Online Student Engagement: A Case Study in Teaching of Programming

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Abstract. *Student engagement is a key indicator of student academic success, especially in the online environment, where students can study anywhere, anytime. In this paper, we analyze track records of the novice programmers' interaction with an online learning environment. The results show indicators of poor and good engagement and can guide teachers in choosing the most appropriate teaching strategy according to the needs of each individual.*

Resumo. *O envolvimento do aluno é um indicador fundamental para o sucesso acadêmico do aluno, principalmente no ambiente on-line, onde os alunos podem estudar em qualquer lugar e a qualquer momento. Neste trabalho, analisamos registros da interação do aluno iniciante em programação com um ambiente de aprendizado on-line. Os resultados apresentam indicadores de fraco e bom engajamento, e podem guiar os professores na escolha de estratégia de ensino mais adequadas de acordo com a necessidade de cada indíviduo.*

1. Introduction

Several factors influence student learning experience. The method of teaching, students' background, and engagement are an example of these factors. Recently, researchers focused their attention on student engagement because there is a robust correlation with positive outcomes of student success [Fredricks and McColskey 2012]

Student engagement is concerned with "the interaction between the time, effort and other relevant resources invested by both students and their institutions intended to optimize the student experience and enhance the learning outcomes and development of students and the performance, and reputation of the institution" [Trowler 2010, Fredricks and McColskey 2012].

Some academic behaviors can signal student engagement. They include regularly attending class, paying attention, participating in instructional activities and class discussions, devoting out-of-school time to studying and completing homework, among others [Farrington et al. 2012].

Creating an enjoyable educational environment and encouraging student engagement is a big challenge [Harris 2008]. A way to improve the learning experience is the

DOI: 10.5753/cbie.sbie.2019.51

usage of technology to support education. The technological support allows students to stay connected to the learning environment anywhere and anytime, changing the learning experience [Coates 2007].

Learning Management System (LMS) aims to support students in dealing with difficulties and improving their performance. It provides tools for course administration and pedagogical functions for designing, building, and delivering scalable learning environments. They help the resource delivery, communication, keep track of activities and assessments, collaborative work, and student management [Dixson 2015].

This study explores the online student engagement of a programming course. We developed a study case in an introductory programming course in which instructors adopted a blended strategy of teaching: face-to-face and online. In a face-to-face class, teachers expose lectures and clarify student doubts. Whereas in practice classes, students answer quizzes and submit the answer of programming assignments through an online system.

In programming education, students develop several programming assignments using LMS. In this study, we tracked the students' interaction with LMS in order to outline their online engagement. So, we intend to profile the novice programmer's behavior in order to help teachers to know who can be on the right learning track and those who can need additional help.

To achieve this objective, we propose a set of indicators of student engagement and correlate them to academic performance. Results show that these metrics can signal how learner progress in the course and allow teachers for monitoring the development of learning activities and define suitable teaching strategies tailored to the needs of each student.

2. Background

2.1. Student Engagement

Student engagement is has been seen as a valid indicator of academic success [Fredricks and McColskey 2012]. It is defined as the interaction between the time, effort, and other relevant resources invested by both students intended to optimize the student experience and enhance the learning outcomes [Trowler 2010, Fredricks and McColskey 2012].

There are three components of student engagement. Behavioral involvement is evidenced by participation in academic, social, or extracurricular activities. Emotional engagement encompasses reactions to relationships with teachers, peers, and institutions. Also, cognitive engagement represents the effort required to understand complex ideas and develop difficult skills [Fredricks and McColskey 2012].

There are some examples of methods to measure engagement. Self-report, interview, and teacher rating are the most common because they are often the most practical and easy to administer in classroom settings. Self- report measures and interviews depend on the answers of students, while the others of the teacher's observation.

2.2. Learning Management System

Learning management systems (LMS) is an Internet-based platform which holds an essential position in higher education. It integrates teaching, learning, and administrative tools for students and teachers. It includes learning platforms, content management systems, and virtual learning environments [Coates 2007].

An LMS intends to enable administrators and mentors to manage the learning process. For this reason, its tools provide online access to course content like lecture notes, readings and quizzes; tools for communication and collaboration; and administrative tools [Coates 2007].

Because of the advantages of online environments, LMS allows students to take courses anywhere and anytime. So, it is widely applied in a face to face class and for the distance course [Dixson 2015].

3. Related Works

There are many studies on student engagement in online learning environments. In general, their focus is on user interaction through applied learning and high-quality course material design. We list in this section researches which give particular attention to student engagement in computing education as follows. Rahila [Umer et al. 2018] aims to predict students who are at risk of failing the course. The paper presents an analysis of assignments related information and engagement data. In that study, the engagement was measured by actions data like viewing course modules, reading forum posts, and submission of assignments. Results show that assignment scores are more discriminative than engagement data.

Gray [Gray and DiLoreto 2016] examines the factors that impact student learning outcomes and student satisfaction in asynchronous online learning courses. The study concludes that learner interaction did not have a significant impact on student satisfaction. On the contrary, both course structure and instructor presence had a substantial direct effect.

Dixson [Dixson 2015] tried to discover what activities might be expected to lead to more highly engaged students. A disappointing result was found: there is no significant difference in student engagement levels between those reporting active vs. passive activities. However, instructors should create opportunities for students to interact with each other not just with the content, and to require they do so.

The main difference among these papers and our research is the indicators used to measure the student engagement [Umer et al. 2018, Gray and DiLoreto 2016, Dixson 2015]. In our research, we suggest the usage of the duration of assignments and pace learning as an indicator of engagement, while these papers only use frequency of interaction.

4. Method and Materials

This research aims to profile the novice programmer's behavior and understand how students spend their time in learning activities. To profile the student behavior can help teachers to know who can be on the right learning track and those who can need additional help.

Our study was followed for these research questions:

- **RQ1**: How many time students spend on learning activities?

- **RQ2**: How do students progress in the course?
- **RQ3**: Is there any indicator of the online engagement related to student performance?

RQ1 aims to provide information about the participation of students in programming assignments during the course period. To achieve this objective, we used metrics related to the participation in learning activities in and out-class-time and the participation in extracurricular activities (simulators and marathons).

RQ2 aims to understand how students prograde in the learning of course content through the metric of **learning pace**. Finally, with RQ3, we intend to find a metric as a good indicator of student performance. For this reason, the data were divided into two groups based on students final performance on the programming course. Group A was formed by students those who had a final grade lower than 7.0 and group B who had a degree a greater than or equal. The student data were only included in the analysis if he/she did not give up before the end of the course.

A research ethics committee authorized the development of this study with CAAE number CAAE: 69427916.4.0000.5182.

To answer the abovementioned research questions, we analyzed records from the online LMS used in "Programação 1" and "Laboratório de Programação 1" of the undergraduate course Computer Science at the Federal University of Campina Grande.

The program content, LMS, teachers, and students of both classes are the same. The difference between them is the place where classes occur. "Programação 1" is in a traditional classroom, while "Laboratório de Programação 1" occurs at informatics lab.

The program is organized in small units content:

- Units 1 and 2 include basic programming elements;
- Units 3, 4, and 5 address conditional statements and loops;
- Manipulation of functions is seen in unit 6;
- data structures in units 7, 8, 9 and 10

The teaching styles used in both courses are based on an active method which includes self-paced, mastery learning, and flipped classroom. With self-paced and mastery learning, instructors break the whole class into a sequence of smaller learning units, each covering about two weeks' worth of material. Students stay in the current unit while hasn't mastery in the content. To advance to the next unit, learners have to demonstrate mastery standard in the assessment.

With the flipped classroom, the content delivery to learners occurs outside and in-class time. As homework, learners are told to study instructional materials, video, and books. In both at home and practice class, they should make assignments and answer quizzes. There are still facultative activities to emulate the assessment environment like a programming marathon and fake test.

The evaluation occurs weekly and has two questions for each content unit. Learners are approved if submits the correct answer to two exercises from the current unit. They can correctly answer one question in test 1 and another in test 2, and even so, be approved in the unit. When an individual is approved, he/she progress to the next unit.

4.1. TST

TST is a Learning Management System developed by a Computing Educational Group from the Federal University of Campina Grande. It has been used to support the teaching process of the Programming Course since 2010. In this online system, teachers can create, update, and remove programming exercises and exams, besides monitor class' progress. Furthermore, TST allows learners to read and solve activities, submit source code, answer a quiz, and track their progress, among others.

TST presents a database of programming exercises grouped by the content unit, which helps the delivery process. Teachers are responsible for planning exercises delivery based on student' progress. They are also responsible for managing the time limit for students to submit their answers according to the learning activity. Exams, simulators, and marathons have a time out to submission, opposite to other modes of activities (quiz, programming assignments).

Students can interact with TST in many ways. They can log in on the system, request new learning activities, submit answers, check if the solution is correct, close activity, among others.

We are mainly interested in a subset of data stored by TST, which includes information about the events of the request and close assignment. An event represents when a user read (open) or close a learning activity.

The trace record used in this study is similar to a list of events. For each one, we extracted the following data from the track record:

- Student id;
- Date and time;
- Learning Activity: content unit, status (opened or closed), mode (exercise, simulator or exam);

5. Indicators of Online Student Engagement

In this study, we believe that student is studying while she/he is interacting with LMS. So, we considered the period and how many times learner is contacting TST as a good indicator of engagement.

We proposed some metrics to understand the student's behavior in an online environment. We use the term **study session** to represent a period in which a student interacts with TST. In our case, the interaction occurs when a user opens or close learning activity.

We divided study time into two moments: *thinking-time* and *break-time*. In our study, the first moment represents the time in which student is focused on to study, thinking, or solving an exercise. While *break-time* is when the student is not engaged in the study doing activities outside of TST. In general, a student spends more time in *break-time* than in *thinking-time*, that is *break-time* is longer period than *thinking-time*.

Figure 1(a) presents time intervals between all events. In 1(a)). In Figure 1 (b), we searched for the point which split small ones from long intervals like as in [de Araujo et al. 2013] and highlight where the range of 23 minutes. After 23 minutes, time interval values increase in more significant proportions.

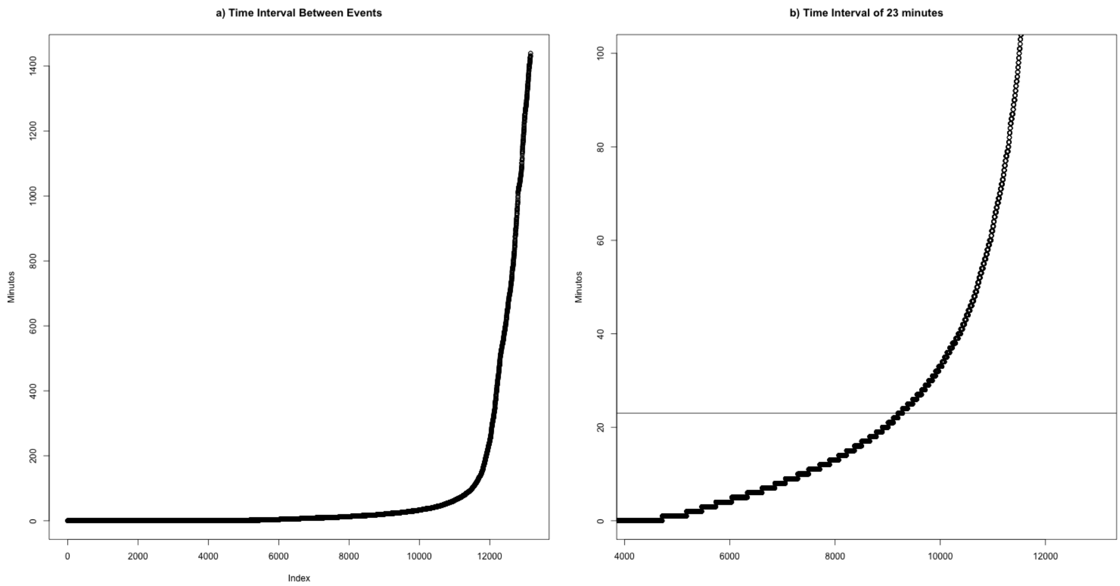

Figure 1. Time Interval between Events

Based on the intervals, we proposed a metric called study session, which includes all events that occurred for a period of fewer than 23 minutes. For example, Figure 2 shows examples of five events on 10/10/2017. At ten o'clock, a student reads an assignment (E1), and solve it after twenty-two minutes (E2). An hour later, she/he reads three activities resulting in events E4, E5, and E6. The time interval between E1 and E2 is less than 23, so both are in Session 1. Unlike between E2 and E3, the range is higher than 23. In this example, we recorded two events in Session 1 and three events in Session 2.

Figure 2. Study Session

We also proposed an indicator named **learning pace**. It suggests how learner progress in the stage of the course, and can help teachers to know who can be on the right learning track and those who can need additional help.

We consider the relationship between the evaluation result and the total of exams as ongoing progress. For example, if in the first test, a learner has been solved two questions of unit 1 and two questions of unit 2, his learning pace is **2** units per test.

The development of homework and participation of extra-class activities are good indicators of student engagement. We registered assignments made out of class time as homework. And the participation in optional activities, like programming marathon and fake test, as indicators of extra-class activities.

6. Results and Discussion

During the semester 2017.2, there were 100 students enrolled in theory and practice programming courses. However, about 16 of them drop out or failed the course. So, we analyzed the data of the remaining 84 students who solved 450 questions during 151 days and generated a track record with 14320 events.

6.1. RQ1: How many time students spend on learning activities?

The study sessions of learners varied between 4h51m and 44h29m, with an average of 18h19m. This shows that there is a difference of more than 900 % between the two extremes, which may mean that some students study hard, while others have studied very little. During the sessions, a total of events ranging from 143 to 718 were recorded, with a mean of 341.4.

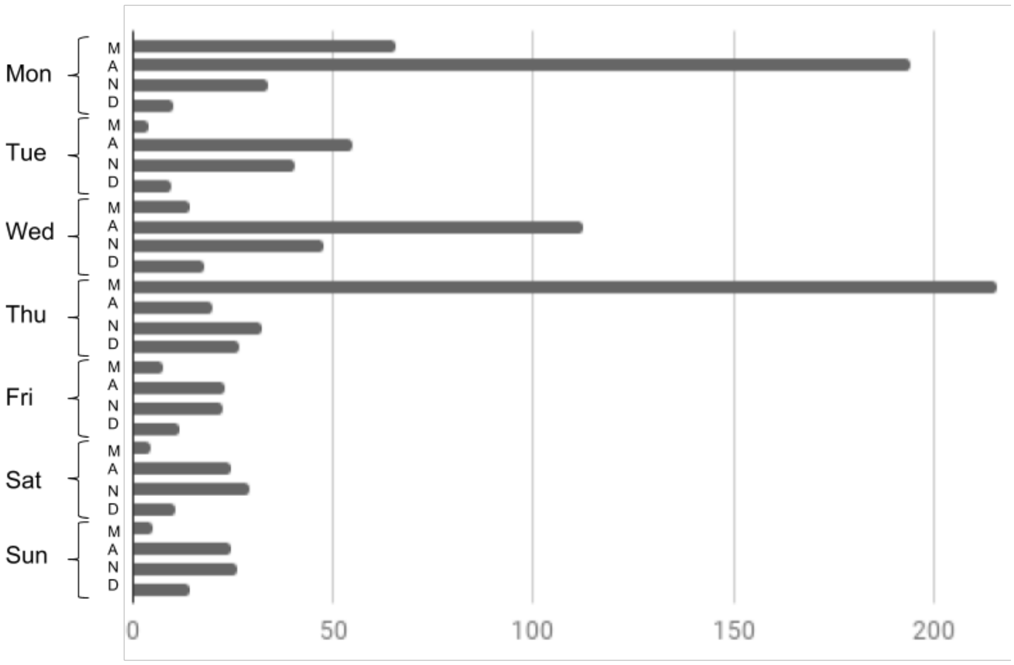

Figure 3. Study Routine

In analyzed semester, classes have occurred on Monday, Wednesday, and Thursday in the morning. And we divided days in four shift: **D**awn, **M**orning, **A**fternoon and **N**ight. Figure 3 presents the study routine and how it occurs over the week. It shows a study peak in exam time on Thursday in the morning. There are other study peaks on Monday in the afternoon and Wednesday in the afternoon. It also suggests that students were dedicated to homework. The first case occurs after a theoretical lesson, while the second occurs on the eve of the assessment. So, we realized that students study more when they are next to class days, and the majority of assignments is made as homework.

The total number of completed questions ranged from 49 to 334, with an average of 147 activities. The number of assignments made outside of class time ranged from 43 to 321, with an average of 140. Comparing the data, we realized that about 97.5 % of the questions are resolved outside of class time. The number of activities solved during the simulation ranged from 0 to 41, with a mean of 21 questions.

6.2. RQ2: How do students progress in the course?

On average, class achieves 1.6 units per test as learning pace. About 54 % of the students had 0.5 unit per mini-test or one question per exam while 2.3 % of the students did five exercises per test.

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Intending to profile student's behavior, we grouped students into two groups based on students final performance on the programming course. Group A was formed by students those who had a final grade lower than 7.0 and group B who had a degree higher than or equal.

Figure 4 presents the difference among values of learning pace from group A and B. The lowest learning rate of group A is 0.5, and the highest is 1.42. Already in group B, the value ranges from 1.08 to 5.

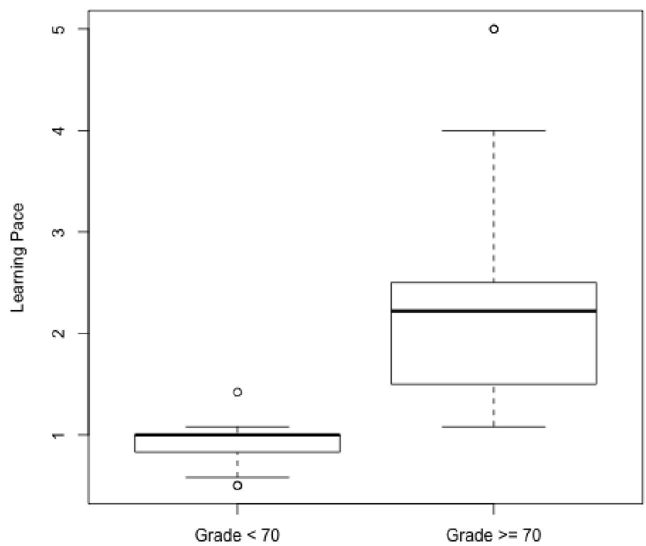

Figure 4. Boxplot graph of Learning Pace: Group A x Group B

Regarding the duration of sessions, group A presented between 291 and 1721, with an average of 833.4. Group B, on the other hand, had meetings between 456 and 2669, and on average of 1299. Concerning the number of events during the sessions, group A is lower than in group B.

Concerning participation in optional learning activities, group A did between 4 and 29 questions, with an average of 19.08. Group B was between 0 and 41, with a mean of 23.5. Using the test t and with a *p-value* = 0.00171, we conclude that group B made more questions in simulations.

With values of learning pace, study session, and participation in optional activities, we can profile a student's behavior of group A. They study during a short time, made fewer assignments, and have less participation in extra-class activities.

Table 1. Correlation between Indicators of Student Engagement

Metrics	**Assign. Made**	**Sim.**	**at Home**	**Pace**	**Session**	**Event**
Sim.	0.34					
at Home	**0.93***	0.32				
Pace	0.25	0.25	0.27			
Session	**0.80***	0.31	0.79	0.31		
Event	**0.91***	0.35	**0.88***	0.20	0.76	
Perform.	0.27	0.25	0.28	**0.82**	0.33	0.22

Table 2. Correlation With Student Performance

Cor.	**Act. made**	**Sim.**	**Study Sessions**	**Events**	**Pace**	**Out. class**
kendall (τ)	0.2736	0.2519	0.332	0.2221	0.8238	0.2867
spearman (ρ)	0.3862	0.3561	0.4727	0.3099	0.9415	0.4097

6.3. RQ3: Is there any indicator of the online engagement related to student performance?

To answer RQ3, we test the normality of metrics using *Shapiro-Wilk* method. We note that the data does not follow a normal distribution because all values of *p-value* were less than 0.05. For this reason, we chose the *Kendall* method to calculate the τ value and estimate the correlation among these metrics.

Table 1 presents the τ value as well as the correlation between the metrics. We highlight the *strong* correlation between the *learning pace* and the *student performance*. We marked with an asterisk (*) the correlation among assignments made and duration of sessions, the number of events and assignments made, and quantity of assignments made at home and quantity of events. All of them have a strong correlation. The strongest correlation is registered among assignments made and homework revealing how much more the student engages in the home study, the more tasks he or she does. The relationship among homework vs. number of events ($\tau = 0.88$) reinforces this conclusion. The correlations registered among the assignments made and the number of events ($\tau = 0.91$) is explained by to make an assignment, the system generates at least three events in the execution trail (read, submit and close). The correlation among the session duration vs. assignments made ($\tau = 0.80$) can indicate how much more the student make assignments, the more time he or she maintain interacting with TST.

Table 2 shows values resulted of the correlation between indicators and student performance. We chose *Kendall* and *Spearman* methods to calculate the τ and ρ values and estimate the correlation among these metrics. We highlighted in grey τ and ρ values of learning pace describing correlation with student performance.

With the analysis of these values, we can profile a students' behavior of high academic performance. They prograde faster, spend more time on homework, make more assignments, and involve in extra class activities.

7. Conclusion

In this study, we aimed to profile an online student engagement in an introductory programming course. As well as the general feeling of teachers, we realized that students study more on the eve of the evaluation. However, there is an increase in study time in the shift after the theoretical lesson. We corroborated that learners who prograde faster, spend more time on homework, make more assignments, and involve in extra class activities tends to have good academic performance.

The main weakness of this study was the assumption that the student is studying if she/he is interacting with LMS.

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