Analyzing Student Programming Paths using Clustering and Process Mining

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Abstract: Learning programming is becoming more and more common across all curricula, as seen by the growing number of tools and platforms built to assist it. This paper describes the results of an empirical study that aimed to better understand students' programming habits. The analysis is based on unsupervised classification algorithms, including features from previous educational data mining research. The k-means method was used to identify the behaviors of six students profiles. The main and interaction impacts of those behaviors on their final course scores are tested using analysis of covariance.

1 INTRODUCTION

Computer literacy is currently booming. In Europe, particularly Germany, and the United Kingdom, profound educational transformations have been initiated since 2016 to promote digital learning in schools and prepare learners to acquire 21st-century skills, including programming. In France, an educational reform of High School curricula launched in 2019 offers a Digital and Computer Science option that includes more than 350 hours of programming learning. This interest in integrating programming learning skills early in the curriculum requires prepared teachers and technological solutions to support them and their students in their daily practices.

To enhance the instructional scaffold offered to learners and help instructors make meaningful pedagogical decisions, researchers have been interested in developing new approaches and tools to support learning programming (McHugh, 1998; Luxton-Reilly et al., 2018). Recent initiatives based on big data collections combined with data mining approaches aim at discovering hidden patterns and better understanding learners' behavior (Sharma, 2015; Spacco et al., 2015), as previous research have shown that the choice of resolution strategies in programming affects learners' performance (Soloway et al., 1983).

Therefore, it is worth investigating what factors influence student achievement in learning programming. The present study examines students' behavior at a fine granularity level of analysis where we have looked for students' behavior at each exercise activity. This approach goes beyond basic statistics or predictive models based only on features. Learner behavior analysis allows teachers/ITS (Intelligent Tutoring Systems) to take the appropriate actions.

Consequently, the study addresses the following research questions:

- How can we identify learners' programming behavior?
- What behavioral interactions lead to success/failure in a programming course?

The paper is structured as follows. The following section presents prior work, whereas Section 3 exposes the research context and presents how this study was designed. Section 4 presents the obtained results. Finally, the conclusion and future works are presented in Section 5.

2 STATE OF THE ART

In state of the art about analysis of students' programming behavior, we can find two main research orientations to analyze students' behavior and predict success in programming. The first is based only on features extracted from the programming activities such as the number of submissions, the number of compilation, the difference in code edit, etc. and the second is interested in students' educational background and

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external factors such as previous academic year and computer experience, cognitive skills, personal information, performance in other modules, etc. (Bergin and Reilly, 2006; Bergin and Reilly, 2005). While others combine the two categories, two obtain multiple data sources for analysis (Koprinska et al., 2015).

Analysis of students' learning behavior has been a significant focus for MOOC learning analytics (Boroujeni and Dillenbourg, 2018; Jiang Zhuoxuan and Xiaoming, 2015). Like Edx and Coursera, MOOC platforms usually provide comprehensive logs of students' interactions with the MOOC platform. These data enable researchers to perform learning behavior analytics at many different granularities, and behavior categories in MOOCs (Wang et al., 2019).

On the other hand, numerous studies have been carried out on information extracted from programming, thanks to the availability of a wide range of tools dedicated to learning programming. Thus, researchers have become increasingly interested in collecting log data on students' programming processes from these platforms and tools to analyze and predict success/failure in programming.

Sharma et al. (Sharma K., 2018) and Adam et al. (Carter et al., 2015) compute features per set of exercises to predict success in the coding exercises. Indicators from students' testing behavior, reflecting the time and effort differences between two successive unit test runs, were used. The authors tried to show differences in students' strategies within different success levels based on the success in the coding exercises. However, using only one local indicator (success of the exercise) can give only a local insight into students' strategies, which could not show how students evolve.

Wang et al. (Wang et al., 2019) present a work where they feed the embedded program submission sequence (as an AST: Abstract Syntax Tree) into a recurrent neural network and train it to predict the student's future performance. This method focuses on a student's sequence of submissions within a single programming exercise to predict future achievement. By training on these tasks, the model learns nuanced representations of a student's knowledge, exposes patterns about a student's learning behavior, and reliably predicts future performance.

In his paper, Blikstein (Blikstein, 2011) describes an automated technique to assess, analyze, and visualize students learning computer programming. He employs different quantitative techniques to extract students' behaviors and categorize them in terms of programming experience.

The review of these studies highlights two critical points. First, in most studies, students' programming behaviors have been measured in a single activity (i.e., at the level of one exercise, one course) without flushing out possibly essential relations with other analysis levels. Second, recent studies mainly use supervised algorithms to predict students' performance, which requires a pre-processed and annotated dataset. Unfortunately, annotating a dataset is a rather tedious process that can be the source of errors. This algorithm tends to work better when more and more data are provided, whereas, in Learning Analytics, the number of learners in a course is an actual limitation.

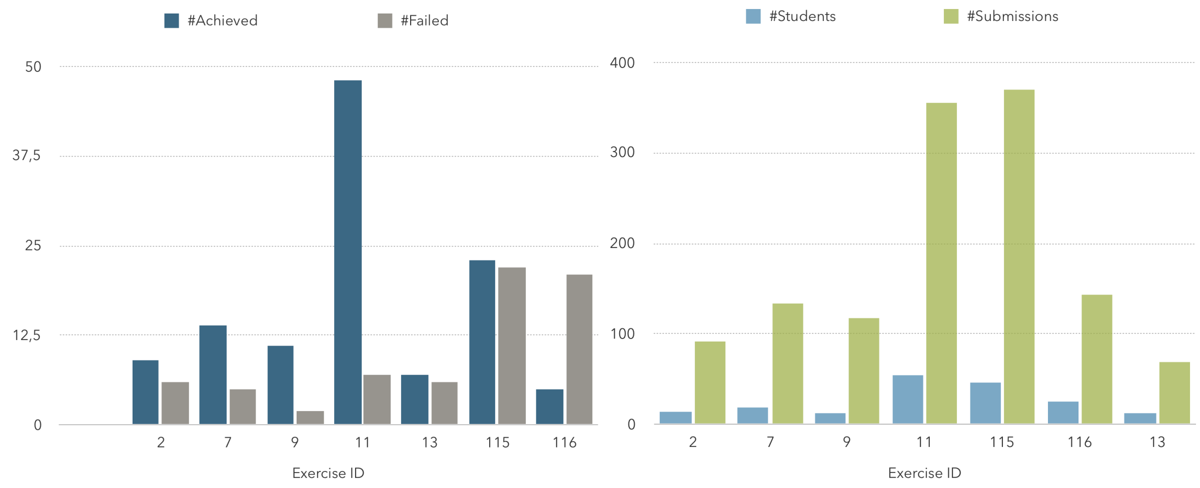
This paper aims to identify the different students' programming behavior and the possible interactions between these behaviors while finding out the relationships with students' performance. Using clustering, we have tried to identify which students are alike and potentially categorize them therein. After that, and using those categories, we have used process mining techniques to look for the significant events in the process of solving exercises in programming for first-year students.

3 DESIGN OF THE STUDY

In this section, information about the design of the study is provided. We introduce the instrument used to identify learners' behaviors and the selected features used.

3.1 Context

The study involves 61 first-year students of an introductory C++ programming university course. Students did not have prior programming knowledge, but they mastered basic operations to use a computer system. The course includes theoretical sessions and one hands-on session of 2 hours per week. In addition to these hands-on sessions, students were suggested to use an automatic assessment tool called *Algo+* for solving some programming exercises in hands-on sessions with an interval of two weeks. This time-interval aims to obtain a significant evolution of students' behavior. *Algo+* lets students write and run their code and returns immediate feedback as an automatic grade assessing students' programs based on unit tests *Algo+*. Seventeen exercises were available through *Algo+* to address different concepts of programming taught during the theoretical sessions. These exercises were defined and described in terms of the relevant competencies of the course. Students had the opportunity to browse the set of exercises and engage in all, some, or none of the exercises. In other



(a) Number of achievements/failures

(b) Number of students and submissions

Figure 1: Data distribution per exercise.

words, exercises deployed in *Algo+* were not mandatory; they were available to students for additional training material. At the end of the course, students were delivered a practical exam to evaluate their skills in C++ programming. Teachers evaluated each exam manually and assigned a score on a scale between 0 and 20, where 0 is the lowest mark and 20 the maximum.

3.2 Data Collection and Selected Features

Data collection was ensured by *Algo+*. Each time a student submits a source code, the following data are collected: (1) the source code of the submission and, if any, (2) the compiler errors; (3) the submission score computed by *Algo+*; and (4) the timestamp of the submission. Among the 17 exercises, seven of them were solved by 61 students. In total, 1282 submissions have been produced by the students. Figure 1 shows the data distribution for these seven exercises.

Starting from the raw data collected by *Algo+*, we computed the following indicators:

- Number of submissions: number of submissions produced by each student.
- Progress: percentage of submissions that passed at least one unit test.
- Syntactic: percentage of submissions that failed to compile.
- Error: percentage of submissions that failed all unit tests.
- Avg. code modification: the average number of tokens (i.e., words) changed between two submissions.
- Avg. time spent: the average time (in seconds) elapsed between two submissions.

Also, we used the students' final course score to investigate how the behavioral interactions are related to students' success. This final course score was used as a dependent variable. Our goal is to explain students' behaviors from her/his activity and the relation with the final course score. The normality of the scores was verified with the Shapiro-Wilk test, and we categorized students into two groups according to their score: At-Risk (score < 10) and Good (score ≥ 10).

Also, we used another variable provided by *Algo+* that represents the achievement of the exercise. An exercise is considered as achieved/failed if a student has proposed a solution that has passed all/not all unit tests.

4 RESULTS

In this section, we will present the results obtained during the analysis of the collected data. We tried to analyze students' behaviors in each exercise. We used k-means with features described in Section 3.2 computed in each exercise. Six groups of profiles have been identified. The characteristics of each cluster are described in Table 1.

ANOVA tests were conducted to validate the clustering results using the clusters as the independent variable and the features as the dependent variables. Results of these tests are reported as follows :

Table 1: Mean and standard deviation of each feature (clusters of level2).

ID	Size	*#Submission*	*%Progress*	*%Compilation*	*%Error*	*Avg.Code*	*Avg.Time*
C1	19	4.3 ± 3.9	32.2 ± 24.0	8.1 ± 13.1	4.9 ± 9.0	3.3 ± 4.9	1.4 ± 1.6
C2	9	4.5 ± 1.7	0.0 ± 0.0	26.5 ± 14.2	51.4 ± 5.3	47.9 ± 21.1	15.3 ± 24.4
C3	57	7.7 ± 6.1	1.6 ± 4.9	88.0 ± 11.9	3.0 ± 5.4	3.1 ± 4.3	1.3 ± 1.2
C4	23	4.6 ± 3.1	10.5 ± 14.7	6.3 ± 10.0	45.3 ± 6.0	9.3 ± 8.1	2.9 ± 4.7
C5	26	5.8 ± 9.8	0.7 ± 2.5	4.3 ± 8.6	85.6 ± 15.2	3.7 ± 5.7	1.2 ± 2.3
C6	52	8.8 ± 6.3	4.2 ± 8.4	49.9 ± 12.4	30.1 ± 12.6	8.1 ± 6.7	2.0 ± 2.1

- Significant difference on the number of submissions ($F[5,180] = 2.83, p = .01$): post-hoc pairwise comparisons show that Cluster6 has a high number of submissions than Cluster1 and Cluster4.
- Significant difference in the percentage of submissions that passed some of the unit test (progress) ($F[5,180] = 28.12, p < .001$): post-hoc pairwise comparisons show that Cluster 1 has a high percentage of submissions in progress than all clusters. Thus Cluster 4 has a significant high percentage of submissions in progress than Cluster 5.
- Significant difference in the percentage of syntactical errors ($F[5,180] = 309.5, p < .001$): post-hoc pairwise comparisons show that Cluster3 has the highest percentage of syntactical errors. Cluster6 has a high percentage of syntactical errors than Clusters 1,2,4 and 5 while Cluster 2 has a high percentage of syntactical errors than Cluster 4 and 5.
- Significant difference on the percentage of erroneous submissions ($F[5,180] = 285.7, p < .001$): post-hoc pairwise comparisons show that Cluster 5 has the highest percentage of erroneous submissions than all clusters. Cluster 2 has a significant high percentage of erroneous submissions than Cluster 1,3,4, and 6. Also, Cluster 4 has a high percentage than Clusters 1, 3 and 6.
- Significant difference in the average number of changes between two submissions ($F[5,180] = 61.7, p < .001$): post-hoc pairwise comparisons show clearly that Cluster 2 makes important changes than the rest of the clusters. Cluster 4 and Cluster 6 make more code changes than Cluster 3.
- Significant difference on the average time spent between two submissions ($F[5,180] = 10.21, p < .001$): post-hoc pairwise comparisons show that Cluster2 has a significant average spent time more than all clusters.

Using the cluster characteristics in Table 1, we describe each learner profile as follows.

Cluster1 represents students who are good at designing the global solution, but they commit syntactical errors due to their haste to get the assessment result.

Cluster 2 represents students who move from one solution to another and change the code profoundly after each submission.

Cluster3 represents students who have difficulties compiling their code.

Cluster4 represents good students; they take time to conceive a solution.

Cluster5 represents students having difficulties designing solutions; they do not spend enough time on program design.

Cluster6 represents students who submit many submissions to get feedback and improve the submitted code; they learn from their mistakes.

4.0.1 Validation using Achievement/Failure per Exercise

A second validation of these 6 clusters is examining the relationship between achievement/failure. A chi-square test of independence was performed to examine the exercise and the six clusters.

The relation between these variables was significant, $\chi^2(5, N = 209) = 39.93, p < .001$. The 6 clusters are associated with the success/failure of exercises. Besides, we want to validate the 6 clusters according to the final exam score. To achieve this objective, we need a student overview of adopted behaviors during programming activities. The next section introduces this representation and presents the analysis.

4.0.2 Validation with the Course Final Score

To obtain an overview of students' behavior in all exercises in terms of the six identified behaviors, we represented students as 6-dimensional vectors to specify each cluster's percentage. In other words, we build a global representation of students in terms of the six clusters (see 1) obtained from the analysis. The six values of each student represent the percentage of how much the student has adopted each behavior.

First, the correlational relationship between clusters and the final course score has been investigated.

Table 2: ANCOVA analysis of effect of each cluster on students' academic achievement.

	Df	Sum Sq	Mean Sq	F value	Pr($>F$)
c1	1	75.20	75.20	11.198	0.00221 **
c2	1	7.85	7.85	1.169	0.28821
c3	1	16.08	16.08	2.395	0.13224
c4	1	0.04	0.04	0.005	0.94162
c5	1	21.88	21.88	3.258	0.08113 .
c1:c2	1	6.90	6.90	1.028	0.31870
c1:c3	1	2.23	2.23	0.332	0.56906
c2:c3	1	17.52	17.52	2.609	0.11673
c1:c4	1	0.41	0.41	0.061	0.80590
c2:c4	1	0.01	0.01	0.001	0.97163
c3:c4	1	4.14	4.14	0.616	0.43877
c1:c5	1	10.02	10.02	1.492	0.23136
c2:c5	1	0.11	0.11	0.016	0.90008
c3:c5	1	29.82	29.82	4.441	0.04355 *
c4:c5	1	17.01	17.01	2.534	0.12193
c1:c6	1	2.14	2.14	0.318	0.57690
c2:c6	1	53.54	53.54	7.974	0.00835 **
c3:c6	1	8.05	8.05	1.198	0.28237
c4:c6	1	13.11	13.11	1.953	0.17253
c5:c6	1	8.50	8.50	1.265	0.26955
c1:c3:c4	1	9.65	9.65	1.437	0.23994
c1:c3:c5	1	83.49	83.49	12.433	0.00138 **
c1:c4:c5	1	0.02	0.02	0.003	0.95437
c3:c4:c5	1	0.35	0.35	0.052	0.82193
c1:c3:c6	1	1.11	1.11	0.166	0.68665
c3:c4:c6	1	11.70	11.70	1.742	0.19685
c1:c5:c6	1	9.36	9.36	1.394	0.24696
c3:c5:c6	1	0.43	0.43	0.065	0.80118
c4:c5:c6	1	16.26	16.26	2.422	0.13014
c1:c3:c5:c6	1	2.19	2.19	0.326	0.57249
Residuals	30	201.46	6.72		

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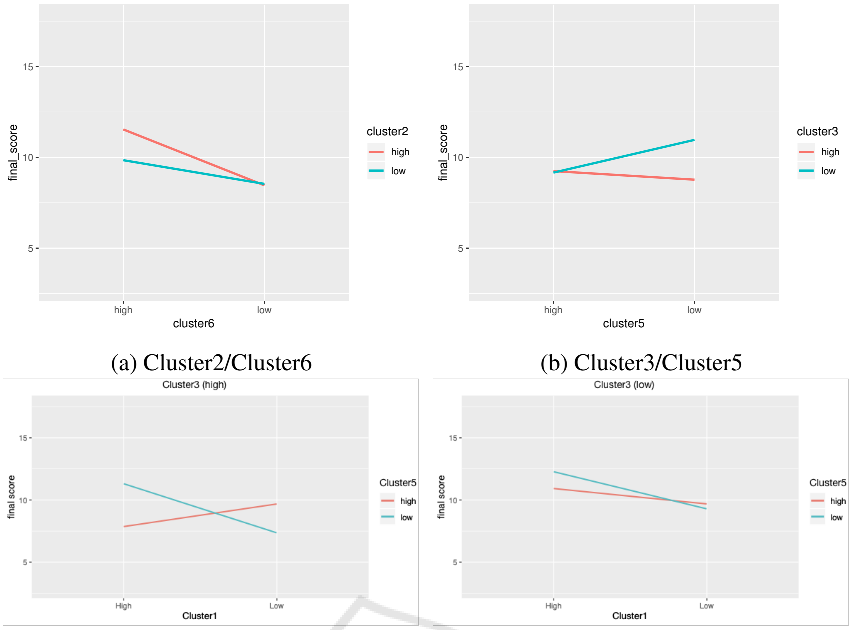
We found that only Cluster1 has a significant positive correlation with the final course score while Cluster3 has an almost significant negative correlation $(0.34, p < 0.05)$.

To investigate more about the relationship between the other behaviors and the final course score, an Analysis of covariance (ANCOVA) was used. ANCOVA is a statistical technique we can use when we want to focus on the effects of the main response variable on other variables' effects. The ANCOVA design is quite similar to the ANOVA design but includes one or more variables as explanatory variables. It was assumed that the regression coefficients between groups were homogeneous (Keppel, 1998). This test is conducted using the final course score as the dependent variable, and the 6-dimensional vector will be the student's attitude in the analysis of covariance (ANCOVA). This test shows a significant effect of the six clusters on the final course score, $F(2,30) = 2.30, p = .02$. The ANCOVA analysis results in Table 2 show that only Cluster1 behavior has the significant main effect, $F(1,61) = 11.19, p < 0.05$, which means that students who adopt the behavior of cluster1 have high final exam scores. On the contrary, students who do not adopt this behavior have low final exam scores.

According to this cluster's characteristics, students adopting this behavior are good at designing the solution for a given problem. They have a remarkable progress rate, joining previous research findings on analyzing programming activities (Lisa Wang, 2017; Bey A., 2019).

However, we found three highly significant interactions effects between behaviors. 2 illustrates these interactions. For ease of comparison, we have categorized the continuous values of the six variables that express behaviors into two categories: Low ($value <$



(a) Cluster2/Cluster6 (b) Cluster3/Cluster5

(c) Cluster1/Cluster5 (d) Cluster1/Cluster5

Figure 2: Significant interactions of clusters that affects students' academic achievement score.

50%) and High ($value \geq 50\%$).

The significant interaction between Cluster3 and Cluster5 ($F(1,61) = 4.44, p = .04$) indicates that the relationship between Cluster3 and the final score depends on the Cluster5. Figure 1(b) shows that when Cluster5 is high, there is no effect of Cluster 3 on the final score. According to the characteristic of clusters, when a student has problems designing solutions (Cluster5), whether they have syntactic problems or not, this negatively affects the final score. However, when Cluster5 is low, there is a negative relationship between Cluster3 and the final score.

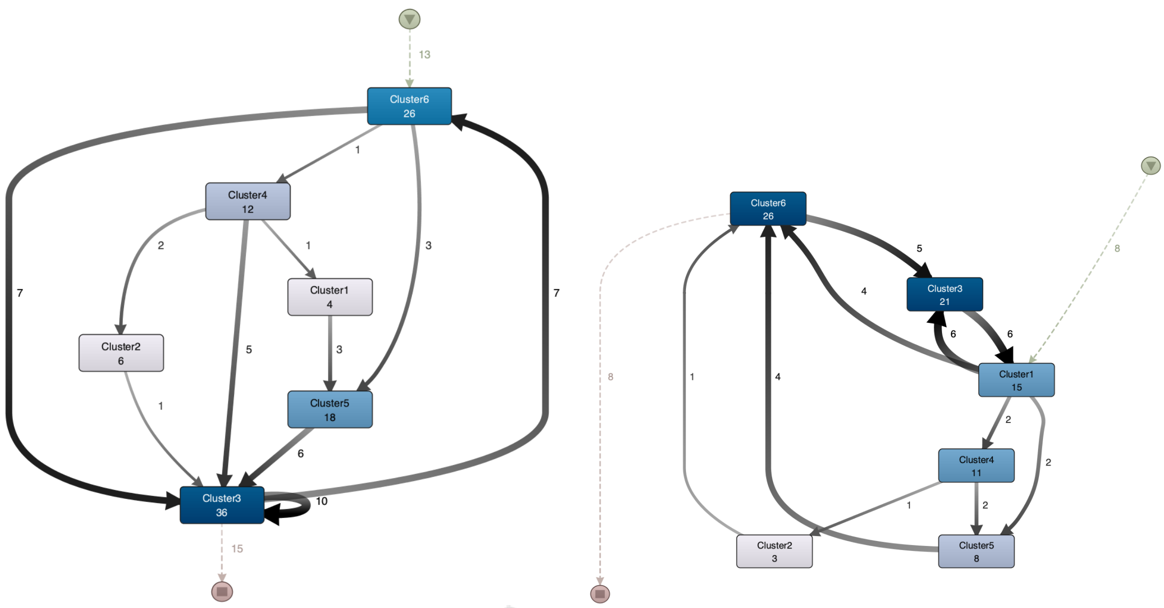
The second significant interaction is between Cluster2 and Cluster6 ($F(1,61) = 7.97, p = .008$). As shown in Figure 1(a), there is a positive relationship between Cluster2 and the final score when Cluster6 is high. However, when Cluster6 is low, there is no effect of Cluster2 on the final score, and it depends on Cluster6. According to these clusters' characteristics, students who make large changes in their code before submitting (Cluster2) obtain a high score when they frequently submit (Cluster6).

Finally, the last significant interaction is between three clusters: Cluster1, 3 and 5 ($F(1,61) = 12.43, p = .001$). That indicates that the impact that Cluster1 has on academic achievement depends on Cluster3 and Cluster 5 and reciprocally. When Cluster 3 is high, the score generally depends on Cluster1 and Cluster5. Figure1c shows that the final score is high when Cluster1 is high and Cluster5 is low. According to these clusters' characteristics, these can be explained by the fact that students who take time to conceive a solution (Cluster1) have a negative relation with students who have difficulties designing the right solution (Cluster5) in terms of achievement. However, when Cluster3 is low (Figure 1(d)), we can observe little interactions between Cluster1 and 5, which means that when students have not serious problems in compiling codes (characteristics of Cluster3), the success of students depends mainly on the fact that students are good or not in designing solutions.

5 MINING THE TRAJECTORY PATTERNS OF HIGH AND LOW PERFORMING STUDENTS

Different methods have been used to investigate the navigation patterns of learners. In our case, we use process mining techniques to inspect trajectory patterns of high and low-performing students. Process mining provides a set of algorithms, tools, and techniques to analyze event data (van der Aalst, 2011). Among the main perspectives offered by this domain is discovery. Discovery techniques allow the interpretation of process models from log data.

Process discovery entails learning a process model from the event log. An event log was built from the clusters obtained in the second phase of analysis (see



(a) At-Risk Students (b) Good Students

Figure 3: Process models for each of good and at-risk students (100% activities, 0% paths detail-only most important flows are shown). There are 6 activities corresponding to the six behaviors. The coloring indicates the frequency of the behavior.

Table 3: The created event log used by the process mining.

Student.ID	Activity(Clusters)	Categories
1	Cluster1	at-risk
1	Cluster2	at-risk
1	Cluster2	at-risk
1	Cluster2	at-risk
2	Cluster3	good
2	Cluster3	good
2	Cluster3	good
...	...	...
...	...	...

3).

We built this event log using the clustering results. As we can notice, we did not use any timestamp because this section aims to find out behavioral changes of at-risk and good students. This event log is used as an input to process mining algorithms to visualize and enact students' actual behavioral trajectory (sequential behavioral changes) (3).

The following difference can be detected when comparing the process flows for these two groups of students. The good students start most of the time as good at designing the global solution. They also commit some syntactic errors due to their haste to get the assessment result (characteristics of Cluster1) and because they are not used to the programming language's syntax. Their transitions from one behavior to another are often toward Clusters 3, which is characterized by the difficulties of compiling codes. Also, a loop between Cluster1 and Cluster3 was identified.

However, low-performing students generally start as trial-and-error; they submit many submissions to get feedback (Cluster6). A self-loop on Cluster3 was identified, which means that most low-performer students struggle to compile codes. Also, we can see a noteworthy loop between Cluster3 and Cluster6. Cluster5, which represents students with difficulties in designing solutions, is also adopted by this category of students who generally have difficulties compiling their codes (Cluster3).

These models confirm some results discussed in the ANCOVA analysis and explain how high and low-performer students change their behaviors.

For example, in high performer students (3b), Cluster1 is the first adopted behavior, which means (according to the characteristics of Cluster1, see Section 4) that the right attitude of students to take the time to design the solution before submitting is a critical aspect to achieve successfulness. After being in Cluster1, high-performer students could adopt the behavior of Clusters 3 and 6 most of the time. This could be explained by the fact that after designing the complete solution at the beginning (Cluster1), those students may have some syntactical errors that they tried to correct by compiling many times to get feedback about the syntactical errors.

However, low-performer students (or at-risk students in the 3a) start by belonging into Cluster6 and stay in CLuster3. This means that students who write a few codes and start by compiling to see the output and get feedback do not perform better according to the course final score.

6 CONCLUSION AND FUTURE WORKS

In this study, we attempted to discover the many behaviors that a beginner learner might exhibit when solving programming problems and how such behaviors might affect a student's performance. Clustering was used in an educational data mining technique to identify students' different groups based on their various programming behaviors.

We could elicit more complicated actions by using an exercise to seek out students' behaviors. We were able to determine which behaviors and types of connections between behaviors contribute to success or failure in a programming course, thanks to them. In other words, we can identify high and low-performing children by observing their behaviors and determining what is wrong with them so that appropriate aid can be provided.

The findings of this study are not about the actions themselves but rather how they can represent students' behavioral overviews and use this representation to predict success by identifying students' shortcomings and strengths. However, we must acknowledge that the current dataset is still insufficient, and we must confirm our research with a larger dataset.

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