Analyzing Students' Persistence using an Event-Based Model

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Abstract. In education, persistence can be defined as the students' ability to keep on working on the assigned tasks (e.g., exercises) despite the difficulties. From previous studies, persistence might be an important factor in students' performance. However, these studies were limited because they only relied on students' self-reported data to measure persistence. This article aims to contribute with a novel model to measure persistence from students' logs, which is general enough to be applied to different educational platforms. In this work, persistence is measured taking students' interactions with automatic correction exercises. Simple metrics such as the average of students' attempts are not valid for a precise calculation of persistence since some exercises should count more for persistence as they have been done incorrectly many times but with some limit so that a single exercise cannot bias the indicator; or when a student answers correctly we should not add new attempts. In this paper, we propose a model to measure persistence on exercises which is valid to many digital online educational platforms. The analysis of students' persistence shows that there are not statistically significant differences of persistence between students who drop out the course or not, although persistence is shown to have a positive relationship with average grades in most of the cases. In contrast, persistence is not related to engagement with videos. These results provide an initial exploration about students' persistence, which can be important to understand how students behave and to properly adapt the course to students' needs.

Keywords: persistence, learning analytics, students' behaviors.

1 Introduction

Digital learning platforms, such as Open edX and Moodle, offer the possibility to gather a lot of information about how students are interacting and engaging with the course contents. This information can be exploited to detect difficulties in the learning process so as to support stakeholders in decision making, for example, through visualizations and dashboards [1]. Students can face many possible difficulties, and these may lead to risk of dropout, failure, lack of engagement or motivation, etc. [2].

Among those difficulties, low persistence of students can also be a problem that could be analyzed through the analysis of students' interactions. There are many ways to define persistence. In general, persistence is a personality feature. In the educational context, many articles consider persistence as staying/continuing their degrees to complete them (e.g., [3-4]). For example, Kimbark et al. [5] considered students were persistent when they enrolled in the following spring semester. However, for many other authors (e.g., [6-7]), persistence is treated as a synonym of perseverance so that a student is considered persistent when he/she keeps on working on a task (e.g., an exercise) after trying to solve it incorrectly [6]. For this article, this latter definition will be considered, and from now, all references about persistence will treat persistence in this way. Particularly, we focus on specific activities in a course and persistence will be measured from interactions with individual exercises so that a student with high persistence is a student who attempts exercises again and again until the correct solution is obtained. However, persistence should not be the average of attempts, a typical indicator in many previous studies. We should only consider attempts until the student solve the exercise correctly. In addition, all exercises cannot count the same since some exercises enable the possibility of being more persistent. Moreover, a limit should be established so that single exercises cannot bias the indicator.

Research in this field has shown that being persistent can lead to a higher academic productivity [8] and academic achievement [9]. Muenks et al. [10] conducted several regression analyses and found that persistence was useful to predict grades, although self-regulated learning (SRL) and engagement variables achieved higher predictive power. Authors in [10] also concluded that SRL skills, such as effort regulation (ability to maintain effort/attention despite tasks are not interesting and there are distractors [11]) and cognitive SRL (which includes planning, monitoring and learning strategies, among others), can be related to persistence. However, high values of persistence do not necessarily mean that SRL skills are good because if students do not self-reflect on what they are doing after attempting each exercise, their learning might be only superficial [12]. Despite further research can be done, these findings suggest that although high persistence is not necessarily positive, low persistence can be negative since students with low persistence lack the ability to confront their problems with the tasks they solve incorrectly. However, these results may depend on the specific context.

In order to alleviate the problem of low persistence, it would be beneficial to be able to measure the level of persistence of students from their events when working in an online environment and know the prevalence of the correspondent behavior. Prior research work has mainly modelled persistence through self-reported data (e.g., [7-10, 13]), but no models have been defined to measure persistence from students' events in a digital platform. Self-reported data have many issues such as students might not be aware of their persistence or they might lie. The development of these models based on students' events would be useful because they would provide information to instructors that they could use to modify their materials and/or provide scaffolding questions (similar to some Intelligent Tutoring Systems [14]) in the exercises to make students easier to progress throughout the tasks and increase their persistence and engagement. Moreover, instructors may take actions to encourage their students to finish their exercises so as to modify students' behavior. Apart from that, if students are warned about their lack of persistence, they may also take corrective actions.

In this context, it is important to not only measure the persistence of each student but also to have aggregated data about the prevalence of persistence (i.e., how persistence is distributed among learners) to define actions. Furthermore, the course context and methodology are important factors because they may affect how persistent students are. For example, students might be more/less persistent depending on the importance/weight of the exercises within the course. Chase [15] also analyzed this issue and concluded that persistence could vary depending on the domain of expertise of the students (e.g., students can be more persistent in courses they find easier). Nevertheless, according to Csikszentmihalyi [16], if exercises are too easy/difficult, students may feel bored/anxious, and that may also affect persistence. Apart from the context, as mentioned above, there can be many other variables (such as academic achievement) that can affect or be affected by the persistence.

In this line, the aim of this paper is to determine a model to measure the persistence of students through their events related to exercises in a digital platform and obtain conclusions about students' persistence. Specifically, the objectives of this work are:

- O1. Propose a model to measure students' persistence based on their interactions in a digital platform.
- O2. Analyze the prevalence of the persistence.
- O3. Analyze how the persistence is related to other variables about students' behavior and performance.

The structure of the paper is as follows: section 2 presents an overview of what has been researched on detection of students' behaviors and particularly on persistence; section 3 describes the context and data collection techniques; section 4 details the model to measure persistence; the analysis and discussion of the results are provided in Section 5; finally, the main conclusions are detailed in Section 6.

2 Related Work

Many algorithms have identified variables related to students' personality [17], sentiments [18] and problems [19], such as heavy work load, among others. One of these possible personality features is students' persistence. Persistence, sometimes also referred as perseverance, is the students' ability to keep on working with effort on a task (e.g., an exercise) after facing difficulties (e.g., after getting a wrong answer) [20]. Many researchers have explored the persistence of students in different scenarios. For example, authors in [6] carried out a study with 10-to-12-year-old students who used a digital educational game. The game was designed to make students face exercises that were unlikely to be solved, and each time the student failed a question, he/she was presented with different options, which were used to measure students' persistence (e.g., continue working, get an easier exercise, take a break to play a game, etc.). Their study showed that students with higher persistence managed to solve tasks at higher difficulty levels. Moreover, Eley et al. [7] analyzed personality profiles from medical students and they found that 60% of them had a profile with high persistence and low harm avoidance (personality trait with tendency towards pessimism, anxiety and worry about problems), which can be important to succeed in medicine.

Furthermore, research has also focused in the analysis of how persistence can be related with other personality features. For example, Credé et al. [21] found a strong relationship between persistence and conscientiousness. Datu et al. [22] also analyzed persistence of Filipino high school students and found that persistence was a good predictor of behavioral engagement, emotional engagement and flourishing (i.e., optimal psychological state, characterized by optimism and great purpose in life [23]).

Apart from students' behaviors, researchers have also analyzed the relationship between persistence and academic performance, although results vary depending on the study. For instance, authors in [13] conducted relative weight analyses to evaluate the relationship between grit (a combination of students' consistency of interests in the topics and persistence for long term goals [24]) and found that the two elements of grit (consistency of interests and persistence) had weak predictive power. Similar conclusions were obtained by Bazelais et al. [25], who found persistence was not a significant predictor of course success, unlike prior academic performance. However, Meyers et al. [26] found that persistence was useful to differentiate between learners who drop out or not in secondary school. This finding was supported by Farrington et al. [27], who concluded that persistence has a direct relationship with grades.

Previous results suggest that more research is needed to analyze the relationship between persistence and success. Also, one of the limitations of the contributions in the literature is that they usually analyze persistence from self-reported data (e.g., [7-10, 13, 15, 20, 22, 25, 26]), and these data may be biased because of learners' beliefs and motivations. Few contributions, such as [28], measured persistence based on students' events. Particularly, they measured persistence as the time spent on attempts where the exercises were not solved correctly. In this article, we aim to contribute with the analysis of persistence based on students' interactions in a digital platform, and we focus on the attempts needed until the student correctly solves the exercise.

Specifically, this paper innovates with a method to measure persistence from students' events collected from the digital platform (objective O1). Moreover, the article also presents a novel analysis about the prevalence of persistence (objective O2) and the analysis of the relationship between persistence and other variables, such as dropout and performance (objective O3).

3 Description of the context and data collection

The analysis of students' persistence was carried out using data from SPOCs (Small Private Online Courses) [29], offered by Universidad Carlos III de Madrid. The institution has a local instance of Open edX and encourages professors to develop SPOCs as a way to support face-to-face courses. Particularly, three possible models of use are defined for the use of SPOCs: (1) SPOCs needed to pass the course or with an important weight in the final grade, (2) SPOCs that are part of the course (often used to be combined with flipped classroom) but do not count for the summative evaluation, and (3) SPOCs that are only a recommended support for the course but that are not mandatory. In total, there are data available from 38 SPOCs, which comprise all the thematic areas of the studies the university offers, mainly Social Sciences, Formal

Sciences and Engineering. However, the characteristics of each SPOC (e.g., syllabus, purpose, structure, etc.) are unknown.

As the SPOCs are hosted in Open edX, data format is defined by edX [30], and there is information available about activity, videos and exercises (there could be potentially other features such as forum data, but SPOCs are mainly designed with just videos and automatic correction exercises). For this analysis of the persistence, only information about exercises is considered because we want to measure if students continue after having difficulties (i.e., getting a wrong answer) and the feedback about how students are doing is only contained in exercises. Particularly, only the events labelled as "*problem_check*", which are the events produced when a student sends the answer to an exercise, are considered. In total, there are 270,183 events in the 38 SPOCs from 3,598 different students. However, there are students who enrolled in more than one SPOC. In order to have the value of persistence for each course, which can be more relevant for instructors as they may only be interested in the data about their courses, the combination of course-student is considered. With this assumption, there are 4,382 pairs of course-student and 210,125 combinations of course-student-exercise. As there are 270,182 events, the global number of attempts for each exercise per student is 1.29.

With regard to the exercises, they can have many different types, such as multiple choice, checkboxes, dropdown, numerical input and text input problems. All these formats admit automatic grading. Grade from each exercise can be a continuous value between 0 to 100%. However, in most of the cases (95%), exercises are graded as correct or incorrect, as the format of the most common exercises can only accept binary values (e.g., a numerical input exercise or a multiple-choice question can only be right or wrong, while checkboxes can admit partial grades). For the analysis, no information is known about the format of each exercise and the number of allowed attempts. This can be an important limitation because, for example, an student cannot be persistent if the instructor designs the exercises so that only one attempt is allowed (which is typical in summative exercises), and a student is very likely to be persistent if there are only true/false questions where the student knows the right answer once he/she gets feedback from his/her initial attempt and sees that the initial answer is wrong.

In order to alleviate the aforementioned limitation, the following filtering criterion was applied: exercises where all students who attempted them had two attempts at maximum were removed. Note that if one exercise is not excluded, there might be students who get it right using one/two attempts and the exercise remains valid for these students. This rule served to (1) eliminate true/false exercises (or exercises where only two options were possible), (2) eliminate easy problems that all students get right with few attempts (they are not useful to show persistence), and (3) eliminate exercises where only 1-2 attempts are allowed (a typical policy in the institution is allowing 1 attempt for summative exercises and 2 attempts for other exercises). Therefore, after the filtering, all exercises had a format and number maximum of attempts that allowed students to show persistence. With these criteria, 656 exercises (from 28 SPOCs) were included out of the 3002 exercises in the SPOC. In order to justify the threshold of considering two attempts at maximum for all students to include an exercise in the calculation, an analysis with three attempts was carried out. For this case, only 189 were included, which is considerably lower than in the case with two attempts. Because of that, for the rest of the analysis, the initial filtering of considering exercises where there was at least one student with three attempts or more is considered (i.e., removing exercises where all students had two attempts at maximum).

4 Description of the model to identify persistence

The persistence in this analysis is related to the extent students keep on trying the exercises until they get it right after doing it wrong. This section focuses on identifying how to model persistence based on students' interactions with exercises. The aim is to define an overall indicator of persistence, although it can be based on the persistence of individual exercises. A priori, it is possible to say that the persistence of a student will be minimum if he never tries the exercise again when he gets it wrong (assuming there are no limits of attempts). Similarly, the persistence will be maximum if the student always ends up getting the right answer after trying the exercise several times. With this idea of persistence, we do not take into account how the student got the correct answer and/or whether persistence is good or bad for learning. If a student gets the answers using a trial and error strategy, it will be probably bad for his learning process (learning will be probably superficial), but the student is considered to be persistent because he/she always gets the right answer (which is our definition of persistence).

Considering the previous ideas, it is easy to determine when a student is fully persistent or not. However, the difficulty is how to model the overall persistence of a student which may sometimes be persistent and sometimes not. For the definition of persistence, the sequence of attempts and the associated results (grades) is considered. For this model, grades of an exercise can only be 0 or 1. This is because 95% of the rows with course-student-exercise in all the SPOCs are only graded with 0-1. This can also be generalizable to quite a few learning environments. The remaining 5% (which can include, e.g., checkbox exercises) has been discretized in 0-1 to be consistent with the rest of the exercises by rounding grades down (e.g., 0.8 is converted to 0). Regarding the sequence of attempts, it contains the grade of each attempt separated by spaces. Table 1 shows some examples of sequences and the idea of associated persistence.

Table 1. Sequence of attempts of difference exercises

ID	Sequence	Idea of persistence
1	0	The student is not persistent as he/she does not try the exercise again (after getting 0) in order to get correct answer.
2	0 1	The student shows persistence as he/she attempts the exercise again to get it right.
3	0 0 0 0 0 1	The student shows persistence and he/she shows more persistence than in case 2 as he/she needed a lot of attempts until getting the answer right.
4	0 0 0 0	The student shows certain persistence as he/she has tried the exercise several times but he/she has not got the correct answer. The persistence should be greater than in case 1 but smaller than in cases 2 and 3.

Table 1 shows that despite the final outcome of the exercise can be the same, the persistence the student shows in each case is different because in some cases the student tried the exercise more times and showed to be more persistent despite the difficulties. Considering this fact, the following assumptions have been made for the model:

- If students get the answer right in the first attempt, no persistence is shown because there is not a situation where an answer is wrong and the student decides whether attempting the question again or not (to show persistence). However, this fact does not mean that students are not persistent. Therefore, events where the answer is correct in the first attempt are excluded. Similarly, re-attempts of correct exercises are excluded because the student already got the correct answer.
- Students show more persistence if they need more attempts to solve the exercise, but they should not be penalized if they solve the exercise with few attempts.

With these assumptions, the aim is to define an indicator of persistence in the range 0-1 for the learner persistence. One initial question is how to consider the persistence of each exercise for the global persistence. One possible approach is to compute a value of persistence for each exercise and calculate the average for all of them. The limitation of this approach is that it does not allow weighting the exercises easily so that exercises where the students show more persistence have a higher weight. For example, in Table 1, a student will get the maximum value of the maximum persistence (1) in both cases 2 and 3 because he/she has attempted the exercises until getting the correct answer. However, the student "shows" more persistence in case 3 because he/she needed more attempts. With "shows", we refer to the persistence which is visible or demonstrated with the exercises (by making attempts). In order to weight the exercises depending on the persistence showed, it is proposed to compute the persistence as a single fraction, where the numerator and denominator increase every time the student shows persistence in each exercise. If more persistence is shown (e.g., case 3), more units will be added to both numerator and denominator to give more importance to the exercise.

This way, this model will increment one unit in the numerator and denominator each time the student attempts an exercise once he/she has got the exercise incorrectly at least once. In order to penalize when a student does not get the right answer, a penalty variable is defined in the denominator. If a student fails the exercise at first attempt and he never attempts the exercise again, the numerator will not change, but he will receive a penalty in the denominator to decrease the overall persistence. Formula 1 shows how to compute the persistence, where *n* is the number of exercises the student has attempted, and *i* represents a particular exercise:

$$Persistence = \frac{\sum_{i=0}^{i=n} \min(attempts_i - 1, stop)}{\sum_{i=0}^{i=n} \min(attemps_i - 1, stop) + penalty \cdot \left(1 - floor(grade_i)\right)} \quad (1)$$

As it has been mentioned, the numerator and denominator increment depending on the number of attempts. As the first attempt is not considered, the value is incremented by the number of attempts of the exercise (i) – 1. The formula also considers a parameter *stop*. The reason is that if a student has a very large number of attempts, their effect could be very strong respect to other exercises. For example, if a student never attempts the exercise again once it is wrong, but he/she does with one exercise and he/she attempts it many times, he may have good persistence because the weight of a single case. To prevent that, the *stop* variable defines the maximum that can be summed for each exercise. In practice, this parameter seems to be irrelevant in this context because from the 58,217 exercises where the student does not get the answer right in the first attempt, only 860 (1.5%) have four or more attempts. Nevertheless, it is included as it may be relevant in other courses where there are more open questions and students may need more attempts to solve the questions.

In the denominator, there is a *penalty* for the non-correct exercises. The final grade of the exercise is discretized in 0-1, as mentioned, with the *floor* function and whenever the exercises is wrong there is a penalty. If the exercise is correct, grade is 1 and the penalty is avoided. With this formula, there are two variables: *stop* and the *penalty*. These variables can be adjusted depending on the context. The idea is that the *stop* represents the number of attempts needed to achieve the maximum persistence that you can show (if the answer if correct). For example, it can be considered that if you attempt the exercise 10 times after the first incorrect attempt, you show the maximum persistence and therefore if you have more than 10 attempts, 10 will be considered to avoid overweighting the exercise in the formula. In this scenario, stop will be set as 10 although it will not affect the results considerably as mentioned.

The idea of the *penalty* is that it represents the number of attempts needed to compensate an event of non-persistence so as to make the overall persistence 0.5. For example, if the *penalty* is 1, if one student gets 0 in one exercise and 1 in another one in the second attempt (sequence 0-1), the persistence would be 0.5. We believe that 1 is a low value because low persistence is shown with the pattern 0-1. In contrast, if the *penalty* is very high, the students would need to demonstrate a lot of persistence to overcome a non-persistent event. In this case, as most questions are answered with 3-4 attempts at most (after doing the filtering, 71% of the exercises are answered with 3 questions at most and 82% with 4 questions at most) and they all have more than two options, we considered a penalty of 4. This way, a non-persistent event can be compensated with two questions with three options at most where the student gets the answer in the last attempt. Nevertheless, this value can be context-dependent and can be adapted in each scenario. Moreover, an instructor may also want to adjust this value according to his/her own criteria depending on the context or methodology. With this approach, the persistence in the example in Table 1 would be $(0+1+5+3)/(4+1+5+7)=9/17 = 0.53$, which is reasonable as the student did not get the correct answer in two of the exercises but he/she attempted one of them several times.

5 Results

In this section, the analyses to achieve the objectives stated in Section 1 and the discussion of the results are presented. First, the analysis of the prevalence of persistence is discussed. Next, the relationship between the persistence and other variables is detailed.

5.1 Analysis of the prevalence of persistence

The first question is about how the persistence is distributed among the students in the SPOC (i.e., prevalence). In order to evaluate this, the model to determine the persistence, presented in Section 4 has been used. As a first result, the histogram of the persistence is provided in Fig. 1. This histogram reflects that most of the students have either a fair/moderate persistence (between 0.3-0.7) or the maximum persistence (persistence above 0.9). Among the 3,062 pairs of course-student where persistence was defined (there were 432 cases where the student always got the answer right and thus there is no information about persistence), 1,216 (33%) cases represented students who were persistent occasionally, i.e., their persistence was between 0.3-0.7. Among those learners, most of them are between 0.4-0.5. Moreover, there are 988 (32%) with very high persistence (above 0.9) while there are only 155 (5%) students with low persistence (below 0.3). The mean of persistence is 0.70, and the median 0.67, which means that many students do not give in when they face difficulties and keep on trying their exercise. The high prevalence of persistence might be due to the considered context since most exercises do not have many possible options so these types of exercises might engage students to make different attempts until they succeed since they know they can get the correct answer with a relative low effort.

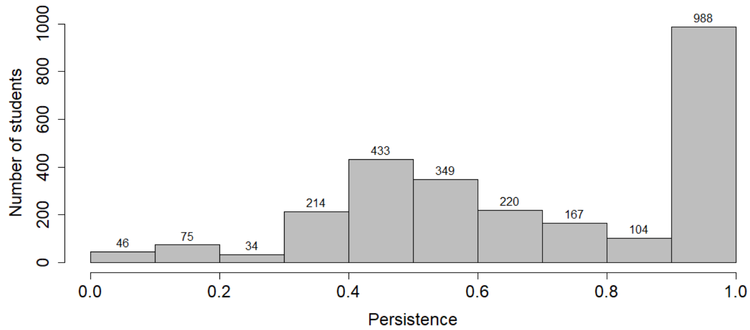

Fig. 1. Histogram with the prevalence of the persistence

In order to delve into the prevalence of persistence, several profiles of students have been identified for each range of persistence, based on an initial exploratory analysis of the data (considering the ranges from the histogram and the percentages of attempted exercises). For this analysis (and the analysis in the next section), persistence values were merged with other indicators about videos and exercises. In some cases, indicators were not available because for example, the student did not have interactions with videos. This resulted in a merged dataset of 2,522 pairs of course-students (after removing the 432 cases with undefined persistence). The description of these profiles is as follows.

- Students who were not interested in the exercises and with low persistence: There were 90 students with less than 30% of attempted exercises and persistence (62% of students with persistence below 30%). Therefore, it was a group of students who did not take the exercises and they only sampled some of them without showing much interest. However, there were a few cases of students who were active in watching videos. In this case, their persistence can be less representative as they put less effort.
- Students with low persistence having done most of the exercises. There were 8 students with more than 80% attempted exercises but with less than 30% of

persistence (6% of students with persistence below 30%). They were students whose average grade of the exercises they attempted was always above 83%. Therefore, they were students who usually got the correct answers at first attempt and they did not care about having some incorrect answers as they were above the passing rate (e.g., 50%). Nevertheless, it was not a frequent behavior as there were only 8 students in this group.

- Average students with low persistence: There were 47 students with less than 30% of persistence and between 30-80% of attempted exercises. This group represented the 32% of students with persistence below 30%. They usually only engaged with part of the SPOC and their interactions with videos were also low as they only watched 27% of the videos on average. The average grade of the exercises they attempted was above 77% for 75% of the cases (above the first quartile), but they only attempted 49% of the exercises on average. Similarly to the previous group, they may not care about doing everything right if they achieved a grade above the passing rate.
- Students with medium persistence: There were 1,192 students with persistence between 30-70%. These students had, on average, 67% of the exercises right in their first attempt, and on average they completed 82% of the exercises they attempted. Therefore, from the 33% of the exercises they did not solve right at first attempt, they got 15% more correct in successive attempts, so they were persistent about half of the times on average. Moreover, they watched on average 38% of the videos.
- Students with high persistence: There were 939 students with persistence above 90%. Although there were 148 students who interacted with less than 20% of the exercises and their persistence was less representative, on average, 48% of the exercises were done, which makes persistence representative enough. These students were often good students as their average grade on first attempt was 80% on average, but these students wanted to have their exercises right and they tried their exercises again until got them right. However, they only watched 31% of the videos on average.

These profiles show that there are very different behaviors in relation to the persistence. This could motivate adaptive tools depending on the different students' profiles. Moreover, there is a considerable portion of students with low interactions with very high/low persistence. In those cases, it is important to note that the persistence is less significant, particularly for those learners with low persistence, as they may be just sampling the exercises without intention to complete them. For other profiles with low-medium persistence, further work should be done to analyze what kind of interventions could be done to raise their persistence.

5.2 Relationship between persistence and students' behavior and performance

In this section, an analysis of how the persistence is related with other variables about students' behavior and performance are presented. Firstly, one of the variables with great interest in the literature is dropout. Many researchers have analyzed which variables affect dropout [2] and they have proposed predictive models to forecast which learners will drop out the course (e.g., [31]). This fact is particularly relevant because of the high dropout rates in the courses [32]. The first part of the analysis aims to discover if there is a relationship between persistence and dropout. In this case, a student is considered to have dropped out if he/she has not completed at least 75% of the exercises of the SPOC. For this analysis, only the first semester of the academic year 2018/2019 will be considered (as the second semester is not finished yet). In order to analyze the relationship between persistence and dropout, a boxplot was made using both variables (see Fig. 2). This figure shows that the persistence of students who do not drop out the course is similar to those who drop out. The mean of persistence for both groups is 0.71 and 0.68, respectively. The difference of persistence, evaluated through the Mann-Whitney test, was not statistically significant (p-value = 0.25). This implies that persistence is not crucial to complete the course. A possible reason is because persistence is only measured with the attempted exercises, and students may try to complete the exercises they attempt (even using brute force if necessary) but they may stop using the SPOC at some point. Another possible reason is that these types of exercises might not discriminate persistent and non-persistent students since as there are few options to select, students make a lot of try-steps. Other reasons may be due to the specific context. Because of that, more research is needed to delve into the reasons.

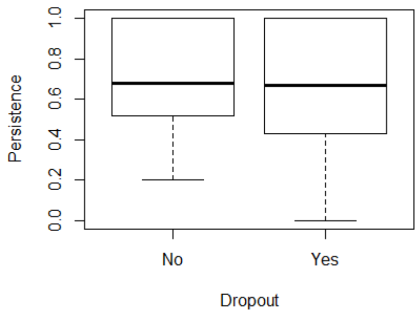

Fig. 2. Boxplot with the relationship between persistence and dropout

After analyzing the relationship between persistence with dropout, the relationship between the average grade (considering only attempted exercises and all the attempts) is presented. Moreover, an analysis of the relationship between the percentage of completed videos is presented to discover whether persistent students also complete the videos or not. In order to analyze these variables, plots have been made relating persistence and the variables (see Fig. 3).

Fig. 3 illustrates that the average grade has clear positive relationship with persistence as the average grade tends to be higher when the persistence is higher. While average grade fluctuates more for students with low persistence, i.e., there can be students with low persistence with high grades and more variance is presented, students with high persistence usually achieve good grades. Nevertheless, there are some cases of students with high persistence but low grades. As the average grade is only computed with attempted exercises, this means that students had a very poor performance on exercises where the number of attempts is limited (which are excluded for persistence but not for average grade). This implies that there may be cases where students can be persistent by using brute force to solve the exercises but they are not actually learning. Thus, persistence do not necessarily mean learning, although it may mean effort. However, the trend is that the average grade is more positive as the persistence increases. This suggests that while persistence is not crucial for success, it can be beneficial and having good persistence can lead to high performance, provided that the student reflects on the questions and do not guess the answers by brute force.

In contrast, when analyzing the relationship between persistence and percentage of completed videos, results show that there is no relationship between both variables (see Fig. 3b). This means that although completing videos is an indicator of constancy and work in the SPOC, it is not related to persistence. There are students that can be very engaged in watching videos but they are not engaged with the exercises and they are not persistent enough to complete them (with correct answers), and there can be other students that use the SPOC to practice with exercises, but they are not interested in watching the videos. Thus, engagement with different course materials can be different, and an instructor should highlight the importance of all the parts they want to ensure students actually cover in the SPOC.

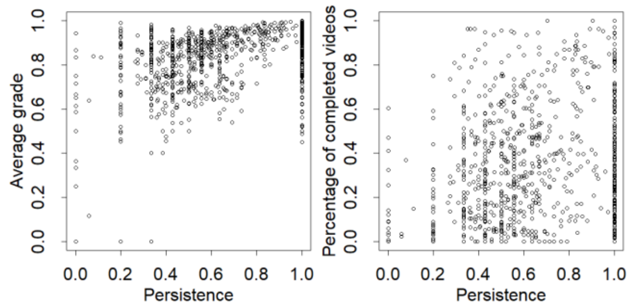

Fig. 3. Relationship between persistence and (a) average grade, (b) % of completed videos

6 Conclusions

This work presents a novel method to determine students' persistence from low-level events. This model can identify the persistence of a student in scale 0-1, taking into account if a student keeps on trying an exercise once he/she fails to solve it correctly or not. The model can be applied to many educational platforms provided data about exercises and attempts are available, although the model could be refined if context is known. With this model, the persistence of the students in 28 SPOCs is computed. The analysis of the prevalence shows that there are many different profiles depending on the persistence. Most students have either a fair/moderate persistence (between 0.3-0.7) or a high persistence (above 0.9). Results show that there are many students with low and fair/moderate persistence who have an average grade above the passing rate on the exercises they attempt and they do not mind having some exercises wrong. In contrast, results show that there are students who always persist until they get their answers right. It is interesting that there are few students with low persistence, but their profiles are different in terms of engagement; some of them are not persistent because they do not keep on trying their exercises until get the correct answer while others are not persistent just because they are not trying the exercises and they just sample some of them.

When persistence was compared with other variables, results also show that there is not statistically significant difference between students who drop out the course or not in terms of persistence. This means that although a learner seems to be persistent in the exercises he/she does, it does not mean that he/she will complete the course. This can happen, e.g., when students attempts few exercises (regardless they persistent in them) and/or use trial and error strategies. Similar conclusions were found with the engagement with videos, as no relationship was found with persistence. In contrast, the average grade was positively related with persistence. However, there were cases where average grade was low but persistence was high, which means that the student was not probably learning, and he/she was getting the correct answers by using brute force.

Despite the abovementioned findings, there are some limitations that are worth mentioning. Results might be tied to the specific context. In our case study, it is unknown the typology and allowed number of attempts of each specific exercise. This is a very important limitation because for example, it is easier to be persistent when questions have a limited set of answers (e.g., multiple-choice questions) than in open-ended questions (e.g., write the number of the solution of the exercise). Indeed, most exercises had a limited number of answers so this could explain higher values of persistence. For this analysis, some filters were included to alleviate this issue but the ideal would be having information about this. Furthermore, another limitation is related to the way persistence is computed. As persistence is a subjective characteristic of people, many measures could be presented, and each one can have its advantages and disadvantages. The measure in this paper can give an idea of how persistent the student is in the exercises he/she has done, but for example, does not consider what it has not been done, and the model does not take into account how the exercises are solved (e.g., it would be bad if a trial and error strategy is used). While the last fact is not the focus on this article, that could be also interesting to include in future models.

As future work, in relationship with the aforementioned limitations, it would be relevant to analyze the persistence in educational platforms where information about the context and methodology is known, and add a corrective factor for non-attempted exercises and exercises where there is no reflection between attempts (e.g., elapsed time between attempts is very short). In addition, it would be relevant to use the model in courses when students may usually need more attempts and grades are not typically binary (0/1). Moreover, it would be interesting to delve into the profiles of persistence. In order to do that, clustering techniques could be used to have a detailed picture of how different students are based on their persistence. Furthermore, a more detailed analysis could be done to explore the relationship between persistence and other variables of students' behaviors and performance, and the types of exercises/resources. In this line, persistence could be also introduced in predictive models, for example, to forecast dropout and or performance, to analyze its predictive power. Finally, it would also be important to analyze which factors can increment/decrease persistence and provide instructors information about the persistence so that they can analyze possible interventions that can enhance the persistence of their students and see if that can have a positive effect on their overall learning.

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