Identifying Student Profiles Related to Success in an Analog Signal Processing Course

Dr. 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.

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.

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.

Benjamin Cosman

Work In Progress: Identifying Student Profiles Related to Success in Analog Signal Processing

1 Introduction

Engineers are vital to economic growth and societal needs and finding ways to improve the offerings of engineering courses is an ongoing national effort [12]. This is an involved effort because students taking the same course can engage with it and experience it in different ways depending on the prior background that they bring with them to the course such as their motivation, sense of belonging and study resources. Researchers in Engineering education are working to identify such sets of student features that play a role in course performance Specifically, researchers studied whether aspects related to their motivation, such as expectancy to do well, is related to course outcomes [1, 8, 9], whether high performing students have different study behaviors than low performing students [10], and whether other sources such as sense of belonging and stress contributes to the struggles that students face [2]. This prior work mainly focused on first year Engineering courses. In this paper we focus on a second year required course that is mathematical and conceptual in nature: Analog Signal Processing. This course involves conceptual problem solving that requires students to think about a problem and conceptually understand it before starting to work on it. This might require different study behaviors than students are accustomed to. Additionally, the course's math content might lead students to doubt their expectations to do well in such a class and thereby affect their motivation.

2 Methods

Our main goal was to discover student profiles that might be associated with performance in an Analog Signal Processing course. We surveyed students in the course offerings in Fall 2022 and checked to see which features correlated with final course grades. We also aimed to discover study resources and resources that might be associated with performance.

2.1 Participants

During Fall 2022, we surveyed 265 students from ECE 210, the Analog Signal Processing course in the introductory electrical engineering sequence, at the University of Illinois Urbana-Champaign. The total number of students in the course was 335. Only students who answered an IRB approved questionnaire were included in the study. The consent and profile questionnaire was sent out via Qualtrics, while the post-exam surveys were sent out using Webtools. All surveys and the questionnaire were part of homework assignments. The main topics covered in the course are resistive circuit analysis, phasor methods, frequency response of LTI systems, Fourier series, Fourier transforms, convolution, impulse and Laplace transform.

2.2 Data Collection

At the beginning of the semester, students were asked to volunteer and answer a questionnaire with 60 questions that were taken from the following validated instruments: the Index of Learning Styles [6, 13], the Intrinsic Motivation Inventory [3, 4], the Growth Mindset Scale [5], and sense of belonging questionnaire [11].

In the questionnaire, there were two types of data sets, Likert response and binary. Specifically, the Growth Mindset and Intrinsic Motivation items of the questionnaire were coded on a Likert-scale from "Strongly agree" to "Strongly disagree". The Learning Styles Inventory questionnaire included 44 items that were binary in nature, students picked the best fit from two presented options, e.g. "I understand something better after I a) try it out or b) think it through". Each of these 44 items belonged to one of 4 learning styles categories: Activist/Reflective, Sensing/Intuitive, Visual/Verbal, or Sequential/Global. Students would thus get a score between 0 and 11 for each category - for example, the 11 items that corresponded to the Activist/Reflective spectrum were added with a score of 1 if the response corresponded to Activist and a score of 0 if the response corresponded to Reflective.

After each exam, students were asked to complete another brief survey with multiple choice questions indicating how much time they spent on several course resources in the week leading up to the exam, as well as how useful those resources were. These included resources were "lecture notes", "textbook", office hours, "old exams", "homework", "attended lectures", "lecture recordings", "Campuswire" and "YouTube or other external resources". To indicate the amount of time spent on each resource, students could select among four options: "Did not use", "$<$ 1 hour", "$>$ 1 hour but $<$ 3 hours" and "$>$ 3 hours". To indicate the usefulness of the resources, students could select among four options: "Not useful", "Somewhat useful", "Very useful" and "Did not use". We assume that the "YouTube or other external resources" option was interpreted by students as educational videos and not for entertainment.

For performance metrics, we used final course grades, midterm course grades and the difference between them (final-midterm).

2.3 Instruments

The Intrinsic Motivation Inventory is an instrument that assesses participants' intrinsic motivation based on the following six subscale scores related to performing an activity: Interest/Enjoyment, Perceived Competence, Effort/Importance, Pressure/Tension, Perceived Choice, and Value/Usefulness. It is designed based on self-determination theory [4]. Students respond on a 5 point Likert scale of "Strongly agree" to "Strongly Disagree" to the following 2 questions from each subscale. “I think this class is going to be boring” and “I think this class is going to be enjoyable”, “I think that I am going to be pretty good at this class” and “This is a class that I cannot do very well in”, “I plan to put a lot of effort into this class” and “It is important to me to do well in this class”, “I am anxious about this class” and “I feel very relaxed about this class”, “I feel like it is not my own choice to do this class” and “I feel like I am taking this class because I have to”, “I believe this class could be of some value to me” and “I believe doing this class is important”.

The Index of Learning Styles [13] is a survey instrument used to assess preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global). The instrument was developed and validated by [13]. Users answer 44 a-b questions with 11 questions for each of the four dimensions. After answering the question students get a score for each of the four dimensions that ranges from 0 to 11. for example, the 11 items that corresponded to the Activist/Reflective spectrum were added with a score of 1 if the response corresponded to Activist and a score of 0 if the response corresponded to Reflective.

Sense of belonging to one's college major is a feeling of membership and acceptance. Prior work identified it as important to student success [7]. One way to assess a sense of belonging is to ask students to report how they think others see them with respect to being savvy in their field [11]. 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”.

Growth Mindset introduced by Dweck [5], is about students' beliefs of where intelligence comes from and how these beliefs influence behavior in the face of challenges. The Growth Mindset Scale [5] assesses student's mindset by asking 3 questions on a Likert scale of 1 to 6 (“You can learn new things, but you can't really change your basic math ability.”, “Your math ability is something that you can't change very much”. “You have a certain amount of math ability, and you can't really do much to change it.”).

2.4 Data Analysis

We conducted a statistical analysis on our data set, which consists of student performance data (i.e. final course grade) and quantitative data from the questionnaire and the surveys. All statistical analysis was done in python using the scipi.stats package. We first checked for normality of the data using Shapiro-Wilk test and determined that the data was not normal. In light of the lack of normality of the data, we used Spearman rank-order correlations and Wilcoxon rank-sum tests for our analysis. A p-value of 0.05 was used in all three tests for significance.

We averaged the individual questions within the motivation category and will refer to that average simply as IMI, within the growth mindset category and will refer to that average simply as growth mindset, within in the belonging category and will refer to that average simply as belonging, within the amount of time spent in each resource and will refer to that average simply by the resource name, e.g. office hours. We also wanted to look more closely at different aspects of motivation concentrating on expectancy. For that reason we subdivided the IMI category and also looked at the questions that have to do with expectancy-value. We refer to that average simply as expectancy.

3 Results and Discussion

Our main goal was to discover student profiles and study resources that might be associated with performance. To this end, we started by trying to determine which personality traits and which study resources were correlated with final course grades. It was determined that final course grade was positively correlated with "midterm course grade", "difference in course grade" (final-midterm), reflector/activist (R/A), expectancy, belonging, IMI and "growth mindset". On the other hand final course grades were negatively correlated with "lecture notes", "office hours", homework, YouTube and "lecture recordings". All these correlations had p-values below 0.02.

It is not surprising "that midterm course grade" and "difference in course grade" (final-midterm) are positively correlated with "final course grades". However, it is surprising that "lecture notes", "office hours", "homework" and "lecture recordings" are negatively correlated. One would expect that using these resources would be conducive of high performance in the course, but students with high course grades used them less. Perhaps students with high course grades do not need these resources, while students with low course grades use them more but inefficiently. Or perhaps the self-reporting is affecting these results significantly. We plan to conduct interviews with students to get a better understanding of these effects.

Once we determined those traits and resources that were correlated with "final course grades", we analyzed them further by trying to determine if there was a significant difference in those traits and study resources between students with high course grades and students with low course grades. For this purpose, the data was split into two sub-groups for comparison of their responses. One group consisted of students who had high course grades and obtained an A or a B in the class, and we will refer to them with the acronym HG. The other group consisted of students who had low course grades and obtained a C, a D or an F in the class, and we will refer to them the acronym LG. The number of students in each group is quite different, 180 students in group HG but only 85 students in group LG. It seems that students with low course grades had a larger proportion that did not consent to the study or did not complete the survey or questionnaire. The course had about 60% students with high course grades, while about 68% of students in the study had high course grades.

The rank-sum test determined, with $p < 0.031$, that there were significant differences between these two groups in some categories. HG students had higher "midterm course grade", "difference in course grade" (final-midterm), reflector/activist and expectancy but less time spent in "office hours", YouTube and "lecture recordings". It is again surprising that student with high course grades used these study resources less often than students with low course grades.

As established earlier, expectancy, belonging, IMI, GM and reflector/activist are positively correlated with ”final course grades”, so we want to understand how these traits are represented among the students. Can we determine a profile of students that are usually successful? If so, we might be able to design an intervention that can assist students with low course grades to perform better. Towards this end, next we establish students profiles for both HG and LG students with respect to these traits. Then we focus on each one of these traits individually.

3.1 Student Profiles

In order to try to obtain a profile of students that perform well in the course, we analyzed the two groups, HG and LG, more closely to try to identify which students possessed more of these high-performing traits than other students: reflectors instead of activists, high expectancy, high sense of belonging and high growth mindset. For example, is it the case that students who have a high expectancy score don’t need to be reflectors, or that students who are reflectors don’t need to have a high expectancy score to succeed? Etc. We analyze individual students to determine which students have all four of these traits, which have only three, which have only one and which have none.

Figure 1 depicts the breakdown of these high performing traits among individual students within each group. It presents the percentage of students in each group with no positive traits, with one positive trait, etc. Most of the HG students have multiple, if not all, of the high-performing traits. In comparison, a smaller proportion of the LG students have multiple positive traits. HG students do indeed have more of these positive traits than LG students with low course grades. Hence, having several of these four traits, reflector, high expectancy, high belonging and high growth mindset, are important in high performance in this course. Among these positive traits, the one that stands out is reflector/activist, where 53.89% of HG students are reflectors, but only 29.41% of LG students are reflectors.

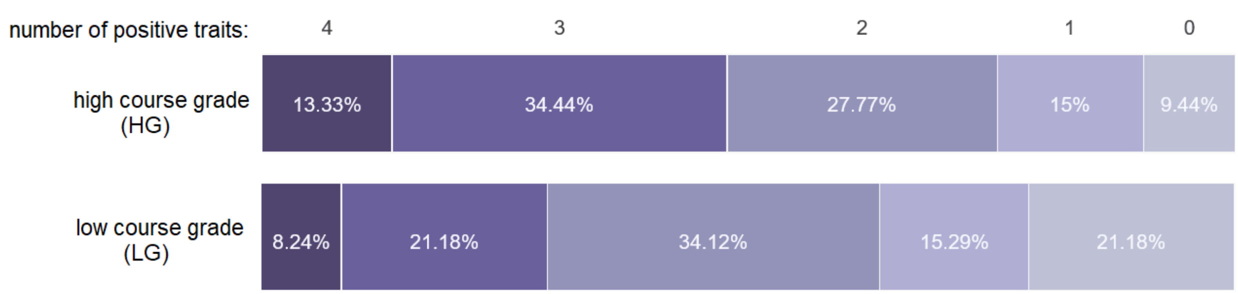

Figure 1: Breakdown of high performing traits among students.

In order to explore the relationship between these high-performing traits more closely, Table 3.1 presents the correlation, ρ, between these high-performing traits, and their corresponding p-values. It is clear that all of these four traits are positively correlated not only with ”final course grade”, but among themselves, and that should be seriously considered when designing an intervention to help students with low course grades.

We have determined that HG students have multiple, if not all, of the high-performing traits,

Table 1: Correlation among high-performing traits.

	final course grade	reflector/activist	expectancy	belonging	GM
final course grade		0.255	0.168	0.146	0.165
reflector/activist	0.255		-0.135	-0.164	-0.168
expectancy	0.168	-0.135		0.045	0.033
belonging	0.146	-0.164	0.045		0.253
GM	0.165	-0.168	0.033	0.253	

while a smaller proportion of LG students have multiple of these traits. Now, we look at each one of these high-performing traits more closely, particularly in relation to the study resources available, in order to possibly create an intervention to help LG students perform better.

3.2 Individual traits

We now explore the each of the four high-performing traits more closely. We start with the reflector trait and its relation to other traits and study resources. We want to determine if there are some study resources that are helpful to students who are not reflectors (they are activists) and what resources do reflectors typically engage with.

Reflector is positively correlated not just with "final course grade", but also with "midterm course grade", "difference in course grade" (final-midterm), expectancy, belonging, "growth mindset", intuitive, verbal and global. Being a reflector is negatively correlated with YouTube and "lecture recordings". All these correlations had p-values below 0.03.

To better understand the differences between students that are reflectors and those that are activists we divided students into two groups based on their reflector score. Group R consists of students with a reflector score above the mean, while group A consists of reflector scores below the mean. The rank sum test identified significant differences, $p < 0.041$, in "final course grade" and "midterm course grade" but not in "difference in course grade" (final-midterm). There was also a significant difference in belonging, "growth mindset", and sequential/global, but not in expectancy, visual/verbal nor sensing/intuitive. This reinforces our finding that the four main traits we used to determine the students profiles are important: reflector, expectancy, belonging and "growth mindset". Among the study resources, there were significant differences in YouTube and "lecture recordings", with R students using those resource less than A students.

If there are some study resources that are used more often among reflectors with high course grades than with those with low course grades, we can use them as part of the intervention we aim to design to help students with low course grades perform better in this course. We divided the reflectors into two subgroups: reflectors with high course grades (R-HG) and reflectors with low course grades (R-LG). The rank-sum test indicated significant differences, $p < 0.05$, in various traits and resources. R-HG students have higher "midterm course grade" and "difference in course grade" (final-midterm) than R-LG students, but R-HG spend less time in "lecture recordings" and YouTube than R-LG students. It appears that students with high reflector scores managed to improve their course grade from midterm to final by studying on their own since there was no correlation with "office hours" nor "attending lectures". The advice here would tend to be for reflectors to reduce their time spent on YouTube, but apparently also on lecture recordings. One could venture to say that perhaps these students are more visual than verbal, but there actually is a negative correlation between reflectors and the visual learning style, so they would be more verbal than visual. The data does not show any positive correlation between reflectors and using the lecture notes nor the textbook. It could be that students self-reporting is skewing the results due to over estimating time spent. We intend to explore this further via interviews.

In order to determine traits or study resources that are conducive to higher course grades among students who are not reflectors (they are activists), we also divided them into two subgroups: activist students with high final course grades (A-HG) and activist students with low course grades (A-LG). The rank-sum test indicated significant differences, $p < 0.007$, in various traits and resources. A-HG students have higher "midterm course grade" and "difference in course grade" (final-midterm) than A-LG students. A-HG students are more intuitive than A-LG students. Among resources, A-HG students spend less time in "office hours", "lecture recordings" and Campuswire than A-LG students. It appears again that HG students do not need to use the study resources as much as LG students.

The other three traits, expectancy, belonging and "growth mindset", have very similar results as reflector and hence, we do not present those results here.

In future work, we plan to examine how we might turn this information into an intervention. We plan to share with students how they compare to other students in the class. This might draw student's attention to the idea that in this class thinking about the solution before attempting to solve it is a good learning strategy. They might revise their study strategy accordingly.

4 Conclusions

In this paper we examined student profiles that might be associated with high course grades in an Analog Signal Processing course with the underlying goal of designing an intervention that will help students improve their course performance. We found correlations between final course grades and four main traits: reflector, expectancy, belonging and growth mindset. While we focus here on the reflector trait, similar approach can be considered regarding expectancy, belonging and growth mindset.

Our analysis indicated that students with higher course grades ranked higher on the reflector/activist trait, which means that they are more likely to respond as Reflectors rather than Activists. For example, when asked to respond to an items such as "When I am learning something new, it helps me to" the students with higher course grades were more likely to choose "Think about it" rather than "Talk about it". Students might revise their study strategy in the class by knowing that thinking about the solution might help before attempting to solve it. We plan to share with students how they compare to other students in the class. In future work, we plan to examine how we might turn this information into an intervention.

Using learning styles does not assume that students cannot change their learning styles throughout their undergraduate studies. This work looks at whether certain self described preferences of learning styles correlate with final course grades in the hope of bringing these preferences to students' minds as they refine their method of study for the particular course.

This approach can be helpful to educators. It is straightforward to survey students using the instruments we collected during the first week of class. Student responses can inform the educator about the student population, their motivation, sense of belonging, mindset and learning styles. An educator can then provide advice to students about the specific factors that correlate with success in this particular course.

Our goal with the post-exam surveys regarding usage of course resources was intended to provide advice to students with low course grades on which resources typically are used by students with high course grades, so that they could use those more regularly as well. However, the data showed that students with low course grades use those resources more than students with high course grades. That was an unexpected result, which we intend to investigate further via interviews because we think that self-reporting is affecting the results significantly.

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