

(Board 56/Work in Progress): How Do Students Spend Their Time Studying in a CS Discrete Math Course?

Yael Gertner, University of Illinois Urbana-Champaign

Dr Gertner joined the Computer Science Department at the University of Illinois in 2020 as a Teaching Assistant Professor. She received her B.S. and MEng in Electrical Engineering and Computer Science from MIT, and Ph.D. in Computer and Information Science at the University of Pennsylvania. She was a Beckman Fellow at the University of Illinois Urbana-Champaign. Her current focus is on broadening participation in Computer Science and Computer Science Education She has been developing materials and teaching for iCAN, a new program for broadening participation in CS for students who have a bachelor's degree in a field other than computer science.

Juan Alvarez, University of Illinois Urbana-Champaign

Juan Alvarez joined the Department of Electrical and Computer Engineering at University of Illinois faculty in Spring 2011 and is currently a Teaching Assistant Professor. Prior to that, he was a Postdoctoral Fellow in the Department of Mathematics and Statistics at York University, Canada, a Postdoctoral Fellow in the Chemical Physics Theory Group at the University of Toronto, Canada, and a Postdoctoral Fellow in the Department of Mathematics and Statistics at the University of Saskatchewan. He obtained his Ph.D. and M.S. from the Department of Electrical and Computer Engineering at the University of Illinois in 2004 and 2002, respectively. He teaches courses in communications, signal processing and probability.

Benjamin Cosman, University of Illinois Urbana-Champaign

Dr. Jennifer R Amos, University of Illinois Urbana-Champaign

Dr Amos joined the Bioengineering Department at the University of Illinois in 2009 and is currently a Teaching Professor in Bioengineering.

WIP: Do Students' Motivation and Time Studying Contribute to Success in a Discrete Math CS Course

1 Introduction

The growing demand for Computer Science graduates has led to growing enrollment in Intro to CS courses. Unfortunately not all students who enter these courses succeed [6]. Researchers in Computer Science education are working to identify sets of student features that play a role in course performance and that could directly lead to the design of interventions that could improve student outcomes [3]. Specifically, researchers studied whether motivation[5] and belonging [4] are related to course outcomes. This prior work mainly focused on introduction to programming courses. In this paper we focus on another important gateway course in the computing sequence: Discrete Math. The theoretical mathematical nature of the course might require new study habits and alter student motivation.

We have identified the following research questions regarding students in a Discrete Math class in an introductory CS sequence:

RQ1: Do students' expectations to do well, value of the course, and time spent studying contribute to their course outcome?

RQ2: Can students who do not expect to do well in the course when they first enter it, can nevertheless engage in study behaviours that lead to positive course outcomes?

2 Methods

We surveyed students in a Discrete Math course at the University of Illinois Urbana-Champaign three times during Spring 2022. Survey 1 was used to get information about students' motivation and belonging as they enter the course in the first week of the semester. Surveys 2 and 3 were given in the middle and at the end of the semester and asked students how they spend their time studying.

2.1 The course

The Discrete Math course is a required course in the Computer Science sequence. It has enrollment of many non majors who are trying to switch into CS. It is a sixteen week course with seven "low-stakes" exams given every two weeks These exams constitute 90% of the

grade. The rest of the grade depends on homework. Students are provided with an online textbook and prerecorded lecture videos. The students are also given many versions of past exams with solutions from several years. The 75 minute weekly meeting time is devoted to a problem solving session in which students work in groups. Attendance is not required and solutions are available.

2.2 Participants

During Spring 2023, we surveyed 478 students out of 801 students enrolled in the course. All the 478 students consented to and answered an IRB approved questionnaire. Students received extra credit for completing the questionnaire.

2.3 Measures

Expectancy was measured in Survey 1. It is a measure based on participants' intrinsic motivation designed based on self-determination theory [1]. It focuses on the aspect of motivation that comes from their expectation of how enjoyable this class will be as well as how well they can do in it. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the following questions and the measure corresponds to the average of the answers while reversing the scale for the first and last one: "I think this class is going to be boring", "I think this class is going to be enjoyable", "I think that I am going to be pretty good at this class", "This is a class that I cannot do very well in".

Value was measured in Survey 1. It is a measure based on participants' intrinsic motivation designed based on self-determination theory [1]. It focuses on the aspect of motivation that comes from the importance and effort that they attribute to this class. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the following questions and the measure corresponds to the average of the answers. "I plan to put a lot of effort into this class", "It is important to me to do well in this class", "I believe this class could be of some value to me", "I believe doing this class is important".

Belonging was measured in Survey 1. Prior work identified belonging as important to student success [2]. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the set of the following 4 questions: "my teachers see me as a computer scientist", "my friends/classmates see me as a computer scientist", "my family sees me as a computer scientist", "I see myself as a computer scientist".

Time Spent was measured in Surveys 2 and 3. Students were asked "Which resources did you use in the week leading up to the exam?" and asked to indicate the number of hours 0, < 1, 1-3, > 3 that they spent on each of 9 resources that are available to them: reading the textbook, watching lecture videos, actively working on solving tutorial problems, reading the solutions to tutorial problems, list of problems and their hints and solutions, attending office hours, reading and posting on an online forum, practicing with past exams, using YouTube and other external resources.

For each student, we averaged the total time spent on each of these resources in the middle of the semester (Survey 2), and at the end of the semester (Survey 3), and Time Spent is the

average of these total times. We hypothesized that there will not be significant differences between how students respond to Surveys 2 and 3 and that their responses are representative not only of that week but rather of the entire semester. We decided to phrase the question in terms of what they did in a particular week rather than generally because we thought it would better capture what students did.

Final Grade. This is the final calculated percent score that students were assigned at the end of the semester.

2.4 Data Analysis

To measure the contribution of Expectancy, Value, Belonging and Time Spent towards Final grades, we fit an ordinary least squares (OLS) model of the form $f_i = \beta_0 E_i + \beta_1 V_i + \beta_2 B_i + \beta_3 T_i$, where f_i is the normalized z-score final grade for student i , E_i is the normalized z-score for Expectancy score, V_i is the normalized z-score for Value score, B_i is the normalized z-score for Belonging score, and T_i is the normalized z-score for the Time Spent score.

We also conducted a follow up statistical analysis on our data set. The data was split into two sub-groups for comparison. A Wilcoxon rank-sum test was conducted to analyze the differences between the two sub-groups of students and a p-value cutoff of 0.05 was chosen as a cutoff for statistical significance.

3 Results and Discussion

Our goal towards RQ1 was to investigate how Expectancy, Value, Belonging, and Time Spent contribute to students' final grades in a Discrete Math course.

We find using our OLS model $f_i = \beta_0 E_i + \beta_1 V_i + \beta_2 B_i + \beta_3 T_i$, when considering the average final grade, with $\beta_0 = 0.15(p = 0.001)$, $\beta_1 = 0.13(p = 0.007)$, $\beta_2 = 0.06(p = 0.211)$, $\beta_3 = -0.19(p = 0.000)$ meaning that a student final grade is predicted to increase by roughly 0.15 of a standard deviation if the student expected to do well, by 0.15 of a standard deviation if the student valued the course. Belonging did not contribute to the Final Grade, and the Total Time spend contributed negatively. Student Final Grade is predicted to decrease by roughly 0.18 of a standard deviation if the student spent more time studying.

As expected, expectation to do well and intending to put effort into the course contribute to doing well in the course. We wanted to investigate this further and ask whether there is significant difference in these measures between students at the top (HG) vs bottom (LG) of the class in terms of Final Grades, between students that self identified as Males and Females, CS and Non-CS majors, and students who are Black, Latin, or Native American (BLN) or not-BLN. The means for these groups are presented in Table3. We see that Males have higher Expectancy than Females, but Females have higher Value than Males. CS students have higher Expectancy and Value than students who are not in a CS Major. But there is no difference in grades between these groups. This suggests that there are individual differences between students' Expectancy and Value and these measures are not the sole contributors

Measure	survey	HG	LG	Male	Female	CS	Non-CS	BLN	Non-BLN
Final Grades		93.41	78.21	87.83	86.00	87.35	87.27	78.66*	87.70
Expectancy	1	3.29	3.04*	3.24	3.07*	3.10	3.05*	3.18	3.19
Value	1	4.31	4.12*	4.19	4.35*	4.28	4.05*	4.12	4.24
Belonging	1	3.47	3.26*	3.34	3.50	3.79	2.90 *	2.98	3.41
Total time	2	10.14	11.43*	10.36	11.39*	10.35	10.74	9.29	10.72
Total time	3	9.93	11.23 *	10.22	11.04*	10.33	11.43	8.7	10.53*

Table 1: Average means for Expectancy, Value, Belonging and Time Spent for HG and LG students, Males and Females, CS and non-CS students, and students identified as BLN or not. A Wilcoxon rank-sum test with the two groups was calculated and is marked with * for $p < .05$ (*)

to course outcomes. Similarly, we see that there was no difference in Expectancy and Value in BLN and Non-BLN groups yet there was a difference in final grades.

Counter to our expectations, Time Spent contributes negatively to course outcomes. We initially expected students who spent more studying and using all the resources available to them to have better final grades. However, our data suggests otherwise. Students that spend more time perform worse in the class because their effort is not effective. However, we see that BLN do spend significantly less time than the Non-BLN and that their grades are lower.

We wanted to investigate this further and ask whether there are resources that are more effective than others. As Table3 shows, students in the HG group with final grades above the median spend more time studying by practicing with past exams than students in the LG group. Students in the LG group realize that they need help and end up spending more time on resources that perhaps are not as effective such as watching lecture videos, using external resources, and reading solutions as opposed to solving problems. It is not surprising that they also spend more time in office hours.

We found that students who spend more time on practice exams performed better in the class. Towards our goal for RQ2 we investigate whether students who had low Expectancy coming into the course could still engage in this activity towards a favorable outcome in the course. We found that students with Low Expectancy (below the median of Expectancy) and High Grade (HG) spent significantly more time on practicing with past exams: 2.4 hours, as compared with students with Low Expectancy and Low Grade (LG): 2.0 hours. Students in the High Expectancy (above the median of Expectancy) group with High grade (HG) and Low Grade (LG) spent 2.0 hours. This suggests that students who began the course with low expectations, can still spend 24 more minutes per week practicing than their peers, and result with improved outcomes. There were no significant differences between the responses to Survey 2 and Survey 3, indicating that in the middle of the semester students already identified a successful study strategy.

Resource	survey	HG	LG	p
Textbook	2	1.87	1.89	
	3	1.88	1.89	
Lecture videos	2	1.18	1.45	**
	3	1.09	1.39	**
Solve problems	2	1.37	1.40	
	3	1.12	1.21	
Read solutions	2	0.97	1.15	*
	3	0.78	1.06	**
List of problems	2	1.27	1.52	**
	3	1.22	1.30	
Office hours	2	0.31	0.44	
	3	0.39	0.58	**
Online forum	2	0.47	0.57	
	3	0.62	0.73	
Past exams	2	2.17	1.95	*
	3	2.24	2.05	*
You tube	2	0.53	1.04	**
	3	0.59	1.02	**

Table 2: Means for Time Spent on each resource for LG (below median) and HG (above median) Final Grade students. * indicates significant differences, ** for $p < .001$

4 Conclusions

In this paper we examined student features that might be associated with performance in a Discrete Math course with the underlying goal of designing an intervention that will help students improve their course performance. We found that expectation to do well and intending to put effort into the course contribute to doing well in the course. We found that over all students who spend more time do not do better in the course perhaps because their time is not spent effectively. Yet, students who spend more time on practice exams performed better in the class. This is especially true for students who come into the course with low expectation to do well. In future work, we plan to examine how we might turn this information into an intervention.

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References

- [1] E.L. Deci and R.M. Ryan. 2012. Self-determination theory. In *Handbook of theories of social psychology*, P.A.M. van Lange, A.W. Kruglanski, and E.T. Higgins (Eds.). Sage Publications Ltd., 416–436.
- [2] Catherine Good, Aneeta Rattan, and Carol S Dweck. 2012. Why do women opt out? Sense of belonging and women’s representation in mathematics. *J. Pers. Soc. Psychol.* 102, 4 (2012), 700–717.
- [3] Soohyun Nam Liao, Sander Valstar, Kevin Thai, Christine Alvarado, Daniel Zingaro, William G Griswold, and Leo Porter. 2019. Behaviors of higher and lower performing students in CS1. In *Proceedings of the 2019 ACM Conference on Innovation and Technology in Computer Science Education* (Aberdeen Scotland Uk). ACM, New York, NY, USA.
- [4] Adrian Salguero, William G Griswold, Christine Alvarado, and Leo Porter. 2021. Understanding sources of student struggle in early computer science courses. In *Proceedings of the 17th ACM Conference on International Computing Education Research* (Virtual Event USA). ACM, New York, NY, USA.
- [5] Duane F Shell, Leen-Kiat Soh, Abraham E Flanigan, and Markeya S Peteranetz. 2016. Students’ initial course motivation and their achievement and retention in college CS1 courses. In *Proceedings of the 47th ACM Technical Symposium on Computing Science Education - SIGCSE '16* (Memphis, Tennessee, USA). ACM Press, New York, New York, USA.
- [6] Christopher Watson and Frederick W B Li. 2014. Failure rates in introductory programming revisited. In *Proceedings of the 2014 conference on Innovation & technology in computer science education - ITiCSE '14* (Uppsala, Sweden). ACM Press, New York, New York, USA.