Types of Dropout in Adaptive Open Online Courses

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Abstract. This study is devoted to different types of students' behavior before they drop an adaptive course. The Adaptive Python course at the Stepik educational platform was selected as the case for this study. Student behavior was measured by the following variables: number of attempts for the last lesson, last three lessons solving rate, the logarithm of normed solving time, the percentage of easy and difficult lessons, the number of passed lessons, and total solving time. We applied a standard clustering technique, K-means, to identify student behavior patterns. To determine optimal number of clusters, the silhouette metrics was used. As the result, three types of dropout were identified: "solved lessons", "evaluated lessons as hard", and "evaluated lessons as easy".

Keywords: Adaptive learning · Dropout · Clustering · MOOC

1 Introduction

Massive Open Online Courses (MOOCs) have the potential to enable free online education at scale but a concern is their low completion rate. A meta-analysis conducted by Jordan indicates that the completion rate have an average of 6.5% and ranges from 0.9% to 36.1% (Jordan 2014). Onah et al. suggested a number of reasons for student dropout in MOOCs: no real intention to complete, lack of time, course difficulty and lack of support, lack of digital skills or learning skills, bad experiences, expectations, late start, and peer review (Onah et al. 2014). One of approaches to decrease student dropout is to provide MOOCs personalization and adaptive learning to improve learning experience in MOOCs (Sunar et al. 2015).

Adaptive learning is the mainstream of the contemporary educational science. The key idea is in recommendation of learning activities to students according to their ability and preferences. In the ideal adaptive learning engine, students do not quit it until they do not achieve their learning goals.

2 Related Work

Dropout rates in massive open online courses (MOOCs) are extremely high, and it is a constant theme in the MOOC literature (Rivard 2013; Huin et al. 2016). This topic is also connected with student engagement in MOOCs (see, for example, Sinclair and Kalvala 2016). Some authors identified various clusters of MOOC participants

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according to their activity. Kizilcec et al. (2013) analyzed three computer science MOOCs and identified four clusters of students: 'completing', 'auditing', 'disengaging,' and 'sampling' (Kizilcec et al. 2013). Anderson et al. (2014) clustered students' engagement into five groups: viewers, solvers, all-rounders, collectors, and bystanders (Anderson et al. 2014). Kovanovic et al. (2016) used k-means clustering on 28 MOOCs from the Coursera platform and identified five groups: enrollees, low engagement, videos, videos and quizzes, and social (Kovanovic et al. 2016). Khalil and Ebner (2016) classified four categories of students based on their activity: registrants, active learners, completers, and certified students (Khalil and Ebner 2016).

Unlike traditional massive open online courses where exist lots of literature on completion rates, dropout rates and student engagement, there is not so much literature for adaptive open online courses. Sonwalkar (2013) proposed an adaptive MOOC that offers the learning content according to learning styles (Sonwalkar 2013). Burgos and Corbí (2014) used a rule-based recommendation model to improve students' performance. Yang et al. (2014) proposed a personalized support on MOOCs discussion forums.

However, the field of MOOC personalization and adaptive learning can be benefited with research in the intelligent tutoring systems (ITS) due to its focus on problem-solving behavior. While MOOC research focused on identification of patterns of student behavior through a course, ITS research analyzed student behavior through the process of solving a given problem. Arroyo et al. indentified cognitive, metacognitive and affective factors that influence student behavior (Arroyo et al. 2014). Mills et al. predicted whether student quit instructional texts: they used supervised machine learning algorithms and prediction accuracy for quitting at any point during the text was 76.5% (Mills et al. 2014).

The aim of this study is to identify different patterns of students' behavior before they drop an adaptive course.

3 Context of the Study

As the case for this study, the Adaptive Python course at the Stepik educational platform was selected. Stepik (https://stepik.org/) is an educational engine and MOOC platform focused on IT and STEM courses. In the Fall 2016, the platform contains more than 60 open courses. Every course on Stepik consists of 3–7 weeks (one week = one module) with 100–150 steps, and has 7000 learners on average. The Stepik platform supports different types of problems: close-ended problems (multiple choice quizzes, matching problems, table problems, and sorting problems), open-ended problems (free responses, text problems, number problems, and math problems) and challenges (data challenge, code challenge, and Linux challenge). Both adaptive and non-adaptive courses have launched on the Stepik platform.

In this study, the data from the Adaptive Python course was used. This course contains 347 lessons with code challenge assignments of various difficulties where students need to write the programming code in Python to solve problems. This course uses an adaptive engine developed in Stepik based on the Roskam model (Roskam 1987, 1997). This model uses the response time to measure the student ability.

The adaptive course interface is shown on Fig. 1. Unlike the case of response-time models where students need to provide the correct answer, at Stepik, students can also evaluate the lesson as too easy or too hard.

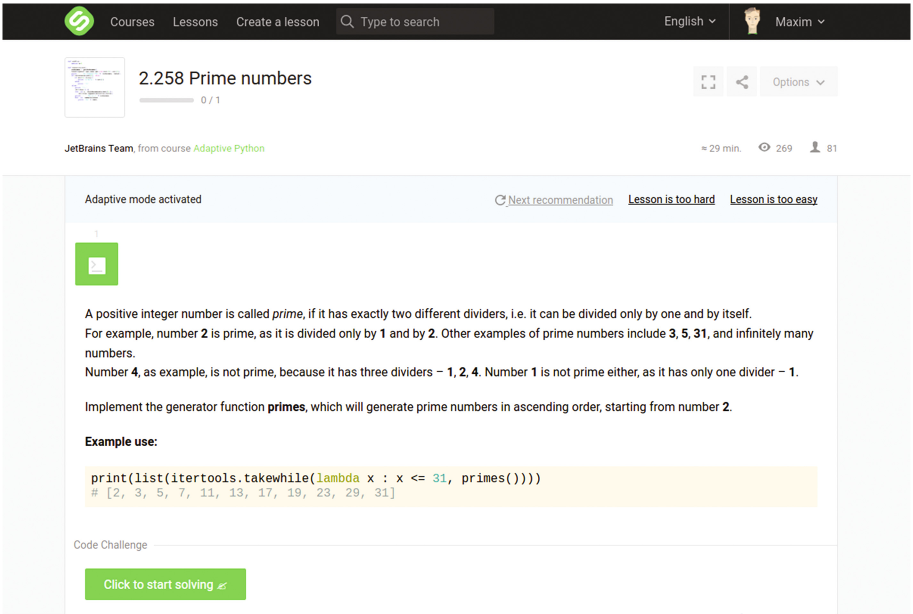

Fig. 1. The adaptive course interface.

Thus, there exist three ways to receive the next recommended lesson: solve the lesson, evaluate the lesson as too easy or as too difficult. When updating the student ability, we compare our prediction with the student performance: solving time, number of attempts, and whether the lesson was evaluated as too easy or too hard. Depending on this, the student ability can increase or decrease.

4 Methods

4.1 Sample

This study uses data from the Adaptive Python course that is launched on the Stepik educational platform. Over the lifetime, this course had over 4500 enrolled students.

We selected the time period from September 1, 2016 to December 15, 2016 that depends on the student activity after the summer break and before winter holidays. We excluded students who studied at the course outside of this period. Anonymous users were also removed.

The final sample contains 685 students and 10994 interactions between students and lessons.

4.2 Measurement

Basic information on student performance inside adaptive course consists of time used for solving lessons, number of attempts, and number of reactions “too easy” or “too hard”. Using this information, student behavior before dropping the course was measured by the following variables:

- Number of attempts for the last lesson. If this number is large, the student can be frustrated and it is more likely that he drops the course.
- Last three lessons solving rate. This indicator was calculated as the weighted average whether student solved last three lessons or used evaluation as too easy or too difficult. The latest values have larger weight (backward discounting).
- The logarithm of normed solving time. Normed solving time is defined as student’s solving time divided to the average solving time for the lesson. It measures student abilities in comparison with other students. The positive value of its logarithm means that the student needs more time to solve the lesson than in average, i.e., the student ability is lower.
- The percentage of easy lessons. This shows how often students evaluate lessons as easy based on their self-estimation.
- The percentage of difficult lessons. This shows how often students evaluate lessons as difficult based on their self-estimation.
- Number of passed lessons and total solving time. These two variables show student engagement in using the adaptive engine.

4.3 Analysis

A standard clustering technique, K-means, to discover student behavior before dropping the course was applied. First, we cleaned the data and removed outliers with solving time greater than the 97%-percentile. We also normalized all the measurement variables used for clustering analysis to reduce the scale effect. Then, we performed the clustering analysis with the K-means technique.

To determine an optimal number of clusters, the cluster silhouette metrics was used: it is a measure of how similar an individual case to its own cluster compared to other clusters. All the analysis was performed in Python with using the scikit-learn library (Pedregosa et al. 2011).

To identify behavioral patterns before students dropped the courses, we also calculated the frequency of last three reactions. For this purpose, we distinguish the situation whether students solved lesson faster than in average (“fast”) or not (“slowly”).

5 Results

After cleaning data and removing outliers in solving time, the sample contains 401 students and 4308 interactions between students and lessons. The K-means technique with the silhouette metrics was performed. The optimal number of clusters is equal to 3, the silhouette metrics is equal to 0.478 (see Fig. 2).

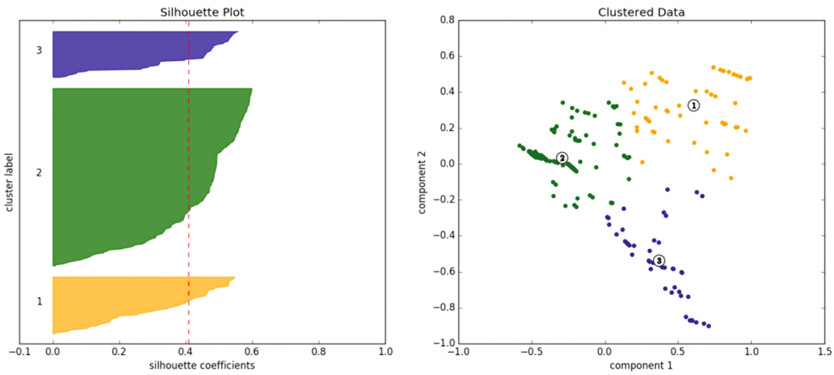

Fig. 2. The silhouette plot and clustered data

The identified clusters define three types of dropout:

1. "Solved lessons" (n = 243; 60.60%) where number of attempts for the last lesson is greater than for other types.
2. "Evaluated lessons as easy" (n = 84; 20.95%) where students prefer to evaluate lessons as easy but not solve them.
3. "Evaluated lessons as hard" (n = 74; 18.45%) where students prefer to evaluate lessons as hard but not solve them.

The descriptive statistics for each cluster are provided in Table 1. Note that there is no significant differences between clusters for total solving time and number of passed lessons (engagement metrics) as well as for the logarithm of normed solving time (proficiency metrics).

The percentage of the last three reactions before students dropped the course was also calculated and ten of the most frequent ones are provided in Table 2. We can note that when the learning content is too difficult for students (because of their self-evaluation as hard or their slow solving), it is more likely that students drop the course.

Table 1. Description of clusters

Variables	Cluster 1	Cluster 2	Cluster 3
Number of attempts for the last lesson	**1.19 (0.11)**	0.62 (0.06)	0.33 (0.07)
Last three lessons solving rate	**0.80 (0.01)**	0.20 (0.02)	0.14 (0.02)
Number of passed lessons	9.20 (0.83)	14.24 (1.74)	12.12 (1.22)
Log(normed solving time)	0.80 (0.07)	0.69 (0.17)	0.59 (0.13)
Percentage of easy lessons	0.04 (0.01)	**0.62 (0.02)**	0.04 (0.01)
Percentage of difficult lessons	0.06 (0.01)	0.03 (0.01)	**0.76 (0.02)**
Total solving time	841.48 (128.55)	595.66 (160.07)	407.10 (166.25)

Bold values show statistically significant difference as compared with the other two clusters ($p < 0.05$). Standard errors are provided in the brackets.

Table 2. The percentage of the last three reactions

Last reactions	Percentage	Last reactions	Percentage
hard, hard, hard	15.65%	easy, easy, easy	3.63%
slowly, slowly, slowly	11.83%	fast, fast, quickly	3.44%
fast, fast, fast	6.87%	slowly, fast, slowly	3.24%
fast, slowly, slowly	5.92%	fast, slowly, fast	3.05%
fast, fast, slowly	4.39%	slowly, fast, fast	2.48%

6 Discussion and Conclusion

Our results indicate that there exist three main patterns of student behavior before they drop the adaptive course. Two of them are related with students' self-evaluation of lessons as hard or easy. This connected with the flow theory where higher challenges than your skills lead to frustration but lower ones lead to boredom (Csikszentmihalyi 1990). Both of them can be reasons for course dropouts.

The pattern "Solved lessons" is related with regular lesson solving. To reduce student dropout, it is necessary to provide students the learning support, for example, in the case where the number of their attempts to solve problems rises. It is important to react on these cases on time as well as predict student dropouts to have an opportunity for pedagogical interventions in advance. The prediction of student dropouts for adaptive courses is one of topics for the further research.

Another topic for the further research is validation of identified clusters with student interview on their learning strategies and motivation. This can provide more insights on student behavior in adaptive courses.

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