh, 1992), ranking tasks (O'Kuma, Maloney, & Hieggelke, 1999), jeopardy problems (Van Heuvelen & Maloney, 1999), and more. As an example, context-rich problems are designed so that the problem is situated in a real-world context, often with extraneous or missing information, and with some level of solver choice in defining the aim of the problem, selecting an appropriate physical model of a situation, and evaluating the results (Heller, Keith, & Anderson, 1992). The real-world context can serve as a low floor because students may have experience with the setting, while also providing a high ceiling when simplifying approximations to the problem are replaced with more real-world practicalities. In addition, the context supports the disposition of professionals to apply physical thinking outside the classroom. Emphasis on development of physical models, estimation, and approximation supports problem solving practices used by professional physicists and allows for multiple solution paths. Context-rich problems and other common formats of physics problems attempt to include pedagogical incentives for expert-like problem solving practices, with varying success. While professional physicists classify problems in terms of the relevant underlying physics principles, novices are more likely to focus on surface features of a problem (Chi, Feltovich, & Glaser, 1981; Docktor, Mestre, & Ross, 2012). To move the students towards move expert-like practices, problems have been structured to emphasize the key physics practices of blending conceptual and mathematical reasoning (Leonard, Dufresne, & Mestre, 1996; Hull, Kuo, Gupta, & Elby, 2013) and employing multiple representations (Kohl, Rosengrant, & Finkelstein, 2007). While context-rich problems provide many useful pedagogical opportunities for students, we also acknowledge that there are times when creating a fantasy or theoretical situation can also be beneficial, because it allows an instructor to emphasize particular concepts without the messiness of a real-world situation.

Does it matter how we use problems?

As emphasized above, it is helpful when problems can be used by a variety of instructors and students, in a variety of settings. In other words, problems do not exist in a vacuum. They serve as a starting point for learning, whether that takes place in the classroom, at home, in a lab, or out in the field. However, there is the whole process of teaching and learning that must take place, which can either enhance or inhibit the value of a task.

The first question is how many people should work on a given task. One way that this has been conceptualized is the notion of a "group worthy problem" (Cohen & Lotan, 1997; Featherstone et al., 2011; Heller et al., 1992). Simply put, any given task is appropriate for a certain number of people. Assigning a one-person task (e.g., procedural computations) to a group results in disengagement, because it is not group worthy. Similarly, assigning a task made for a team to a single person will result in frustration. So, when thinking about whether a problem is good or not, it is also a matter of thinking about how many people it is good for.

Another issue relates to how an instructor uses a task. In other words, what sort of scaffolding does the instructor provide? In mathematics, this issue has been conceptualized in terms of the math tasks framework with the idea of cognitive demand (Henningsen & Stein, 1997). When using a task in the classroom, there is the task as given, the task as framed by the instructor, and the task as implemented by students. These "tasks" may differ, because a teacher can provide scaffolding (e.g., support towards completing the task) or extensions (e.g., asking new and harder questions) during the enactment of a task. These techniques modify the cognitive demand of the task, influencing what students learn. It is common for instructors to over-scaffold tasks, which may remove their learning potential by only leaving the trivial aspects of the task for the students to complete.

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So, even if a task is good to begin with, it might be trivialized in implementation. Similarly, skilled teachers can take relatively mundane tasks and transform them into something worthwhile.

Related to the idea of cognitive demand is Bloom's Taxonomy of Cognitive Domains (Bloom et al., 1956), which has been taken up extensively by biology educators. Bloom's taxonomy organizes the type of thinking required by a task into six levels. These six levels can be further grouped as lower-order cognitive skills (knowledge, comprehension) and higher-order cognitive skills (application, analysis, synthesis, evaluation) (Crowe et al., 2008). Just as with cognitive demand, the way a teacher enacts a task can be used to engage higher-order skills, which would help make something into a "good problem." That said, recent inventory of end-of-chapter problems from popular General Chemistry textbooks noted a serious lack of problems in the higher cognitive categories, a situation that could very well limit both instructor and student access to examples of more meaningful learning opportunities (Dávila & Talanqer, 2010).

Another issue at hand in problem solving is working memory. As previously stated, "expert" problem solvers in a discipline are much better able to pay attention to the relevant features of a problem, while ignoring other aspects that are more peripheral (Chi et al., 1981). This relates to working memory, insofar that better problem solvers are able to better utilize their working memory by paying attention to the relevant features at hand (Passolunghi & Siegel, 2001). In contrast, less effective problem solvers may become bogged down because they are trying to attend to too many things at once. Through practice problem solving, students can better develop these metacognitive skills, and thus become better at problem solving as a practice (e.g., Schoenfeld, 1985).

Finally, one might consider the way that an exploration around a problem is sequenced. In science education, the Knowledge Integration (KI) framework describes a process for developing conceptual understanding (Linn et al., 2003). KI involves a four-step process: (1) elicit ideas, (2) add new ideas, (3) develop criteria, and (4) sort out ideas (Slotta & Linn, 2009). The developers of KI then embed this sequence into a variety of different project types (e.g., investigation, controversy, critique, design). If a particular part of the sequence is removed from how one engages with a task, less learning results (Slotta & Linn, 2009). This emphasizes that the curriculum surrounding a problem matters, and can either set up a problem for success or failure.

Are the STEM disciplines all the same?

Up to this point, one might simply think that good problems are good for any discipline. Indeed, certain pedagogical features are relatively standard across disciplines. For instance, it is hard to imagine a discipline in which good pedagogical practice would mean making problems too difficult for most of the students, or trivializing them to the point where there is nothing left for students to do. At the same time, we acknowledge that the STEM disciplines are actually quite diverse, and simply referring to them simultaneously in a single acronym obscures this diversity. One of our goals with this paper is to highlight such diversity. We begin to do so by highlighting that the major problem types in disciplines are quite different, owing to the disciplines themselves.

In the biosciences, the use of case studies is a powerful tool for learning (Allchin, 2013). Such problems are particularly valuable because they provide students with an opportunity to use evidence to make predictions about authentic problems that highlight complexity of living organisms and their environments. Chemistry education often focuses on coordinating macroscopic, submicroscopic, and symbolic representations of chemical phenomena (Talanquer, 2011). This coordination models the reasoning patterns of experts, who tend to think about chemistry using the three domains simultaneously. In the geosciences, spatial navigation and mapping are key practices for field work (Riggs, Lieder, & Balliet, 2009). In physics, there is a huge emphasis on building simplified models from which theoretical generalizations can be made (Hestenes, 1987; Brewe, 2008). Computer science centers on developing programs, so debugging and programming are key parts of the problem-solving process (Layman et al., 2007). In engineering, building solutions to real-world problems is the goal, so there is a focus on designing, prototyping, testing, and refining (Ikonen, Piironen, Saurén, & Lankinen, 2009). Finally, (pure) mathematics revolves around conjecturing, argumentation, and proof; it is deductive rather than empirical (Harel & Sowder, 2007). A summary of these problem types is given in Table 1.

Table 1.

Canonical problem types by discipline

Discipline	**Problem Type**	**Values / Implications**
Biosciences	Case Studies	Reasoning from evidence
Chemistry	Representation	Coordinating macro, submicro, and symbolic
Geosciences	Spatial Navigation	Guiding field work
Physics	Model Building	Articulation of physical laws
Computer Science	Programming/Debugging	Creating tools
Engineering	Design Challenges	Real-world solutions
(Pure) Mathematics	Proof/Argumentation	Theory building

This is not to say that each discipline has only one core practice or type of problem. Rather, we argue that certain problem types are emblematic of certain disciplines and rarely used in others. This is due to fundamental differences in the nature of the disciplines and their valued practices. For instance, while it is possible to have mathematical proofs that speak to the science disciplines, it is rare for a proof to afford opportunities to develop disciplinary knowledge in science disciplines, because they are empirical while pure mathematics is not. This means that developing good problems across the disciplines has an extra level of challenge involved.

What is disciplinary learning?

Having considered some of the nuances of problems across STEM disciplines, we introduce a framework for thinking about learning in the disciplines. This gives us another way to think about which problems are good – they are the ones that result in more learning. Within the STEM disciplines, there are a variety of guiding documents that set out standards for what students should know and be able to do. Here we draw on two frameworks from the National Research Council: Adding it Up in mathematics (National Research Council [NRC], 2001), and the Science Education Framework for science and engineering disciplines (National Research Council [NRC], 2011). Taken together, we can draw out a few key areas of focus across all STEM disciplines.

The Science Education Framework has three major areas of focus for student understanding: disciplinary practices, crosscutting concepts, and core disciplinary ideas (NRC, 2011). Practices are things such as developing and using models, analyzing and interpreting data, or explaining and justifying one's ideas, that are key to doing the work of STEM professionals. Crosscutting concepts are big conceptual ideas like patterns, systems, and conservation, that are relevant to many disciplines such as physics, biology, and chemistry. Finally, core disciplinary ideas are concepts such as forces (physics), evolution (biology), and the particulate nature of matter (chemistry), that are critical to understanding particular disciplines. In biology, these concepts and practices are clearly described by the 3D-LAP (Laverty, et al., 2016) and Vision and Change (AAAS, 2011), which makes biology exemplary in this regard of describing the desired disciplinary knowledge at the undergraduate level. In chemistry, the discipline's "anchoring concepts" (as they are operationalized in an undergraduate curriculum) are articulated in the American Chemical Society Examinations Institute's Anchoring Concepts Content Maps (ACCM) (Murphy, Holme, Zenisky, Caruthers, & Knaus 2012; Holme, Luxford, & Murphy, 2015), which have been established by the Chemistry community at large, with input from participants of several workshop and focus group sessions. Other disciplines have varying specificity in documents describing the core ideas of the discipline, but this is mostly at the K-12 level.

Drawing from Adding it Up, there is a conceptualization of mathematical proficiency as having five strands: conceptual understanding, procedural fluency, strategic competence, adaptive reasoning, and productive dispositions (NRC, 2001). Conceptual understanding relates to math concepts, operations, and

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relations. Procedural fluency is the ability to carry out procedures with flexibility, efficiency, and accuracy. Procedures are things like performing integration by parts, balancing a chemical equation, or constructing a Fourier series. Strategic competence relates to solving mathematical problems and adaptive reasoning relates to interpreting and explaining mathematical ideas. Finally, productive dispositions relate to how one sees and identifies with the discipline. Ideas like "steady effort in learning mathematics pays off," "deep thinking, not speed is valued," or "math is useful in the real world" would be considered productive dispositions.

Taking these two frameworks together, we offer four main categories: concepts, practices, procedures, and dispositions. We condense crosscutting concepts and core disciplinary ideas together in the category of concepts, recognizing that some of these may be specific to a discipline while others are cross-disciplinary. We also condense strategic competence and adaptive reasoning together in the category of practices, seeing as these are both core disciplinary practices in mathematics. Of the four areas, we de-emphasize procedures compared to the others. Procedures are not unuseful, but in most typical curricula, they receive far more attention than the other three categories. Thus, part of the work of good problems is to counteract this narrowing of the curriculum.

From the perspective of our framework, a problem can be considered "good" when it helps students learn along these four dimensions. The pedagogical and other features described above all make it easier for a student to engage meaningfully with a problem, but there must also be something meaningful to learn from the problem, which these dimensions describe. A good disciplinary problem supports growth along these dimensions with respect to that particular discipline (e.g., a good physics problem would help students develop the practices and dispositions of a physicist). A good multidisciplinary problem (Choi & Pak, 2006) does this for multiple disciplines (e.g., the practices and concepts of both mathematics and physics). One can also think of interdisciplinary problems (ones that build concepts in multiple disciplines and help integrate them) or transdisciplinary problems (those that also include a humanities context). For this paper we focus on disciplinary and interdisciplinary problems.

According to these classifications, it is possible to have a physics problem that includes mathematics, which is a good physics problem but not a good mathematics problem. In this sense, it could be a good disciplinary problem, and a multidisciplinary problem, but not a good multidisciplinary problem because it does not help build core ideas or practices in multiple disciplines.

Method

This paper builds on conversations from two interdisciplinary STEM education conferences: Breaking the Boundaries in STEM Education, hosted on April 7 at Loyola Marymount University; and Transforming Research in Undergraduate STEM Education (TRUSE), hosted from July 5-9, 2017, at the University of St. Thomas. There were approximately 20 participants throughout the day in the Breaking Boundaries problem solving strand, and approximately 40 in a follow-up breakout session on disciplinary problems at TRUSE. We acknowledge the conversations in these sessions as the inspiration for this paper. The participants in these sessions were Discipline-Based Education Researcher (DBER) scholars who spanned the disciplines of mathematics, physics, chemistry, and biology, with minimal representation of geology, computer science, and engineering.

During the TRUSE session, participants were first split up at different tables, by discipline, so that they could brainstorm features of good problems and exemplary problems within their disciplines. We draw from these problems in our analyses below. Afterwards, participants were split up into cross-disciplinary tables, and tasked to generate good interdisciplinary problems. We also offer some of these problems below with commentary on why this was a very difficult task.

Good Disciplinary Problems

Mathematics: Filling Bottles

The first problem was a mathematics problem that was suggested by the presenters (see Figure 1). This problem focuses on core ideas in calculus, notably function and rate of change. This problem also has core practices of representation (e.g., generating graphs from some realistic situations). As it relates to everyday life, the problem can promote productive dispositions that math is supposed to make sense and that functions do not necessarily need to be defined by a single algebraic formula. The problem de-emphasizes procedures, but there are some procedural aspects of labeling axes and putting together graphs.

You are filling up bottles with liquid coming from a tap at a constant rate.

1. For each bottle, sketch a graph of the height of liquid in the bottle as a function of time.
2. For each bottle, sketch a graph of the rate of change of the height of liquid in the bottle as a function of time.

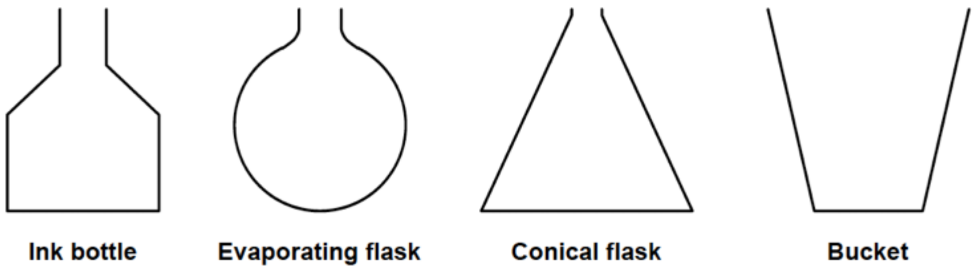

Figure 1. Filling bottles

This task is a nice example of a problem with a low floor and a high ceiling. For the first part of the task students can readily reason that in each case a graph of height versus time would be increasing and hence everyone can make some progress. Issues of concavity, average rate of change, and instantaneous rate of change, and the connection between the graph of a function and a graph of its rate of change can also emerge for students, making the ceiling quite high. In particular, the second bottle shape change point in the ink bottle offers an opportunity for students to informally and intuitively reason about instantaneous rate of change, even if this concept has not formally been defined in their calculus class. For example, Marrongelle and Rasmussen (2008) describe how offering alternatives for the shape of the graph at the point where the second bottle transition from spherical to cylindrical (see Figure 2) can be generative for eliciting justifications that foreground instantaneous rate of change.

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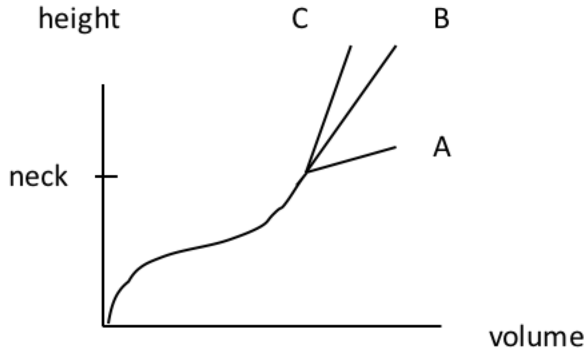

Figure 2. Which graph most accurately reflects what happens at the neck of the bottle?

The problem also has multiple solution pathways. For example, we have seen some students approach this problem by imagining a cup of water being poured in the bottle, marking on the image of the bottle how high they conjecture that the water rose, adding another cup of water and marking again on the bottle how high the water rose, etc. This cup by cup process would then be graphically re-represented and students can justify why it would make sense to connect the points with either straight line or non-straight line segments. Graphs of height versus time can also be generated by dynamically imaging how fast the water is rising as water flows into the flask at a constant rate. This type of reasoning is emblematic of what Carlson et al (2002) refer to as covariational reasoning, which is a foundational disciplinary way of conceptualizing how two quantities simultaneously change. While this task does not lead to formal deductive proofs, it does lend itself to conjectures, argumentation, and justification - key disciplinary practices in proving.

Physics: Superman: The Ride

The second problem is a context-rich physics problem written by one of the authors, who was actively involved in the Breaking Boundaries sessions. The problem statement is in Figure 3. As with many context-rich problems, this problem requires students to identify a calculable target variable that can be used to answer a non-quantitative question via comparison. The problem could be framed with a more explicit and more scaffolded question, such as "Assuming the brakes do not fail, is the safety track long enough?" However, we prefer this more open-ended question because it gives students valuable practice in identifying and justifying their assumptions and in determining which variables are calculable and relevant. As this problem is solved by groups in class, the instructor can reframe the question as necessary if students oversimplify the problem or have trouble identifying a calculable approach.

This question can be answered by calculating the distance that the car needs to stop under the influence of friction and comparing to the length of the safety track or calculating the speed after travelling the length of the safety track. Multiple solutions paths are available; this problem can be effectively solved using forces and kinematics, conservation and the work-kinetic energy theorem, or the impulse-momentum theorem. The instructor can have students explore the alternate solution paths as extensions to the problem. Each solution path requires a different physical model of the situation. Logically complete solutions require the students to articulate and justify approximations as part of their model, such as assuming negligible air resistance.

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I once rode Superman: The Ride at Magic Mountain. The ride accelerates a car through a launching station, then the track turns vertically upward. The car rises up the track to a height of 415 ft, then falls back down under the influence of gravity and stops again back at the starting point. The braking mechanism at the end of the ride malfunctioned so the car continued through the launching station onto a safety track where it was stopped by friction. I estimate that the coefficient of friction was 0.5. I can see that the safety track is 750 feet long. The ride specs say that the car weighs 6 tons. I also noticed that the brakes did partially engage. The ride attendant apologized for the malfunction and offered to let us ride again without waiting in line. Should I get off?

Figure 3. Superman: The Ride

The physics concepts used in this problem vary by choice of solution path. Regardless of the path, the solution requires employing at least two fundamental physics concepts (e.g. energy and forces, forces and kinematics, or energy and momentum). Any solution is likely to include at least two representations: a sketch of the ride and a motion diagram, free body diagram, or energy bar chart. Physics practices supported by this problem include defining a good question, identifying an appropriate physics principle, and application of physical laws. Once a physics principle has been chosen and translated into an equation using the appropriate physical law, the calculational procedures are simple algebra. Dispositions of physics experts encouraged by this problem include examining everyday situations for underlying physics, seeing physics as relevant to everyday life, modelling by making simplifying assumptions and approximations, and interpreting the conceptual meaning of calculated results.

Chemistry: Structure-Property Relationships

The third problem was suggested by a group of chemists; versions of this problem are well-known and published as exemplars (Laverty, et al., 2016). The problem stem presents two substances that possess the same molecular formula (dimethyl ether and ethanol, C2H6O) along with representations of their molecular structures (i.e. Lewis structures, Figure 4). The problem consisted of six prompts related to these two substances: (1) what intermolecular forces (IMFs) would be present in a container of dimethyl ether? (2) what IMFs would be present in a container of ethanol? (3) draw a collection of dimethyl ether molecules, showing the strongest IMF for this compound, labeling the location and type of IMF you are drawing; (4) draw a collection of ethanol molecules showing the strongest IMF for this compound, labeling the location and type of IMF you are drawing; (5) using the relative strengths of IMFs, predict which compound would have the higher boiling point and explain why; and (6) suggest a way in which a mixture of ethanol and diethyl ether could be separated and use your previous responses to support your suggestion.

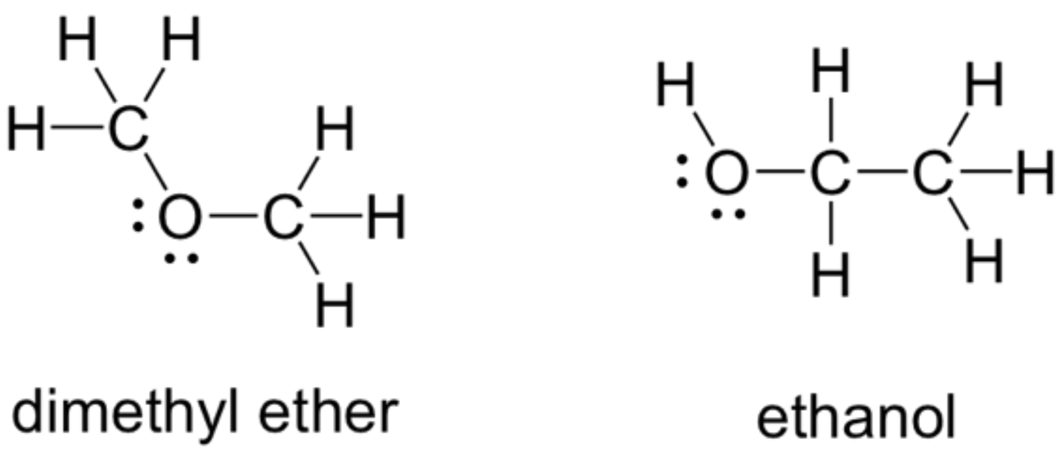

Figure 4. Data for structure-properties relationship problem

The chemists identified a number of reasons why this represents a "good problem." First, the problem centers on two core chemistry disciplinary ideas: (1) chemical compounds have geometric structures that influence their chemical and physical behaviors; and (2) intermolecular forces (electrostatic forces between

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molecules) dictate the physical behavior of matter. While chemistry's core ideas are articulated in a variety of ways, language from the ACCM was used here. Alignment with articulated disciplinary core ideas was considered a hallmark of "good problems" by the chemists because such organization mirrors how experts think about and reason within their own disciplines (National Research Council [NRC], 2000). Moreover, this problem is aligned with well-documented difficulties that students have when attempting to connect macroscopic properties to representations of molecular-level structure (Cooper et al., 2012). Thus, if implemented properly, this problem could aid students in overcoming a common struggle encountered when working with one of chemistry's core ideas.

Second, this problem requires students to engage in practices central to science in general and to chemistry specifically. Integral to Coppola's appeal to "Do Real Work, Not Homework" is the perception that students are only learning about science if they do not engage in the practices that are central to doing science (Coppola, 2015). The result of the former is, of course, the many shortcomings experienced by those who engage in rote versus meaningful learning (Mayer, 2002). Eight scientific and engineering practices were articulated in A Framework for K-12 Science Education (NRC, 2011) and there is little reason to believe that these practices should not be applied to the college classroom (Cooper, et al., 2015). An analysis of the "good problem" above using the Three-Dimensional Learning Assessment Protocol (3D-LAP, Laverty, et al., 2016) demonstrates that it is well-aligned to the scientific practices of Developing and Using Models—students are asked to construct models of the strongest IMFs present in samples of dimethyl ether and ethanol, make a prediction about a phenomenon (boiling points) using these models, and provide reasoning that links the model to the prediction. Moreover, this problem is aligned with a disciplinary practice articulated in Sevian and Talaquer's Chemical Thinking Learning Progression: analysis, the development and application of strategies for detecting, separating, and quantifying chemical substances (Enke, 2001; Sevian & Talaquer, 2014).

Lastly, this "good problem" is well-aligned (or has the potential to be, given how it is implemented in the classroom) with attributes of the aforementioned "Real Work" framework (Coppola, 2015). The problem balances convergent and divergent tasks; it demands that students construct responses that (a) can be identified as "right" or "wrong" (e.g. prompts 1, 2, and 5) and (b) that are more generative in nature, whose accuracy is defined within a set of common guidelines (e.g. prompts 3, 4, and 6). Absent from the problem articulation is how it is to be operationalized in a real learning environment; such choices could further align the "good problem" with the ideals of Real Work. For example, the problem could incorporate peer presentations, review, and critique so as to allow learners to develop explanatory knowledge; additionally, the problem could incorporate technology to permit learners to develop models using multiple modes.

Biology: The 'Dino Problem'

Variations of the 'Dino Problem' (Bray Speth et al., 2009; Grant 2008, cartoon adapted from Frank Hauser, Jr., published in Science, vol. 250, pp. 1103, 1990) have been used in biology education long before the TRUSE conference, but this problem was identified as a "good" by some of the biology education researchers that attended the conference. While this cartoon appears to be deceptively simple, it can actually pose real challenges for undergraduate biology students.

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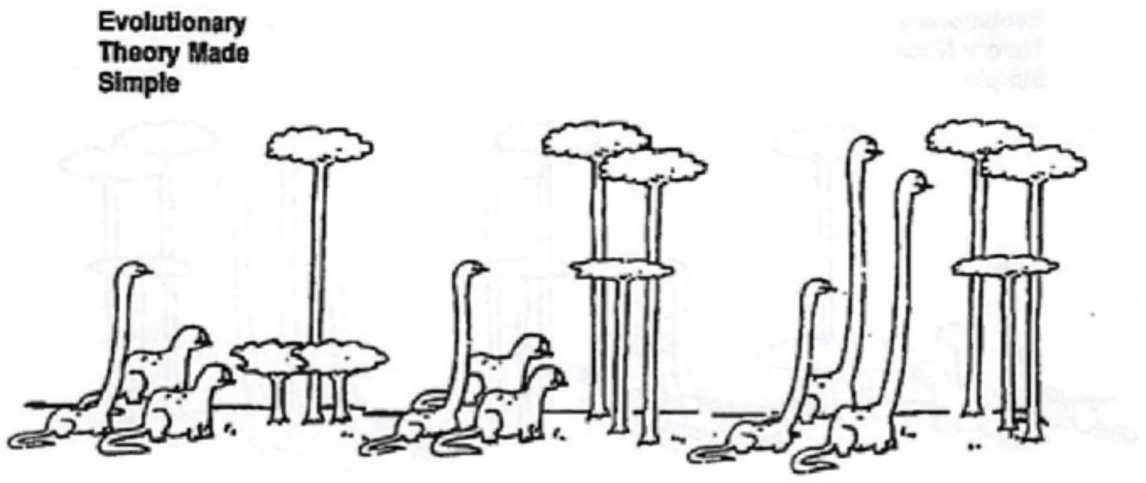

The cartoon above represents change that has occurred in a population of animals and a population of plants over thousands of years (time is read from left to right). Use your current understanding of evolution by natural selection to explain how the changes came about.

Figure 5. The Dino Problem

We consider the 'Dino Problem' to be a "good problem" for a number of reasons. First, this problem asks students to reason about evolution by natural selection, a core biology concept as recognized by reports from the NRC (2011) and AAAS (2011). A good response from a student needs to be quite complex and make use of all the principles that govern evolution by means of natural selection (i.e. variation within a population, genetic basis of that variation, trait inheritance, differential survival and reproductive success, and changes in phenotype frequency over time). To generate an exemplary response, students have to 1) recall the multiple principles that govern natural selection, 2) apply these principles to this hypothetical scenario, and 3) integrate the changes occurring in both of these populations by connecting with those governing principles. Even after instruction, biology students struggle to successfully incorporate all of the necessary principles when presented with this assessment.

Second, this problem explicitly asks students to generate a reason for why change came about, and therefore, students are primed to present their explanation in terms of cause and effect (a crosscutting concept). Also, this problem asks students to reason about two different populations (animals and plants) over time. By presenting these organisms in tandem (both pictorially and textually), students are encouraged to consider the interactions occurring between the organisms. So, we would argue that the 'Dino Problem' supports at least two crosscutting concepts from the NRC framework and the resulting 3D-LAP: a) cause and effect and b) systems and system models.

Third, this problem asks students to make inferences on the hypothetical evolutionary scenario depicted in the cartoon. Students are expected to generate an explanation for populations' change over time using their understanding of evolution by natural selection (Bray Speth et al., 2009). Because this question is situated in a hypothetical scenario, students would not be able to simply recall knowledge they have previously learned. Instead, students would need to apply the principles of natural selection in this new scenario, connecting those principles with the inferences they make from the figure to construct an accurate explanation of the evolutionary event, a task that is known to be very difficult for students. As a result, we would classify this as a higher-order cognitive question along Bloom's taxonomy (Crowe et al., 2008) that supports the scientific practices of a) developing and using models and b) constructing explanations that have been identified by the NRC (2011) and the resulting 3D-LAP (Laverty, et al., 2016).

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Good Interdisciplinary Problems

When participants in the TRUSE session were placed into interdisciplinary tables, they had a much harder time coming up with "good" interdisciplinary problems. Some groups were more successful than others (see below), but the fact that groups consisting of experts of multiple STEM fields had difficulty generating problems highlights the challenge of generating good, truly interdisciplinary problems.

Although participants struggled to generate many problems, the process itself elucidated some salient features of good interdisciplinary problems. Good interdisciplinary problems must have a contextual intersection that is interesting and relevant to multiple disciplines. A problem with a very narrow, discipline-specific context does not easily allow for the integration of multiple disciplines. For example, having students from biology and chemistry balance a chemical equation gives them practice of an important procedure used in both fields, but it does not allow for the biology students to bring in their domain-specific knowledge to add to the solution. Oftentimes instructors (and textbook authors) try to rectify this issue by making the surface features of the problem relate to a second discipline, while the deep feature remains discipline-specific—asking students to balance a chemical equation related to glycolysis does not automatically make it a biology problem as well.

However, a rich context is not a sufficient condition for a good interdisciplinary problem. Good problems should generate knowledge in multiple disciplines. One way to do this is through the application of a crosscutting concept. Every scientific discipline is unique, but many of them use the same tools and concepts to tackle problems, such as energy (Watkins, Coffey, Redish, & Cooke, 2012) and conservation laws, which can be applied in a large range of situations. A bonus consequence of the universality of these crosscutting concepts is that members of each discipline think about, focus on, and invoke different aspects of the underlying concept when solving problems. This leads to a more creative and dynamic problem-solving process as students from different disciplines can unlock different parts of the problem, which then uncover new entry points for the other disciplines to add to a possible solution.

The application of crosscutting concepts emphasizes the interconnectedness of the various disciplines and helps fight the compartmentalization of concepts by discipline. Science is not done in a vacuum; big, important scientific problems facing humanity like curing cancer or minimizing the effects of climate change require creative solutions and the cooperation of many scientists from different disciplines. Group solving of good interdisciplinary problems mimics how science is done "in real life." This is a way to promote dispositions that are valued across multiple disciplines. It provides students—who will eventually be the ones working on these big, important scientific problems—an opportunity for them to act as proto-practitioners in a classroom setting. Here are two examples of possible interdisciplinary problems created during the TRUSE session.

Climate Modeling

Keeping in mind that a good interdisciplinary problem should have broad contextual relevance, one group suggested climate modeling as a candidate for a suite of problems but did not agree upon a specific problem statement (again highlighting the difficulty of writing problems like this). Such a large and complex topic allows for the integration of many different STEM disciplines, but can quickly become overwhelming if the focus is not narrowed enough that the beginning, or at least a toehold, of a solution can be seen. One such question could be "What effect would a 10% decrease in the amount of carbon dioxide in the Earth's atmosphere have on the oceans and their ecosystem?" Geologists, environmental scientists, and biologists would bring their knowledge of the climate and Earth as a system to the solution. This base knowledge would provide a starting point for the group to rally around, and others could build on it in various ways. Testing possible models would necessitate some level of computational modeling and, thus, writing computer code, in which mathematicians, computational physicists, and computer scientists all have expertise. An understanding of the chemistry of the oceans and the atmosphere and the effect temperature has on relevant reactions and chemical equilibria, such as acidification of the oceans due to increased dissolved carbon dioxide, is crucial for an accurate and complete

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model of the planet's climate. A broad topic like climate modeling requires input from practitioners of many different STEM fields, each of whom would bring valuable discipline-specific practices and core ideas necessary to completely understand the problem at hand.

Fat Problem

This problem is simply stated as: "If you were to lose five pounds of fat, where does it go?" The most obvious applications of this problem relate to biology and chemistry: What is fat? What is its chemical structure? How and why is fat created in the body? How and why is fat broken down in the body? How is the broken-down fat expelled from the body? Biologists might take a big-picture, system-level view of the problem by looking at the various metabolic processes, while chemists might focus on the products and energetics of the specific reactions involved.

Although this problem is clearly relevant to biology and chemistry, members of other disciplines can provide valuable insight into its solution. Applied mathematicians and physicists, who generally value modeling and theory building, can provide a simple model from which generalization can be made. They could also work on various scaling arguments to see how the size of the organism affects the conversion process itself, as well as the relative amounts of product and heat generated. For example, how might the solution found initially for a human change for a mouse? A cat? An elephant? A blue whale?

In addition to a rich and relevant context, this problem requires the use of crosscutting concepts like energy and conservation of mass. A chemist would be interested in the thermodynamics and energetics of the individual chemical reactions, reactants, and products. A biologist might take a broader view of these reactions and focus on the energetic coupling of one reaction to another, say, or how the release of energy due to a specific reaction affects the organism as a whole. Conservation laws require the defining of a system, which changes depending upon what is being solved for. Mass must be conserved in a given chemical reaction, which is shown by a balanced chemical equation; an organism, on the other hand, can "lose weight" due to interactions and transfers between it and the surroundings.

This problem is also an example of a "low floor, high ceiling" problem. The problem is simple on its face – "Where does the fat go?" – and is very approachable for scientists and non-scientists, alike. This initial simplicity belies a possibly complex and intricate solution that can be extended to further applications or other related problems. For example, students could propose and then perform experiments to test the predictions generated during the problem-solving process. They could burn a sample of fat in an enclosed space and measure the amount of carbon dioxide produced or any resulting temperature changes. This then leads to another good interdisciplinary problem relevant to many disciplines—the interpretation of actual scientific data with respect to a system of interest.

Discussion

This paper tackles the problem of what makes a good problem. STEM DBER scholars across their disciplines have spent a considerable amount of time thinking about problems, but there is certainly no consensus across the disciplines. Nevertheless, scholars have developed a variety of different, yet complementary, frameworks that can be used to think across the disciplines. For instance, mathematics educators use the idea of cognitive demand to describe what type of thinking a task requires, whereas biologists have taken up Bloom's taxonomy. Here we benefit from the interdisciplinarity of the authors, as it provides us access to literatures and concepts that we otherwise would not be familiar with.

Although we took different lenses to the problems above, we note common features including real-world connections, reinforcement of conceptual understanding, multiple solutions paths, a low floor and high ceiling, and building dispositions of professionals in the discipline. We propose that good problems in any STEM discipline will include at least some of these features, though any individual problem need not contain all

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of these features. While these are similar features, they are also discipline-specific. Each discipline favors certain concepts, dispositions, and real-world connections (e.g., engineering design vs. theory-building). Indeed, as we reflect on our collaborative work through these sessions, we recognize that for an individual who does not have disciplinary expertise, it may be very difficult to tell whether or not a problem is good.

We also reflect on the extent to which students across the disciplines actually have the opportunity to engage in good problems. In physics, for example, despite wide consensus among physics education faculty on the benefits of the features of good problems, many instructors persist in assigning problems that are not well aligned with their learning goals (Yerushalmi, Cohen, Heller, Heller, & Henderson, 2010). Textbook analyses in mathematics also points to the impoverished nature of tasks for instructors to choose from. For example, Lithner (2004) found that in a mainstream calculus textbook, 90% of the tasks could be solved by superficial reasoning (e.g., relying on recall, keywords, pattern matching to worked out examples). Thus even if an instructor wanted to assign good problems, either for homework or for collaborative work in class, finding or developing such problems can be a challenge.

Finally, creating interdisciplinary problems was a challenge for members of our sessions. Because a good deal of disciplinary knowledge is required to engage with many problems, interdisciplinary problems require deep understanding of multiple disciplines. This is difficult to achieve unless one is teaching in a truly interdisciplinary environment. Another possibility that we see is using different problem types across disciplines. For instance, programming is ubiquitous in computer science, but it could also be used in physics, integrating the two subjects better. Similarly, mathematical biology is a new area that has emerged in mathematics. While it is challenging, we remain optimistic for possibilities of truly interdisciplinary problems.

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RESEARCH REPORT

Equity during peer conferences: A linguistic comparison by race and gender

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Abstract: *This paper provides an analysis of students' peer assessment conversations in introductory college calculus. Prior research shows that this type of activity can support meaningful student learning. However, previous studies have suggested that students from different groups (e.g., by race or gender) may have different opportunities to participate in such discussion-based activities. Accordingly, this paper explores the participation of students in peer assessment conversations, by focusing on the types of feedback and word choices used by different groups of students, by race and gender. Based on computer-aided textual analysis, this paper provides insights into the types of words used by different students in the class. While there was evidence of inequities in participation between men and women, the results for race were inconclusive. These results suggest that peer conferences have some potential for producing more equitable participation in calculus.*

Keywords: Equity, peer assessment, participation

Introduction

Imagine walking through a large-enrollment introductory STEM classroom with hundreds of students trading papers and providing constructive feedback on one another's problem solving. As you walk around the classroom, you overhear a student conferencing with their peer:

> Part three of your solution is clearly wrong. You didn't even show units and your answer doesn't make sense when interpreted physically.

As you continue walking, you overhear another student:

> I'm not sure about your response to number two. I wonder if you could show more work, and could you explain more to me about what you were thinking? I have a feeling that you may have computed the distances using an incorrect model of the physical setup.

What could you say about the relative status of the speaker and listener in each example based on the words they used? Which words would help you draw inferences?

In the first excerpt, the speaker strongly asserts that their peer's work is incorrect. This type of feedback discusses the product of the work but provides no insight into why an incorrect answer may have been reached. In contrast, the second speaker describes what they think about their peer's work, with a strong focus on the problem-solving process. That is, the speaker is concerned with why the listener may have had an incorrect result, not just that it was an incorrect result. While feedback is known to promote learning, not all feedback is

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equally useful, with feedback that focuses on the why being more helpful than that focusing on the what (Hattie & Timperley, 2007; Reinholz, 2017b). Thus, by analyzing the types of feedback across a variety of speaker-listener pairs, it may be possible to infer something about the value of these interactions to promote learning.

What else could you infer? In the first excerpt, few first-person pronouns are used. Rather than saying what they think about their peer's solution, the speaker simply makes statements about what the listener's solution should be. In contrast, the second excerpt features a large number of 'I' statements. The feedback is clearly coming from the perspective of the speaker. Such pronoun usage can reveal status hierarchies (Pennebaker, 2011). The first speaker, who uses many more second-person pronouns is likely of higher status than the second speaker who uses primarily first-person pronouns. Thus, simply by looking at the types of pronouns students use in the conversations, it may be possible to uncover subtle status hierarchies in the classroom.

This paper focuses on the use of words as they relate to status hierarchies. Research shows that students with less status have fewer opportunities to learn, which is a source of inequity (e.g., Cohen & Lotan, 1997). This paper addresses the following research question:

> *What quantitative patterns exist in the language used by students in different racial and gender groups in peer feedback conferences?*

In light of this question, the implications of using peer feedback as a tool to create more equitable learning opportunities are discussed. This paper focuses on mathematics, but the results should generalize to other disciplines, especially given that the focal activity, Peer-Assisted Reflection (PAR) (Reinholz, 2015a), has been used across STEM disciplines.

Theoretical Framing

Classroom discourse is a key part of learning (Bransford, Brown, & Cocking, 2000; Lampert, 1990; Sfard, 2008). However, students simply speaking during class through low level contributions is insufficient (cf. Cazden, 2001; Mehan, 1979). Rather, students need to engage with disciplinary content in ways that require higher-order thinking (cf. Stein, Grover, & Henningsen, 1996). This means that students should not merely provide answers to short computations, but rather, they should spend time explaining disciplinary concepts.

Discourse is a powerful learning vehicle, but it is also a means of potential inequity (Esmonde & Langer-Osuna, 2013; e.g., Herbel-Eisenmann, Choppin, Wagner, & Pimm, 2012). For instance, students from certain groups tend to receive lower-level participation opportunities, based on their gender (Sadker, Sadker, & Zittleman, 2009), race (McAfee, 2014), and immigration status (Planas & Gorgorió, 2004). These students tend to be those who are already underrepresented in the STEM disciplines (i.e. women, and students of color). While the actions leading to such patterns are unintentional, they have negative consequences for many learners, and must be addressed.

Equity is a matter of justice (Secada, 1989). An equitable classroom is one in which students receive instruction in accordance with what they need as learners. This means that equity is subjective and depends on the feelings and experiences of individual learners. As such, it is difficult for an outsider to make strong claims about what is an equitable classroom, because they cannot share the same lived experiences as individual students in the classroom. Nevertheless, it is clear that if students from historically-marginalized groups receive fewer opportunities to learn (i.e. less than equal) than their historically-dominant peers, that would signify inequity. In this way, equality is taken as a necessary but insufficient baseline for equity (Secada, 1989). In other words, if all students receive at least equal opportunities to participate, it is a positive (yet insufficient) step in the right direction.

Educators have worked for decades to reduce inequity, but it still remains prevalent in a wide variety of mathematics settings (Adiredja & Andrews-Larson, 2017; Gutiérrez, 2008; Leyva, 2017; Martin, 2003; President's Council of Advisors on Science and Technology, 2012). Through these efforts, some powerful techniques have

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been developed for supporting equity. One well-known example is the set of techniques associated with Complex Instruction. These instructional moves (e.g., framing tasks as requiring multiple, diverse skills to be completed; assigning competence to low-status students) help mitigate status hierarchies in heterogeneous classrooms, leading to more equitable outcomes for all students (Cohen & Lotan, 1997; Nasir, Cabana, Shreve, Woodbury, & Louie, 2014). In other words, power imbalances (e.g., who is perceived as a high-status) lead to less equitable outcomes (Engle, Langer-Osuna, & Royston, 2014; Langer-Osuna, 2016), but when these imbalances can be addressed, learning becomes more equitable (Cohen & Lotan, 1997).

Against this backdrop, the present study focuses on issues of equity and status in peer feedback conferences, particularly with respect to race and gender. Peer conferences are an important feature of peer assessment (cf. Falchikov & Goldfinch, 2000; Topping, 2009) and offer unique opportunities for addressing issues of inequity in discourse. In particular, peer conferences generally involve only two students, so the complexities of promoting participation from all students in a small group or a whole class are reduced. Moreover, peer conferences position students as competent authorities, because they must critically judge the work of their peers, which provides them with space in the classroom to act as experts (cf. Engle & Conant, 2002; Reinholz, 2015a).

Finally, it is worth noting that race and gender are complex, socially-constructed identities, which organize the social positioning of individuals (Davies & Harré, 1990). As such, putting students into these discrete categories can be problematic, because it obscures this complexity; gender is not a binary, and the reality of students' lives is much more complicated and their identity might change under different circumstances. Nevertheless, such essentialization can be 'strategic,' as a tool to highlight or address inequities (Gutierrez, 2002). The value of using static categories to promote equity can be seen in stereotype threat research.

Stereotype threat occurs when high-pressure circumstances (e.g., taking an exam) cue negative stereotypes related to academic performance in particular domains (e.g., Black and Latinx students as bad at math). This could happen, for instance, when there are only five women taking an exam in an introductory course with over 100 men, because their identities as women would be highly salient in this context. When comparisons are cued in such social contexts, it negatively impacts the performance of students from certain groups, thereby further marginalizing them (Spencer, Steele, & Quinn, 1999; Steele, 1997).

To see how stereotype threat operates, it is important to temporarily flatten the complex categories of race and gender, so we can understand how racialized and gendered stereotypes marginalize particular students. Thus, this strategic essentialism makes it possible to illuminate subtle patterns of inequity (e.g., men speaking more than women), as a step towards greater equity. Still, complementary approaches that treat social markers more fluidly are necessary too (e.g., Nasir, McLaughlin, & Jones, 2009).

Method

Context

The present study took place in Calculus I at a large, Hispanic-serving, PhD-granting institution with high research activity. There are approximately 30,000 undergraduate students (45% women). The racial demographics of undergraduates are roughly: 4% African American, 0.3% Native American, 6% Filipino, 7.3% Asian, 0.3% Pacific Islander, 8.3% International, 27.6% Hispanic/Latinx, 6.2% multiple ethnicities, 35% White, and 5% Other/Unknown. Data for the mathematics department and the particular calculus section were not available, but as shown below, the demographics of students in the course does not represent the full diversity of the university, as is typical in introductory calculus.

The course consisted of a combination of large lectures (100-200 students) taught by full-time instructors and smaller breakout recitation sections (30-40 students) taught by Graduate Teaching Assistants. This paper focuses on a single large-lecture section (N=124) taught by the author, which met three times weekly

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for 50 minutes at a time (Reinholz, 2017a). In addition, students in the lecture met twice weekly for 50 minutes for their recitation sessions, but those sessions are not a focus of this paper.

Design

Each week students engaged in a peer assessment learning activity called Peer-Assisted Reflection, or PAR (Reinholz, 2015a; Reinholz & Dounas-Frazer, 2016), for a total of 14 assignments. The goal of PAR is for students to develop self-assessment skills as they assess the work of their peers (Black, Harrison, & Lee, 2003; Reinholz, 2015b). Specifically, PAR consists of a four-part cycle through which students: (1) complete a draft solution to a conceptual mathematics problem for homework, (2) reflect on their solution by identifying which aspects of their solution they would like to receive feedback on, (3) trade papers with a peer in class and exchange peer feedback, and (4) revise their work before turning in their solution. Students receive homework credit both for the correctness of their solution and for completing the PAR process, which encourages students to revise their work (in practice nearly all students do so). Prior studies show that PAR has a significant positive impact on student learning (Reinholz, 2015a, 2016), but the learning impact of PAR is not the focus of the present study.

This implementation of PAR differed from prior iterations (in nearly 20 classroom contexts, across STEM disciplines), because it took place in a large-lecture course, which imposed different logistical constraints. In terms of the actual PAR process, students were able to engage productively during their large lecture sessions: they simply turned to a peer, traded papers, and conferenced about their work. The course structure also meant that students received limited feedback on their PAR solutions and engagement in the PAR process, however, the instructor was constrained by the logistics of teaching a large course.

In this implementation of PAR, students chose their partners. Because students chose their partners, they often picked students with whom they were friends or more comfortable. This resulted in a large number of same-gender pairings. For instance, of the conversations that included women, 42 of them were entirely comprised of women, and 29 of them were mixed gender. This indicates that women were mostly talking with other women. As such, the results of this study may differ if random assignment of partners was used, as in some prior iterations of PAR.

During the feedback exchange component of PAR (step 3), students read each other's work silently for five minutes and write comments, and then have five minutes to discuss their feedback. Forcing students to engage silently with each other's work before the discussion helped ensure that students actually talked about their peers' solutions, not just the problem. Moreover, PAR positions both students as competent, as they both provide feedback to one another, rather than creating an asymmetric relationship in which only one student provides feedback to the other. This was a feature designed to promote student authority (cf. Engle & Conant, 2002). In the context of a large-lecture course, this was intended to provide all students with opportunities to engage in meaningful talk about mathematics, which can otherwise be difficult to facilitate in whole-class conversations.

Participants and Data

A total of 84 students participated in the study (in a class of N=124). For all of these students, demographic information was collected from the university's office of Institutional Research (see Table 1).

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Table 1.

Participant demographics (N = 84)

	Women	Men	**Total**
African American	0	3	**3**
Asian/Pacific Islander	4	11	**15**
Hispanic	8	16	**24**
International	0	1	**1**
Multiple Ethnicities	1	4	**5**
White	9	19	**28**
Unknown	4	4	**8**
Total	**26**	**58**	**84**

The primary data source for this article was students' peer conversations. During their PAR conferences students recorded their conversations (the second part of their feedback exchange) using audio recorders on their cellular phones. For students who did not have a cellular phone, they were offered the use of a dedicated audio recorder, but no students elected to use this option. A total of 172 conversations were recorded. While the majority of conversations consisted of student dyads, some of the conversations involved three students at a time. To account for a variable number of students in certain conversations, a unit of 'participant-conversations' was used for analysis, which represents how many times some student from a particular group participated in some conversation. The demographics of students by participant-conversations is given in Table 2. Because of the small number of contributions from the international students they were dropped from racial group analyses, as were the students of unknown race.

Table 2.

Breakdown of demographics for participant-conversations (N = 370)

	Women	Men	**Total**
African American	0	12	**12**
Asian/Pacific Islander	37	36	**73**
Hispanic	22	83	**105**
International	0	2	**2**
Multiple Ethnicities	1	16	**17**
White	45	97	**142**
Unknown	11	8	**19**
Total	**116**	**254**	**370**

To support data analysis, all conversations were transcribed and linked to student names. This allowed for demographic information to be attached to each individual student contribution. Cleaning of the dataset and data analysis was completed in R statistics, using a variety of text processing packages (e.g., stringi, lsr, lexicon). This cleaning process involved removing punctuation and converting all text to lowercase so that it could be processed using the appropriate packages.

Analytic Methods

Feedback Types. Student conferences were analyzed for the type of feedback provided using a prior coding scheme that focused on process, product, and person feedback (Reinholz, 2017b). By looking at the different types of feedback provided by students, it was possible to explore if there were differences in feedback style based on race or gender. Process-focused feedback describes how to reach a mathematical solution or why the solution works. Product-focused feedback describes whether or not answers given are correct. Person-focused feedback consists of praise or negative personal comments; in practice, negative personal comments have almost never been encountered in empirical studies of PAR. Further information about these categories can be found elsewhere (Reinholz, 2017b).

Linguistic Inquiry. To analyze student word usage, Linguistic Inquiry and Word Count 2015 (LIWC) software was used (Pennebaker, Boyd, Jordan, & Blackburn, 2015). LIWC provides a standard for automated text processing that allows results to be compared across numerous sources. LIWC provides output on numerous dimensions, including four summary scales (ranging from 0 to 100):

1. Analytical Thinking – higher numbers indicate more formal logical thinking, while lower numbers suggest more informal, personal text;
2. Clout – higher numbers signify status and confidence, while lower numbers imply humility or a tentative, hesitant style;
3. Authentic – high numbers represent honest and personal text, while lower numbers are guarded and distant text;
4. Emotion – higher numbers are more positive and upbeat, while lower numbers are anxious, sad, or hostile.

In addition, I considered the use of first-person pronouns to indicate lower status, and second person pronouns to indicate higher status (Pennebaker, 2011). I also considered positive and negative emotion words, informal language, and cognitive language. All of these variables are standard outputs from LIWC. Table 3 provides examples of words from these different categories (Pennebaker et al., 2015).

Table 3.

Example words used in LIWC analysis

Category	**Example**
Positive emotion	Love, nice, sweet
Negative emotion	Hurt, ugly, nasty
Informal language	Damn, OK, hmm
Cognitive language	Cause, know, ought

While language analyses can provide insight into peer conferences, they must be interpreted with caution. A wealth of literature highlights differences in word usage based on gender (Argamon, Koppel, Fine, & Shimoni, 2006), task characteristics (Newman, Groom, Handelman, & Pennebaker, 2008), topic (Bamman, Eisenstein, & Schnoebelen, 2014), and age (Huffaker & Calvert, 2005). Still, some commonalities exist across settings. For instance, women tend to use first-person singular, cognitive, and social words more, while men use more articles, and there are no meaningful differences in the use of first-person plural or positive emotion words (Pennebaker, 2011). While less attention has been given to racialized differences in text analysis (e.g., pronoun usage), a vast literature connects issues of race, culture, identity, power, and discourse (e.g., Holland, Lachicotte, Skinner, & Cain, 1998; Leonardo, 2009; Nasir, Hand, & Taylor, 2008).

In sum, one can expect differences in word usage by students from different groups in the peer assessment process, simply by virtue of their membership in particular gender, racial, or other demographic groups. Yet, it will be difficult to predict in advance what these differences will be. Nevertheless, this paper will provide a reference as others continue to look at such patterns of word usage in other educational contexts.

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Results

The amount of words and type of feedback was analyzed and are presented overall as well as by gender and by ethnicity. Results from the Linguistic Inquiry using LIWC (such as amount of clout that) are also presented.

Overall amount of talk and type of words used

Table 4 provides a summary of word usage for the class as a whole. To contextualize these results, they are compared to two prior iterations of PAR (Reinholz, 2017b). These prior iterations of PAR also took place in introductory college calculus, but in smaller class sizes. Like Phase II of the prior study, students in the present calculus class also had whole-class discussions about how to give feedback to their peers. These conversations were not part of the Phase I study. Table 4 shows that in the present study each student contributed an average of 149.09 words to each conversation. The standard deviation of 92.80, however, reveals a large variance in how individual students participated.

Table 4.

Classroom-level word usage (by participant conversation)

	Present (N=370)	Phase I (N=116)	Phase II (N=184)
Total Words (Mean)	149.1 (SD=92.8)	163.2 (SD=80.5)	295.2 (SD=117.8)
Process Words (Mean)	6.0	4.9	9.00
Product Words (Mean)	1.3	0.7	1.1
Person Words (Mean)	3.5	2.4	2.5

Table 4 also shows that conversations during the present study were shorter than those in prior iterations. The Phase II conversations contained more feedback in these three categories than did the current study. Yet, when looking at density of feedback--the amount of feedback based on how many words were spoken--it is highest in the current study. In other words, it seems that students were saying more with fewer words, and likely with less off-topic talk. Given variation in the implementation of PAR and student populations, it is difficult to identify the cause of these differences.

Amount of talk by gender and race

Figure 1 shows a large spread in the amount of talk by gender. The spread for amount of talk by men was much larger than women (many words and few words). Thus, at least at the individual level, gender differences appear in amount of talk, indicating both lower-status and higher-status men. Figure 2 provides the same data for race. Here we see that the spread was greatest for White students, and White students spoke more on average than their peers in other racial groups.

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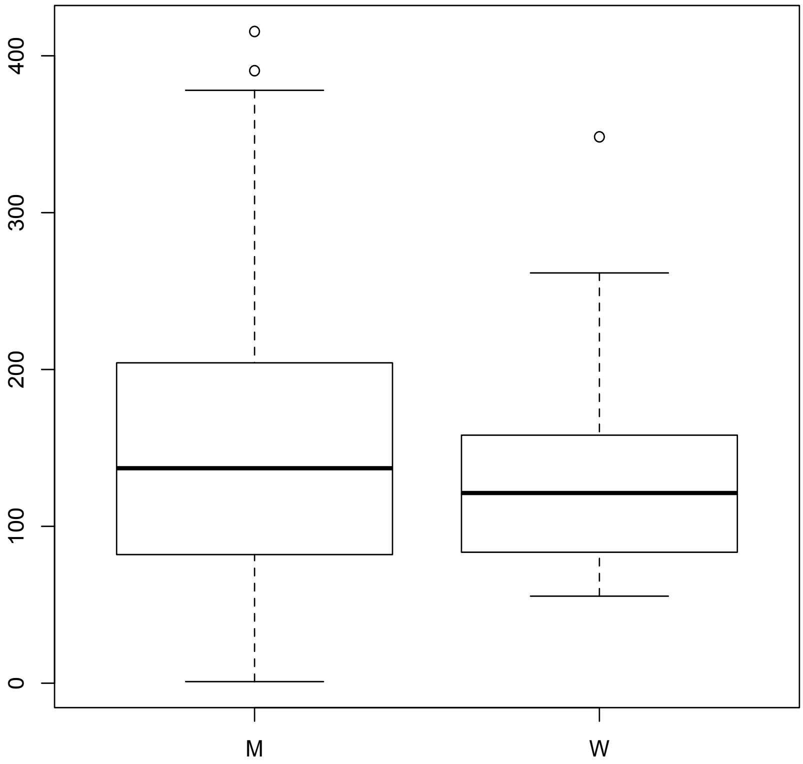

Figure 1. Average number of words per participant-conversation by gender

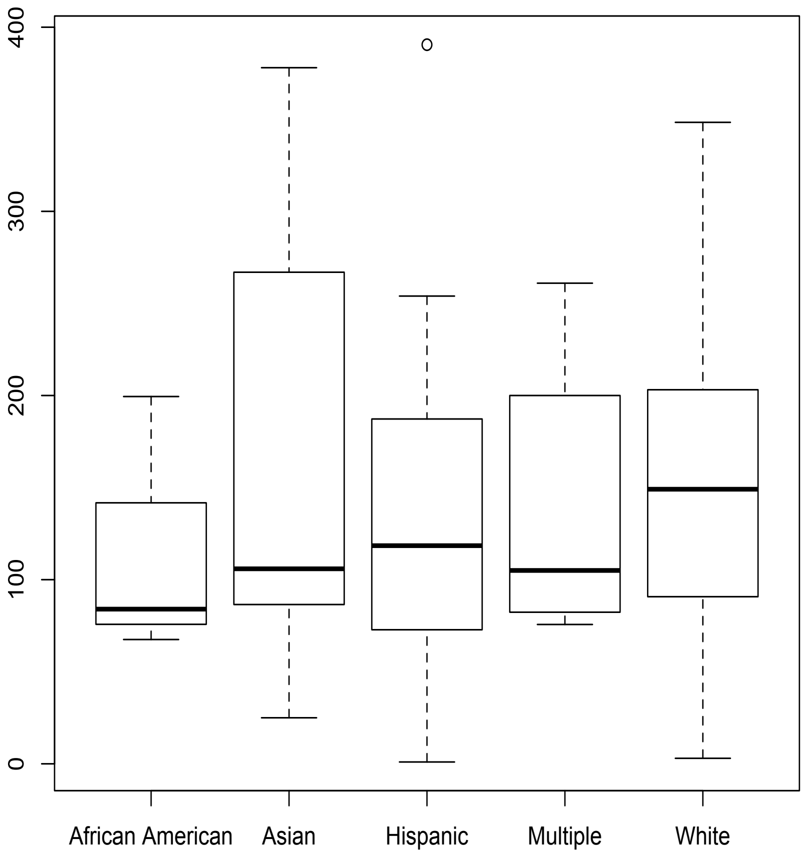

Figure 2. Average number of words per participant-conversation by race

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Type of feedback by gender and race

Figure 3 shows feedback types by gender. The data are expressed as an "equity ratio" (Reinholz & Shah, 2018). Actual participation is the count of coded items through classroom observation using EQUIP. Expected participation is based on a group's demographic representation in the classroom. The equity ratio can fall into three categories: greater than one, less than one, or equal to one. To illustrate, imagine a classroom where 40% of students are women. If actual participation from women is 60% of total participation, then the equity factor would be 1.5—this indicates disproportionately greater participation from women relative to their demographic representation. If actual participation from women turns out to be 30%, then the equity factor would be 0.75—this indicates disproportionately less participation. If actual participation is 40%, the equity factor would be 1.0, which indicates proportional participation. Overall, this metric makes it possible to make claims about equity while accounting for differences in the raw numbers of students from different social marker groups in a given classroom.

Here we see that men contributed more total words than one would expect $\chi2(1, N = 55284) = 102.67$, $p = 3.9 * 10\text{-}24$, Cramer's $V = 0.53$ (large effect size). Women used more person-focused feedback (i.e. praise), $\chi2(1, N = 1387) = 39.18$, $p = 3.85 * 10\text{-}10$, Cramer's $V = 0.33$ (medium effect size). Men used more product feedback (i.e. describing right or wrong), $\chi2(1, N = 484) = 19.2$, $p = 1.2 * 10\text{-}5$, Cramer's $V = 0.22$. There were no significant differences for process words.

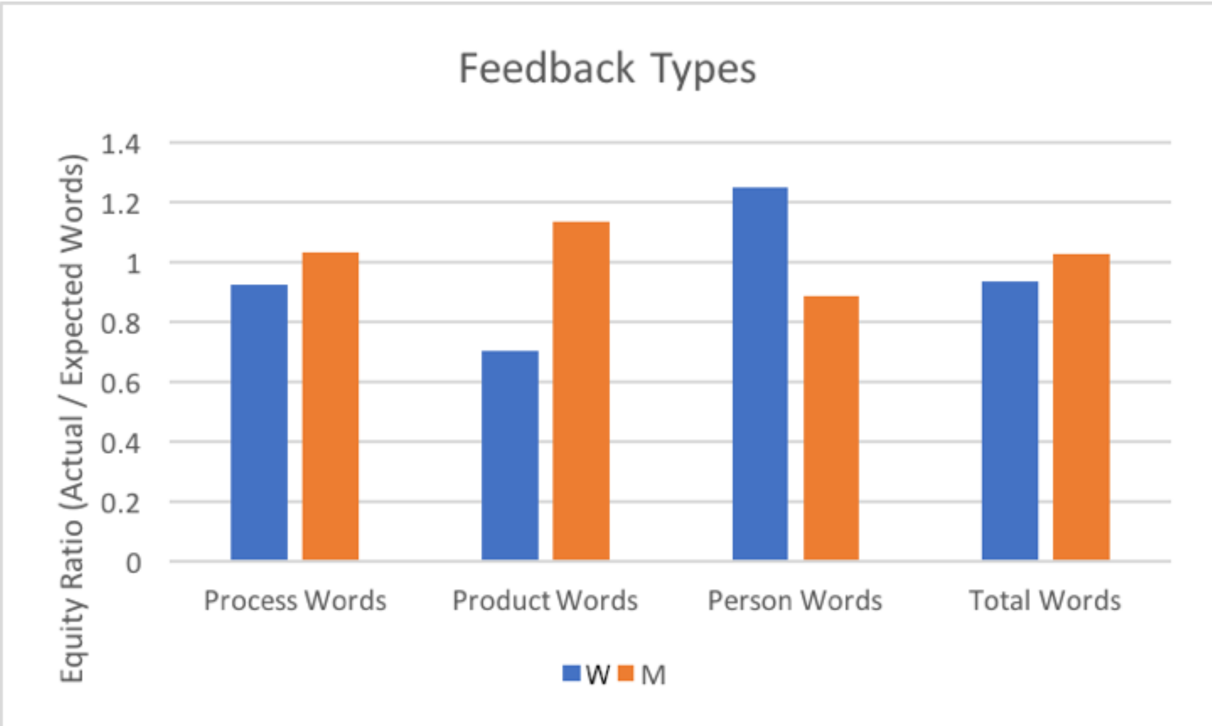

Figure 3. Feedback types by gender

What can be inferred from these results? Figure 3 indicates that men and women behaved the same when it came to giving process-focused feedback, which is the most valuable type for learning. Yet, there were also stylistic differences with men focusing more on correctness of the solution and women offering more praise. This may also speak to possible status issues, with men feeling more confident to make assertions about correctness. On the whole, men did talk more, but the equity ratio for total words was near one. Thus, this statistically significant difference may have less practical significance.

Figure 4 shows feedback type by race. Here we see that Black and White students contributed more total words than one would expect $\chi2(4, N = 51955) = 400.59$, $p = 2 * 10\text{-}85$, Cramer's $V = 0.54$ (large effect size). Differences were also significant for person-focused feedback $\chi2(4, N = 1314) = 15.44$, $p = 0.0038$, Cramer's

V = 0.11 (small effect size). There were no significant differences for process words or product words, after correcting for multiple comparisons. Again, there were no differences for process words, the most important type of feedback, but there were some potential differences in status indicated by total number of words.

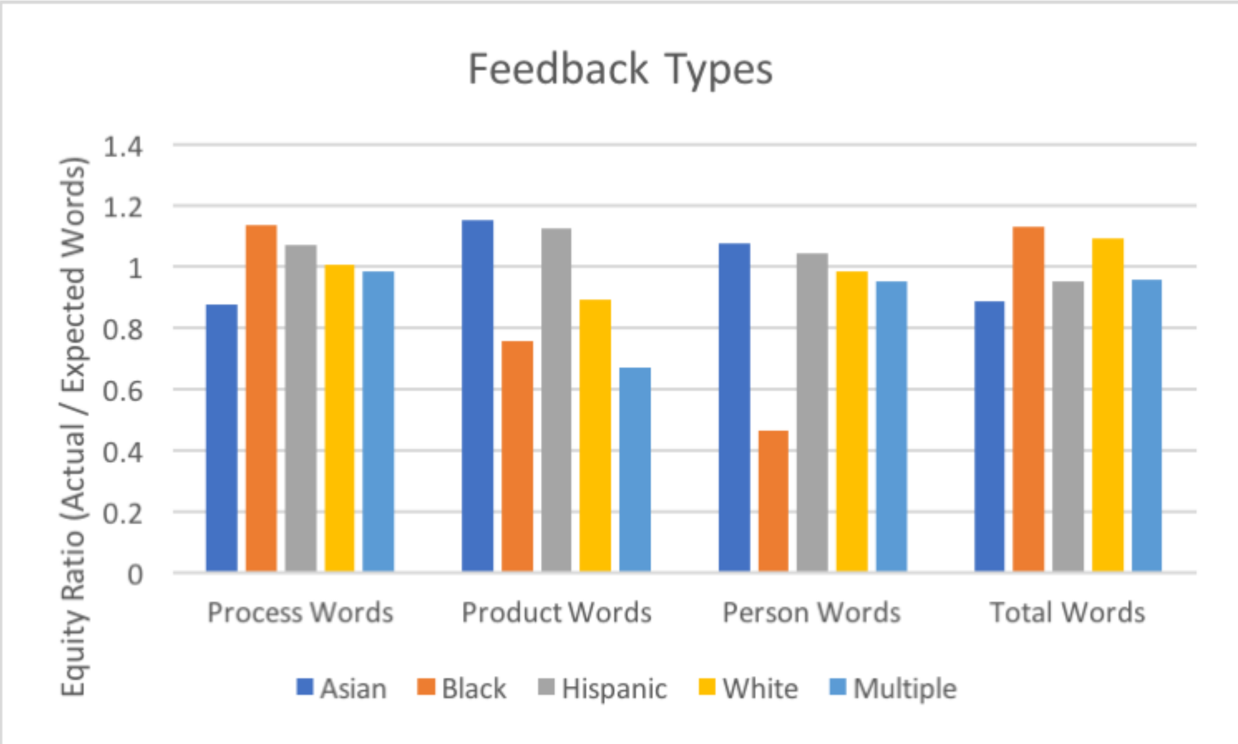

Figure 4. Feedback types by race.

Linguistic Inquiry

Table 5 provides a summary of LIWC output. For reference, the results for natural speech have been included in the right column (Pennebaker et al., 2015).

Table 5.

LIWC results

	Women	Men	Asian	Black	Hispanic	White	Multiple	(Ref.)
Analytic	16.6	21.2	21.2	33.3	16.4	19.2	17.2	18.4
Clout	49.4	52.9	47.4	48.1	60.5	48.8	46.8	56.3
Authentic	46.3	49.4	48.0	56.3	45.6	50.4	58.0	61.3
Tone	87.8	79.2	84.3	69.4	77.6	83.6	85.6	79.3
Selected Results								
Pronouns	18.6	19.1	17.8	17.7	20.0	19.1	20.3	13.6
I	4.1	4.6	4.1	5.2	4.4	4.6	5.8	4.8
You	3.5	3.8	3.1	2.9	4.7	3.5	3.7	4.0
Impersonal	10.0	9.4	9.6	8.4	9.7	9.8	9.5	7.5
Positive Emotion	4.2	3.6	4.0	3.1	3.6	3.8	3.9	5.3
Negative Emotion	0.6	0.7	0.7	0.8	0.8	0.6	0.5	1.2
Cognitive	17.4	17.1	17.1	18.3	17.8	16.9	16.7	12.3
Informal	4.7	3.7	5.3	5.9	3.2	4.0	3.1	7.1

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The results show modest gender differences in each category, with women using fewer analytic words, having lower clout, speaking more distantly, and being more upbeat in the feedback. The women tended to use more positive emotion words, and a more informal style. These results indicate that the men were likely of higher status, consistent with the sociometric surveys and total talk length.

There were also differences by race. For instance, Hispanic students had the highest clout. We also see the Black students in the sample had high levels of analytic speech and clout (although not as high as Hispanic students). This shows that Hispanic and Black students were able to take on positions of relatively high-status in the way that they discussed mathematics in these conferences. More notably, we do not see a bias toward White and Asian students, as research in other settings might suggest (Stinson, 2008).

Beyond this descriptive analysis, Table 6 provides the ANOVA results for the four summary variables for gender and Table 7 is for race. When these tests for statistical significance were computed, no significant differences were found. Thus, at least for this dataset, it was not possible to detect statistically-significant differences in these key LIWC variables. Thus, it may be the case that there were far more similarities than differences in how students engaged in their conferences.

Table 6.

ANOVA results for LIWC summary variables by gender

	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Analytic	1	1019	1019.0	3.027	0.0856*
Residuals	82	27602	336.6		
Clout	1	9	8.5	0.016	0.899
Residuals	82	43292	527.9		
Authentic	1	365	364.9	0.65	0.423
Residuals	82	46058	561.7		
Tone	1	2330	1330.2	2.431	0.123
Residuals	82	44868	547.2		

Table 7.

ANOVA results for LIWC summary variables by race

	Df	Sum Sq	Mean Sq	F Value	Pr(>F)
Analytic	6	467	77.9	0.213	0.972
Residuals	77	40537	526.5		
Clout	6	2763	460.5	0.875	0.518
Residuals	77	44606	579.3		
Authentic	6	1816	302.7	1.121	0.358
Residuals	77	44606	579.3		
Tone	7	3710	618.4	1.121	0.358
Residuals	77	42488	551.8		

Discussion

Promoting equity in classroom interactions is a challenge and an ongoing concern for undergraduate mathematics (e.g., Adiredja & Andrews-Larson, 2017). This paper focuses on quantitative analyses of student speech as it relates to status. The results showed some areas of inequity in peer conferences (e.g., some

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individuals speaking more than others), but on the whole the results were promising for equitable opportunities to participate in this activity. There were no statistically significant differences in LIWC categories for race or gender, and for analytic speech and clout, numerical differences actually favored Black and Latinx students. It is possible that such differences would be statistically significant in a larger dataset. Still, men did have a greater total talk time, which may be an indicator of higher status. Moreover, since opportunities to talk are opportunities to learn, the men in the class may have taken up proportionally more of these opportunities to learn.

Does this actually represent equity? It is unclear. Equity is a value judgment, and one that is difficult to make as an outside observer. Moreover, the present study is limited because it did not include student interviews or any other mechanism to provide further insight into students' subjective experiences. Still, it appears that peer conferences provided opportunities for students of various groups to engage meaningfully, which is a step in the direction of equity.

As a tool to promote equitable engagement, peer conferences have a great deal of potential. Because students work in a one-on-one setting, it is less likely that students will not have an opportunity to participate at all. More than just participating, structured peer conferences help students learn exactly what is expected of them and the types of feedback they should provide, which helps all students engage with mathematics in more meaningful ways (i.e. focusing on processes over products or praise). The structured nature of the activity makes it more likely that students from different groups will have an equal opportunity to contribute, rather than allowing historically dominant students to dominate. While this study took place in mathematics, peer assessment (and in particular, PAR), has been used in a variety of STEM settings (e.g., physics, biology), so the results likely generalize across domains, at least to some extent. Future research is required, however, to more fully determine the extent to which peer conferences can produce more equitable participation in calculus.

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RESEARCH REPORT

Reflective Apprenticeship for Teaching and Learning Mathematical Proof

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Abstract: *This article explores teacher learning in a graduate-level analysis course for teachers. Drawing from the frameworks of extreme apprenticeship and Peer-Assisted Reflection (PAR), the course created authentic learning experiences for the teachers that served as models that they could use in their own classrooms. This paper describes how the teachers developed across the four dimensions of extreme apprenticeship. While this paper is grounded in mathematics, the extreme apprenticeship and PAR frameworks are cross-disciplinary, and thus there are implications for teaching and learning in all of the STEM disciplines.*

Keywords: Mathematical analysis, extreme apprenticeship, Peer-Assisted Reflection

Introduction

Who can be a mathematician? What is mathematics all about? How should mathematics be taught? We tend to answer these questions based on our experiences with our own mathematics teachers: what they looked like, what they asked us to do, and how they taught us. However, this poses a challenge for new teachers who are expected to teach in increasingly innovative ways and address new content standards. How does one teach mathematics in a way that they have seldom experienced?

Prospective teachers generally experience a variety of pedagogies in their mathematics education courses. However, these particular activities often contrast their regular mathematics courses, which are primarily lecture-based. This can cause problems, because prospective teachers have limited opportunities to experience innovative pedagogies as mathematics learners themselves. As such, I argue, it is critical that students have similar learning experiences in their mathematics courses too.

This article focuses on an analysis course for teachers. I take the lens of extreme apprenticeship (Vihavainen, Paksula, & Luukkainen, 2011), in which teachers are given opportunities to experience the type of learning experiences that they would create for their students. To support their apprenticeship, the students engaged in Peer-Assisted Reflection, or PAR (Reinholz, 2015a), as a way to help them reflect on mathematical proof. This paper addresses the following question:

> How were teachers in the course able to use PAR to engage with the four components of extreme apprenticeship?

Teachers in the present study applied their experiences from this course in their own teaching in various ways. Teachers used specific pedagogical strategies (e.g., PAR, team-based learning), content areas (e.g., space-filling curves, countable sets), and particular activities from class (e.g., iteratively constructing Hilbert curves using whiteboards or construction paper). To address the above question, I focus specifically on three of the

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five K-12 teachers in the course, because they spontaneously chose to implement PAR in their K-12 teaching.[1] I focus on PAR, because it was a structured pedagogical practice that the teachers could use in a variety of settings, unlike more specific aspects of the course, such as particular content. Also, I choose to focus on the K-12 teachers to take the lens of in-service teacher development. Graduate Teaching Assistants in the course also applied their experiences from the course in their own teaching, but because of the differences in their setting, an exploration of their work is beyond the scope of this article.

Note, using ideas from the analysis course in K-12 teaching was not an explicit goal of the course, but rather, the students found their learning experiences so worthwhile that they decided to use them in their own teaching. While this paper is grounded in proof and mathematics, both extreme apprenticeship and PAR are interdisciplinary frameworks, and thus the implications of this paper speak to teaching authentic practices in all STEM disciplines.

Background

The sociocultural turn in mathematics education has placed an increasing emphasis on how students learn through engaging in social practices (e.g., Cobb, Stephan, McClain, & Gravemeijer, 2011; Lave, 1996; Sfard, 1998). As a result of this turn, there is now rich empirical evidence (e.g., Freeman et al., 2014) for much earlier educational theories that focused on the ideas of learning by doing, or experiential learning (e.g., Dewey, 1933; Kolb, 1984). A key component of experiential learning is reflection: the act of processing an experience, action, or practice to gain further insight into the experience to better inform and guide future actions (Reinholz, 2016). Reflection is seen as a fundamental component of teacher education, to help teachers develop reflective practice (e.g., Averill, Drake, Anderson, & Anthony, 2016; Reinholz, 2017; Sherin, Jacobs, & Philipp, 2011).

In the present study, students were supported to reflect through a particular course activity, Peer-Assisted Reflection (PAR; Reinholz, 2015a). PAR is a structured peer review process involving the following steps: students work on a draft of a problem, exchange feedback with a peer, and then revise before turning in their solutions. PAR helps students develop stronger self-assessment skills as they develop objective lenses from critiquing the work of their peers (Black, Harrison, & Lee, 2003; Reinholz, 2015b). In this course, teachers used PAR to annotate one another's proofs and provide constructive feedback. Thus, PAR was used to support the learning of proof, a core mathematical practice. PAR is a cross-disciplinary technique, and has also been used in other disciplines such as biology, engineering, and physics (e.g., Reinholz & Dounas-Frazer, 2016).

To create space for students to annotate each other's work, students completed their proofs using a two-column format. The left column was for formal mathematics and the right column was for annotations. Annotations were used for a variety of purposes. Authors could comment on their thought process, include relevant diagrams and definitions, and express areas of confusion. For peer review, students used annotations to provide feedback to each other. Authors used pencil for their annotations, while reviewers used pen, which allowed these two types of comments to easily be distinguished. See Appendix A for a sample of the written work associated with PAR.

Reflection was seen as a smaller component of a larger educational framework called extreme apprenticeship (Vihavainen et al., 2011). This framework has its roots in cognitive apprenticeship, and focuses on learning through practice. The method is guided by four key principles:

1. Learning by doing. You can only master something by actually practicing it.
2. Continuous feedback. Feedback should be ongoing and bidirectional.
3. No compromise. Seek to attain high levels of understanding.

[1] A fourth in-service teacher later used PAR in their teaching, but this was conveyed in a personal communication, after the course had completed (so no data were collected for this teacher).

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4. Apprentice to mastery. Students eventually become experts in the method.

These four principles were embodied into the PAR process and how it was used in the class. Students engaged in authentic practice of conjecture, peer review, and revision, just as professional mathematicians would. This supported learning by doing. Continuous feedback was implemented by students both giving and receiving feedback from their peers. The idea of no compromise guided how students were to think about proof: high standards of argumentation were required. Students were expected to overcome some of the key issues in learning proof, such as using empirical arguments (e.g., Healy & Hoyles, 2000; Martin & Harel, 1989) or misunderstanding the logical necessity of deductive argumentation (Fischbein, 1982). Finally, the presence of the fourth principle, apprentice to mastery, was emergent in students' work. While a goal of the course was to model good pedagogy for students, it was not actually anticipated that students would already begin to use teaching techniques that they experienced as students in their own K-12 teaching. Here, as the teachers used PAR with their students, it signified them coming to the role of masters of the process.

As stated above, PAR was used to help students gain authentic experiences with proof. In particular, the course emphasized the process of proving and the many functions that proof can serve. For instance, proofs in this course were intended to both prove and explain mathematics (De Villiers, 2003; Steiner, 1978). In this way, proofs can actually serve a pedagogical function, teaching others how to "do" mathematics (Hanna, 1990). Above all, proof was understood as a social process. It wasn't just about ascertaining truth, but also communicating ideas under a certain set of social norms (cf. Harel & Sowder, 2007; Mason, Burton, & Stacey, 2010). In this way, PAR served a number of roles in this classroom setting: teaching students mathematics, teaching them about proof, and teaching them how to teach mathematics.

Method

Context and Participants

The target course, taught by the author, served students in a Master's degree program in mathematics education in the US. These students are referred to as teachers throughout this article, to distinguish them from the students that they were presently teaching or may teach in the future. A total of 13 teachers were in the analysis course, all who consented to participate in the study. There were five in-service teachers, five Graduate Teaching Assistants (GTAs), two prospective teachers who were not yet teaching, and one mathematics graduate student.

The course content was graduate-level analysis, but in contrast to a traditional course, it featured the use of student-centered pedagogies to help the teachers develop mathematical ideas. While the course had a strong emphasis on proof, it also emphasized discovery of mathematics through inquiry, exploration, and creativity. Most class sessions involved students working in teams on mathematics problems in an inquiry-oriented way, summarized with whole-class discussions and team presentations. Teacher exposition was a small component of the course. Team-based learning was used to organize collaborative work (Michaelsen, Parmelee, McMahon, & Levine, 2008). Team-based learning involves using consistent groups throughout the semester, team-based assignments, and team contracts to establish norms. Students participated in the PAR process each week with a single homework problem.

Data Sources

There were two primary data sources, corresponding to questions on the first and second midterms in the course. The following questions was taken from the first midterm:

> Take an idea from this semester so far and describe how you could use this in your teaching. You may talk about a class you're already teaching, or something you envision yourself teaching in the future.

On the final, there was the following question about proofs:

Write an essay about what makes a good proof. Obviously it should be mathematically correct, but what else matters? Please address the following questions, using concrete examples when possible:

1. How does your experience with proof in this class compare to your experiences with proof in other classes?
2. What does a "good proof" look like? What information does it provide for a reader?
3. What should you include in an annotation of your own proof, to make it easier for a peer to understand?
4. What type of feedback should you provide to a peer (when annotating their work) to help them create a good proof?
5. What are the implications for the teaching and learning of proof?

Note that neither of these questions (nor the course) actually required students to apply anything they learned to their own teaching. Nevertheless, the teachers began to spontaneously use many ideas from the analysis course in their work with their own students. In the results that follow, I describe how PAR helped students engage in the four principles of extreme apprenticeship.

Results

The 13 teachers discussed a variety of connections between their learning in the analysis course and their own teaching. They discussed specific pedagogical strategies (e.g., PAR, team-based learning), content areas (e.g., space-filling curves, countable sets), and particular activities from class (e.g., iteratively constructing Hilbert curves using whiteboards or construction paper). Here I focus on three teachers that decided to use PAR from the course in their own teaching (a fourth teacher later used PAR but this happened after data collection was complete, so it is not reported on here). In particular, I use student reflections to show how PAR supported teachers to embody the four principles of extreme apprenticeship, which helped them transfer PAR to their own teaching.

Learning by Doing

The first principle of extreme apprenticeship is learning by doing. Through PAR, students were actually engaged in the very process of conjecturing, proof writing, and academic peer review that professional mathematicians would practice. Each of the three focal teachers, John, Dana, and Melvin, noted how this authentic practice supported their learning. John drew connections to constructivism, Dana to the process of peer annotation, and Melvin to the proof process, not just a proof itself.

In what follows, John highlights his perceived "disconnect" between his experiences as a student learning proofs in prior courses and what he understands as a teacher to be good pedagogical practice:

> There seems to exist a disconnect between the constructivist tenets and leanings of math education research and the traditional instruction of proof. Students are to make their own meaning of mathematics based on prior knowledge, yet when it comes to proof they are to conform to rigid conventions and opinions of elegance as defined by now dead white men.

As this quote highlights, John felt that PAR allowed him to actually learn by doing proofs, in a constructivist fashion. This was different from simply being expected to understand the "rigid conventions" of proofs constructed by someone else. John continues to contrast his experience with PAR and authentic engagement as pleasing,

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> This diatribe, born from past frustrations, sheds some light on why I remain so pleased with my experiences with proof in this course (and in this school, really). I don't feel like the crazy person in the room for saying, "Copying it off the internet doesn't mean anything," and I'm no longer negatively reinforced for refusing to turn in "work" produced in this way. Proof has begun to feel personal - I feel as if I have some say in how I might structure certain problems or at least present my work. Additionally, the PAR process has completely changed the way I approach proofs and the way I teach. I feel as if the annotations column and its free form have given me a voice and choice in proof that didn't exist prior.

John describes his ownership over proof, how it has become something personal for him. Because he was able to engage in the process of proving, rather than just be given proofs as a thing to know, he developed his own knowledge in learning by doing. Rather than simply trying to achieve the right answer, proof become a practice that he authentically engaged with.

Dana similarly described how this course "opened her eyes" when it came to proof. Through working on PAR, she became to embrace the peer review process of annotating another student's work, and felt empowered that she could teach this process to her students. She remarked,

> My experience in this class has opened my eyes to how to create and write a proof. Not only has this class taught me how to write a proof, but it has taught me how to read and analyze other people's proofs (which is a whole different monster). This is the first time I experiences the annotation process of a proof. Initially I found it annoying and did not understand the purpose of annotations…Overall, my experience with proof is constantly changing and I know it will change even more when I have to teach proof. I have not yet taught proof in the high school level, but I now feel that I am prepared to teach students how to write a proof.

Like John, Dana emphasized practices associated with proof, of reading and analyzing other's work. Again, learning by doing was a key aspect of coming to understand proof through PAR.

Finally, Melvin also described having a very different experience with this proof in the course. As with the other students, Melvin emphasized the process of proving, not just a proof as a thing to know,

> Proofs in this class have been dramatically different from proofs in other math courses. Most proofs that I have worked with were used to serve on purpose and that was to show conjectures were true… This course was different in that I was pushed to think about proving things rather than the proof itself…The PAR process was a big part of the reason I looked at proofs differently in this course.

These responses illustrate how the extreme apprenticeship principle of learning by doing was a key part of how teachers engaged with the PAR process and how it influenced their perceptions of proof. Because teachers engaged with a structured practice (PAR), on a weekly basis, it became a part of their repertoire of what it meant to know and do mathematics.

Continuous Feedback

Extreme apprenticeship also emphasizes continuous, bi-directional feedback. While this is traditionally between a teacher and student, PAR offers an opportunity for students to provide bi-directional feedback to each other. In this way, students learn both from the process of giving and receiving feedback (Reinholz, 2015b). All three of the teachers in the course included in this study emphasized how this was a reflective process that allowed them to better clarify their own thinking.

John began by discussing how the opportunity to review and revise his work eliminated his fear of failure,

> Having the opportunity to review a draft with a peer and then revise my work has taken the fear of failure out of the process. How does one fail a draft? The process also makes my own growth undeniable when I compare many of my drafts to their revised counterparts.

As John describes, continuous feedback and revision turned working on the problems into a learning process, rather than just something that had to be done to achieve a grade. John goes further to describe how he has benefitted from the feedback of his peers,

> While this is in part due to the spaced practice nature of the PAR process, it is also because of the feedback I receive from and provide to peers. Some of the best feedback has been in the form of questions: Is it legal to go from here to here? Can we assume this? Questions like these help me spot unsafe assumptions, or simply missed steps. Both push my learning.

Finally, John describes the other component of continuous feedback, in that he also learns from giving feedback,

> I've also provided feedback about the structure of peers' proofs that helps me clarify my own thinking. For instance, I might struggle to follow the flow of a peer's work due to a muddled introduction/setup, and then recognize the same flaw in my own work (or at least identify areas where I could be more explicit).

This quote shows how giving feedback and recognizing the strengths and weaknesses of others' work allowed John to apply the same reflective lens to his own work. As John's quotes highlight, PAR gave him a mechanism to continually recalibrate his understanding, and more importantly, his understanding of his own understanding.

Dana also described the value of peer feedback, but for her it was important to connect to her work as an actual practicing teacher. Because she actually had to engage in the process of giving and receiving feedback as a student, she became more aware of important considerations for teaching her students,

> Giving peer feedback on a proof is useful if done correctly. This is the first time I have ever given or received peer feedback. From this experience, I have learned what works best and important issues to remember when implementing this into my future lessons. I do give feedback to my students, however it would be nice to teach students how to give peer feedback. I think it is a good tool for students to learn how to annotate and critique work…I would make sure students felt comfortable giving feedback and learned how to be honest with their peers…Honest feedback is beneficial…[t]here are many reasons why one would feel uncomfortable to giving back honest feedback, so I can understand why students would hold back initially.

Here Dana is able to connect her authentic experience as a student to her work as a teacher. She highlights a key consideration – being able to give honest feedback – and how she needs to address it with her students.

Melvin focused his writing on the metacognitive aspect of peer feedback, through the annotation process. Melvin also draws attention to the dual processes of explicating his own thoughts and making sense of a peers' thoughts.

> The annotations were focused on metacognition and the thought process about writing the proof. Having to write about my thought process and then reading someone's thought process helped me develop new ideas and new strategies to approach proofs…When reading a proof for annotation, it is important for the reader to make sure that anything that is not obvious to them is indicated. I believe that if the reader must ask for clarification then the reader should indicate that that part of the proof is not clear.

The process of explanation that Melvin describes is very different from writing a typical mathematics solution, in which the only audience is the teacher. Because the reader was an equal, he had to write his proofs in a different way, to support their understanding. In sum, these teachers were able to recognize the importance of continuous feedback in the PAR process and how it could influence them as students and teachers.

No Compromise

The third principle, no compromise, was embodied into how students perceived proofs. In contrast to student perceptions of proof as empirical, the students had developed conceptions in line with the deductive logic of professional mathematicians. This is indicative of a high level of understanding and of a sophisticated way to think about proof.

John described the need to induce certainty in the audience. He elaborated that to do so, it must follow certain conventions (i.e. deductive logic) with supporting evidence,

> [B]y definition a proof is something that induces certainty in its audience. Leaving out necessary steps could stonewall this function…Inducing certainty in readers, however, requires an understanding of their possible perspectives. It is the author's purpose, then, to communicate the certainty of their claims by providing supporting evidence and connecting that evidence to their claims through valid reasoning. This communication is best achieved through an organized structure that allows the reader to expect certain conventions and thus anticipate possible paths.

As John describes a proof, he notes that there are both mathematical components (valid reasoning) and social components (possible perspectives). This shows his understanding that writing a proof does not just happen in vacuum, but is a social process. John goes on to elaborate what some of the mathematics components,

> [A]ny good work will begin with definitions relevant to the given information or conjecture… in addition to definitions, the introduction and setup of a proof should include a clearly identified claim or conjecture that is to be proven or disproven…This section should intentionally answer the questions, "What are we about to prove?" and, "What do we need in order to accomplish this?" This is where the author familiarizes the reader with the tools that will be utilized to complete the proof (i.e. variables should be introduced and defined here, parameters should be set in this space, etc.).

This shift to focusing on definitions was a major epistemological shift for many of the students in the course, who still did not have a strong sense of exactly what was required for a proof to be valid.

Dana also describes the need to have an organized structure, and that "more than a picture" is required to actually have a proof,

> A good proof should have an organized structure, contain the given and proof statement, and have self-annotations. In the very beginning of a proof, it is nice if the given is clearly stated along with the proof statement. Having a clear statement of what is given and what is being proved is helpful for the reader… It is not sufficient enough to prove something with just a picture or diagram.

Melvin also emphasized the importance of definitions and how to build logic on them. He also emphasized communication of helping someone "out of context" understand where things came from,

> A good proof has multiple parts that make it understandable to someone who is reading it out of the context from the situation it was written in. A good proof is based on a definition and starts with some claim followed by a definition. A good proof highlights this definition and manipulates it to show the claim that is required to be true…Proofs should also make sense in terms of the "side work" that is required. Most textbook proofs have the major steps that help get to prove the claim but many of those steps seem to come from nowhere. Every line should lead to another line without any gaps in the logic of the proof. After this course, I believe that a good proof includes why the author of the proof did what he/she did.

Just like John, Melvin emphasizes aspects of proofs related to mathematical logic and social communication. In sum, the students were able to display a sophisticated understanding of a good proof, having no compromise on this quality of the work. It was a high standard that students worked hard to attain each week.

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Apprentice to Mastery

The final aspect of extreme apprenticeship is that the apprentice becomes a master. Here we can see this embodied in the teachers actually using PAR, the process they were using as students, as a teaching tool in their own classrooms.

John began talking about PAR on his first midterm. To frame his use of PAR, John discussed the concept of teacher clarity (Hattie et al., 2017). He said "As a new teacher I was heavily coached on making each lesson's learning intentions visible to my students through the use of daily 'Purpose' statements." John elaborated that students "needed a way of self-assessing whether or not they had achieved the purpose of the day." John discussed his struggles with this. "While I am pleased that success criteria are now available to students, I am not pleased with the proportion of students taking advantage of this tool." He then described how he was going to use PAR to address this issue,

> Engaging in the PAR process has been an excellent learning experience. Self-assessing and providing feedback to peers are two areas that are far easier to promote than to implement. The PAR process, however, takes both of these elements and wraps them up into a pre-existing routine – homework. Because of this, I plan to use the PAR process (as modeled for us in class) to make success criteria more visible to students.

Here John was able to connect ideas from this course to a real problem of practice he was experiencing as a teacher. Later in the semester, John talked to me on multiple occasions about how he was using PAR with his students. In a final reflection on the second midterm he talked about his experiences,

> I am proud to say that I can recognize a good thing when I see it, and that I have successfully transferred the experience to my students. I have always fostered a culture of collaboration in my classroom, but this PAR process facilitates the feedback component better than anything I've tried in the past.

John was enthusiastic about his use of PAR as a teacher in his own K-12 classroom. Similarly, Dana was able to use ideas from analysis with her high school students. She described,

> I love the idea of how we use the PAR in our class. I have tried to incorporate this into my lesson plan because I think it is a wonderful idea for students to look at other students' solutions…I altered it slightly to make it work for high school students. We do a PAR every Friday…Friday PARDAY is what I call it.

Dana's enthusiasm was evident. She actually brought scanned work from her 9th grade class to share with our analysis class. When sharing that work with our class, she remarked, "initially I was skeptical that I would be able to use anything from this class in my own teaching, but it turns out that I have been able to."

While Melvin had not yet implemented PAR in his class, he had already made definite plans to do so in the coming year, as a part of another grant-funded project he was involved in. Melvin described his class as "entirely task based with little to no direct instruction." He discussed his plans "to use the PAR process in a course I will be teaching next year." He described his rationale,

> Giving my students the opportunity to revise their work, gives them an opportunity to review their thought process. This gives them an advantage when it comes to assessments and the SBAC [Smarter Balanced Assessment Consortium] because they are required to justify their work and explain their thoughts. By doing the revisions, my students will gain the skills needed to know what mathematical advice is worthwhile and what advice does not help their cause, because not every annotation they get back is always going to be correct.

The SBAC was a standardized test Melvin had to prepare his students for. He also discussed the value of creating appropriate pairs,

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> With the integrated courses, the students often run into problems where they can analyze the geometrical portions or they can solve the algebraic portions but not connect the two. If the ideal students are paired, they would make up for each other's lack of knowledge.

Melvin spoke with me about these plans after our class sessions, to receive further advice around implementation. In sum, these three teachers were already able to thoughtfully implement PAR in their teaching, or had laid out concrete plans to do so.

Discussion

Learning to teach is challenging, especially with few models for what one might achieve in their classroom. Thus, content courses are a key site for the learning of new teachers, because they can provide such models. More than providing content knowledge, when teachers have authentic learning experiences, they can draw upon them for their own teaching. This brief article highlights how three focal teachers were able to embody the four tenets of extreme apprenticeship and become masters, implementing PAR in their own teaching.

It is noteworthy that these teachers were never explicitly asked to use anything from the analysis class in their own teaching. Nor were they explicitly instructed on how connect the course with their own teaching. Rather, their insights were spontaneous. In many cases, the teachers were excited by the new content and methods that they were learning and they were eager to use them in their own practice. As such, this article highlights the importance of and potential for teachers' pedagogical learning in mathematics content courses.

The PAR cycle seemed particularly valuable for the teachers, as it gave them a clear model of a structured teaching technique that they could use. Although it was not the focus of this article, many of the teachers in the class described prior negative experiences with proof and how PAR opened up space for them to engage with proof differently (e.g., John's "diatribe born from past frustrations"). It is possible that teachers recognized their own struggles as mathematics learners, which allowed them to empathize with their students. When the teachers had a positive experience with PAR, they then worked to transfer that experience to their students.

While this article focused on just three of the five in-service teachers, other members of the course also connected with their experiences. For instance, the student in the course who was not in a mathematics education program wrote the following,

> I never intended to be a teacher, but I must say I was inspired by this class to maybe think about it. It was so pleasant to be in a classroom full of teachers. In other classes, my classmates were never easy to approach and share information. It was the total opposite in this class. They were all just as supportive!

Although this is the reflection of just a single student, it adds evidence in support of the importance of math learning experiences for teachers.

Methods such as PAR and extreme apprenticeship can be used together to create authentic learning experiences for teachers in higher-level courses, which may ultimately impact the future practice of those teachers. Given that PAR has been used in a variety of STEM subjects, and extreme apprenticeship is also a cross-disciplinary framework, there is great potential for these results to also apply to other STEM disciplines. These frameworks help students learn by doing, which the results of this article suggest can be effectively implemented even in higher-level content courses.

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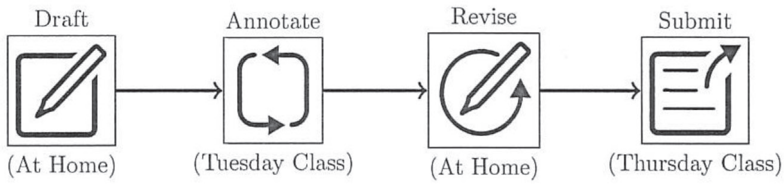
Appendix. Sample PAR work

The PAR Process



Write your solution in the left column. The right column is used for annotations. If you provide feedback to your peer, you will annotate their solution. After class, you will annotate your own solution as well (and write "self" on the annotated by line). In your submission, use the annotation column to explain how you did (or didn't) response to peer feedback.

Problem Statement: Continuity

There are a number of different ways to define continuity, starting from the definition you are familiar with for real numbers, to other definitions that can work in more abstract metric spaces. Here are two of them:

1. A function f is continuous at a point c in its domain if for every $\varepsilon > 0$ there exists a $\delta > 0$ so that for all x with $|x - c| < \delta$, $|f(x) - f(c)| < \varepsilon$.
2. A function f is continuous at a point c in its domain if for any neighborhood $N_1(f(c))$ there is neighborhood $N_2(c)$ such that $f(x) \in N_1(f(c))$ whenever $x \in N_2(c)$

Your goal is create two functions, the happy function and the sad function.

1. For the happy function, find a point c at which it is continuous, and prove that it is continuous using both of these definitions.
2. For the sad function, find a point c at which it is not continuous, and prove that it is not continuous using both of these definitions.

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DRAFT

Solution 3/7 **Annotated by:**

Def: A function f is continuous at a point c in its domain if for every $\varepsilon > 0$ $\exists$ a $\delta > 0$ so that $\forall x$ w/ $|x-c| < \delta$, $|f(x) - f(c)| < \varepsilon$

Def: A function f is continuous at a point c if for any neighborhood $N_1(f(c))$ there is a neighborhood $N_2(c)$ s.t. $f(x) \in N_1(f(c))$ whenever $x \in N_2(c)$.

1. Find a function that is continuous at point c.

Let $D = \mathbb{R}$ and $f(x) = x^2$. Show f is continuous at $x=1$ → easier

Pf/ need to show $|x^2 - 1^2|$ is arbitrarily small when x is close to 1.

$|x^2 - 1^2| = |x+1||x-1|$

need to control the size of $|x+1|$ to make the difference small.

suppose $|x-1| < 1$

By the triangle inequality this implies $|x| - 1 < 1$ or $|x| < 2$ (*)

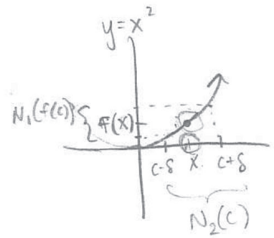
Then $|x+1| \le |x| + 1 < 3$ → why do you need this?

Set $\delta = \min\{1, \frac{\varepsilon}{3}\}$

Then $|x-1| < \delta$ implies

$|x^2 - 1^2| = |x+1||x-1| < 3|x-1| < \varepsilon$

$\therefore$ f is continuous at $x = 1$



(*) $N_1(f(c))$ radius of 2

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SUBMISSION

Solution 3/14

1. Happy function

a) let $D = \mathbb{R}$ and $f(x) = x^2$. Show f is continuous at $x = 1$.

Pf/Need to show $|x^2 - 1^2|$ is arbitrarily small when x is close to 1.

$|x^2 - 1| = |x+1||x-1|$

Suppose $|x-1| < 1$

By the triangle ineq. this implies $|x| - 1 < 1$ or $|x| < 2$

Then $|x+1| \leq |x| + 1 < 3$

Set $\delta = \varepsilon/3$

Then $|x-1| < \delta$ implies

$|x^2 - 1^2| = |x+1||x-1| < 3|x-1| < 3\delta \leq 3\left(\frac{\varepsilon}{3}\right) < \varepsilon$

$\therefore$ f is continuous at $x = 1$.

b). Suppose $x = 1$ and $N_1(f(1))$ is the neighborhood of $f(1)$ and $N_2(1)$ is the neighborhood of 1.

Suppose $f(x) \in N_1(f(1))$. Then $|f(x) - f(1)| = |f(x) - 1| < r_1$ where r_1 is the radius of $N_1(f(c))$.

If $x \in N_2(1)$ then $|x-1| < r_2$ where r_2 is the radius of $N_2(1)$

Let $r_2 = \frac{r_1}{|x+1|}$. So $|x-1| < \frac{r_1}{|x+1|}$. and $x \in N_2(1)$

$\therefore$ f is continuous at $x = 1$

Annotation

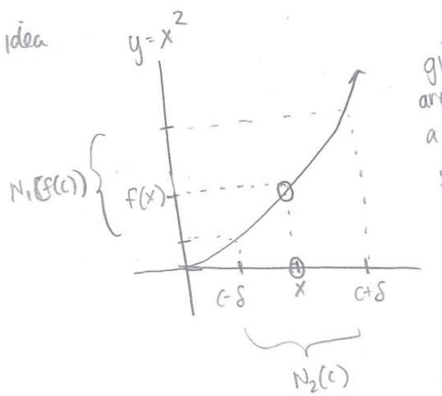
Def: A function f is continuous at a point c in its domain if for every $\varepsilon > 0$ $\exists$ a $\delta > 0$ so that $\forall x$ w/ $|x - c| < \delta$, $|f(x) - f(c)| < \varepsilon$.

Def: A function f is continuous at a point c if for any neighborhood $N_1(f(c))$, there is a neighborhood $N_2(c)$ s.t. $f(x) \in N_1(f(c))$ whenever $x \in N_2(c)$.

need to control the size of $|x+1|$ to make the diff small.

I included more details here

got this idea from



continuous

given a neighborhood around $f(c)$, we can make a neighborhood around c so all values map to $f(c)$

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RESEARCH REPORT

Breaking Boundaries in Computing in Undergraduate Courses

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Abstract: *An important question in undergraduate curricula is that of incorporating computing into STEM courses for majors and non-majors alike. What does it mean to teach "computing" in this context? What are some of the benefits and challenges for students and instructors in such courses? This paper contributes to this important dialog by describing three undergraduate courses that have been developed and taught at Harvey Mudd College and Loyola Marymount University. Each case study describes the course objectives, implementation challenges, and assessments.*

Keywords: Computing, undergraduate courses, computational thinking, STEM courses

While computing has become an integral part of the STEM disciplines, best practices on how to incorporate computing effectively into a STEM classroom remains an open question. The distinction between the concept or paradigm—computing or computation—and the predominant tool for executing this paradigm—the computer—remains a point of debate or misunderstanding; there is only agreement that current problems in STEM fields benefit greatly from the integration of computation into the methods and thinking of these disciplines.

In many cases, computers are used as a tool to help with calculations and data collection or analysis. In other cases, computers are used to help demonstrate concepts. Still in other scenarios, computers are viewed as a vehicle to help discuss "computational thinking" as a problem-solving process. In general, many efforts have been made in recent years to teach computing concepts and skills in undergraduate STEM courses. Educators and researchers have engaged in a healthy debate on the benefits of such courses, and on the notion of what "computational thinking" is in the first place (Papert, 1980 and 1996; Wing, 2006; Barba et al., 2016). A key theme of the Breaking Boundaries conference was, therefore, to discuss some successful practices of integrating computing in undergraduate STEM courses and curricula.

This paper seeks to contribute to this ongoing dialog by using three case studies to both (1) explore the potential benefits and challenges to students in computing-infused STEM courses and (2) examine the potential benefits and challenges for faculty in designing and implementing such courses. Our hope is that the lessons that we have learned in these case studies will be useful to educators who are considering developing and implementing computationally rich STEM courses.

We begin by addressing the question: What does it mean to teach "computing" in a STEM course? As mentioned above, computation can mean many different things ranging from using computers to conducting virtual experiments to teaching programming. In our context, we mean teaching computational problem-solving skills that provide students with the ability and confidence to explore, analyze, and solve a range of problems that they have not seen before. This may involve using existing software tools, writing one's own programs from scratch, or developing algorithmic solutions. This is in contrast to using software to visualize

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Dahlquist, K. D., Dionisio, J. D., Libeskind-Hadas, R., & Bargagliotti, A. (2018). Breaking Boundaries in Computing in Undergraduate Courses. *Journal of Research in STEM Education*, *4*(1), 81-100.

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the behavior of systems, to find solutions to a mathematical problem by running provided code, or varying parameters in existing software. While all such uses of computers are potentially valuable, the distinction that we draw in this paper is between using the computer as a tool to teach or convey a concept versus developing a set of broadly-applicable computational skills, techniques, and problem-solving strategies. In this context, we seek to better understand the benefits and challenges of such courses for both students and instructors.

We describe three case studies based on courses developed and taught at Harvey Mudd College (HMC) and Loyola Marymount University (LMU). These courses include a range of computational skills and techniques. The first case study describes a non-majors' introductory computer science course developed at HMC that covers foundational computing and programming concepts in the context of problems in biology. The second case study describes a non-majors statistics course developed at LMU that teaches concepts in statistics using student investigation of real datasets and a just-in-time delivery of material in response to questions posed by students. The third case study describes a biological databases course at LMU that brings upper-division computer science and biology majors together to explore research problems that involve expertise in both computing and biology.

For each case study, we begin by providing motivation for and background of the course, some details about the target audience and course logistics, and a discussion about the perceived benefits for students and the challenges for both students and the faculty teaching the course. Finally, we conclude with a synthesis of the lessons learned from these three case studies.

Case Study 1: Teaching Introductory Computer Science in a Biological Context

Ran Libeskind-Hadas

Department of Computer Science, Harvey Mudd College

Motivation and Background: Harvey Mudd College is a STEM-focused liberal arts college. As part of the college's common core curriculum, every student is required to take an introductory computer science course in the fall of their freshman year. We have developed a version of this course called "CS 5 Green" that uses applications from biology to motivate programming and computational problem-solving. This course covers nearly all of the computer science content in our "standard" introductory course but presents the material "just in time" to explore and solve problems that arise in the life sciences. The course is taught using the Python programming language both because that is the language used in our other introductory courses and because it provides a level of abstraction that permits writing interesting programs within the first few weeks of the course.

Learning Objectives: This course seeks to provide students with foundational and broadly-applicable programming and computational problem-solving skills. Our goal is to provide students with tools and techniques to formulate a computational problem precisely, design an algorithm to solve the problem, design a well-structured program to implement the algorithm, and learn to test and document the program.

Specifically, by the end of the course, students should be able to design, implement, and test programs that use control structures (if-then-else), loops (for and while), recursion, object-oriented design, and basic data structures. In addition, the course exposes students to foundational theoretical ideas including efficiency of algorithms and computability. Students should be able to explain these concepts and use them in the design of their own algorithm solutions when relevant.

All of the course content is motivated by questions and applications from biology, both to help bring the material to life and to demonstrate how computation is relevant to other STEM disciplines and to society in general.

Target Audience: The course is designed for students with no prior computing background and only a single high school biology course. Approximately 20 HMC first-year students (10% of the freshman class) elect to take this course. HMC students are invited to indicate their preference for one of four introductory courses that are offered (this course, the standard offering, or one of two more advanced sections for students with

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considerable prior computing experience). In addition, the course is available to approximately 20 declared life sciences majors (sophomores through seniors) from four other neighboring colleges (Pomona, Pitzer, Scripps, and Claremont McKenna) in the Claremont Colleges consortium.

Structure and Content of the Course: The course is structured as a sequence of 3-week modules, each of which presents a fundamental question in biology and then provides students with the programming concepts and tools that allow them to write programs (from scratch) that explore the motivating question. Ultimately, students use their programs to make their own discoveries on data that we provide.

The first module of the course opens with the story of Typhoid Mary and the discovery that typhoid is caused by the ingestion of Salmonella enterica typhi. Strangely, while this strain is pathogenic, other strains of salmonella are not. Why is this? With this question, we begin developing the programming concepts (basic data types, functions, loop structures) that allow students to write their own programs to explore the DNA sequences in bacterial chromosomes. Using their own programs, they search for differences in the pathogenic and non-pathogenic strains. In the second week of the course, students write their own programs to compare the GC content (the proportion of G and C nucleotides in the DNA) of strains of bacteria and discover that the pathogenic strain of salmonella has very different GC content from that of other bacteria. The following week, students write programs to identify the specific region of the salmonella genome where pathogenic and non-pathogenic strains differ and, ultimately, write programs that use randomization methods to identify the pathogenic genes themselves. Once the students discover these genes, they use the online BLAST tool to learn about the origins of these genes. Over the three-week duration of this module, students learn to write small programs that use basic data types, control flow (if-else), and loops (for and while loops).

The second module of the course poses the question "What determines the sex of an individual organism?" We explain that the sex determination systems in mammals and birds are different and ask if those systems evolved independently or had a common origin. Sequence alignment techniques provide a tool for answering this question. This module explains the concept of sequence alignment and introduces students to recursive sequence alignment algorithms. Students learn how the algorithms work, modify them to their needs, and implement them from scratch. Students quickly discover that these recursive algorithms are very slow, motivating concepts in efficient algorithm design. We show students the method of "memoization" (a simpler version of dynamic programming) and students use that method to accelerate their sequence alignment programs. Ultimately, students are able to use their programs to align avian and mammalian genes, identify orthologs, and use the algorithmic method of best reciprocal hits to answer the question of the origin of these two sex determination systems. In this module, student learn to write recursive functions, accelerate them using memoization, and learn and implement general-purpose algorithms (e.g., best reciprocal hits).

The third module explores the origins of modern humans using phylogenetics. Students learn a relatively simple phylogenetic inference algorithm (UPGMA) and use that algorithm to construct the phylogenetic trees for ancient and modern primates using provided data. Ultimately, students are able to find evidence for and against different theories of the evolution of humans and the relationship between modern humans and neanderthals. In this part of the course, students design, implement, and test larger programs that integrate the techniques that they have learned in the past modules.

In the final module, students learn foundations of object-oriented programming and use those concepts to write and conduct their own simulations of a variety of biological phenomena.

At the end of the course, students are presented with three choices for a 2-week final project that integrates many ideas from the course. For example, in one project, students use a maximum likelihood method to infer the regulatory network for a set of genes. These projects typically require approximately 200 lines of code and then ask students to use their programs to explore several provided datasets. Figure 1 shows two examples of student work.

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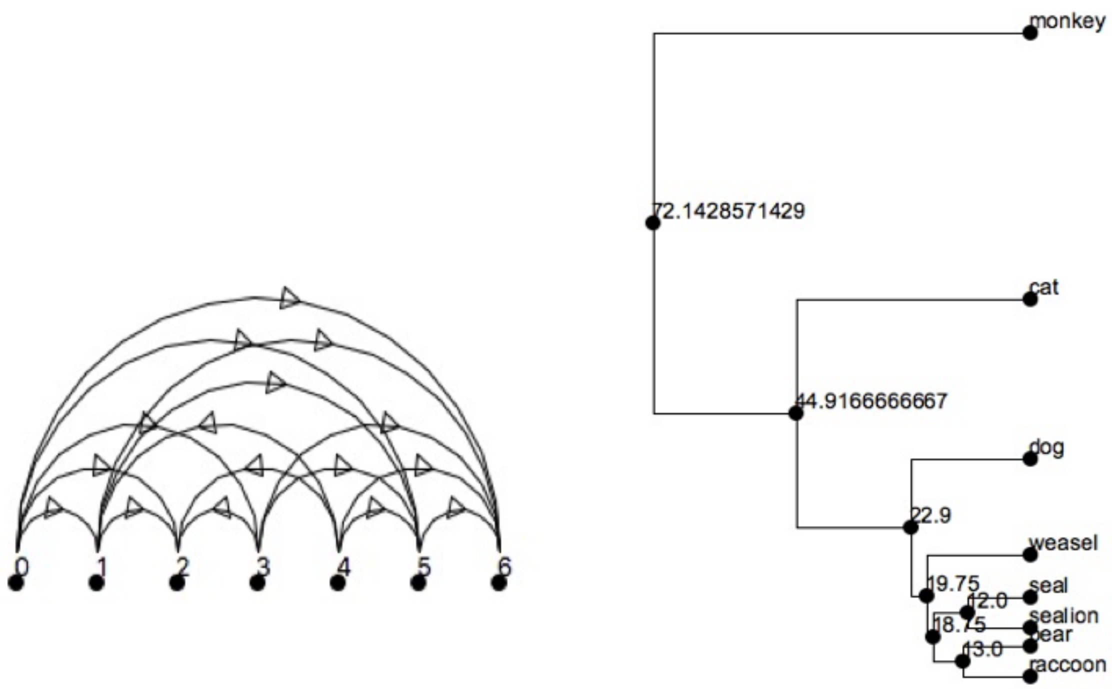

Figure 1. Examples of the output from student-written programs. (Left) A maximum likelihood gene regulatory network for six genes inferred from binary expression data. (Right) A phylogenetic tree inferred using the UPGMA algorithm.

Course Logistics: This is a one semester (14-week) course taught each fall. The course meets twice each week for 75 minutes per lecture and has an open 2-hour lab each Friday afternoon where students are encouraged to get started on their weekly assignments. Python's relatively simple syntax allows the instructor to use most of the class time to talk about principles.

The course has been taught since 2009 and is co-taught by a computer science professor and a biology professor. In the first several iterations of the course, the biology professor would give the first lecture each week to motivate the problem and introduce or foreshadow the basic computing approach to that problem. The second lecture would be given by the computer science professor and would dive into the computational tools required to solve the problems that week.

After several iterations of the course, the two instructors became sufficiently comfortable with all of the content. In recent offerings, the instructors have divided the material into multi-week units, with one instructor lecturing for two or three weeks of classes at a time. Both instructors are always present in class and in the Friday open labs. The course is now sufficiently mature that new instructors have begun teaching the course. In the near future, it is expected that one professor will teach this course alone (e.g., either a computer science professor or a biology professor).

Benefits and Challenges for Students: Students in this course gradually achieve proficiency with developing algorithmic solutions to computational problems and designing, implementing, and testing programs that implement those algorithmic solutions. Based on our assessment of their capstone student projects and performance on the final exam, students seem to develop a strong sense of confidence in transferring their computational competence to new domains. As one indication, the students were surveyed near the end of a recent offering of this course and asked them: "Have you used the skills learned in this class to write a program to solve a problem in a different class this semester when programming was not required for that assignment?" The overwhelming majority of students in the course responded in the affirmative.

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Anecdotally, students who have chosen "CS 5 Green" have reported that their decision to take this course was based on (1) an interest in the life sciences, (2) trepidation about taking a more traditional computer science course, and (3) curiosity about the connections between computing and biology.

Life sciences students from the other Claremont Colleges have reported that (1) they recognize the importance of computing in the life sciences, (2) their academic advisor recommended this course, or (3) they are engaged in a research project (e.g, a senior thesis project) that requires some computational sophistication.

Our assessment is that the interdisciplinary nature of this course makes it more inviting for students who have misgivings about taking a traditional introductory computer science course. In addition, students with an interest in the life sciences are drawn to the course because of potential applications to their current or future work.

In end-of-semester course evaluations, students report working an average of 7.5/hours per week outside of class. However, 25% of students report working 10 or more hours per week outside of class. This is more than the "standard" introductory computer science course but still within the normal range for first-year courses at the college. Some students report that they perceive that the material in this course is "harder" than in the "standard" introductory course. Finally, while most students report that they find the connections between the computer science and the biology to be smooth and well-integrated, some students don't see those connections as clearly or find the integration of topics to be less smooth than desired.

Benefits and Challenges for the Instructors: One of the clear benefits of this course to the instructors is the joy of working with colleagues in other fields. The collaborations are both intellectually stimulating and have led to other interactions in both teaching and research.

There are also, of course, a number of challenges. We learned that for the first several iterations of the course, co-teaching did not result in half the work for each instructor. There was substantial overhead in planning the lectures, assignments, and exams. In addition, both professors were always in the classroom and lab together. Fortunately, both professors' home departments treated this course as a full course rather than a half course worth of teaching - at least for the first several years. This investment by the two departments was critical for the success of this course.

Another challenge is the variation in the backgrounds of the students. HMC first-year students have (at most) a year of high school biology background whereas the off-campus life sciences majors have typically completed several college-level biology courses. Conversely, HMC students are generally very comfortable with mathematical concepts (e.g., basic concepts in probability and mathematical logic) whereas that comfort-level among off-campus students is more varied. Most of these challenges were largely worked out by the second offering of the course, but this is an issue that requires constant vigilance on the part of the instructors. Instructors have learned to use motivating examples that are mostly unfamiliar even to the biology majors and to encourage students to work in pairs during class time exercises and some programming homework assignments. These strategies help "level the playing field" for the class and appear to mitigate most, but not all, of the disparities in student background.

Outcomes and Assessments: The course appears to be successful across a number of dimensions. For example, on the college's 7-point Likert scale teaching evaluations, the mean response to the question "This course stimulated my interest in the subject matter" was 6.69 (n = 26, college mean = 5.65). On the question "I learned a great deal in this course", the mean was 6.73 (n = 26, college mean= 5.92).

One outcome of this course is that there has been a growing interest in computational biology at the college. Several years after the first offering of this course, the college approved a new "Mathematical and Computational Biology" major. Many graduates from this major have gone to top PhD programs in computational biology and related areas while others have gone to work in life sciences companies.

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Case Study 2: Introductory Statistics through Investigation

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Department of Mathematics, Loyola Marymount University

Motivation and Background: LMU offers a general education introductory statistics class, Math 104, that fulfills a quantitative reasoning graduation requirement. The students in this course are non-STEM majors. Over the last five years, the course has been re-envisioned as an introductory statistics course for data-literate consumers. The thought process for this redesign is that students need exposure working with and understanding data that they will encounter in their daily lives. The course is thus organized as a project-based course in which each project brings to light different statistical topics and ideas students may encounter in their daily life. Each project, or "investigation", uses compelling and relevant data sets that engage students in learning statistics through current events.

Learning Objectives: The course seeks to provide students with the ability to carry out statistical investigations, to compute and carry out some statistical procedures (e.g., descriptive statistics, hypothesis testing, regression), and to discover how statistics fits into our lives. The course strives to demonstrate how statistics can be used to answer interesting and compelling questions with data.

Target Audience: The course is designed for non-STEM majors fulfilling a math general education graduation requirement. Typically, there are 25 students enrolled in each section. Student majors include dance, sociology, communications, and others.

Course Structure and Logistics: Two to three sections of Math 104 arentaught each semester (15 week). The sections of the course reported on in this paper meet twice each week for 75 minutes in a computer lab. The course is founded on three important, fundamental, and particularly timely themes in statistics. Students need to (1) employ technology, (2) explore real data sets, and (3) practice communicating statistical ideas and results. Moreover, statistics should be guided and taught through the statistical investigative process of formulating a question and collecting/considering appropriate data, choosing the appropriate analysis technique and interpreting the results to answer the question (Franklin et al, 2007). The material commonly taught in introductory statistics courses often focuses on techniques, but such methods are often "necessary but not sufficient" for modern data analysis (Hardin, Hoerl, Norton, & Nolan, 2015; Ridgeway, 2015). In contrast, this course is aimed towards the modern data consumer.

The course has a total of ten projects that are completed throughout the semester. The statistical ideas and techniques covered in a project are then used in subsequent projects. Each project is typically assigned on a Tuesday, lasts approximately one week (two class periods) and is submitted the following Tuesday. All work is done electronically –project assignments are given on a Powerpoint slide in the form of an investigative question and all projects are written up with a one- to two-page limit and submitted on DropBox. As an example, some of the project assignments from the fall of 2016 included the following investigative questions:

- Does texting while doing another activity distract from the task at hand?
- Do our presidential candidates say what we think they say? Are there differences in the way the presidential candidates Clinton and Trump speak?
- What are evidence-based suggestions to reduce the public landfill?
- What region or country of the world do you recommend providing aid to in order to reduce the world's child mortality rate?
- How does religion and region of the world impact the presence of terrorism?

For each question, students are expected to construct a data-supported write-up that follows the Guidelines for Assessment In Statistics Education (GAISE) investigative process of formulating a question,

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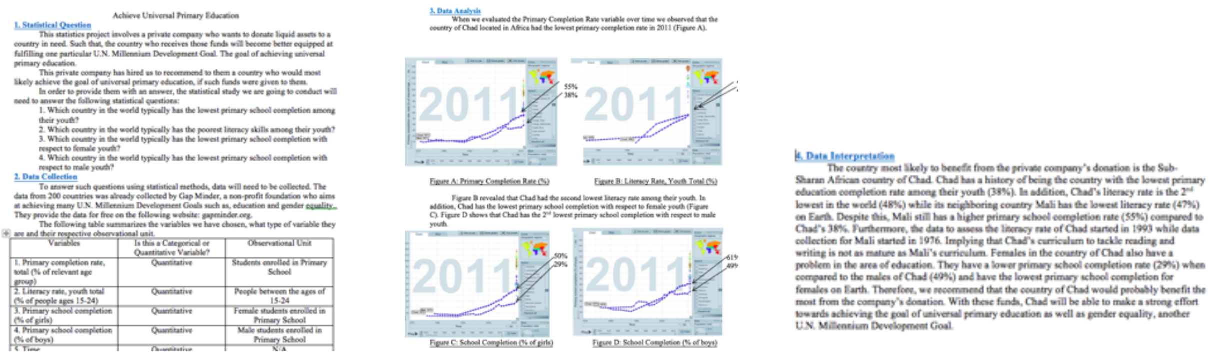
collecting/considering data, analyzing data, and interpreting results (Franklin et al., 2007). The four components of the GAISE process are labeled in the student write-ups. Figure 2 illustrates a student's write-up that clearly shows the labeled four components of the GAISE report.

Each project is guided by an investigative question that is posed to the students as their only instruction. The goal of each project is to answer the investigative question in a coherent well-presented document. Students are given access to a relevant data set to help answer the investigative question at hand. This data set is either made available through a class group created in statistical software StatCrunch or may be accessed through a website. The course makes heavy use of StatCrunch, a point-and-click web-based statistical software package that is very easy to use.

Because the course is taught in a computer lab, students work on StatCrunch on a daily basis. The data include typically upward of 1000 observations and may or may not be cleaned. In addition, three of the ten investigations require students to interact with the data through apps (heat maps, multivariable scatterplots, etc.). Most of the data sets are multi-dimensional, offering many opportunities for multiple entry points for students to answer the investigative questions.


Achieve Universal Primary Education

1. Statistical Question

This statistics project involves a private company who wants to donate liquid assets to a country in need. Such that, the country who receives those funds will become better equipped at fulfilling one particular U.N. Millennium Development Goal. The goal of achieving universal primary education.

This private company has hired us to recommend to them a country who would most likely achieve the goal of universal primary education, if such funds were given to them.

In order to provide them with an answer, the statistical study we are going to conduct will need to answer the following statistical questions:

1. Which country in the world typically has the lowest primary school completion among their youth?
2. Which country in the world typically has the poorest literacy skills among their youth?
3. Which country in the world typically has the lowest primary school completion with respect to female youth?
4. Which country in the world typically has the lowest primary school completion with respect to male youth?

2. Data Collection

To answer such questions using statistical methods, data will need to be collected. The data from 200 countries was already collected by Gap Minder, a non-profit foundation who aims at achieving many U.N. Millennium Development Goals such as, education and gender equality.. They provide the data for free on the following website: gapminder.org.

The following table summarizes the variables we have chosen, what type of variable they are and their respective observational unit.

Variables	Is this a Categorical or Quantitative Variable?	Observational Unit
1. Primary completion rate, total (% of relevant age group)	Quantitative	Students enrolled in Primary School
2. Literacy rate, youth total (% of people ages 15-24)	Quantitative	People between the ages of 15-24
3. Primary school completion (% of girls)	Quantitative	Female students enrolled in Primary School
4. Primary school completion (% of boys)	Quantitative	Male students enrolled in Primary School
5. Time	Quantitative	N/A

3. Data Analysis

When we evaluated the Primary Completion Rate variable over time we observed that the country of Chad located in Africa had the lowest primary completion rate in 2011 (Figure A).

Figure A: Primary Completion Rate (%)

Figure B: Literacy Rate, Youth Total (%)

Figure B revealed that Chad had the second lowest literacy rate among their youth. In addition, Chad has the lowest primary school completion with respect to female youth (Figure C). Figure D shows that Chad has the 2nd lowest primary school completion with respect to male youth.

Figure C: School Completion (% of girls)

Figure D: School Completion (% of boys)

4. Data Interpretation

The country most likely to benefit from the private company's donation is the Sub-Saharan African country of Chad. Chad has a history of being the country with the lowest primary education completion rate among their youth (38%). In addition, Chad's literacy rate is the 2nd lowest in the world (48%) while its neighboring country Mali has the lowest literacy rate (47%) on Earth. Despite this, Mali still has a higher primary school completion rate (55%) compared to Chad's 38%. Furthermore, the data to assess the literacy rate of Chad started in 1993 while data collection for Mali started in 1976. Implying that Chad's curriculum to tackle reading and writing is not as mature as Mali's curriculum. Females in the country of Chad also have a problem in the area of education. They have a lower primary school completion rate (29%) when compared to the males of Chad (49%) and have the lowest primary school completion for females on Earth. Therefore, we recommend that the country of Chad would probably benefit the most from the company's donation. With these funds, Chad will be able to make a strong effort towards achieving the goal of universal primary education as well as gender equality, another U.N. Millennium Development Goal.

Figure 2. Example Student Write-Up with Labeled Components

All projects are group-based. Groups range from 2 to 4 people depending on the project. Each group is expected to turn in one final write-up for each project. The groups rotate for each project and thus students in the class typically work with every person in the class at least once during the semester. Group work is an appropriate pedagogy that aligns nicely with the course theme of communication.

Students work on their projects in class. Students are encouraged to ask questions in class and the instructor addresses the answer to the entire class. This "just in time" teaching provides students with relevant and necessary statistical content to help them complete the project. Often, these "teaching moments" comprise 10 to 20 minutes of lecture-style presentation where a question is expanded upon and several examples are given. Students are then asked to work through similar problems on their own before returning to their project.

Benefits and Challenges for Students: Initially students struggle to understand the expectations of the course. Most students choosing this course do so to fulfill their general education requirement for quantitative reasoning. Students enrolling in this course are typically "math-phobic" and many express anxiety and worry about being enrolled in a college math course. Because of the open-ended nature of the projects in the class, some students initially struggle to produce high quality work. Some students focus merely on the computation of statistics, insisting that they want formulas to compute. Some create graphical displays without reasoning about whether the graphical display is appropriate for their situation. Over the course of the term, however, students mature in both their statistical understanding and communication skills.

The structure of the class requires students to engage with the computer as an investigative tool to answer statistical questions. Consequently, students naturally engage in computational thinking through problem-solving. In addition, due to the emphasis on communication in the course, students view their computational skills as a toolkit for problem solving. Due to the open-ended nature of the projects, students develop creative

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problem-solving skills.

Benefits and Challenges for Instructors: The main challenge of teaching this course is the grading of the projects. Currently, no research-based rubric is available to grade open-ended statistics projects of the sort that are given in this class. There are two main dimensions that each project needs to be graded on: the correctness of the statistics and the clarity of the exposition. These two dimensions are often difficult to separate. For example, one may encounter a project that is well-written, convincing, and clear but contains some statistical errors.

Recently, a new grading scheme was implemented in an effort to alleviate some of the difficulties and to provide important feedback to the students. A course grader was assigned to the course. For each project, the grader and the instructor separately graded each paper. The course grader read each paper for clarity of communication. The course grader was not provided with the assignment before grading and had to deduce the assignment from the student write-up. The clarity of the project was assigned a grade on a 5-point scale. Then, the instructor read the same submissions without seeing the grader's score. The instructor read the projects for correctness and assigned a grade on a 5-point scale. The two grades were added together and each assignment received a final grade (out of 10 possible points). The next iteration of this course will clarify the specific point assignments on each of the Likert scales. For example, a score of 5 on content means that no errors were committed in the write-up, a 4 might mean that there are 1-2 minor errors but no major ones, etc.

A second difficulty with grading is the printing of the projects. While one could opt to grade the projects electronically, it is difficult to navigate the logistics of grading electronically and then to return the graded projects to the students. With 25 students per section and ten projects of two pages each, the volume of printing is very large. While a notable effort was made to make the course "paperless," (the investigations were given on a Powerpoint slide and turned in electronically) printing of the projects was sometimes necessary. Students turned in assignments using Microsoft word, PDFs, and several other ways. Not all of these allow for track changes to record grades and comments. Therefore, at times, some assignments needed to be printed in order to be graded. This was slightly contradictory to the general philosophy of the course that was exposing students to statistics through technology. In the fall of 2016, approximately 20 total projects throughout the semester were printed.

Outcomes and Assessments: The course appears to be successful across a number of dimensions. Student attitudes are generally very positive towards statistics at the end of the course. For example, on the college's 5-point Likert scale teaching evaluations for the fall 2016 semester, the mean response to the question "This course stimulated my interest in the subject matter" was 4.03 in one section and 4.43 in another section (n1 = 20 & n2=21, department average= 3.49). Students were asked two open-ended questions: What did you find to be most beneficial about the course? And What would have made this course more effective for you? Across the two sections, the course received 25 positive comments and three negative comments. Of the positive comments, five of them specifically mentioned the projects. The other positive comments focused on the fact that the class connected statistics to the daily lives of the students and overall was effective and enjoyable. For example, students wrote "I learned how to apply statistics to my daily life" and "learning that stats IS applicable to everyday life," and yet another student mentioned " I found the hands-on learning to be beneficial." The negative comments were: "I felt like what was expected was unclear," "receiving [insufficient] feedback on my grades," and "the course would have been more effective if we were given less projects." These comments highlighted the difficulties noted above about the grading of the course. Providing constructive feedback for a course of this type is a challenge.

As the semester continued, student grades on the projects improved. While mini-project 1 had an average score of 6.2 (out of 10 points), the last project before the final raised the average to 7.7 points. Overall, the sophistication of student write-ups improved over time. For example, consider the work from group A who worked together on some of the projects throughout the semester. In mini-project 4 (Figure 3), the project where they wrote a letter to the LA county sanitation department, the group used simple histograms and bar

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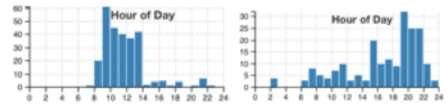
graphs and only referred to their graphics in a limited manner in the write-up. They only refer to the graphs minimally in their writing and also include other statistics that are not recoverable from the graphs.

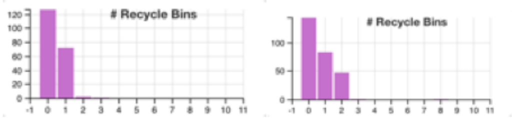
Dear LACSD,

People in the community are throwing away too many items that could be recycled. Using a Trash Demo data set, which was collected by high school students using an app to record their behaviors of throwing out trash for 5 day periods, we see staggering issues with how trash is being filtered between recycling and landfill. It was recorded that there were 1,302 recyclable items. Of those 1,302 items, only 715 made it into recycling bins, which is just under 55%. The other 45% were thrown in trash bins, resulting in a 33% increase in items that will be heading into a landfill. To address these issues, we recommend more education for the community, as well as distributing recycling bins to every residency and school in the community, including houses, apartments, and condos.

There is a vast lack of education on what is recyclable and why recycling is important. While many children at school are told that recycling is important, they are unaware of the devastating effects that result from not recycling. Moreover, many students are unaware of what is and what is not recyclable. To aid in bettering this understanding, a video could be shown to students in school that would provide them with real footage of environmental issues caused by landfills and would explain what is and what is not recyclable. In addition, the video could be broken down into segments and aired at night as commercials to target households. To further help households identify what is and what is not recyclable on a regular basis, flyers could be sent in the mail and used as reference. These flyers would ideally be placed on the refrigerator door or any location that can be easily seen. Through observing the graphs of hours of the day, we can see in the left graph that the high schoolers throw things out during school hours between 8am and 1pm, and in the right graph they throw things out at home between 2pm and 10pm.



As for distributing recycling bins, we can observe through the graph on the left that most teens do not have recycling bins at home, or at least indoor ones as opposed to the large outside bins. In the graph on the right, we can see that there are more recycling bins at school; however, there is still a significant amount of teens *not* seeing recycle bins at all. To solve this issue, we propose that more recycling bins are distributed to all households and schools. Moreover, we propose that schools place their recycling bins so that there is always at least one visible bin.



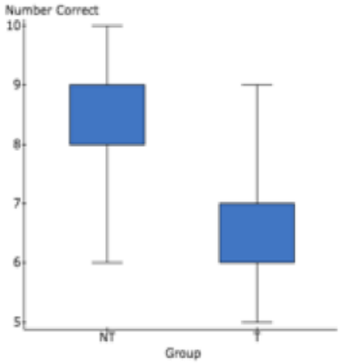
Sincerely,

Figure 3. Group A mini-project 4

In the next mini-project (Figure 4), group A's analysis and interpretation integrated their graphics in a better way. For example, they discuss several aspects of the box-plot including overlap and IQR and utilize this information to draw their conclusion. As their work further progresses throughout the semester, their interpretations became more sophisticated as they notate more information in their output. In mini-project 8, they reference output and graphical displays and directly use it to support their answer. In this project, the group explored Redfin housing data they obtained from the internet to examine what factors impacted housing prices.

Data Analysis

Looking specifically at the boxplot below, the Q1 for texting is 6 and the Q3 is 7, while for the non-texting group Q1 is 8 and the Q3 is 9.



Data Interpretation

Based on the data collected, it is evident that there is a significant difference between the scores of the non-texting and the texting groups. By looking at the boxplot, one can see that the spread of test scores for the non-texting group is higher than the spread of test scores for the texting group. This is supported by the fact that the Q1 for non-texting is 8 and the Q3 for texting is 7. In addition, the calculated difference between the average test scores is about 1.4 with the average test score for non-texting being 8.1 and the average test score for texting being 6.7. This difference is significant given that the chance of this randomly occurring is only 1% which was calculated in StatCrunch using the Z Stat function, in order to understand the possibility of this naturally occurring. In conclusion, texting significantly affects a person's ability to comprehend given information seeing as the scores between the non-texting and texting group do not overlap and the difference in means is extreme enough to be considered significant.

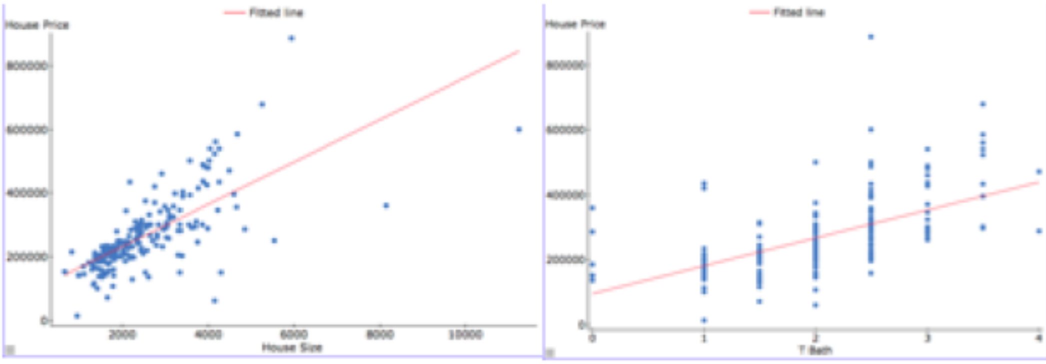
Figure 4. Group A Mini-Project 5

By using StatCrunch, we were able to determine the multiple linear regression and create two separate stat plots for house price and house size, and house price and number of bathrooms. The results are provided below.

Multiple linear regression results:
Dependent Variable: House Price
Independent Variable(s): House Size, T Bath
House Size = 29144.134 + 53.290598 House Size + 50569.315 T Bath

Parameter estimates:

Parameter	Estimate	Std. Err.	Alternative	DF	T-Stat	P-value
Intercept	29144.134	15643.365	≠ 0	197	1.8630348	0.0639
House Size	53.290598	4.6370349	≠ 0	197	11.492387	<0.0001
T Bath	50569.315	7414.0867	≠ 0	197	6.8207073	<0.0001



For this data set, the y-intercept is 29144.13. Both variables, house size, a quantitative variable, and number of bathrooms, a categorical variable, demonstrate a linear pattern; the relationship between both variables and house price is positive. The coefficient for house size is 53.29. The coefficient for number of bathrooms is 50569.32. The house size standard error is 4.64. The standard error for number of bathrooms is 7414.09. The confidence interval for house size is <.0001. The confidence interval for number of bathrooms is also <.0001.

On average, the base price of a house is $29,144.13. In looking at the multiple linear regression results, we can see that, on average, house price will increase by $53.29 for every additional square foot, given that the amount of bathrooms stays the same. We can also deduce that, on average, house price will increase by $50,569.32 for every additional bathroom, given that the house size stays the same. Given the P-value of <.0001 for house size, we can conclude that house size and house price are highly correlated. Given the P-value of <.0001 for number of bathrooms, we can also conclude that number of bathrooms and house price are also highly correlated. However, the standard error for bathrooms is very high in comparison to the error regarding house size. All of this information allows us to conclude that both bathrooms and house size have a significant relationship in regards to house size.

Figure 5. Group A Mini-Project 8

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Group A's progression, through mini-project 8 (Figure 5), serves as an example of what many groups achieved. As the course continued and their communication skills improved, mini-project write-ups became more complete. Because communication was one of the learning outcomes of the course, this improvement served as an indicator of overall success.

Case Study 3: A Biological Databases Course Promotes an Open Science Ecosystem for Teaching, Learning, and Research with Undergraduates

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Motivation and Background: The Biological Databases course that we have co-designed and co-taught at Loyola Marymount University (LMU) is a cross-listed upper-division biology and computer science course (BIOL/CMSI 367). It has evolved over the last nine years to promote an open science ecosystem (John R. Jungck, personal communication; Crouzier, 2015), encompassing both teaching and research with undergraduates (Figure 6). The initial course offering in Spring 2006 was a master's-level computer science course in bioinformatics that sprang from the co-authors' desire to initiate a teaching and research collaboration (i.e., implement the teacher-scholar model) around an open source bioinformatics project that would exemplify a pedagogy founded upon open source principles (Dionisio et al., 2007; Dionisio & Dahlquist, 2008). We shifted the focus of the course to undergraduates in Fall 2008 and have taught it six times over the last nine years, roughly on an every-other-year basis, due to departmental and college constraints on staffing team-taught courses.

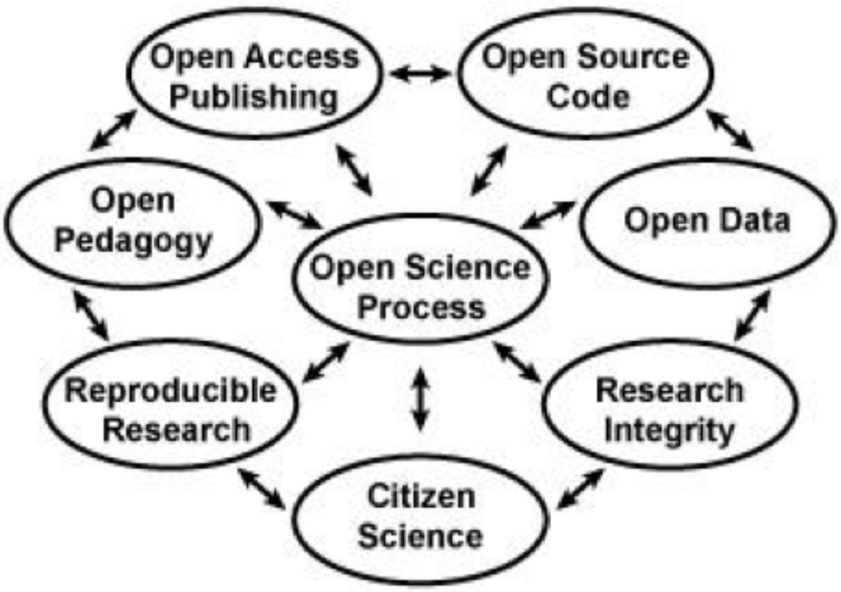

Figure 6: An open science ecosystem centered on an open science process of authentic research projects carried out in the Biological Databases course and in subsequent independent research with undergraduates. Open science relies upon the availability of open source code, open data, and open access to the scientific literature. Our public course website promotes an open pedagogy where students collaborate and learn science and engineering best practices with the benefit that resources are also available to other educators and the scientific community at large. Students learn how to conduct reproducible research and act with research integrity. They leave the course empowered to conduct citizen science, whether in graduate or professional school, or in other career paths. The products of student research in the course and research lab are then contributed back to the scientific community

as open source code, open data, and documentation in the form of reports and presentations, closing the loop on a meaningful experience that teaches them skills in information, data, and computer literacy. Arguably, this figure could be drawn as a fully-connected graph; we chose not to do this for the purposes of clarity.

The course culminates in a final project where the students are grouped in interdisciplinary teams of three or four to carry out an original research project. Their goal is to create a GenMAPP-compatible Gene Database (Dahlquist et al., 2002, Salomonis et al., 2007) using the open source XMLPipeDB software (Dionisio & Dahlquist, 2008) for a bacterial species not currently supported by GenMAPP, and then use the Gene Database to analyze published DNA microarray data for that species. For example, the Fall 2015 cohort created Gene Databases for Bordetella pertussis, Burkholderia cenocepacia, Shewanella oneidensis, and Shigella flexneri. Since 2008, students have created Gene Databases for 19 species. These student-generated Gene Databases are posted on our public code repository (first hosted by SourceForge, and now GitHub: https://github.com/lmu-bioinformatics/xmlpipedb) for use by the wider scientific community. This approach embodies the concept of a "problem space," which is the intersection of disciplinary knowledge, an open research question, and resources such as data and analysis tools to carry out a research project (Jungck et al., 2010). In support of this, course content is selected to directly serve whatever knowledge and skills will be needed by students to effectively execute the project. This is an example of "just-in-time" learning that has the advantage of being guided by expert "coaches" and utilizes the prior knowledge and skill set of students from complementary disciplines to form a learning community (Riel, 2000). Thus, biology topics include the fundamentals of genetics, molecular biology, and biochemistry needed to understand the data stored in biological databases, as well as the biotechnologies used to gather these data in a high-throughput manner. Computer science topics include what biological databases are, why they are important (and needed), the challenges that arise in compiling them effectively, and the relational database model.

Learning Objectives: The course's objectives are based upon L. Dee Fink's taxonomy of significant learning, which is divided into foundational knowledge, application, integration, the human dimension, caring, and learning how to learn (Fink, 2003). Long after the course concludes, it is hoped that students:

- Understand how biological information is encoded in the genome and can apply this knowledge to a variety of tasks and problems;
- Understand the core concepts, structure, and functions of a database, ranging from individual files to a full relational database management system, and can perform useful tasks with such data;
- Show discipline and proficiency in day-to-day science and engineering best practices, such as maintaining journals and notebooks, managing files and code, and critically evaluating scientific and technical information;
- Recognize and care about how the biological and technological issues presented in the course relate to and affect society, our daily lives, and ourselves;
- Have skills and tools for leaving one's comfort zone, flourishing outside of it, and learning more about biology and computer science on one's own; and
- Learn how to communicate and work effectively with colleagues from different disciplines.

Of special note are the last two objectives. At the beginning and throughout the semester, we emphasize to the students that leaving one's comfort zone, by definition, makes you uncomfortable, but that we are there to support them in the role of coaches, giving them guidance and opportunities to practice new skills, and cheering them on to achieve something that they did not know they could do. Taking on this role requires courage (Palmer, 1997) because in these courses we often find ourselves in the position of student, rather than expert, in the opposite discipline. Furthermore, the inevitable troubleshooting of technical and research issues can make the course appear as disorganized or "messy" instead of as running smoothly. We must be willing to show vulnerability to the students, trusting that such messiness and the resultant troubleshooting are actually

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creating teachable moments. We must accept that the students may not see the value of the hard work involved until well after the course has concluded.

The last objective is modeled by the co-taught nature of the course: it is hoped that students witness a firsthand example of this collaboration in the interactions we have with each other as a biologist and a computer scientist working toward common goals, including teaching the course effectively, assisting students with our complementary expertise, and mentoring the course's team research project, which occupies the last third of the semester. This objective is also supported by assigning homework partners from complementary disciplines each week.

Target Audience: Since LMU does not have an official degree or program in bioinformatics, the course is designed for upper-division biology and computer science majors, but has also been enrolled in by interested students in other majors (applied information management systems, chemistry, biochemistry, biomathematics, mathematics, mechanical engineering, psychology, and studio arts) as well as by students in the University Honors Program. Class size has ranged from 11 to its cap of 16, with the goal of producing teams of three or four to work on the research project for their designated bacterial species. Because at LMU instructors cannot assume that biology majors will have taken introductory computer science courses or that computer science majors will have taken introductory biology, there are no stated pre-requisites for the course except for upper-division standing in the Seaver College of Science and Engineering (a requirement we have waived in several cases). To attract students to the course, it is designed to fulfill multiple degree requirements. This course fulfills the three separate requirements in the LMU Core Curriculum as an "Integrations"-level Interdisciplinary Connections course carrying upper-division Information Literacy and Oral Communication "flags" (cf., http://academics.lmu.edu/media/lmuacademics/universitycorecurriculumfacultyresources/Core%20Document_RevisedFeb817.pdf). For biology majors, this course counts additionally as an upper-division molecular area requirement; for computer science majors, this course also counts as a science elective.

Course Structure and Logistics: The course meets twice a week for 75 minutes each session, for one semester (15 weeks). Office hours provide additional contact time as per usual and are designated as "technical support" time in case students have issues performing tasks or even just running the software required for the course. We note that the coursework involved could easily fill an additional 3- or 4-hour laboratory session. The addition of a lab session has not been sought, however, due to the disparate ways that the Biology and Computer Science programs assign teaching credit for laboratory courses.

The course is hosted on a MediaWiki site on an LMU computer science server. All assignments and student work are hosted on this wiki, which we made public with the Fall 2013 cohort. Materials from the most recently completed course in Fall 2015 can be viewed at: https://xmlpipedb.cs.lmu.edu/biodb/fall2015, while the current Fall 2017 course-in-progress (at the time of this writing) can be viewed at https://xmlpipedb.cs.lmu.edu/biodb/fall2017. Students complete weekly individual assignments and share reflections on the course wiki, which typically alternate between biology and computer science topics. The use of the course wiki for assignments is a gentle introduction to coding for non-computer science majors and serves as the first platform in the course from which to introduce the value of open source code and software engineering best practices. For example, the wiki demonstrates the concept of version control with the history of all contributions being readily available. We emphasize that students should work incrementally and annotate the summary field before saving a change to the wiki, by reporting back the number of contributions each student makes week-to-week, as well as the percentage of changes where the summary field was annotated. In addition, documentation of workflows via an electronic notebook kept on the wiki is part of every assignment. Collaborative work between the biology and computer science students is encouraged through assigning new homework partners each week to encourage students to take advantage of the domain-level expertise of the different majors. The shared reflections provide opportunities for metacognition about their individual learning processes, reflection on the interpersonal qualities needed for successful teamwork, and discussion of ethics case studies. Extensive feedback is provided by the instructors each week on each student's User Talk page. The actual grades are kept

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private on LMU's learning management system (formerly Blackboard, now Brightspace). Working publicly in this manner demonstrates how an open science process works.

The course has three phases which roughly divide the 15 weeks evenly: 1) Building Blocks (Genetic Code and Manipulating Text); 2) Going Deeper (Gene Expression Data and Relational Databases); and 3) Integrating for Research (Gene Database Project). The first "Building Blocks" part of the course introduces foundational material in molecular biology and computer science. Instead of strict sequential content, however, the topics are chosen in a way that points specifically toward the research project at the end of the semester—i.e., they are chosen based on what students need to know in order to execute the research project effectively.

The "Going Deeper" second part of the course introduces new content and also contains a dry-run of the research project for a species with known results. Students build a GenMAPP-compatible Gene Database for Vibrio cholerae from the current raw XML sources from UniProt and Gene Ontology. They perform a statistical analysis of the results of a published DNA microarray study on pathogenic versus laboratory strains of the bacterium (Merrell et al., 2002). They then combine the statistical analysis results with the gene database in GenMAPP (Dahlquist et al., 2002; Salomonis et al., 2007) to determine whether they draw the same conclusions as the study's authors and to directly observe the effects of database changes over time on the analysis of the data. This exercise is a powerful example of the need for reproducible research because the exact analysis the original authors performed (Merrell et al., 1992) cannot be replicated due to a lack of information in the methods of that paper. Moreover, student groups use a Gene Database produced by the previous class' cohort and compare it to results they generated to see how changes in databases will change analyses over time.

To conclude the semester, in the third part of the course, "Integrating for Research", the students are grouped into teams of three or four which then perform the same gene database building and published study comparison exercise for a bacterial species that has yet to be represented in GenMAPP. The typical class size produces four such teams and thus four gene databases to study the results of four real-world bacterial studies. To carry out the project, each student on the team is assigned the role of coder, quality assurance officer (QA), or data analyst. Each team also chooses a project manager. Class meetings for the last month of the semester are then devoted to both team meetings and guild meetings to receive feedback and guidance on the project. Guilds are composed of students from different teams who play the same role on the project (inspired by Wright & Boggs, 2002). All coders and QA meet with Dr. Dionisio and all project managers and data analysts meet with Dr. Dahlquist. The students create team web sites on the course wiki to manage their projects and the deliverables: the Gene Database, documentation, and a processed DNA microarray dataset that they analyzed using their new database, a group report and presentation slides, and individual statements of work and reflections on learning.

The oral communication and information literacy assignments are integrated with the course content and final project. In the first information literacy assignment, groups of students review, evaluate, and present about an individual biological database chosen from among those reported in that year's annual Nucleic Acids Research Database Issue (e.g., Galperin, Fernández-Suárez, and Rigden, 2017) according to a provided rubric. In the second information literacy assignment, which was developed in collaboration with a librarian, the students must use online literature (e.g., NCBI PubMed, ISI Web of Science, Google Scholar) and gene expression databases (e.g., NCBI Gene Expression Omnibus, EBI ArrayExpress) to find the articles and data for their projects. This is followed by journal club presentations where the coder and QA officer present the genome sequencing paper for their species and the GenMAPP users present the microarray paper. The entire team delivers a final research presentation to the class.

In addition to these information literacy assignments, we also reflect on a case of scientific misconduct involving Dr. Anil Poti, formerly of Duke University, who manipulated microarray data to support his claim that he could determine which patients would respond better to a chemotherapeutic drug (Baggerly & Coombes, 2009; http://bioinformatics.mdanderson.org/Supplements/ReproRsch-All/Modified/StarterSet/;and citations within). This case comes at a crucial juncture in the semester where the students have just learned about the intricacies of analyzing microarray data and drives home the need for careful documentation in the interests of reproducible research and open science.

Challenges and Lessons Learned: Having taught this course roughly every other year since 2006, we have found the course to entail a large amount of work, for both the students and the instructors. It has already been noted in the first case study in this paper that co-teaching does not reduce the work involved in a course. We have been fortunate that this has been recognized by both our departments and the college, and we have each received a full unit of teaching credit each time we have taught the course. The fact that our course fulfills multiple university core curriculum and major requirements aids in justifying the team-teaching. The large workload falls into three main areas, grading of weekly assignments, dealing with technology issues, and troubleshooting the research projects themselves.

The stated learning objective of "showing discipline and proficiency in day-to-day science and engineering best practices, such as maintaining journals and notebooks, managing files and code, and critically evaluating scientific and technical information," will only be met if students are given opportunities for repeated practice and are given substantive feedback to motivate improvement and, eventually, self-regulation. With this in mind, the instructors provide detailed feedback on the weekly wiki assignments, assigning points to the software engineering best practices noted in the section on Course Structure and Logistics. Such detailed feedback is time-consuming, but necessary to hold students accountable for these "process" skills. Even so, we have found that only rarely does a student completely internalize what it means to keep a good electronic notebook; as instructors, we struggle with how to teach this skill. We surmise that students with a stronger sense of ownership of their learning process or the research project perform better in this area. We somewhat manage the workload by being particularly conscientious and timely graders at the beginning of the semester in the first phase of the course when expectations are being set and student habits are being formed. If we get behind on grading in the second and third phases of the course, we then deliver oral feedback to the class or individual students until we can catch up.

The second area that contributes to the workload for the instructors is the technology itself. Inevitably, the wiki server goes down a few hours before an assignment deadline each semester, sometimes for a few hours, once for a few weeks (where we had to move to a different hosting site). Monitoring email and communicating with students in timely fashion is key to alleviating student stress and frustration. Furthermore, since we use research-grade software, albeit open source, it is vital to have a computer lab with all software properly installed. We assist students with installing software on their own laptops, but have run into myriad issues with this over the years, which fall into the area of providing computer, instead of instructional, support. In recent years, we have been able to grant students card key access to the lab, which has alleviated some of the software installation issues. We note that while the current generation of students are considered "digital natives," modern operating systems have been so successful at easing system navigation such that many students have only vague notions of what files are and how they are stored in directories. The lack of a mental model for how computers function impedes some of the higher-level skills we are trying to teach, but is absolutely necessary to succeed at bioinformatics research. Indeed, "95% of bioinformatics is getting your data into the right file format" (Dahlquist et al., 2016).

The third contributor to the high workload for instructors and students in this course is the real-world research project that student teams carry out at the end of the course. The instructors choose the species for the research projects, but the students must find an appropriate published DNA microarray dataset to analyze and build the actual gene database. This type of real-world study is a double-edged sword. On one hand, it lends relevance and impact to the course content and the product of their research will be shared with the scientific community. On the other hand, the projects can vary widely in difficulty level, despite initial vetting of datasets by instructors. Particular challenges faced by student groups over the years include inadequate gene identifier mapping by the source databases and numerous issues with the microarray datasets, including missing samples, missing column headers, missing identifiers, and the inability to match samples reported in a published paper

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to data posted to a published repository. Even without these unanticipated challenges, the data analysis pipeline for each project is unique, requiring customization of instructions for each team's coders, QA, and data analysts, especially in the areas of data cleaning and statistical analysis. The "realness" of the project demands genuine rigor and attention to detail, particularly with taking notes and recording processes and results—a skill which as we note above is genuinely underpracticed by some students. In the end, the projects become an object lesson in what (not) to do when sharing open data, reinforcing why best practices are needed, and relating back to materials we use from DataONE.org earlier in the course (https://www.dataone.org/education-modules).

A final challenge with conducting this course "in the open," where all student work is visible to everyone in the course, is dealing with cases of academic dishonesty. We have had cases where students have directly copied work from other students and turned it in as their own. While the ease of copying and pasting from the wiki enabled the plagiarism in the first place, the date/time-stamping of each change in the wiki's history also enables determining the direction of copying. Each time we have taught the course, we have sought to improve the clarity of what is allowed and not allowed. In the current semester, we discussed some academic honesty case studies up front. In addition, we now require an "Acknowledgments" and "References" section for every student-generated wiki page. Students must acknowledge those with whom they have worked, and any website from which they borrowed "syntax" (wiki style or coding). They must include an academic honesty statement (While I worked with the people noted above, this individual journal entry was completed by me and not copied from another source) and sign it with their wiki signature. The References section must include a properly formatted citation for any source from which they borrowed content. Furthermore, by connecting their own work to the case of scientific fraud we examine in the course, we hope to instill in them the values of the scientific community and to demonstrate how dishonesty can do harm.

Outcomes and Assessments: In addition to rubrics for course deliverables, we employ additional strategies focused on making group assessment as fair and thorough as possible. Presentations are evaluated by student peers and not just the instructors: students are provided with half-page questionnaires for every presentation not made by them, with questions framed to encourage constructive criticism and reflection. Deliverables for the final project include an explicit "Statement of Work" item where each student expresses in writing the specific contributions that they made toward the project.

The assessment of learning outcomes would be greatly aided by a pre- and post-course survey instrument that could measure learning gains in the areas of computer, data, and information literacy. To our knowledge, such an instrument does not exist. The Course Undergraduate Research Experience (CURE) survey is geared towards more traditional laboratory work in biology (Denofrio et al., 2007), and the Research on the Integrated Science Curriculum (RISC) survey also does not seem to capture what we do in this course (http://www.grinnell.edu/academics/areas/psychology/assessments/risc-survey). We also feel that student course evaluations are a limited way to measure learning outcomes, especially for a course such as this. Over the years, the evaluations have been influenced by factors such as technical hurdles faced, unanticipated difficulties of the final project, class dynamics, students' intrinsic interest in the course at the outset, and whether the evaluations were combined or separated by instructor. In recent years, we have improved our recruitment efforts to find interested students and we have also learned to manage student expectations. We consistently remind them that they should expect some discomfort from "leaving their comfort zone" and that conducting real-world research projects is difficult, yet rewarding. As a result, for the 2015 course evaluations, all of the numerical scores for every item beat the Biology Department-, College-, and University-wide averages. The lowest score of 4.53 (out of 5) was for "increased interest in subject matter" and the highest score of 4.93 was for "instructor available for discussion." The overall effectiveness of instruction was 4.60, which was substantially improved from the 3.93 of Fall 2013. The written comments remarked upon the challenging pace of work with assignments due every week and gave some constructive criticism as to the structuring of due dates. These critiques were also paired with praise for some of the course design principles of homework partners and collaborative work, however. The 2015 evaluations matched what we both felt as instructors, that the course really "clicked" that year and that students achieved far more than any previous class. We are wary, though, of making the course

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too "frictionless," i.e., making it run so smoothly that few hurdles need be overcome by students. We believe that "messiness" has value. Indeed, we have had to retire the long-standing XMLPipeDB project because the GenMAPP software (Dahlquist et al., 2002; Salomonis et al., 2007) on which it was based was finally rendered non-operational by a Windows update sometime in early 2017. Instead, we are designing a new research project for the students centered on our open source GRNsight software (Dahlquist et al., 2016).

One important outcome of the course: it has provided the opportunity for many students, who might not have been involved in research during their undergraduate careers, to conduct an authentic, interdisciplinary research project. Of those, at least a dozen continued the research projects begun in the course as independent study in subsequent semesters, leading to conference presentations and capstone projects for both the biology and computer science majors. One of these students complained early in the semester about the difficulty of the work, but by the end turned around, feeling amazed and proud of what he accomplished, and joined our research team. It is these student outcomes that inspire us to do this work.

Conclusion

We hope that continuing innovation in undergraduate STEM education will continue breaking boundaries: boundaries that inhibit student entry into STEM fields due to negative preconceptions; boundaries that artificially separate STEM disciplines; and boundaries that limit creative exploration due to a lack of powerful computational and statistical toolkits. As computers become increasingly important in the STEM disciplines, it is important to investigate optimal uses of computers in the classroom. Beginning with Papert's seminal work and Wing's widely-referenced 2006 follow-up, the call for computational thinking as an important skill for the 21st century has resonated with many. This paper highlights three case studies that view computational thinking as a problem-solving process, beyond merely learning how to use or program a computer. All three courses utilized and developed computational thinking in their students through the creative problem-solving process--students were given a broad range of problems and tasks for which they had to employ the computer to help them solve.

The three case studies described in this paper include an introductory computing course for STEM majors, a "hands on" statistics course for students from all majors, and an upper-division course that brings computer science and biology majors together to explore open-ended research problems. While the levels, audiences, and objectives are different, these courses share an important common feature: challenging concepts are brought to life via computing through the use of compelling applications and creative explorations using real data. The case studies demonstrate that while bringing computing into courses in biology and statistics may seem interdisciplinary at first, such computing can actually be an integral part of the learning of disciplinary concepts. We hope that these case studies help point a way forward towards the integration of computing within the STEM disciplines.

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RESEARCH REPORT

Antecedents, Processes, and Outcomes of an Interdisciplinary, Conference/Collaboration: A comparative Study of Three Interdisciplinary Working Groups

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Abstract: *There is a growing recognition of the need for interdisciplinarity in science, technology, engineering and mathematics (STEM) education. The purpose of the present study is to identify antecedents, processes, and outcomes of an interdisciplinary, collaborative conference and ongoing collaboration. The Breaking Boundaries in STEM education conference was developed with multiple goals, including fostering collaborative interdisciplinary scientific writing for publication among teacher-scholars who participated in one of three interdisciplinary working groups. One hundred teacher-scholars with interest in STEM education participated in the conference. A comparative study of three working groups from the conference was conducted using a triangulation of qualitative and quantitative methods. Surveys and behavioral observations were completed at the conference, and phone interviews with attendees were conducted 3-4 months later. Groups varied in their readiness to collaborate. Several themes emerged that might explain why one group was highly productive, one group was moderately productive, and one group was not productive at completing publications after the conference. Groups with a narrower disciplinary span, stronger leadership presence, a paper champion, motivated leader, and a leader with a strong recent history of publishing on the topic, were more ready to collaborate, and they experienced faster, smoother completion of publications. Further research and more passage of time, such as a few years, is needed to determine the quantity, quality, span of disciplinarity, novelty, and generativity of the publications over time. The generalizability of these themes to other interdisciplinary collaborative studies is briefly discussed.*

Keywords: Problem solving, interdisciplinary activities, problem choice, disciplinary tasks

Introduction

There is growing societal recognition of the need for interdisciplinary research in STEM education. For example, in order to enhance contributions of discipline-based education research to the understanding of undergraduate science and engineering education, the National Research Council recommended that interdisciplinary studies of cross-cutting concepts are needed (National Research Council, 2012). In recognition of the potential benefits of interdisciplinary efforts (including better solutions to societal problems and challenges), small-scale grants and very large initiatives have been established to promote interdisciplinary collaborative intellectual innovations (e.g., publications). Over the past two decades, large-scale efforts have grown with increasing investment by government and private foundations in initiatives. The National Cancer Institute's $70-million initiative established Transdisciplinary Tobacco Use Research Centers at seven universities in 1999

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(National Cancer Institute, 1999). Center applicants had to incorporate a transdisciplinary model (Rosenfield, 1992) indicating how they would strive to achieve transdisciplinarity. The Breaking Boundaries conference exemplifies a small-scale effort, and the conference is evaluated in this paper.

Transdisciplinary collaboration

Transdisciplinarity is an ideal goal of many interdisciplinary collaborative efforts. Transdisciplinarity denotes the strongest form of interdisciplinarity with the highest level of interaction among collaborators and can be defined as a process in which individuals work jointly using a shared conceptual framework that draws together discipline-specific theories, concepts, and approaches to address a common problem (Rosenfield, 1992). Transdisciplinary collaborative research has been described as collaboration among scholars representing two or more disciplines, with the products of that collaboration reflecting an integration of conceptual and/or methodological perspectives drawn from two or more fields. In the present paper, we will focus broadly on interdisciplinarity rather than transdisciplinarity specifically. For more information about interdisciplinarity and the factors that influence the success of transdisciplinary scientific collaboration, please see what has become a vast literature, which includes empirical articles and books by Daniel Stokols, Juliana Fuqua, and Julie Thompson Klein (e.g., Stokols, 2008; Fuqua, Stokols, Gress, Harvey & Phillips, 2004; Klein, 1996).

In the present paper, we discuss interview themes from an evaluation of the Breaking Boundaries in STEM-Ed conference/collaboration, a new regional, interdisciplinary conference/collaboration. We identify the antecedents, processes and outcomes of the conference/collaboration that can be generalized to other interdisciplinary scholarly collaborative endeavors. Social psychology, organizational psychology, preventive medicine and health promotion studies, and the science of team science provide our lens through which we view findings.

Background: About the conference

An interdisciplinary conference/collaboration[1], Breaking Boundaries in STEM Education, was held on April 7, 2017, to discuss developments and foster opportunities in undergraduate STEM-Ed locally in Southern California. Building on the goal of increasing the number and diversity of students in STEM pathways as well as improving those students' skill sets, the proposed conference was organized around three timely and important themes in STEM education: (1) equity, (2) problem-solving, and (3) computational thinking.

These themes served as the guiding framework to organize participants. All three themes are pressing issues in STEM education that can be studied through discipline-based education research (DBER) and scholarship of teaching and learning (SoTL) research. For each theme, there was a contributed paper session, workshop, and working group. The goal was to engage in a deep discussion of how DBER and SoTL research can help shed light on commonalities as well as how challenges can be approached across disciplines for each theme. The organization of the conference was led by CREATE-STEM (or Collaborative Research on Evaluating, Advancing, and Transforming Education in STEM, http://www.create-stem.org) and the Center for Teaching Excellence (http://academics.lmu.edu/cte). Both Loyola Marymount University organizations have wide visibility in the Southern California area, and the individuals who have run these organizations helped organize the Breaking Boundaries conference.

The Breaking Boundaries conference had several aims, one of which was for attendees to share ideas and collaborate to write a manuscript for publication. To combat the problem that STEM-Ed scholars have no (or almost no) venues to publish cross-disciplinary work, the organizers sought a new journal, Journal of Research in STEM Education (or J-STEM) and arranged for a special issue to be written by conference working groups. The three working groups at the conference were expected to collaborate on the conference day and

[1] This conference was designed to help facilitate an ongoing, local collaboration or network among STEM-Education researchers and interested others. Organizers debated whether they were mainly running a conference or an ongoing collaboration. Organizers could not find another word that accurately captured the collaborative nature of the conference and the ongoing collaboration. For the sake of simplicity, "conference" is the term used in this paper to refer to both the conference and ongoing collaboration.

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after the conference, before submitting manuscripts to the journal. The submission ideas were expected to emerge and be influenced by the conference working group.

There are many other ways to define the success of a conference/collaboration besides publications. In fact, the aims of the Breaking Boundaries conference/collaboration were to help STEM education scholars, researchers, and teachers do the following:

- learn about new scholarly work on three themes (problem-solving skills, computational skills, and equity);
- be inspired to gather more information about the themes (problem-solving skills, computational skills, and equity);
- be inspired to change teaching practices;
- be inspired to pursue new research ideas or pathways;
- find potential future collaborators on STEM-Ed relevant research;
- cultivate future collaborators which would lead to new outcomes, such as "seeds" (or ideas and intellectual products (including a publication manuscript, grant proposals, or conference presentations).

Evaluating the full impact of the Breaking Boundaries conference is beyond the scope of the current paper.

The Breaking Boundaries conference was structured to include traditional conference sessions of plenary talks, conference presentations, and a poster session as well as more innovative workshops and three working groups organized by themes (problem-solving, computational thinking, and equity). Attendees self-selected into working groups based on their interest. In an effort to enhance confidentiality, the working groups will be referred to, below, as Groups A, B, and C.

In this paper, we use comparative analysis to analyze antecedents and processes that may have influenced each group's productivity, defined as completing interdisciplinary, collaborative manuscripts.

Research questions

What antecedents and processes might impact interdisciplinary, collaborative efforts? Specifically, what factors might explain why three interdisciplinary working groups differed in their readiness to generate publication manuscripts based on group discussions?

Methods

Approximately 100 people registered for the one-day Breaking Boundaries conference, held in April 2017. An estimated 90% of registrants came to the conference and participated. An official count was not taken.

Before the conference, three conference organizers (the principal investigator and co-principal investigators of the grant) led the development and oversight of the conference. They decided to divide participants into three working groups. Conference organizers recruited two or three group leaders to develop and run each working group (Groups A, B, and C). Multiple meetings and conversations were held between conference organizers and group leaders for several months prior to the conference.

Behavioral observations, surveys, and interviews of conference participants serve as the data source for the present paper. At the conference, behavioral observations were made informally at multiple times. In addition, a brief evaluation form which was written by a conference organizer was distributed after the afternoon working group session (as well as other conference sessions). The form instructed attendees to use a scale of 1 (low) to 5 (high) to rate the session's content, presentation, opportunities for engagement, interaction

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with others, and interdisciplinary exchange.

A few months after the conference, interviews were conducted with 10 conference participants in July and August 2017 by phone (or by email with one participant). Much of the present report is based on these interviews. Interviews ranged from 20 minutes to over three hours in length, and occasionally an interview was conducted over a few days. Before interviews began, conference organizers decided to select participants who represented diverse backgrounds. Diversity was not defined in terms of ethnicity or race, but in terms of academic discipline (e.g., mathematics, physics, computer science), their rank (e.g., assistant professor), centrality to conference leadership (conference organizer, group leader, non-leader), and knowledge of STEM-Ed research (minimal vs. extensive).

Interview questions were developed to assess the factors that influence the collaborative processes and outcomes before, during, and after the conference. For example, respondents were asked to describe the extent to which they have established new intellectual linkages with other conference attendees and actually began intellectual linkages as a result of the conference (such as working on a conference publication).

Results and Discussion

Factors that influence collaborative readiness to develop interdisciplinary products (i.e., publications)

Four months after the conference, it was clear that the working groups differed greatly in their readiness to complete a collaborative manuscript for publication fully or partially based on group discussions. This difference was also clear during the conference. Group A showed the most collaborative readiness, and they published collaborative interdisciplinary papers. Group B has made progress on but has not completed any papers by the time the present report was written. Group C showed the least readiness and has not worked on drafts of publication manuscripts. Next, we present several antecedents and processes that may explain why Group A was the most ready to collaborate. Many of the antecedents, processes, and outcomes are listed in Table A. Some factors are not listed due to lack of complete data from all three groups.

What is a narrow disciplinary span? A narrow disciplinary span characterized Groups A and B more than Group C. What is a narrow disciplinary span? Interdisciplinary collaborative endeavors can be characterized as narrow or broad in disciplinary span of the collaborators. Previous scholars have provided a typology of interdisciplinary research, and they suggest that disciplines range from narrow to wide in span. Narrow interdisciplinarity involves: (a) interactions between disciplines with the same paradigms, same methods, and disciplinarity outputs that can be easily integrated; (b) few disciplines involved (which simplifies communication), (c) representatives of disciplines are in the same organization, and (d) representatives from disciplines that share the same disciplinary culture (Van Dusselddorp & Wigboldus, 1994). We refer to "narrow disciplinary span" as a small range of 2 or more disciplines which are similar (e.g., rely on similar methods of analyzing phenomenon and share similar world views). Mathematics and physics are disciplines that are similar and exemplify a narrow disciplinary span whereas sociology and biology would constitute a large disciplinary span.

It can be difficult to categorize interdisciplinary span when scholars are from different disciplines but share similar fields of expertise. A collaboration that is categorized only by discipline may appear to have a large span, but might actually have a narrow span. Biologists who study biostatistics and mathematicians who study statistics may have much in common. Also, psychologists who study and teach neuroscience and the functioning of the prefrontal cortex of the brain have much in common with neuroscientists. Psychologists who study team effectiveness have much in common with certain business and management professors.

Table A.

Comparative table of antecedent conditions, processes, and outcomes for the three working groups

	Group A	Group B	Group C
Overall readiness to publish	High	Medium	Low
Antecedents and processes			
Disciplinary span: narrow vs. wide	Narrow	Moderate	Wide
Group has a paper champion	Yes	Somewhat	No
Group has a shared history	Yes	Yes	Not clear from interviews
Physical environment: collaborator offices are spatially proximal	At least two members' offices are proximal	Not mentioned in interviews	Not mentioned in interviews
Group leaders have published recently on topic (Note: Group leaders had great expertise in the topics, but some had not published recently on the topic.)	Yes	Yes	No
Group leaders' conference organizing experience	Strong	Strong	Not consistently strong across leaders
Group size	Rather small	Medium	Rather large
Physical environment: meeting space characteristics	Small room with one table	Medium-size classroom	Large classroom
Leadership: Oversight by organizers	High Conference organizers were at the working group	High Conference organizer was at the working group	Low No conference organizer was at the group
Outcomes			
Publication progress as of 4 months later	Major progress. Publications submitted	Moderate progress. Publications in progress.	Minimal Progress.
Potential for publishing transdisciplinary, collaborative papers	Unclear – analysis of papers needed	Unclear – analysis of papers needed	Weak

Scholars have noted that interdisciplinary collaborations can be characterized as having "horizontal" integration or "vertical" integration between disciplines (Stokols, Fuqua, Gress et al. 2003). Horizontal integration occurs between similar disciplines that share similar levels of analysis (e.g., physics and mathematics). Vertical integration between disciplines involves linkages between disciplinary concepts that are much more distant in their levels of analysis micro levels of analysis is conducted by geneticists and macro level of analysis is conducted by sociologists).

How might a narrow disciplinary span impact groups? Groups with a narrow disciplinary span are less diverse than those with a wide disciplinary span. Previous social and organizational psychological research supports the notion that group diversity has an impact on group processes and performance.[2]

[1] Source: Langford (in press) and personal communication with Dr. Sara Langford, author of the encyclopedia entry "Diversity and teams".

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Diversity has been defined in multiple ways. Scholars have indicated that diversity is often defined and studied in terms of demographics (or similarly "bio-demographics", "surface level" variables, or "relations-oriented" variables) such as age, gender, ethnicity, and race. Another definition of diversity is more central to the core of an individual (or "deeper" including cognitive ability, personality traits, values, beliefs, and attitudes, Harrison, Price, Gavin, & Florey, 2002). Compared to diversity defined as demographics, "deeper-level" diversity has been found to be have a stronger impact on team dynamics and team process outcomes (Woehr, Arciniega, & Poling, 2013) as well as performance (Vodosek, 2007). In a study of team effectiveness (Woehr, Arciniega, & Poling, 2013), a 40-item scale was used to assess individuals' values, including whether an individual values being creative and thinking up new ideas. Deep-level similarity resulted in more team cohesion, less conflict, and greater efficacy. In another study, diversity was defined as group members' dissimilarity in horizontal and vertical individualism and collectivism (or cultural diversity, Vodosek, 2007). Group diversity was found to be associated with satisfaction with the group and perceived performance of the group. Group similarity was adversely related to three types of intragroup conflict types (relationship, process, and task conflict), which were associated with unfavorable group outcomes (e.g., satisfaction with the group and productivity).

There is some consensus among psychologists that diversity (particularly task-oriented diversity) can impede group cohesion and enhance creativity, but the impact on task performance is not clear (Langford, in press). More group similarity (defined in terms of values and attitudes) may lead to less conflict, more cohesion, more satisfaction, and more rapid and immediate productivity. Alternatively, more group diversity is associated with more conflict, less cohesion, less satisfaction, and less rapid, immediate productivity (Vodosek, 2007; Woehr, Arciniega, & Poling, 2013). Cross-functional teams (which means diversity is defined in terms of subject-matter knowledge) increases conflict while completing a task, but also improves creativity and performance in general (e.g., increased effectiveness and efficiency; Langford, in press).

According to empirical studies of research centers, a narrow disciplinary span can facilitate a quicker, more smooth-running collaboration that can lead to more likely completion of tasks such as the development of intellectual outcomes (e.g., conference presentations and publications), as illustrated in a study of two transdisciplinary scientific collaborative research centers. A wide disciplinary span can lead to collaborators having communication difficulties including speaking different disciplinary 'languages' and having different world views, which can lead to conflict and challenges with productivity. A narrow disciplinary span might lead to more rapidly developed intellectual outcomes yet may not necessarily lead to a very novel product that generates many other new ideas. A wide disciplinary span can lead to more novel outcomes that could potentially have an even greater impact (Fuqua, 2002; Fuqua, et al. 2004). Entire disciplines and fields that are novel and highly generative of new ideas come from wide disciplinary spans. For example, psychoneuroimmunology emerged from two very different disciplines and changed psychologists' and immunologists' understanding of stress.

Disciplinary span of groups A, B, and C. Groups with a narrower disciplinary span were more likely to publish manuscripts. Behavioral observations of Group A suggest that the members shared similar disciplines (e.g., mathematics and physics), Group B shared at least four similar disciplines, and Group C had many very different disciplines (including physics, mathematics, and psychology). (A full analysis of the disciplines of each group are not available due to lack of data. Future research could include such analysis, including an analysis of the extent to which vertical and horizontal integration between disciplines was attempted and occurred).

Group A members were able to have some shared understanding of their topic and of the concepts they were discussing. They shared enough language and concepts to discuss their topic well from their different disciplinary perspectives. Interviewees commented that they enjoyed learning from one another about how their topic was defined. They were able to identify similarities and differences in their disciplinary approaches. Two respondents noted that they gained new ideas from these discussions and began working on a publication. They were from the same department (and in the same discipline), and they had not previously collaborated.

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Not everyone who entered Group A stayed. The disciplinary span was perceived as too narrow for some individuals. One social science professor entered the group and commented that his/her disciplinary background was too different from the others. The professor felt intellectually excluded and described the experience:

> "I walked into the working group session a little late and saw a group of people looking at handouts with many formulas on them and talking about ____ [the group topic]. I found it to be a little intimidating, confusing, and off-putting because I could not understand the written symbols on the handouts nor could I understand what the group was talking about. My discipline does not require students to do such work. The topic is not a major part of my discipline, and we discuss it differently…much more macro. We rarely assign homework that requires those skills, and rarely are numbers needed. The group members [Group A members] seemed to share disciplinary language and concepts in a way that I could not. Although someone who was leading the group was very nice, enthusiastic, and encouraged me enthusiastically to stay, I felt intellectually isolated and unable to contribute or benefit from these conversations. I decided to leave and find a new group."

Although several disciplines were represented (biology, mathematics, statistics, computer science), the group may have shared similar perspectives. The similarity in perspective may have helped the group efficiently collaborate. In the group, two similar disciplinary perspectives dominated, according to an interviewee. Multiple professors had experience thinking about and working on the same topic but from different perspectives (and some of them had worked together on publications before).

Group B attendees were not sure of the interdisciplinary span of their group, but they indicated that the group shared at least four similar disciplines, including mathematics economics, and statistics. Their answers suggest that the span was moderately wide, but more data is needed to determine the span of Group B. Group C was represented by a wide span of disciplines. Social scientists, including psychologists, were together with physicists, chemists, and others. The topic did not require knowledge of numerical formulas, and thus attracted individuals representing multiple disciplines. There were no handouts with formulas. One social science scholar commented,

> "As I looked around the room at the attendees, the handouts, and the presentation slides, it appeared that we had a wide range of disciplines represented. I felt that scholars from many disciplines would be able to understand the concepts we were discussing. Although we all probably understood the presentations and discussions, we did not figure out how to bridge ideas or start a manuscript together."

In addition, one interviewee noted that the topic was not closely related to what STEM educators are required to know in order to do their jobs. The topic is traditionally considered a social science topic, and it is not a concept that is taught to most STEM students on a regular basis.

One paper "champion" (or motivated paper leader) A commonly endorsed viewpoint was, "A paper needs a champion, meaning at least one person who is highly motivated to take on a collaborative project such as leading the writing of a manuscript for publication. If no one is highly motivated, it won't happen."

Group A and Group B but not Group C had paper champions. In Group A, one person took initiative and acted as a paper champion. This person was not assigned to lead the group but might have been motivated to take on the role due to a strong interest, a strong background in the topic, and a job rank (not full professor) in which publications are required for future promotion. Group B had a paper champion who was assigned to help lead the group. Group C had members assigned to lead the group, but they did not have a paper champion.

What makes a paper champion? What makes a paper champion willing to collaborate across disciplinary bounds? Many factors may contribute to a person becoming a paper champion. A few are listed in the present paper (e.g., past history of publishing on the topic). Daniel Stokols and colleagues have argued that a "transdisciplinary ethic" (Stokols, 1999; Stokols, Fuqua, et al., 2002 may be essential among interdisciplinary

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scientific authors working to achieve intellectual outcomes that are novel and merge disciplinary concepts. Transdisciplinarity refers to the strongest form of interdisciplinarity (Rosenfield, 1999; Stokols, 1999). A transdisciplinary ethic is characterized by factors such as openness to collaborate. Interview responses suggest that the champions of the papers in Group A and B showed characteristics of a transdisciplinary ethic.

In the future, a 'transdisciplinary ethic' scale could be given to potential collaborators and leaders to predict who is the most likely to be open to collaborate. No such scale was used for the Breaking Boundaries conference.

Shared working history and social cohesion, social capital, and informality of relationships. Even though a person may want to champion a paper (and be willing to spend sufficient time writing it), other factors matter. A shared working history and/or social cohesion, social capital, and informality of relationships might contribute to smooth working relationships with collaborators, which may foster more rapid productivity (Fuqua et al., 2004).

There was insufficient data to fully analyze these factors, but some evidence suggests a pattern. In Group A, at least a few members had built up social capital, informal relationships, and a shared working history--working together in some capacity for multiple years. For example, of couple of people collaborated for multiple years as officers in a discipline-specific organization. In Group A, some members shared working history in organizations. In Group B, at least two members had written a manuscript before and continued to work together to write a manuscript for the group. In Group C, the working history of members was less clear, according to interviews. It seemed as if the Group C leaders did not have a strong history of working together on projects, according to one respondent.

Having such helpful processes helped group A and B members. "It was easy to contact my writing partner and ask a few questions. I trusted his response. We worked well informally," said one respondent. "I didn't have to write a formal email, wait for a response, etc."

Spatial proximity of collaborators. Spatial proximity of collaborators may also be associated with more time spent in communication, social cohesion, and collaborative productivity (Festinger, Schachter, & Back, 1950; Fuqua et al., 2004; Zhan, 1991). Some productive collaborators mentioned that they share a hallway and department with their collaborator (a paper champion). Their responses suggested that they appreciated working down the hall from each other. Environmental psychologists have suggested that sharing a physical space such as a hallway at work where you pass by one another regularly can lead people to get to know one another and build up more trust, informal relationships, and friendliness. The actual physical distance between individuals "as the crow flies" matters less than the shared spatial distance (or functional distance). Interdisciplinary scientific collaborators who share hallways in the same building were found to be more likely to develop intellectual innovations such as publications (Fuqua, 2002).

Sharing space and time together outside of one's work office can also be helpful. (What is the point of scientific conferences if they don't help transmit ideas that can lead to improved intellectual and educational innovations?) One interviewee mentioned that although his/her office is in the same building as another conference attendee, the off-campus conference location was particularly helpful to them. With some recognition that collaboration may be best fostered off campus (even when one shares a building on campus), one respondent happily explained, "I have been thinking about working more with [name deleted]. We have done a little prior collaborative work together. I guess we needed a conference more than 30 miles from campus to get us to together in the same space with time to talk about our mutual research interests, even though our offices are relatively close." The respondent added, "We don't normally go to the same discipline-specific research conferences, so I appreciated the opportunity to go to a local conference [in the same place] which did not require a lot of travel and to be at the same conference with a more general theme of STEM that works for both of us.

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Past history and motivation to publish on the topic. A strong recent history of publishing may reflect an individual's current motivation to publish. Multiple recent publications on the topic were evident in Group A and B leaders' publication history (according to online faculty pages). In fact, the topic of the group was in the title of several past recent publications of Group A and Group B paper champions.

All of the group leaders had strong, positive reputations as experts with exceptional knowledge and strong presence at conferences. It should be noted that a combination of factors matters for motivation to publish. One of the co-authors from Group B had a strong background in Group B's topic (and this person was not yet a full professor, which might be related to a greater motivation to publish.)

Conference organizing experience. Some Group A and B leaders mentioned that they had previous experience leading and/or running a conference (e.g., recruiting speakers). They said that they were fully aware and prepared for the extensive and challenging work required to run a new conference. In contrast, a Group C leader had limited familiarity organizing a conference, and this person appreciated learning from the experience. This respondent suggested he/she would do things differently in the future such as not wait to get information necessary to run her group. One Group C leader also mentioned that conference organizers did not provide certain materials an information that were supposed to be given during preparation for the session, which may have impacted the session.

Maintaining a shared vision. In many ways, conference organizers had a shared vision among themselves and with group leaders that facilitated accomplishment of conference goals. Conference organizers, however, did not always have consistent shared vision. They varied, reportedly, in how much they prioritized these goals: (a) generate collaboration between existing researchers for publication, (b) get educators to adopt research-based instructional methods and collect data in their classes, and (c) bring new teacher-scholars together and get them interested in each other's ideas, which would expand the population of researchers who might support each other and work together.

One conference organizer felt that although several discussions were held before the conference about what the working groups should do, the leaders of Groups A, B, and C showed different skills in enacting the vision. The leaders in Groups A and B seemed to be able to enact the vision of collaborating on a manuscript, possibly partly because the group organizer who prioritized and valued collaborative writing the most was in one of those groups. (There were multiple goals for groups, and all group leaders were reported to have accomplished other goals well).

The leaders in Group C may not have had enough conversations ahead of time to help leaders understand, agree with, plan, and execute the plan to write publications, according to one respondent. The Group C leaders may not have agreed or were not skilled at enacting the vision (e.g., publication writing).

Conference organizers felt they were not always in agreement about exactly what their roles were. This would have been less challenging if the host university had provided more resources such as a staff member to help run the conference.

Oversight by central leadership. Conference organizers had difficulty figuring out how to balance their administrative duties--making the conference run smoothly and troubleshooting administrative problems--with their desire to be in the rooms attending presentations and helping to lead discussions all day.

Conference organizers felt that they were careful to work with group leaders and have planning meetings prior to the conference. Yet in retrospect, conference organizers realized that more oversight was needed before and during the conference. They said that at least one conference organizer should have gone to each group at the conference and ensured that the conference goal of publication writing was being achieved. Conference organizers stated that they wanted to participate in Group C, but only participated in Groups A and B. (Many individuals who missed attending Group C said that they wanted to attend the attractive-sounding topic of Group C).

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In Group A, attendees said the group had highly engaged, interactive, knowledgeable, and motivated participants, partly due to a strong voice of leadership in the room. It should be noted that multiple people chose this group as their top choice, so this group may have generally been a more popular topic for conference participants, which might explain why people were even more motivated to publish together. A strong presence was maintained by conference organizers in Groups A and B, and they helped make sure the groups made progress on their ideas and on planning a publication, according to interviewees.

Group C had no strong conference organizer presence. One conference organizer realized later it might have been helpful to have one of them in the room to help guide conversations. Group C had group leaders who tried to motivate group members. Group C members were not highly motivated, however. Group C did not find a champion or others to organize a paper.

One interviewee indicated that Group C had a few attendees in the room who would have been interested in leading the paper or writing sections of the paper, and some of these people were leaders in other ways during the conference day. These attendees were not sure what the topics or structure of the paper would be, and they were not sure who was leading the paper writing. The attendees felt like they were "just participants" and not the group leaders, so didn't want to "step on the toes of the Group C leaders in the room." Another interviewee indicated that participants and leaders were feeling a little shy or overly formal. This person suggested that it might be a helpful if the group attendees or leaders would have stepped in and helped the group make more progress.

One respondent in Group C commented on how leaders could have helped: "Group C was different than Group B. Group B did not spend a lot of time trying to decide who would be the leader or what the structure of the paper would be. Instead, Group B spent more time working on ideas for papers (including a summary of the themes generated in the group during the conference). Group members were to be co-authors writing about what they do in their classroom. One respondent remarked, "What a nice idea….write a quick paper about what I do in the classroom. If our group had heard that idea [in Group C], I think I would have been much more likely to write a paper for publication."

In other words, oversight as well as an easy-to-follow model of a publication idea would have been appreciated by group members. Respondents indicated that it would have been helpful if a conference organizer or leader had been in Group C and said, "It's easy to write a paper together. Here's a model paper we are using in Group B. It will take less than 2 hours of time commitment from authors. One author explains how this topic is taught in their own classroom. Other authors do the same. Then one person writes the introduction and conclusion. If that had happened, Group C might not have overestimated the time needed to write a paper for publication."

Rewards and motivation of non-full professors. The promotion and reward systems established by universities provides rewards for professors for publishing if they are not yet promoted to the rank of full professor. Unlike full professors (who have relatively minimal rewards for publishing), people who have the rank of postdocs, assistant professors, and associate professors usually need to publish as part of their jobs.

In the groups, it was not full professors who were champions of the papers. Non-full professors led writing efforts during and after the conferences, according to one respondent. When asked why, one respondent mused, "Assistant professors and associate professors are 'hungrier to publish.'" Another respondent indicated that full professors are required to teach but are not required to do research, and thus, many full professors cease to publish research, especially when they have other commitments such as a higher service load in their departments. Another responded added, "Full professors can spend more time working on other projects such as service to the university and starting new centers. The main way to be promoted after you are full professor is to become an administrator. Leading university committees, initiatives, and centers are more important than publications for any full professors who want another promotion."

A conference leader who enjoys collaborative discussions and who had recently been granted full professorship explained why he/she was not championing a paper nor co-authoring a collaborative manuscript at the conference. "I need to do my own work at this point. I'm tired of doing other people's work." This individual sounded a bit unmotivated and worn out from leadership responsibilities and collaborating with others while having other unfinished publications. Furthermore, this respondent added that his/her group's discussions ended up going in a particular direction that was not very interesting or relevant to this individual.

Small group size. One social scientist and interviewee felt that the group size might have affected how informal, empowered, and engaged group members felt. Perhaps if Group C had been smaller in size, group members might have felt more comfortable speaking up and not worried about "stepping on others' toes."

There have been some mixed results in studies of whether small groups perform better. In a study in which team sizes ranged from 5 to 12 members working on specific goals in a hospital, smaller teams were found to be more effective at meeting the assigned goals (Vinokur-Kaplan, 1995). Other studies indicate smaller teams show better performance (Gooding and Wagner, 1985; Ingham, Levinger, Graves, and Peckham, 1974; Pelled, Eisenhardt, and Xin, 1999). According to one meta-analysis, however, larger teams showed slightly better performance on complicated tasks in uncertain environments (Stewart, 2006).

Larger groups can have greater access to resources (e.g., time, money, and expertise), but smaller groups can have better communication and less social loafing. Overall, small groups are generally more likely to be more successful at quickly completing goals. Many other factors may play a role as well, including the function and characteristics of the group. Small and medium-sized research centers (up to 50 members) generated interdisciplinary knowledge more than large centers did (Rhoten, 2003). (Definition of small teams is not consistent across studies. 20-member teams are considered large in some studies.) When a group is medium or large in size, sometimes smaller sub groups form and work together more efficiently and have faster productivity as they make "middle-range" linkages or intellectual integration that is not shared across the entire group (Fuqua, 2002).

Conference organizers tried to keep the number of participants roughly equal when the conference began so that no group was particularly large. An observer walking by the classrooms said that Group A's group size appeared small, Group B's appeared medium, and Group C's appeared large. By the afternoon session, conference organizers agreed that Group A was small, Group B was a bit larger, and Group C was largest. One respondent in Group A felt that keeping Group A small was a good idea. This person implied that when group gets too large, interdisciplinary collaborative discussion is more difficult. This respondent had much experience organizing STEM-education conferences.

Physical environment: Meeting room and seating configuration. The physical environment may have also influenced how creative members felt, how easy it was to feel engaged rather than to sit back and feel isolated, and how easy it was to communicate and foster a shared vision of an intellectual collaborative interdisciplinary product. Group A had a working space which might have been ideal for fostering shared discussions during the afternoon. One interviewee commented that the room appeared great for attempting to develop a shared vision of outcomes for the group. A person in the group recalled that the room was a nice, rather small meeting room with one long table and seats that faced each other. The participant said,

> "I liked the feel of the room. It encouraged participation. It was hard to 'hang back' in it. I could hear well. I could talk without having to drown out other conversations. My comments could be heard easily. Overall, it was easy for participants to see each other and feel part of one conversation."

Group B was held in a moderately sized room. In contrast to Group A and B, Group C was assigned a large room (e.g., a large classroom in the afternoon and a large lecture hall in the morning). The large classroom in the afternoon "appeared to be a regular classroom with tables that did not move around," recalled one respondent. "It felt too large." Seating was around small tables with some chairs facing away from the front and from others, making it difficult to generate a shared collaborative vision. It was not easy to have small group

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discussion, and the main leaders and presenters appeared relatively far away at the front of the room. One Group C respondent commented about the lack of a nice space:

> "I didn't really know anyone near me in the room. If I am collaborating with new people and trying to be creative, I prefer to be in a nice, interesting space where I feel inspired and sociable– a space that allows me to more easily move my desk and change the physical environment so that I can collaborate…a space that feels more interesting can help me feel more engaged and creative than a regular classroom. At a teaching conference, I was in a fantastic, renovated large room. I felt engaged, inspired, focused, and maintained a positive attitude. I was able to talk well with others and listen to the leaders because the space made it easy to listen and communicate. In the past, I was part of an initiative that was a large, national interdisciplinary collaboration of PIs. The national funding agency scheduled meetings at unique retreat locations with the goal of enhancing collaboration. People talked about how great and inspiring those locations were. Couldn't the university support us being in one of the nicer rooms? In the future, I would enjoy coming to this conference again, but I would like to be in a nicer space that fuels my creativity." This individual mentioned that physical environmental research has indicated that creativity is enhanced by the physical environmental factors.

Process/Outcome: Positive evaluative responses. Having a positive attitude toward the working group might facilitate the outcome of publications.

More positive attitudes were held by Group A and B members than Group C members, according to the interviews and questionnaires completed at the end of working group session. Happiness with how the group went, engagement with the group, and optimism for future group collaboration were expressed more in Group A and B interviews than in Group C. Compared to Group C, Groups A and B provided higher ratings of the working group session, as shown below in Table B. A one-way ANOVA (as shown in the table below) indicated that the differences were statistically significant.

Table B.

Means and ANOVA results for Evaluations for Group A, B, and C after the afternoon Working Group

Survey Item	Group	N	Mean	SD	F	Sig.
Content	A	8	4.75	0.46	7.508	0.003**
	B	12	4.75	0.45		
	C	7	3.857	0.69		
Presentation	A	8	4.63	0.52	6.968	0.005**
	B	9	4.89	0.33		
	C	6	3.67	1.03		
Opportunities for Engagement	A	8	5	0	2.976	0.06[a]
	B	12	5	0		
	C	8	4.75	0.46		
Interaction with others	A	8	5	0	5.357	0.01**
	B	12	5	0		
	C	8	4.63	0.52		
Interdisciplinary Exchange	A	7	4.57	0.79	1.253	0.304 (not sig.)
	B	12	4.92	0.29		
	C	8	4.63	0.52		

Survey question: "On a scale from 1 [low] to 5 [high], please rate the overall session: content, presentation, opportunities for engagement, interaction with others, and interdisciplinary exchange."

*p<=.05, **p<=.01, a p = .06 statistical trend (two-tailed t test)

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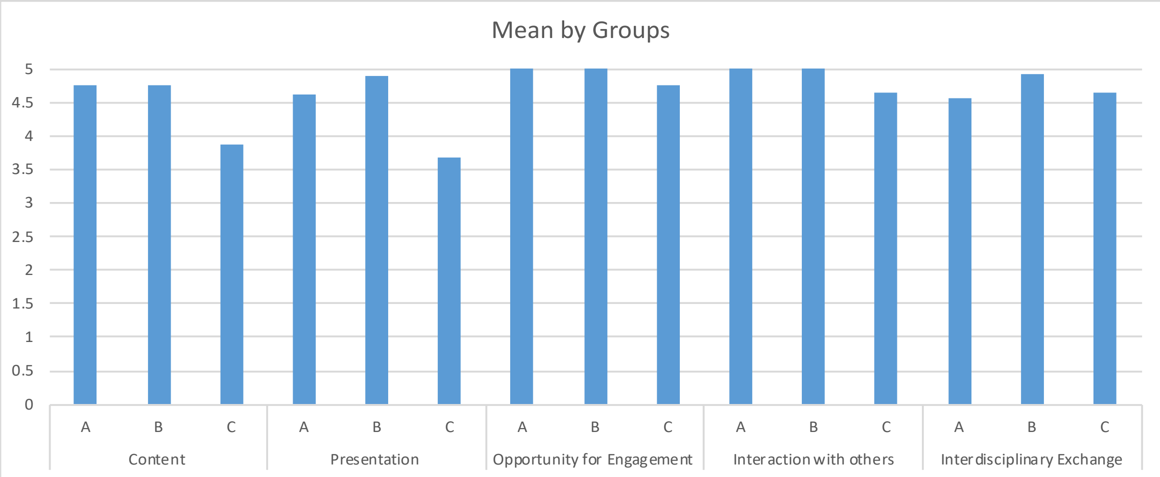
Table C.

Perceptions of Group A, B, and C working group at the conference*



*This chart shows the Table B means in bar graph form.

One limitation is that rather few participants (approx. 25%) completed the questionnaires, possibly because these working group questionnaires were handed out at end of the day before the conference dinner. Multiple individuals said they needed to leave early to reduce their exposure to heavy Los Angeles area traffic. It is unknown whether the results would have been different if more people had participated. One participant in group C (the largest group) did not complete the questionnaire because she did not want to provide negative ratings that might make anyone, such as hard-working leaders, look overly 'bad'. "I didn't want to fill out the questionnaire for Group C. The conference organizers and sessions leaders put a lot of time and effort into it. I appreciated their efforts. However, I was not totally satisfied or engaged in the working group." This individual did not seem upset, but merely had expectations that were not met.

Outcomes

Publication manuscripts. As of the writing of the present paper, two manuscripts have been submitted by Group A, which means their group was the most productive, defined in terms of completing publication drafts. Group B has shown some progress. They have one manuscript that is reportedly "well underway," another in progress, and a third possibly in progress. They have exchanged some emails and ideas in the past few months about the manuscript. One of the papers might be submitted by two group members who started a manuscript before the conference, and have revised it based on ideas from the conference. Group C has not made progress yet on writing or submitting a collaborative paper. (Again, there are many reasons why this group might be the least ready to collaborate.)

In case this report appears to be overly critical of Group B or Group C for being less ready to submit publication manuscripts, we would like to reiterate that writing manuscripts for publications was only one of several desired outcomes of the conference. Overall, the conference was highly appreciated and valued by many attendees in all groups. Teacher-scholars at the conference were expected to learn new scholarly work on three themes (problem-solving skills, computational skills, and equity), be inspired to gather more information about these themes, and be inspired to improve teaching practices, and find future potential collaborators who could provide support for future endeavors.

Analyses have not been conducted to determine whether Group A and B papers are transdisciplinary and collaborative. Perhaps the group most ready to collaborate (group A) will not be the group that accomplishes transdisciplinarity over time.

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A long-term collaboration. While the present paper is focused primarily on comparing the three groups' readiness to write publication manuscripts (esp. interdisciplinary collaborative scholarly manuscripts), there are many other ways to define the short- or long-term success of a conference (e.g., new ideas for teaching STEM, social support for ideas, new ideas for publication, long-term collaborations). Also, an individual attendee might gain ideas that lead to novel ideas in a solo-authored publication or a new teaching strategy which reduces the D/F/W rate (D or F letter grades and withdrawals).

A time frame longer than a few months is needed to see whether ideas evolve, and what factors facilitate manuscript writing. One conference organizer said:

> "I envisioned the paper publications as a carrot [incentive] or a short-term outcome, not the final outcome of a collaboration. I envisioned that people could continue a more long-term collaboration or at least a network…I don't know how well these paper publications are leading to a long-term collaboration. I want to know what other collaborations people have begun and what other outcomes people are achieving in the short-term and long-term."

An organizational psychologist explained that more time is needed to assess the outcomes of small group endeavors, and three years is a better marker of the outcomes of a group than three months.

Concluding Thoughts

More information about the antecedents, processes, and outcomes of interdisciplinary scientific collaborative efforts is needed. Further research and more passage of time such as a few years is needed to determine the quantity, quality, span of disciplinarity, novelty, and generativity of groups.

It is possible that groups with characteristics such as Group A may be smooth-running and productive over a short period of time. It is not clear whether such groups will continue being productive over a longer time frame. Furthermore, it is not clear whether the most heterogeneous groups will eventually develop the most novel ideas, that will lead to important innovations in STEM education.

Different definitions of success and ways of measuring success are needed. The number of manuscripts submitted to a journal within a few months after a conference is a limited way of measuring success. The quality, quantity, novelty, generativity, and many other factors should be assessed as well. Some innovations may impact education and society at large by ameliorating problems through programs and policies, but their effectiveness may not be realized for quite some time.

This paper focused on whether three working groups from a conference/collaboration published manuscripts, but the concepts could be applied to larger endeavors with different outcomes. The themes in the present paper are likely to generalize to other interdisciplinary scholarly collaborative endeavors. We recommend that teacher-scholars in any phase of a collaboration (planning to collaborate, collaborating, or reflecting on collaboration) consider the factors outlined in this paper as they consider the success of their team.

Our results suggest that several antecedent conditions and processes may impact group productivity. In particular, disciplinary span, leadership, physical environment, social cohesion, and group size may influence individuals' readiness to develop innovations such as interdisciplinary, collaborative publications. A narrow disciplinary span may lead groups to more rapid, smooth-running collaboration that results in innovative interdisciplinary collaborative products and publications. Products that emerge from collaborations with a wide disciplinary span might be more novel, generate more important new ideas, and have a bigger impact on science and society. Numerous other variables may influence collaborative productivity. More research is needed, particularly empirical research, to track and evaluate the processes and outcomes of interdisciplinary scientific and scholarly collaborative endeavors.

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