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Using Participatory Narrative Inquiry to Explore Cooperative Education in Computing Education*

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Abstract

This paper reports on an exploratory study using a novel methodological approach, Participatory Narrative Inquiry, to explore computing students' experiences in a cooperative education (co-op) program. This work was conducted at a medium size, private, student-centered university in the Western United States, where many computer science students take part in a co-op program. We conducted interviews with five students who had participated in a co-op and report on themes that emerged from the data. The initial findings suggest that there are opportunities for future work using Participatory Narrative Inquiry to study cooperative education and students' educational experiences more broadly.

1 Introduction

Work-based learning aims to integrate academic learning with real-world experiences [3, 7]. Across the world, different models have emerged, such as the placement years and degree-level apprenticeships in the UK and the "Duales Studium" in Germany. In the US, work-based learning commonly takes the form of internships and co-op programs, which involve students working for an employer in paid positions at one or multiple points during their education. Its benefits, especially in terms of career outcomes, have been widely reported in the literature [10]. Several institutions, such as Northeastern University and Drexel University, have incorporated cooperative education into their curricula. At the university where this study was conducted, students taking part in the co-op program typically work for an employer for two terms (e.g. the summer and fall semester following their junior year).

In this work, we use a narrative approach to explore students' experiences in the co-op program. Narrative methods have previously been used to study students' and graduates' educational experiences [1, 4]. Research has shown that we construct stories to make sense of our lives [9], so narrative methods – which aim to elicit stories from participants – are an especially appropriate way of exploring lived experiences. We use an approach called Participatory Narrative Inquiry (PNI). To our knowledge, this approach has not been used in computing education research to date, but is similar to the SenseMaker tool that has been introduced in engineering education research [11].

Participatory Narrative Inquiry combines aspects of mixed-methods research and oral history approaches. As one of the founders of PNI observes: "PNI is an approach in which groups of people participate in gathering and working with raw stories of personal experience to make sense of complex situations for better decision making. PNI focuses on the profound consideration of values, beliefs, feelings, and perspectives through the recounting and interpretation of lived experience." [5] We chose Participatory Narrative Inquiry because of its ability to elicit stories from a larger number of participants and to engage participants actively in the research process.

This work aims to address the following two research questions:

- How can Participatory Narrative Inquiry be used to investigate students' experiences in computing education?
- How do students make sense of their experiences in a cooperative education program?

2 Methodology

We obtained ethics approval and contacted all 99 computer science students at a medium size, private, student-centered university who had completed a co-op since spring 2019 with an invitation to participate in this study and to share their experiences in the co-op program. (There was a lower number of students who took part in a co-op in 2020 and 2021 due to the COVID-19 pandemic.) The overall response rate was low, likely because the co-op office at the university only retains students' university email addresses, which are deactivated after graduation.

We ultimately conducted individual interviews with 5 students. Three of these students were in their senior year and two had already graduated. The interviews lasted between 30 minutes and 1 hour and were audio recorded, transcribed, and anonymized. During the interviews, participants were asked to choose from and respond to one of the following prompts, which were specifically designed to elicit stories.

- Describe the moment when you decided to participate in the co-op program. What went through your mind?
- What was the highest or lowest moment of your experience in the co-op program? What happened in that moment?
- Looking back over your experiences in co-op, what one moment stands out to you in terms of what came later?
- Can you recall a time during your experience in the co-op program that will stay with you for a long time - for any reason, good or bad? What happened that you will remember?
- If none of these questions appeal to you, please choose any experience you had during the co-op program - good or bad - that you would like to tell us about. What happened that mattered to you?

After responding to the prompt of their choice, participants were also invited to revisit the list of questions and to respond to additional prompts, which all of them chose to do.

As part of the analysis, we initially identified the stories participants told. Mattingly argues that stories "are about someone trying to do something, and what happens to her and to others as a result" [8]. We thus used indicators, like personal pronouns, past-tense verbs, and time references to identify stories in the transcripts [5]. We found a total of 18 stories.

Participatory Narrative Inquiry typically involves participants themselves making sense of their stories. However, none of the interviewees responded to an invitation to participate in such a "sensemaking session". We invited several volunteers who were familiar with Participatory Narrative Inquiry to take part in such a session instead. As part of this session, participants completed the following steps:

- Read through the stories and gave each story a title
- Arranged stories on a temporal axis (i.e. before, during, or after co-op)

- Considered whether or not a story reflected a successful co-op experience
- Discussed any emerging themes from the analysis

In the following, we highlight initial findings from this work.

3 Findings

As part of the sensemaking session, participants identified several themes in the data. One of these themes was related to students' experiences applying for co-op positions. At the university, students planning to take a co-op are required to complete a one-credit course designed to help them prepare their resume and to connect them with employers the university has established relationships with.

> *I'd say the hardest part for me was just getting my foot in the door and actually getting the co-op itself, because once you're in the co-op, assuming it's the right fit, you'll learn no matter what. You'll pick it up. You'll mess up. You'll learn. You'll do cool things. So you'll have a great time. But actually landing the co-op itself was really difficult for me. It was kind of stressful, especially for my semester. I heard that we had a whole lot of computer science students and not a lot of openings. So there was the big name [company] and I didn't get that. I'm like, "Well, I guess I'm doomed." Because all of the other ones [. . .] sounded like I.T. jobs or just general engineering jobs, not specifically focused for computer science. So then my other option was applying outside of [the university] through LinkedIn and that sort of thing. But it's way harder to get a response there.* (Student 1)

Some students also sought out co-op positions outside of the university's relationships with employers. One student attended a conference where he spoke with a recruiter and was able secure an interview and ultimately a position in this way.

> *The reason I went to the conference in the first place was because I didn't have anything else. I had had an interview with [large software company] and I couldn't get any interviews anywhere else. I applied to at least over 75 positions. It was a point where I'm like, "OK, I know I'm putting the work in, but nothing's coming from it." So, you know, to go to the conference, get the position that I wanted, and looking back on it now I'm glad that the other stuff didn't work out so I could be where I am today.* (Student 2)

One question that emerged in the sensemaking session was about how the co-op students fit into their workplace. While this depends in part on the workplace environment, the interview participants reported positive experiences.

> *I think it's the people that still stand out to me and that I still think about. They were very involved in our professional development. The IT director would come and talk to us and take us to meetings and teach us about financial developments – not only relevant to the work that we're doing, but he was also supporting our growth outside of the stuff we're doing. So I think they were involved and if we didn't know something, they would make us sit down and teach us all the concepts from scratch, even if it took an hour or two. They were always super helpful.* (Student 5)

> *The highest moment in my co-op was when was tasked with presenting to the VPs of the whole operation and facilities. So it's me, I'm just an intern, and I was presenting in this boardroom to the VPs about my project. I would say that was the highest moment, because, you know, I'm just 22 and they're all in their 50s and 60s. I put on a suit and they said it was a very good presentation.* (Student 4)

The second quote is related to a theme of accomplishments. Students discussed how a sense of autonomy during the co-op helped them build their confidence.

> *What really helped was the independent projects that I was able to take, where they said, "it's up to you, you can do it or not." So I was able to do some programming and automate some stuff. So I felt very accomplished. And I think that's one of the things that made me want to continue and I still do that to this day. That's basically helped with my confidence, because I was successful once and now I have that confidence in myself that I can do it again.* (Student 5)

> *My highest moment for it was when I actually got to make my own script, because for the most part, I was just fixing bugs, working on documentation, that kind of thing. But I was assigned an actual task of creating a little Python script [...]. And it took me a long time to get it. But I was really proud of that because that was my contribution to the project. I did it all by myself. And it was it was really nice seeing that I could actually do it, especially when the people were getting back to me like, "hey, this actually works. Thanks for making it."* (Student 1)

The experiences described by this student are an example of *legitimate peripheral participation* [6]. While "fixing bugs" and "working on documentation" may seem like minor contributions, they are nonetheless valuable. This matches prior findings in the literature on work-based learning in the UK [2].

Finally, the participants in the sensemaking session also identified an opportunity related to students' transitions to and from their co-op. At this university, students are required to return for (at least) one semester after their co-op. Several students reflected on this return to the university:

> *I hear that for a lot of other students, they take the co-op up and then they come back to the university and they're like, "Why am I doing this? What's the point? I have another job." But, personally, it's OK. It's kind of like when you're at one, you're wishing for the other and then vice versa.* (Student 1)

> *When I did have to come back, it was kind of strange, because I'd been working full time for six months. [...] It was just a weird transition from working every day, waking up at six and then driving to the city, going inside the office, checking in. And then all of a sudden I can wake up anytime I want. I could do my homework anytime I want. It was freeing and it was also just so different. It took a while to get used to.* (Student 3)

This differs from prior findings, such as in the UK, where students reported approaching their final year at university differently after spending a year in industry [1]. Indeed, for many of the students in that study, their work-based learning experience served as a turning point. Future work may explore this transition to the university as well as differences among work-based learning models further.

4 Conclusions

This paper makes two main contributions. First, it contributes a study in computing education using a novel methodological approach, Participatory Narrative Inquiry. Second, it offers a narrative perspective on students' experience in a cooperative education program and identifies aspects that educators at other institutions may consider. As this was preliminary study with a small number of participants from a single institution, the findings presented here are naturally limited. However, there are opportunities for future work to use Participatory Narrative Inquiry to further explore students' experiences in co-op programs and in computing education more broadly.

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Investigation of Social Cognitive Factors Affecting Computing Transfer Students *

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Abstract

There is a disproportionate racial and ethnic enrollment of students in community colleges. Alongside this disproportionate enrollment, underrepresented minority (URM) students also have lower retention rates than their peers. While the literature addresses some of the factors that impact students' degree completion, there still exists a gap in overarching factors that affect URM students. This study aims to explore the specific personal and social factors that impact URM Computing transfer student success. Specifically, exploring factors using Bandura's social cognitive theory (SCT). Data was gathered with two methods, one-on-one interviews with students and a self-assessment of the student's abilities in

the three categories of the SCT: self-efficacy (SE), outcome expectation (OE), and goal setting (GS). The analysis showed that the average rating of the SE and GS of post-transfer students was slightly higher than the Pre-transfer group. Moreover, stratification of word clouds from surveys of the data showed overarching factors between pre and post-transfer groups. Pre-transfer students were impacted by time and income.

1 Research Problem

In recent years the need for a large workforce specializing in STEM fields has increased. However, along with the need for more workers there has also been a focus on decreasing disparities in the representation of diverse populations in STEM. The U.S. Census Bureau lists 71% of STEM workers as non-Hispanic white with only 6% and 7% being black or Hispanic, respectively. Similarly, only 13% and 27% of engineers and computer scientists are women [12]. Part of this disparity can be attributed to the lack of representation and persistence of underrepresented minority (URM) students in colleges. To begin addressing these disparities in the workforce it is imperative to build an understanding of the factors impacting URM success in college specifically at the community college (CC) level as many URM students begin their journey there. Among the students enrolled in community colleges 29% are first-generation along with 42% and 52% of all Black and Hispanic students beginning their academic journey at CC [4]. As [6] states, "For many ... URM populations, community colleges serve as an entry point to post secondary education and offer a unique opportunity in the preparation of a future STEM workforce that reflects the diversity of the U.S. population". In order to build a more diverse workforce that is representative of the population, URM students must be properly supported and have the needed resources to be successful at CC and 4-year institutions. While the literature extensively covers academic factors affecting URM transfer success, in order to establish more equitable practices and support, a holistic understanding of the social and behavioral factors of URM students is crucial. The authors have previously examined personal and academic factors impacting transfer students [17], so this paper focuses on social and behavioral factors, specifically aspects of Bandura's Social Cognitive Theory [1].

2 Review of Related Literature

2.1 Behavioral factors

Previous research has identified elements such as engagement with communities, social belonging, academic uncertainty, and the transfer process, which impact the success of transfer students. Transfer students have a higher success rate when engaging with the community [15]. There is additional success when students feel that they have course-level social belonging [8]. A decline in academics stems from situations where students try to balance work with academics and relationships or do not have a sense of belonging, leading to a feeling of academic uncertainty [9]. Transfer students have less time in the new environment, so it is harder for them to adapt [2]

2.2 Conceptual Framework

Bandura's Social Cognitive Theory (SCT) [1], depicted in Figure 1 was used as a working guide for understanding the underlying personality traits driving student success. The SCT serves as a psychological framework used to understand the relationship between environmental factors and one's motivation, learning, and self-regulation [16]. Under this model, it is understood that an individual's self-conception and personal beliefs will be a greater predictor of their future success rather than their previous achievements. Within this context, our interest was in evaluating students' perception of themselves quantitatively within the three constructs of the SCT, self-efficacy (SE), goal setting (GS), and outcome expectation (OE).

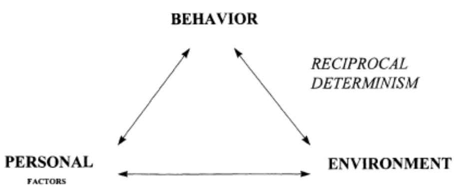


Figure 1: Model of the relations between the three classes of determinants in Bandura's (1986) conception of triadic reciprocity

Self-efficacy can be defined as an individual's belief in their own capacity to be successful in achieving a given goal. SE is identified as a factor in predicting student behavior and overall academic performance [11]. As stated by [14], "Efficacy beliefs help determine how much effort people will expend on an activity– the higher the sense of efficacy, the greater the effort, persistence, and resilience (p544)." Self-efficacy is thought to be pivotal to the human agency as a person will not participate in an activity if they do not believe that they can produce results [11]. [3] used the SCT model and SE was found to be the most dominant predictor of academic performance among a sample of 404 high school Information Technology students.

Goal-setting is the behavior of setting a goal for the future and actively taking steps to eventually achieve it. Bandura [1] indicates learners are motivated by goals and plan and execute their behavior accordingly.

Outcome expectation is the anticipated result of engaging in a given behavior. OE is not thought to be as significant as self-efficacy in predicting a student's performance, rather it is thought that there is an interplay between the two constructs in an individual's overall behavior. As stated by Bandura, "In social, intellectual, and physical pursuits, those who judge themselves highly efficacious will expect favorable outcomes..." [1].

3 Methodology

This study used data derived from the self-report Likert scale, interviews, and survey responses. This form of measurement allows for collecting quantitative data for otherwise unmeasurable constructs. Since understanding a student's self-perception under the SCT model was not otherwise directly accessible, this data collection method allowed insight into the needed modalities. Furthermore, the data was then analyzed with two methods under the three previously defined constructs within the SCT and by stratification with word clouds.

3.1 Integration of Framework

The population consisted of students attending both community colleges (CC) and 4-year institutions in four different states. All students were enrolled in a computer science or related program, and students had either transferred to a 4-year institution after attending CC or were currently enrolled in a CC. The interviewees' data was evaluated under the SCT, and the dependent variables used were GS, OE, and SE, while the independent variable was transfer status. The transfer student data set was analyzed using first-generation status, low-income status, ethnic minority, and sex as independent variables. The dependent variables were average transfer GPA, average overall GPA, and average increase from transfer GPA to institutional GPA.

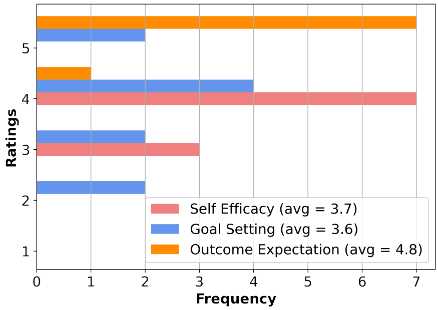
3.2 Data Collection Method

The SCT data was collected by interviews with 15 students from the target population and a self-reported survey of 65 students. The interview consisted of several questions aimed at assessing students' decision-making processes: SE, OE, and GS. These interviews were comprised of six or seven questions depending on whether students were currently attending CC with an intent to transfer (six questions) or had already transferred to a 4-year institution (seven questions). Consequently, the data from particular questions in both interviews and surveys were utilized to create word clouds, examining issues relevant to both pre-transfer and post-transfer students.

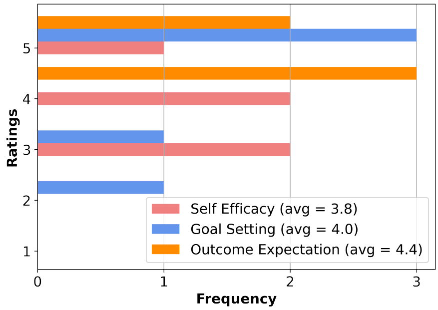
The first five questions were open-ended questions that allowed students to describe their personal and academic experiences. Questions 6 and 7 were closed-ended questions with self-reported measurements of their own personal OE, GS, and SE. This was measured by asking students to rate themselves in terms of their self-perception as a highly confident student, as someone who sets goals each semester, and as one who is motivated by previous experiences of self and others. For the stratification within the survey segment, a word cloud was created, and the questions where the word cloud was utilized included a pre-transfer question (Q16) that asked the respondents to list the information they used when deciding between a community college and a 4-year university. Additionally, they were prompted to mention any information they felt was needed but not available, such as the proximity of a 4-year university, better job opportunities at a 4-year university, ease of transfer, cost considerations, and guidance from family and friends. For the post-transfer word cloud stratification, a combination of interview and survey questions was employed. The relevant post-transfer questions (Q6 and 25) requested participants to share any particular experiences they deemed important as a transfer computing major student.

4 Results

Evaluating under the SCT model, the hypothesis was that students who had already transferred from CC to a 4-year university would on average rate themselves higher in SE, GS, and OE. The expectation is that students who successfully transferred would have a higher self-rating specifically in SE as indicated by their previous success [5, 7, 10, 13, 14]. As seen in Figure 2, it was found that the average rating of the group of post-transfer students was slightly higher than the pre-transfer group in both measurements of SE and GS. However, it should be noted that the sample size for the two groups was not even and a larger sample size would allow for a more accurate reflection. Similarly, the students interviewed in the pre-transfer group consisted of individuals who intend to transfer to a 4-year institution. For this reason, it is possible that this group already had higher levels of self-perception in the given constructs as they already held this expectation for themselves. In the future having a sample population of students who do not intend to transfer out of CC to a 4-year institution would allow for better insight into the correlation of these constructs on student persistence to transfer.



(a) Pre-Transfer



(b) Post-Transfer

Figure 2: Student responses to Questions 6 (a) and 7 (b)

The most urgent concerns impacting students before transferring are time and income. Income is crucial regarding the affordability of attending a 4-year university, relying on either parental income or their own. Time is a significant factor as it affects their income situation. This stems from the notion of opportunity cost, where the more time individuals spend in school, the less time they have to earn money.

(a)Pre-Transfer Survey Q16

(b) Post-Transfer Survey Q6 and Interview Q25

Figure 3: Word clouds of 65 students' responses

5 Conclusion

This paper first reported a literature review to identify the key social factors, based on the SCT theory, that influence the transfer decision, particularly for students from traditionally disadvantaged groups. Secondly, an exploratory analysis was performed on these factors by interviewing 15 current students. The results revealed that their rating of SE and GS were higher after transfer than pre-transfer. This suggests that the post-transfer students felt better about their academic success than the Pre-Transfer students. Thirdly, word cloud analysis from a survey of 65 students indicated that cost is the main factor for CC students in deciding where to start their degree. Based on these results, the survey will be extended to a larger group of students across multiple states, and the combined results from factors ascertained to design an AI-driven advising system for transfer students, particularly URMs. The researchers anticipate that this will be beneficial to transfer students, their advisors, and other stakeholders of higher education.

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Rethinking Linear Algebra for Computer Science: Applying Vygotsky's Theory of Learning*

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Abstract

This paper explores the application of Vygotsky's educational theories within the teaching of applied linear algebra for computer science students. The key point of this pedagogical study is a case study on principal component analysis (PCA), illustrated through noisy image compression, which serves as a representative example of the comprehensive teaching methodology applied throughout the course. This case study highlights the integration of key linear algebra concepts—eigenvectors, eigenvalues, covariance matrices, dot products, and change of basis matrices—demonstrating their application in a tangible real-world scenario. Employing MATLAB as a mediational tool, the teaching approach is scaffolded in accordance with Vygotsky's theory of learning, which progressively builds upon students' existing knowledge. The significance of aligning teaching practices with Vygotsky's theories lies in their proven ability to enhance conceptual understanding and student engagement, ultimately creating a deeper learning experience.

1 Introduction

The modernization of teaching applied linear algebra through computational tools is essential for equipping students in engineering and computer science with practical problem-solving skills. At the University of Illinois Urbana-Champaign, a refreshed applied linear algebra course featuring these tools saw a rise in popularity and enrollment, showcasing the pivotal role of such tools in making linear algebra education more engaging and relevant [5]. This trend is indicative of a broader need across disciplines for computational proficiency moving away from theory-laden approaches and empowers students to apply linear algebra concepts to diverse professional fields [5, 4, 2].

Incorporating Vygotsky's educational theory, my pedagogical approach at Boston University and soon at California State University, Chico, positions both the teacher and the student as active agents in the learning process. Vygotsky's emphasis on the social aspects of learning aligns with the collaborative environment I encourage in my classroom. Here, the teacher's role transcends providing assistance; it involves cultivating high-quality, meaningful interactions that significantly contribute to students' learning experiences [6]. This method, deeply rooted in social constructivism, leverages the dynamics of social interaction to facilitate the evolution of students' understanding, epitomizing Vygotsky's concept of good learning within the Zone of Proximal Development (ZPD)—a space where students thrive under skilled guidance and scaffolding [8].

The paper's structure is as follows: Section 2 outlines Vygotsky's educational theories. Section 3 applies these theories to the teaching of PCA with noisy image compression. Finally, Section 4 provides concluding remarks.

2 Integrating Vygotsky in Linear Algebra Teaching

Lev Vygotsky's social development theory [8] and its application in modern education have gained increasing relevance, particularly in the integration of technology in learning environments. The ZPD and the role of the More Knowledgeable Other (MKO), typically the instructor in a classroom, are central to this theory. Contemporary educational research validates the significance of these concepts in enhancing collaborative and socialized learning [1, 3]. Recent trends in educational research, as noted by [7], show a growing interest in how cultural contexts and social dynamics influence computer technology's role in education. This aligns with the increasing acknowledgment of Vygotsky's socio-cultural theory in educational practices.

In my teaching of linear algebra, I employ Vygotsky's principles by using MATLAB as a mediational tool, bridging theory with practical application.

This approach, emphasizing scaffolding, allows students to progress within their ZPD from basic to advanced linear algebra concepts. As students apply linear algebra concepts like eigenvectors to new contexts such as image compression, they assimilate new information into their existing cognitive schema, modifying their understanding to accommodate new insights. Interactive lectures and team-based problem-solving create a collaborative learning environment, encouraging students to actively construct knowledge. This method not only improves computational proficiency but also aims to deepen conceptual understanding, underscoring the real-world relevance of linear algebra.

This paper presents a case study that exemplifies the application of these principles: using PCA in noisy image compression as a practical teaching example. This case study is not just a representation of how linear algebra can be taught through Vygotsky's lens but also demonstrates why such an approach is vital in today's educational landscape. It addresses the need for teaching methods that promote critical thinking, adapt to diverse learning styles, and prepare students for challenges in a technologically advanced society. By integrating Vygotsky's educational theories, the goal is to equip students with not just academic knowledge but also with skills essential for lifelong learning and professional success.

3 Teaching of PCA

Students begin their study of eigenvectors and eigenvalues by employing both manual calculations and MATLAB. By this point in the course, they have developed proficiency in computing the eigenvectors and eigenvalues of 2×2 and 3×3 matrices. However, the broader significance and practical applications of eigenvectors and eigenvalues remain unclear to them. As a result, these concepts currently exist in isolation, appearing as standalone topics without apparent connection to their broader mathematical or real-world relevance.

To enhance intuition, I employ MATLAB's `eigshow` command, allowing students to visually grasp eigenvectors and eigenvalues of a certain 2×2 matrix $\mathbf{A}$. This command visualizes how each unit vector $\mathbf{x}$ is transformed into the corresponding eigenvector $\mathbf{Ax}$, highlighting the scaling relationship between $\mathbf{Ax}$ and $\mathbf{x}$. This concept is depicted in Figure 1.

At this stage, my lecture becomes interactive, inviting student questions while tracing the unit circle with the green vector $\mathbf{x}$, and guiding them to identify when the blue vector $\mathbf{Ax}$ becomes an eigenvector of the matrix $\mathbf{A}$.

MATLAB serves as a mediational tool, aligning with Vygotsky's theory which underscores the importance of tool usage and integration in students' developmental processes. As students advance in their linear algebra studies, their engagement with such tools transitions from mere eigenvector computa-

Figure 1: The left image demonstrates **x** (green vector) as an eigenvector of matrix **A**, transforming into **Ax** (blue vector) as a scaled version of **x**. The right image shows that the green vector is not an eigenvector of **A**, as its transformation **Ax** (blue vector) does not maintain the same direction as **x**.

tions to a more profound understanding of the underlying mechanics of these computations.

After introducing students to eigenvectors, I present three 10×2 matrices (referred to as **data** and as seen in Figure 2 where I have plotted them) to demonstrate two-dimensional data compression: one matrix with data along the $y = x$ line, another along the x axis, and the third along the y axis. The complete MATLAB code is available in the Appendix A and Appendix B and Appendix C of this paper.

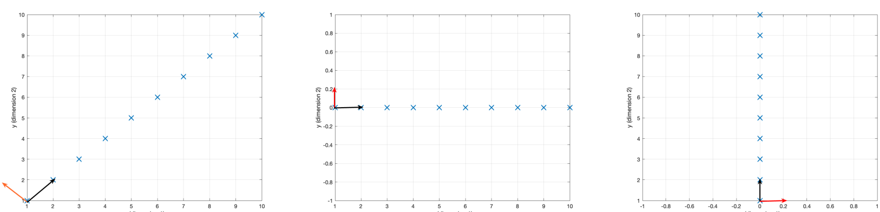

Figure 2: First image shows data along the y=x line, the second image displays data along the x-axis, and the third image represents data along the y-axis.

The students' task involves identifying the optimal vector for compressing two-dimensional data, as depicted in Figure 2. This figure clearly shows that the best compression vector coincides with the direction of the maximum data spread. In the three scenarios presented, this corresponds to along the $y = x$ line, the x-axis, and the y-axis. Through this exercise, students learn that the optimal compression vector not only aligns with the maximum spread but also captures the entire variance of the original data. This is visually represented in each plot of Figure 2 by a black arrow, indicating the direction of maximum variance. Specifically, the variance is 18.33 for data along the $y = x$ line and 9.1667 for data along the x and y axes. To quantify this variance, students calculate it either manually or using the *var* function in MATLAB.

I then encourage my students to create a 2×2 covariance matrix for each of the three **data** matrices. In these matrices, the diagonal elements represent the variance along the x and y axes. This exercise aids in understanding that the total variance of the **data** matrix, which they previously calculated manually or using MATLAB's *var* function, is equal to the sum of the diagonal elements in the covariance matrix. The off-diagonal elements are determined by the relationship between the x and y dimensions in each data set. The covariance matrix is $\begin{bmatrix} 9.1667 & 9.1667 \\ 9.1667 & 9.1667 \end{bmatrix}$ when the data points lie along the $y = x$ line. Conversely where data points are aligned along the y-axis and x-axis respectively, the covariance matrices are $\begin{bmatrix} 0 & 0 \\ 0 & 9.1667 \end{bmatrix}$ and $\begin{bmatrix} 9.1667 & 0 \\ 0 & 0 \end{bmatrix}$.

Computing eigenvectors for these matrices using MATLAB's `eig` command, students discover that the primary eigenvector (black arrow) aligns with the direction of maximum spread, and its eigenvalue represents the total variance. Additionally, they observe a secondary eigenvector (red arrow), perpendicular to the first and indicating zero variance, as evident from its eigenvalue of 0. This observation reinforces the understanding that the primary eigenvector captures all the variance of the original data matrix. The collaborative approach I adopt in my lectures aligns with Vygotsky's scaffolding concept and ZPD. ZPD is the gap between what a student can do without help and what a student can do with help. The initial exercise where students draw the black vector indicating maximum spread now seamlessly integrates with their newfound understanding gained from computing eigenvectors of the covariance matrix. This progression illustrates the scaffolding process and helping students through the ZPD, where early, simpler tasks lay the foundation for grasping more complex concepts.

Students often raise two key questions at this juncture: (1) Why does computing the eigenvectors of a covariance matrix indicate the direction of maximum spread? (2) How does this method apply to randomly generated or multi-dimensional data? In addressing students' queries regarding the covariance matrix and its application to multi-dimensional data, I engage in a collaborative problem-solving process. To address the first query, instead of the 10×2 **data** matrix from Figure 2, I now consider a mean-adjusted $n \times d$ matrix referred to as **data**. Compressed data is defined as $\mathbf{data_c} = \mathbf{data} \times \mathbf{c}$, where $\mathbf{c}$ is the compression vector and $\mathbf{data_c}$ is the compressed data along the $\mathbf{c}$ vector. The goal is to find the compression vector $\mathbf{c}$ that maximize the variance of $\mathbf{data_c}$, given by $\mathrm{Var}(\mathbf{data_c}) = \frac{\mathbf{data_c}^T \times \mathbf{data_c}}{n}$. This is similar to the exercise that my students engaged previously with Figure 2 in finding the black vector pointing in the direction of the maximum variance. The optimization problem then is to maximize $\mathbf{c^T} \times \mathbf{data^T} \times \mathbf{data} \times \mathbf{c}$, where $\mathbf{data^T} \times \mathbf{data}$ represents the covariance matrix $\mathbf{C}$. This translates to aligning the vector $\mathbf{C} \times \mathbf{c}$ with the vector $\mathbf{c}$,indicating that $\mathbf{c}$ is an eigenvector of $\mathbf{C}$. This is because in order to maximize the dot product of the vectors $\mathbf{c}$ and $\mathbf{C} \times \mathbf{c}$ the vector $\mathbf{C} \times \mathbf{c}$ must be in the same direction as $\mathbf{c}$. Through this interactive and joint exploration, I aim to transition students' understanding from a social plane, where learning is collaborative and external, to a cognitive plane, creating internalization of these concepts. This internalization process will be assessed later through individual assignments, allowing me to evaluate each student's independent grasp and application of the learned material.

For the second question, I use a 360×640 grayscale image as the **data** matrix. The complete MATLAB code is available in Appendix D of this paper.

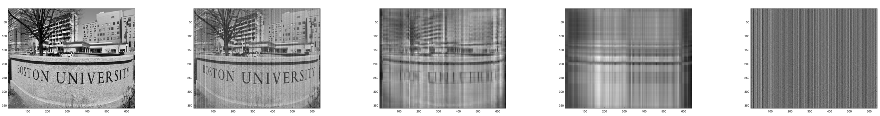

Figure 3: Grayscale Image Compression: Original image and its compressed versions using the 100 largest, 30 largest, 1 largest, and 500 smallest eigenvectors.

Students observe from Figure 3 the effects of image compression using different numbers of eigenvectors. What my students are truly amazed by is that there is very little to no variance captured by the 500 smallest eigenvectors (based on their eigenvalues). These visual examples highlight the importance of variance preservation and demonstrate that discarding eigenvectors with minimal variance has a negligible impact on image quality and can lead to higher compression without losing much of the information captured in the picture. This hands-on MATLAB experience provides students with a concrete understanding of linear algebra concepts, as they visualize the practical effects of image compression with different numbers of eigenvectors.

As students observe and discuss the outcomes of different compression levels, they are engaging in a social learning process, which then transitions into individual understanding and cognitive development. The use of MATLAB as a mediational tool in this experiment not only simplifies the complex concept of dimensional reduction in PCA but also makes the learning experience more engaging and relatable. This process, aligning with Vygotsky's educational theory, transitions learning from a social context – collaborative discussions and guided exploration in the classroom – to internal cognitive processing.

4 Conclusions

In conclusion, integrating Vygotsky's theory into linear algebra teaching fosters an engaging, collaborative, and effective learning environment, crucial for students' mastery and application of the subject.

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Appendix A MATLAB Code for compression along the y=x line

```
%compression on Y=X line
x = 1:10;
y = x;
plot(x, y, 'X', 'MarkerSize', 10, 'LineWidth', 2)
xlabel('x (dimension 1)')
ylabel('y (dimension 2)')
grid on
data=[x' y']
[V,D]=eig(cov(data))
% Compute the mean of data
meanData = mean(data);

% Scale factor for the eigenvectors
scaleFactor = 5;

% Plotting the scaled eigenvectors
hold on; % Keep the current plot
quiver(meanData(1), meanData(2), scaleFactor * V(1,1),
    scaleFactor * V(2,1), 'r'); % First eigenvector
quiver(meanData(1), meanData(2), scaleFactor * V(1,2),
    scaleFactor * V(2,2), 'k'); % Second eigenvector
hold off;
```

Appendix B MATLAB Code for compression along the X axis

```
%compression on X axis
x = 1:10;
y = zeros(1,10);
plot(x, y, 'X', 'MarkerSize', 10, 'LineWidth', 2)
xlabel('x (dimension 1)')
ylabel('y (dimension 2)')

grid on
data=[x' y']
[V,D]=eig(cov(data))
% Compute the mean of data
meanData = mean(data);
```

```
% Scale factor for the eigenvectors
scaleFactor = 5;

% Plotting the scaled eigenvectors
hold on; % Keep the current plot
quiver(meanData(1), meanData(2), scaleFactor * V(1,1),
    scaleFactor * V(2,1), 'r'); % First eigenvector
quiver(meanData(1), meanData(2), scaleFactor * V(1,2),
    scaleFactor * V(2,2), 'k'); % Second eigenvector
hold off;
```

Appendix C MATLAB Code for compression along the Y axis

```
%compression on Y axis
y = 1:10;
x = zeros(1,10);
plot(x, y, 'X', 'MarkerSize', 10, 'LineWidth', 2)
xlabel('x (dimension 1)')
ylabel('y (dimension 2)')
grid on
data=[x' y']
[V,D]=eig(cov(data))
% Compute the mean of data
meanData = mean(data);

% Scale factor for the eigenvectors
scaleFactor = 5;

% Plotting the scaled eigenvectors
hold on; % Keep the current plot
quiver(meanData(1), meanData(2), scaleFactor * V(1,1),
    scaleFactor * V(2,1), 'r'); % First eigenvector
quiver(meanData(1), meanData(2), scaleFactor * V(1,2),
    scaleFactor * V(2,2), 'k'); % Second eigenvector
hold off;
```

Appendix D Noisy Image Compression

```
%compression on BU.jpg example
img_in=double((rgb2gray(imread('BU.jpg'))));
numberOfDataPoints=size(img_in,1);
```

```
numberOfDimensions=size(img_in,2);
numberOfEigenVectors=100
imagesc(img_in);
colormap(gray);  % Set the colormap to grayscale
[V,D]=eig(cov(img_in))
imagesc((V(:,numberOfDimensions-numberOfEigenVectors:
    numberOfDimensions)*V(:,numberOfDimensions-
    numberOfEigenVectors:numberOfDimensions)'*img_in')')
```

Enhancing Learning in CS Capstone Courses Through Advanced Project Matching*

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Abstract

Optimal group formation and project matching are critical and challenging tasks for instructors. We developed the Student-Project Matching Tool to optimize these processes and piloted it in a Computer Science Capstone course at the University of California, Irvine. The tool ensures that the team formation process balances individual preferences, project compatibility, and the overall performance potential of each team by considering students' skills and interests and sponsor projects' needs to maximize teams' success. Student perspectives and feedback showed an increase in student satisfaction with their team and the project they were matched to. Similarly, positive sponsor evaluations of the teams demonstrated that sponsors were pleased with the teams they were matched to. This tool provides the basis for effective team formation and project matching in Capstone courses, with a focus on maximizing student learning outcomes, real-world experiences, student-project ownership, and the number of fulfilled skills that each project requires for completion.

1 Introduction

For many decades, researchers and instructors have aimed to optimize team formation in student engineering projects. Brickell et al found that allowing for the self-formation of teams led to negative student attitudes towards their courses, instructors, projects, and more [1]. With justification for instructor-created teams established, the focus has shifted towards optimizing the team formation process. To this end, Layton et al wrote a digital tool in an attempt to computationally pick the "best" teams by asking students questions and weighting their responses [6]. However, these approaches' matching strategies are solely dependent on the variables each instructor or researcher chooses to incorporate in their algorithm, not taking into account project needs directly. For instance, Smyser and Jaeger found that a key factor of success in capstone teams is in students' passion and ownership of their project [7]. Therefore, it is crucial that we not only optimize the matching of students into teams, but also the matching of students to projects, ensuring that all project skills requirements can be fulfilled.

Since Conn and Sharpe in 1993 [2], it has become commonplace for many capstone courses to match student teams to industry-sponsored projects. However, this introduces another layer of complexity to the team-formation and matching process, as industry stakeholders have their own set of team requirements. Thus, any computational team-forming tool must not only optimize student-centered variables but also stakeholder-centered variables.

1.1 Goals

The primary goal of this study was to design and test the Student-Project Matching Tool (SPMT) for a CS Software Engineering (SWE) Capstone course. This innovative platform is designed to aid instructors in forming student teams and matching them with industry-sponsored projects to improve student outcomes. Specifically, we designed the SPMT to support the following outcomes: (i) increased student-project buy-in/ownership, (ii) broadened student skillsets, and (iii) fulfilled project skills requirements.

We tested our desired outcomes by piloting the SPMT in a six-month-long CS SWE Capstone course at the University of California, Irvine (UCI) during the 2022-2023 academic year to form student groups and assign them to the best industry-sponsored project match. The SPMT determined the best match by considering students' interests and skills in SWE topics relevant to each project, and conversely ensuring that the skills across all students in a group collectively met the needs of the project they were matched to.

2 Student-Project Matching Tool

The SPMT consists of three parts: data collection, the Student Project Matching (SPM) Recommender, and the final set of teams (see Figure 1). Prior to data collection, we needed to first define what skills are currently valued by

Front-end - Web	**Front-end - Mobile**	**Back-end**	**Databases**	**ML/AI**	**Data Science**
UI/UX	UI/UX	Java	Oracle	Python	Python
HTML	Kotlin	PHP	MySQL	OO Lang.	JavaScript
CSS	Java	Python	PostreSQL	PyTorch	R
Javascript	Swift	C#	MongoDB	TensorFlow	Tableau
React	Unix OS	Ruby		AWS	Power BI
Angular		REST APIs		Docker	Spark
Vue.js		TCP/IP			Hadoop

Table 1: Skills, tools and frameworks in each SWE category for which students had to rank their level of familiarity in the Student Intake Survey.

SWE employers. To do this, we identified six main categories of SWE jobs and searched for them on three popular job-search websites [3, 4, 5]. We then selected the first ten job postings for each category on each website and extracted the SWE skills mentioned in their descriptions. Skills that were included in 70% of a category's job postings were then selected for incorporation into the data collection step of the SPMT. Lastly, the industry partners reviewed the full list of SWE categories and the resulting skills, which are listed in Table 1.

2.1 Data Collection

Data collection was comprised of two student surveys and one project sponsor survey. In the Student Intake Survey, students were asked to indicate their level of confidence in each of the SWE skills listed in Table 1, as well as which skills they wished to develop or continue improving. In the Sponsor Intake Survey, industry sponsors determined what languages, frameworks, and technologies would be needed for each project. Industry sponsors also submitted 3-minute video project descriptions, and students were asked to rank their interest in each project on the Student Project Ranking Survey.

2.1.1 Sponsor Intake Survey

The Sponsor Intake Survey consisted of 38 questions to learn about the sponsor and their project. Five questions collected sponsor and project information and the mentors' availability to provide technical guidance. The remaining 33 questions asked for the level of relevance of various programming languages, frameworks, and technologies which mapped to the SWE categories in Table 1.

2.1.2 Student Intake Survey

The Student Intake Survey consisted of 72 questions, and its main goal was to understand students' backgrounds and technical goals. Five questions cap-

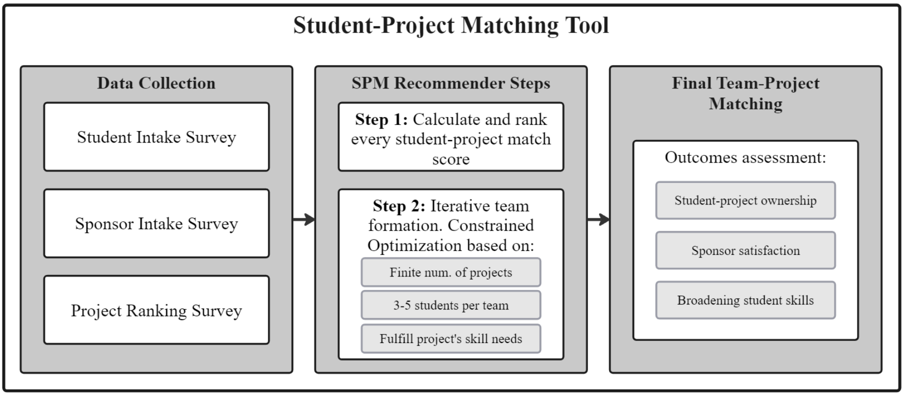

Figure 1: Overview of tasks performed by the Student-Project Matching Tool.

tured students' personal information and demographics. Eight questions captured students' background and goals, focusing on confidence in the field, SWE topic interest, courses taken and grades obtained, and interest in being a team lead. The remaining 59 questions focused on capturing a students' technical background and soft skills. Specifically, the questions focused on students' experience level across a variety of programming languages, frameworks, and technologies. Questions were formatted as single-response multiple-choice, multiple-response multiple-choice, and Likert scales.

2.1.3 Student Project Ranking Survey

Industry sponsors were asked to create short video and text summaries of their projects to pitch to students. Students were then asked to fill out the Student Project Ranking Survey, which consisted of 14 questions and the sponsors' video and text descriptions. Students ranked their level of interest for each of the sponsor projects on a 3-point Likert scale (High Interest, Somewhat Interested, No Interest). In the remaining questions, they were able to propose their own project, list potential team members, and express interest in being a team lead.

2.2 The SPM Recommender

The SPM Recommender was designed to measure students' fitness and rank them accordingly for each available Sponsor Project by assessing their skills, interests, and knowledge identified through the Intake Surveys. The SPM Recommender was comprised of two steps implemented using Python.

During Step 1, the SPM Recommender imported the responses to the three surveys, iterated through every available industry-sponsored project, and calculated a project score for each student. This score was based on the student's interest and skill levels for each SWE category, and the SWE category's level of relevance for each project.

In Step 2, student groups were formed and matched while meeting the following constraints (also outlined in Figure 1): Each group must have a maximum of 5 students, only one group can be assigned to each project, there is a finite number of projects (ten for the piloted capstone course), and the project's skill needs must be fulfilled. These constraints collectively guided the team formation process, striking a balance between individual preferences, project compatibility, and the overall performance potential of each team.

3 Results and Discussion

In 2023, we conducted a six-month CS Capstone course at UCI where we piloted the use of the SPMT. We then evaluated the effectiveness of the SPMT by gathering feedback from both students and sponsors. We compared this feedback to that gathered in the 2022 course taught by the same instructor when students were placed in teams based solely on their project and team member preferences. Results show that the SPMT maximized the opportunity for students to learn new skills since it considered student interests in the matching process, and it increased student satisfaction with their groups and projects. The SPMT not only helped to match students with better educational projects but also acted as a catalyst in boosting student-project ownership and a deeper understanding of the SWE profession. This also led to higher sponsor satisfaction with the group formation and project matching during the piloting period.

3.1 Sponsor Feedback

Sponsor feedback during the pilot was compared to feedback during the previous year before the SPMT was introduced. At the end of the first term in both offerings, sponsors had the opportunity to review their team's performance.

In the year before the SPMT, two out of the six project reviews expressed discontent with student progress and preparedness. Industry sponsors stated that "the students' readiness to do hands-on programming was less than expected" and "they veered off of the original requirements which led to a gap between what they developed and what was expected". Additionally, only one sponsor expressed satisfaction working with their team.

The benefits of the switch to SPMT in 2023 were evident in the shift of general sentiment to much more positive reviews during the feedback stage.

Out of nine submitted team reviews, four sponsors recognized their team's efforts by sharing that the teams are "really scrappy", "doing a great job", "show high levels of enthusiasm", and "quick learners". In contrast, only one comment pointed to areas of improvement, saying that "communication could be better", which was not one of the skills targeted by SPMT. The shift to primarily positive feedback from sponsors shows the teams' ability to meet their sponsor's expectations, highlighting the value of the team matching tool.

3.2 Qualitative Student Feedback

Student course evaluations provided a means of understanding student experiences before and after the introduction of the Student-Project Matching Tool.

In 2022, 15 out of 29 students filled out the survey. One question asked students to mention any aspects of the course that could be modified to improve their learning. Of the 15 responses, three mentioned that team and project matching could be improved.

Overall, feedback pointed to the common weaknesses encountered when only considering project and team member preferences in the matching process.

In 2023, 43 out of 47 students filled out the survey. The total number of responses almost tripled due to the larger class size and higher response rate. Despite a higher number of participants, only two responses to the improvements question mentioned the lack of technical knowledge for the project. This type of comment was expected because the tool was designed to challenge students to acquire new skills that they showed interest in.

4 Conclusion and Future Work

In conclusion, the SPMT pilot in a Computer Science Capstone course has demonstrated positive outcomes, enhancing student satisfaction with skillset growth, team formation, and project assignments. Acknowledging the initial limitations in the availability of industry-sponsored projects during the pilot, our future work focuses on diversifying opportunities and expanding the pool of available projects. We plan to optimize the SPMT by testing various matching algorithms to maximize student learning when limited projects are available. Additionally, new, more targeted feedback surveys will be designed to gather deeper insights for ongoing refinement of the SPMT. The SPMT shows promise as a tool for enhancing team formation and project matching in SWE, and ongoing efforts should continue to focus on improving student learning outcomes and real-world experiences.

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Confidence and Competence: The Impact of National Cyber League Participation on Career Development in Cybersecurity*

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Abstract

This study investigates the career impacts of participating in the National Cyber League (NCL) cybersecurity competition. It assesses the effect of such competitive experiences on job interview opportunities, interview performance, and the practical application of skills learned in the competition to professional roles. Data was collected through a survey of NCL participants. Results indicate a significant link between participation in the NCL and increased confidence in cybersecurity abilities through hands-on experience which was noted to be absent in their formal education. Furthermore, the competition served as an incentive for further learning in the field of cybersecurity.

1 Introduction and Related work

Cybersecurity competitions have been recognized for their pedagogical benefits, engaging learners, and providing hands-on experiences[3, 6, 8]. Participants in cybersecurity competitions report increased motivation, better understanding of professional requirements, and enhanced teamwork skills through cooperation on team based competitions[1, 4, 10]. Furthermore, these competitions foster improved collaboration abilities as participants work together in team-oriented challenges[5].

Despite cybersecurity competitions existence of over two decades and the growing popularity of them, the existing body of research has not extensively explored cybersecurity competitions from the viewpoint of cybersecurity professionals already in the field[3]. Moreover, there is a scarcity of research comparing the skills demanded in cybersecurity positions with those imparted through participation in such competitions[11].

To address this gap, Wee et al.[11] investigated the alignment between the skills demanded by the cybersecurity workforce and those honed through cybersecurity competitions. Their research centered on participants of New York University's Capture the Flag (CTF) event during Cybersecurity Awareness Week (CSAW). Utilizing data from a substantial prior survey, which explored the demographics drawn to cybersecurity and ways to enhance competitions, the study homed in on 89 professionals from the initial 217 respondents who were working in the cybersecurity sector. Analysis of 16 multiple-choice questions from the "much larger survey" revealed that 89.9% of these professionals placed high value on the skills developed in competitions. Additionally, over half attributed their career choice to these competitions, and 69% recognized the competitions as potent recruitment channels for the industry[11].

2 Methods

This research aimed to determine whether participation in the National Cyber League (NCL) was perceived as beneficial for securing employment in the cybersecurity sector and to what extent the competencies developed during the NCL were applicable to participants' current professional roles. To assess this, the study surveyed NCL participants who are now working in the field of cybersecurity.

The NCL was selected for its approach to addressing common issues found in some cybersecurity contests. Concerns regarding the depth and focus of some competitions suggest they may not fully prepare participants for the diverse range of skills required in the industry[2, 6, 9]. Additionally, competitions often lack formal training for entrants[9], presenting a significant barrier as many events necessitate extensive prior knowledge[2].

The NCL's structure comprises four phases: the Gym, with guided challenges for skill-building; the Practice Game, encouraging collaborative problem-solving; the Individual Game, for personal skill assessment; and the Team Game, where groups of up to seven collaborate[7]. Each phase offers a variety of difficulties across nine cybersecurity categories that correspond with the National Institute of Standards and Technology's (NIST) National Initiative for Cybersecurity Education's (NICE) work roles. These categories include cryptography, password cracking, log analysis, network traffic analysis, forensics, web application exploitation, scanning, enumeration and exploitation, and open-source intelligence, providing a comprehensive range of skills development and assessment for participants.

To recruit participants for the survey we contacted NCL alumni via two different channels. First, we utilized LinkedIn to identify individuals who had mentioned NCL in their skills section and held a current position within the cybersecurity field. We then sent out connection requests on LinkedIn and successfully established connections with 62 professionals. Upon connecting, we sent each individual a direct message on LinkedIn with an invitation to contribute to our research, which read: "I'm hoping you can take about 10 minutes to help me with some research that I am doing. I'm studying how/if the NCL helped prepare you for your career in cybersecurity." The message also included a link to the survey hosted by Survey Monkey. We received completed surveys from 34 individuals in the group, a 55% response rate.

Next, we partnered with the National Cyber League (NCL) to contact 6,013 of their college graduate alumni, whose expected graduation dates were known from their registration details. Although we were not certain of their actual graduation status or whether they were employed in the cybersecurity sector, we proceeded with the outreach. From this group, we received 47 completed surveys, resulting in a response rate of 0.8%.

The survey consisted of 35 questions; it included 27 quantitative queries using a Likert scale, five open-ended qualitative inquiries, one binary yes/no question, and two queries for consent to disclose their identity, followed by a prompt for their name and email address. The survey was conducted online via Survey Monkey, with each response's start and end times, as well as their IP address, being logged.

3 Results and Discussion

The survey consisted of question on four main topic areas: 1) the influence the NCL had on their interest in cybersecurity, 2) the skills acquired through the NCL, 3) the impact of the NCL on employment, and 4) the relevance of the NCL to their current role. We had a total of 81 responses.

3.1 Quantitative Results

Participants largely agreed on the following, as indicated by the distributions skewed towards higher values:

1. Motivation to Learn About Cybersecurity: Responses concentrated around

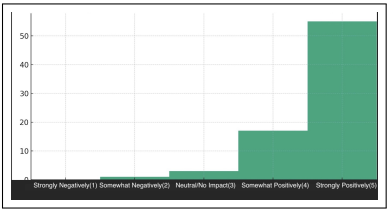

Figure 1: To what extent did the NCL impact your motivation to learn more about cybersecurity. either positively or negatively?

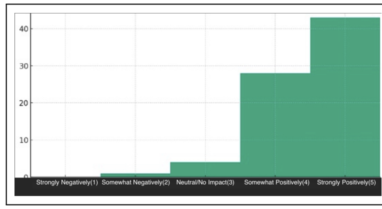

Figure 2: To what extent did the NCL influence your understanding of cybersecurity, either positively or negatively?

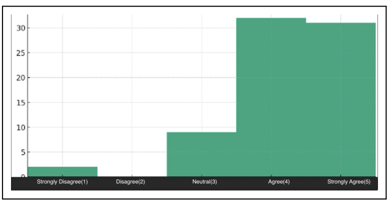

Figure 3: The NCL provided hands-on experience that was not available in my formal education or training.

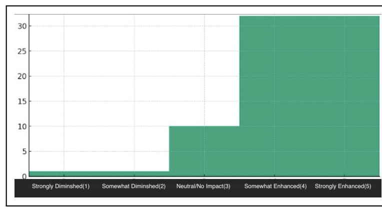

Figure 4: To what extent did the NCL affect your confidence in the cybersecurity field, either positively or negatively?

high values, indicating a strong agreement on increased motivation (see figure 1). Mean = 4.66, Standard Deviation = 0.62

2. Understanding of Cybersecurity: A skew towards higher ratings suggests a consensus on the NCL's positive impact on understanding cybersecurity (see 2). Mean = 4.49, Standard Deviation = 0.66
3. Hands-On Experience Not Available in Formal Education/Training: The peak at higher values indicates agreement on the value of NCL's hands-on experience (see figure 3). Mean = 4.22, Standard Deviation = 0.86
4. Confidence in Cybersecurity Field: A skew towards higher scores suggests a strong consensus on the NCL enhancing participants' confidence (see figure 4). Mean = 4.22, Standard Deviation = 0.83

Participants had more varied opinions on the following, as indicated by more evenly distributed responses or lack of a strong single peak. For the question about the NCL being discussed during the job interview, the responses were more spread out, indicating varied experiences regarding the discussion

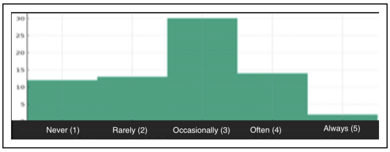

Figure 5: Have you encountered problems in your current job that resembled those presented in the NCL?

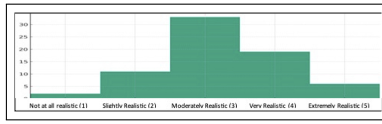

Figure 6: How closely did the activities in the NCL mirror real-world cybersecurity scenarios?

of NCL in job interviews (42.31% yes and 57.69% no). When asked about encountering similar problem in their current job, the distribution suggests varied experiences about encountering NCL-like problems in current jobs (see figure 5). Responses were also distributed for the question about real-world relevance of NCL challenges, reflecting varied opinions on how closely NCL activities mirror real-world scenarios (see figure 6). The rest of the quantitative questions are listed below in figure 7.

3.2 LinkedIn versus Email Group

Generally, the group that was contacted via LinkedIn showed higher mean scores across most questions compared to the large group contacted via email. This indicates a trend of more positive or affirmative responses among LinkedIn group members on various aspects of the NCL's impact. However, for most of the questions, the measured size of the difference was not significant. This was indicated by a Cohen's d score of less than .4.

However, four questions had a noticeable difference in responses between the LinkedIn group and the email group. The question "Participating in the NCL helped me secure a job in the industry" had a mean response for the Email Group of 2.95 and 3.88 for LinkedIn group. The t-score was 3.48 and Cohen's d value was -0.80. This indicates a noticeable difference in how the two groups answered this question. The other three questions that had a more positive response from the LinkedIn group and a similar Cohen's d value were: 1) "Higher motivation to learn about cybersecurity", 2) "During your job interviews, was the NCL discused?", and 3) "Have you encountered problems in your current job that resembled those presented in the NCL?"

3.3 Qualitative Results

Based on the answers provided when asked about which aspects of the NCL were discussed during interviews, it was infrequently initiated by the inter-

Quantative Questions	Average (1-5)
To what extent did the NCL impact your motivation to learn more about cybersecurity, either positively or negatively?	4.67605634
To what extent did the NCL influence your willingness to engage in solving a cybersecurity problem, either positively or negatively?	4.52112676
To what extent did the NCL influence your understanding of cybersecurity, either positively or negatively?	4.49295775
To what extent did the NCL affect your self-directed learning capabilities, either positively or negatively?	4.3943662
To what extent did the NCL influence your pursuit of lifelong learning in the cybersecurity field, either positively or negatively?	4.30985915
To what extent did the NCL affect your confidence in the cybersecurity field, either positively or negatively?	4.23943662
I have recommended or encouraged others to participate in the NCL based on my experience.	4.22535211
The NCL provided hands-on experience that was not available in my formal education or training.	4.21126761
I found the learning experience in the NCL to be more beneficial than traditional classroom or online courses.	4.16901408
The hands-on challenges in the NCL were the most beneficial for my professional development.	4.07042254
I believe that participating in the NCL offered a competitive edge when applying for jobs in the industry.	3.87323944
To what extent did the NCL positively influence the expansion of your thinking abilities?	3.85915493
The skills and knowledge I gained from the NCL are directly relevant to my current job responsibilities.	3.8028169
To what extent did the NCL influence your ability to abstract and generalize cybersecurity concepts?	3.78873239
Participating in the NCL influenced my choice of cybersecurity specialization or area of interest.	3.69014085
Participating in the NCL helped me secure a job in the industry.	3.4084507
To what extent did the NCL enhance your group collaboration skills?	3.31428571
How closely did the activities in the NCL mirror real-world cybersecurity scenarios?	3.21428571
I found networking opportunities through the NCL beneficial for my professional journey.	3.18309859
I am interested in mentoring or guiding future participants in the NCL.	3.17142857
Some aspects of the NCL were less relevant or useful for my career in cybersecurity.	3.12676056
I believe there is a gap between the challenges posed in the NCL and real-world cybersecurity threats.	3.12676056
Have you encountered problems in your current job that resembled those presented in the NCL?	2.73239437
Do you remain active in cybersecurity competitions post-employment?	2.21428571
To what extent was the interviewer familiar with the NCL during your job interviews?	1.97101449
To what extent, if any, did hiring managers indicate that your participation in the NCL influence their decision to interview you?	1.73913043

Figure 7: Quantitative survey questions showing the average of the answers (scale of 1 to 5)

viewers themselves. Instead, interviewees brought up the NCL as a topic of conversation, emphasizing their rankings and the technical proficiency they gained through participation. NCL discussions served as evidence of knowledge, passion, and engagement with cybersecurity, compensating for a lack of prior work experience for some candidates.

In response to the question regarding encounters with problems in their current jobs resembling those presented in the NCL, several common themes emerged. Many respondents highlighted the importance of skills related to log analysis, event monitoring, and alert handling, which they found to be reminiscent of NCL challenges. While some specific job tasks closely aligned with NCL challenges, others noted that the NCL had provided them with valuable skills and knowledge that they applied indirectly to real-world problems.

4 Conclusions

An individual's belief in their capability to succeed is a crucial element in pursuing a career in cybersecurity and, according to NCL alumni that completed our survey, there is a strong consensus that participating in the NCL enhanced their confidence. There was also agreement on the value of NCL's hands-on experience which was not available in their formal education. They indicated that participating in the competition not only positively enhanced their understanding of cybersecurity, but also motivated them to learn more about it.

But did competing in the NCL get them their current job? There wasn't consensus to this question. Less than half reported that they talked about the NCL during their job interview. For those that did, many reported that they were the ones that brought it up. During their interview they used the NCL as a talking point, pointing out their ranking and the practical hands-on skills acquired which they felt help compensate for their lack of prior work experience.

Overall, the NCL has improved the competence and confidence of past participants now in the cybersecurity field. To bridge the existing skills gap and expand the pool of cybersecurity professionals, it's imperative to engage a younger audience with cyber competitions like the NCL. Further investigation might explore the impact of presenting these challenges prior to high school; might this cultivate a more diverse group of students intrigued by cybersecurity?

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Results of an Online Algorithms Course with Mastery Grading and Optional Oral Examination

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Abstract

In the summer of 2023, a mastery grading scheme with weekly exams was implemented in an online upper-divsion introductory algorithms course with 123 enrolled students (117 after the drop deadline), with optional oral exams for additional attempt opportunities. Student reception to this system was overwhelmingly positive, with high student final grades, while still maintaining a high level of academic rigor.

1 Introduction

The traditional grading system has well documented flaws [5, 6], and many alternative systems have been developed to attempt to address them [2, 3, 8]. This experience report uses a system which addresses the issue of single-chance exams. That is to say, the system where, for each topic in the course, it is assessed on exactly one exam, and if a student performs poorly on that exam, there are no opportunities to make up the grade by demonstrating later mastery of the subject.

The most common reason for not implementing multiple-chance systems is due to grading overhead. In courses such as an introductory algorithms class, automatic grading is often infeasible, because designing algorithms and writing mathematical proofs are common forms of assessment [7]. As such, manually grading exams across all topics in the course every week could be impracticable, particularly for those with strained course staff to student ratios.

Furthermore, creating new questions each week is also a challenge. While topics such as Dynamic Programming and NP-completeness are rich domains to create problems from, topics such as Greedy and Divide and Conquer algorithms have notably smaller design spaces.

Despite these constraints, multiple-chance grading schemes have been explored in algorithms courses in the past. The earliest example we are aware of is [9], where the authors explored having the exam grade split by topic, and made the final exam a "second chance" for each one. [1] allowed reassessment on topics via a limited number of "tokens" to limit grading load, while [10] didn't have proctored exams, and instead had assessments entirely through take-home assignments, allowing students to resubmit any programming assignment freely, and each week resubmit 1 or 2 written assignments from a previous week. However, all of these differ from our work, since none of these systems had weekly proctored exams on every topic.

2 The Course in Context

The course explored in this experience report was taught at UCLA, a large and very selective R1, over the summer of 2023, where initially 123 students enrolled (6 of whom eventually dropped), plus an additional 5 students audited, and one student made up an incomplete (which involved taking the exams, so they are part of the data). There was one student who never submitted any assignment/assessment, and never attended lecture. This student will be discarded from the data from this point on. The course staff consisted of the instructor of record and 2 PhD student teaching assistants. The instructor of record was teaching the course for the first time at this institution. The PhD students were required to hold exactly 2 hours of office hours each week (and no more by union contract). Both graded 1/3 of the exams (with the instructor grading the final 3rd), and assisted the proctoring of the exams. Over the summer, UCLA allows visiting students from other universities to take classes for course credit at their home institution. While numbers were not provided, a sizable percentage of the students enrolled were visiting students, perhaps as high as one third of the student population.

The course was 9 weeks long and taught entirely online, with lectures taking place over a Zoom classroom. Lecture attendance was typically between 40 and 60 students. Around 50 students or so noted inability to attend lecture live due to difficulties with time zones, internships, or other factors. Exams were conducted through the LMS, with a lockdown browser requirement and a recorded live Zoom proctoring to attempt to crackdown on cheating. There were no reported incidents of cheating, though there was one suspected case (the student failed regardless).

The grade in the course had two components. The first component was comprised of summative assessments. This was referred to as the "baseline grade." The second was comprised of formative assessments, and was referred to as "grade modifications."

The baseline grade was based on the pass/fail status of the 4 core topics of the course: dynamic programming, greedy algorithms, divide and conquer algorithms, and NP-completeness. To pass, students needed to solve a single exam problem (giving and algorithm and/or proof). If at the end of the course, for each of those 4 topics, they received a pass on the corresponding topic on at least one exam, then they would receive a "baseline A." If they passed three out of the four, then they would receive a "baseline C." Otherwise, they would receive a "baseline F" and have no way to pass the course.

The grade modifications were just another way to present the formative assessments. Every one of the four topics had a reading assignment (from a Zybooks textbook [4]) and a homework assignment (composed of 2 questions for the topic). Dynamic Programming also had a programming assignment. Each of these was graded on a pass/fail basis, and for each "fail," the letter grade was lowered by one step (e.g.: an A would become an A-, an A- would become a B+, and so on). The homework assignments had two chances to pass. Either the submission would be completely correct, or, so long as the submission was "in good faith," a "reflection" could be submitted to pass, where students would note what mistakes they made, why they made them, and what they would do differently in the future to not make the same mistake again.

Finally, there was one "extra credit" opportunity based on a bonus lecture about network flow. The week 9 exams and final exam each had a bonus question involving network flow. If students passed one of these questions, then their grade would be raised one step. Notably, this was the only way to have an A+ in the course, which UCLA allows (but does not effect GPA).

2.1 Exam details

There were two exam slots each week, held 8 hours apart. As previously mentioned, these were done via the LMS on a lockdown browser, while being proctored on Zoom. The reason for having two timeslots was to accommodate students abroad and with internships. Also, students were allowed to (and several did) attend both sessions if they were able to and wished to have additional attempt opportunities. Furthermore, all topics additionally appeared on a final exam in the final week, and the first 3 topics had 2 bonus opportunities attached to review sessions, while the final topic (NP-completeness) had 6 bonus opportunities attached to review sessions.

Students were also allowed attempt oral exams. The student could schedule a time with a member of the course staff, who would give a problem to the student via the Zoom whiteboard. If the student was able to solve it, then they would pass the topic. If not, then they would get feedback to improve.

In total, excluding oral exams and counting both morning and afternoon exams, there were 16 dynamic programming exam chances, 13 greedy chances, 8 divide and conquer chances, and 11 NP-completeness chances. All questions were pulled from a database of questions made by the instructor, a TA, or taken and modified from a question from another instructor (with permission).

3 Data

Grading Type	Pre-N	Pre-μ	Pre-σ	Post-N	Post-μ	Post-σ	Δ (Conf. Int.)	P-value	T-score	df	σ_M
Curved	62	4.60	3.23	34	4.88	2.88	0.29 ($\pm$1.32)	0.6678	0.4305	94	0.663
Weighted	**62**	**7.21**	**2.08**	**34**	**6.26**	**1.91**	**-0.94 ($\pm$0.86)**	**0.0311**	**2.1883**	**94**	**0.432**
Standards-Based	62	7.66	1.90	33	7.67	2.17	0.01 ($\pm$0.85)	0.9901	0.0125	93	0.431
Pass/Fail	62	6.23	2.36	32	6.53	2.60	0.31 ($\pm$1.05)	0.5670	0.5745	92	0.532
Partial Credit	**62**	**9.24**	**1.29**	**31**	**7.81**	**1.66**	**-1.44 ($\pm$0.62)**	**0.0001**	**4.5867**	**91**	**0.313**
One Chance	62	3.79	2.28	31	2.90	1.83	-0.89 ($\pm$0.93)	0.0634	1.8794	91	0.472
Multiple Chance	62	8.84	1.27	31	8.87	1.98	0.03 ($\pm$0.67)	0.9244	0.0952	91	0.339

Table 1: Data from student rating of grading systems, testing whether the change of rating is significant using an unpaired two-tailed t-test. "Pre" refers to the Pre-survey and "Post" refers to the post survey. N refers to the sample size, μ refers to the mean, and σ refers to the standard deviation. Δ (Conf. Int.) contains the change in mean and confidence interval with $\alpha = 0.05$. The bolded entries are the statistically significant ones. σ_M is the standard error.

The course had both a pre-course survey, given before the first day of class, and a post-course survey, given after the final exam. In both, students were given a description of each system, then asked to rate them from from 1-10. The data from this can be seen in Table 1.

In both the pre-survey and post-survey, students were asked whether they would prefer a multiple-chance system graded as pass/fail or a single-chance system graded with partial credit. In the pre-survey, 80.6% of respondents said they would prefer the multiple-chance system as opposed to 19.4% the single-chance system. The post-survey widened the gap to 87.9% vs 12.1%.

Question	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
This grading system made me enjoy the course more than I would under a traditional system	1	1	0	12	20
This grading system made me less stressed about exams	2	2	3	9	18
The grading system helped me learn iteratively over time	0	1	3	5	25
I would take a course with a similar system to this again	2	0	0	5	27

Table 2: Course grading system questions

There were also class-specific questions. Opinions about the course grading system are shown in table 2. When asked about the helpfulness of the bonus sessions, 14 gave a 5/5, 4 a 4/5, 2 a 3/5, and 1 a 2/5. When asked about the most helpful part about them, 10 students indicated the exam chance, 4 the review session, and 8 students that both were equally helpful. The 8 respondents whom had taken oral exams were asked about the helpfulness of them. 3 students said 5/5, while 5 indicated 3/5. Finally, Table 3 shows the number of students that passed each topic each week. Only 6 of the passes were from oral exams (3 DP, 2 Greedy, and 1 Divide and Conquer).

Exam Time	Topic			
	DP	Greedy	D&C	NP
Week 3	56	0	0	0
Week 4	29	0	0	0
Week 5	4	46	0	0
Week 6	6	33	66	0
Week 7	14	18	31	0
Week 8	5	8	12	61
Bonus Exams	3	4	3	36
Week 9	4	4	5	8
Final	0	1	0	7
Never passed	0	3	0	5

Table 3: Number of students that passed each topic in each week. Some students that passed DP later dropped.

4 Discussion and Conclusion

4.1 Threats to Validity

The post-course survey had less respondents (34) than the pre-course survey (62). This could bias the results, since the population that completed the post-course survey may be different than those that completed the pre-course survey.

4.2 Student Suggestions

Student feedback about the system, received via survey, course evaluations, email, or private discussions, can broadly be broken up into the following themes:

1. Have it be easier to check what one's current course grade is, and provide better feedback on when one is "in danger"

2. Make the drop from a baseline A to a baseline C less harsh somehow

3. Introduce some sort of partial credit into the system, especially for the programming assignment

The first is simple enough and will be done in future instances of this system being used. The other two are are more difficult to address. One possible idea is using a "conditional pass" on sufficiently close answers, where the student must complete an alternative assignment to demonstrate full mastery.

4.3 Instructor Reflection

Even with a large course, the grading burden was bearable, The largest number of unpassed topics in any week of the course was during week 6, where there were around 220 unpassed topics. Furthermore, the actual number of attempts was lower. So, even in the worst week, making worst-case assumptions when splitting work equally among the course staff, at a grading time of 10 minutes a question, grading would take no more than 10 hours, with most weeks being far less. Thus, with a sufficiently large question bank, the work for the course is manageable even when teaching 2, or possibly even 3, courses during the academic term.

The system being pass/fail with multiple chances allowed the course to have a policy about "good faith" submissions. In essence, students were expected to be truthful and not submit an answer they knew was wrong. If the student didn't know, they were expected to report what they attempted, and what difficulties they encountered. This was beneficial when grading, as regularly students would report their answer to be wrong, and write what was confusing them or causing them difficulty, removing the time spent grading trying to figure out if an unorthodox solution is correct, and blithely reporting to a student why it doesn't work. Instead, the time could be spent simply looking at what students report difficulty with, and giving advice directly for those points.

Another thing to note is that the entire first class was spent discussing the philosophy of grading and why the grading system is what it is. Anecdotally, students responded very well to this, and it made the class excited to try the system and see how it worked for them. Discussing the motivations for the "unnattractive" lacking of partial credit seemingly lead to less students being upset about it, and indeed, the only statistically significant change in their view of grading systems was a less positive view of partial credit systems.

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