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Classification of Learning Patterns and Outliers Using Moodle Course Material Clickstreams and Quiz Scores

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Abstract: In this study, learning patterns and outliers were classified using learning logs in Moodle, and a method was proposed to identify learners who were struggling in class based on the relationship between learning patterns and outliers. The proposed method utilizes the deviation between the learner's course material clickstream and the quiz score accumulated in Moodle to classify the learner into one of four learning patterns. As the number of lessons increased, many learners transitioned through four learning patterns. However, some of the top or bottom learners on the final quiz score may repeat the same learning pattern, which tends to result in outliers.

Keywords: Learning pattern, educational data mining, learning analytics, clickstream, quiz score, outlier, unsuccessful learner, Moodle

1. Introduction

Even in a class in which a large number of learners participate, more effective intervention will be possible if appropriate time-based observation of learning behavior can be performed for each individual. The main purpose of this research was to analyze the learning behavior of students and to clarify the relationship between the classification of learning patterns and the occurrence of outliers. Outliers here are quiz scores and material clickstreams that are far from average.

Learners can have various styles of learning patterns, but in this study, they were considered as follows. (1) If a learner browsed the course materials appropriately according to the progress of the lesson, the learner was considered to be highly interested in the lesson and that the lesson was taken successfully. (2) On the other hand, when the number of material clickstreams, that is, the number of material openings, was small or when the materials were not opened, the learner was considered to have low interest in the lesson and a learning pattern with insufficient engagement. (3) Furthermore, the material browsing pattern is expected to affect learners' scores on weekly quizzes and final exams.

Therefore, determining whether a learner understands the content of the material based on their scores in the quizzes and exams is possible. In this study, the learning materials' clickstream and the results of 13 quizzes were analyzed, and a method for classifying the students' learning patterns and outliers was proposed.

2. Related Research

Engagement is also measured from various aspects in motivational research in the field of education. Questionnaires are used to analyze answers to the psychological state of motivation to engage in learning activities, and question items are used as variables for measurement from multiple perspectives (Skinner et al., 2009b). Behavioral engagement has also been shown to directly regulate academic performance in individual learning situations, suggesting its importance in learning (Steinmayr et al., 2018). In this study, the learning log automatically recorded by Moodle was used to analyze learners' engagement. Behavioral engagement is defined as learning and academic engagement, including active behavior, and measures such as attention to learning and indication of effort. Therefore, clickstreams for browsing materials and quiz scores can directly define grades and are considered factors related to conventional behavioral engagement.

Many studies on learning patterns have been conducted in the past. In one case, learners completed a questionnaire, and the characteristics of their learning patterns were analyzed using factor analysis (Vermunt & Donche, 2017). Recently, research on new learning patterns utilizing a learning management system (LMS) or e-book systems has been conducted (Hsiao et al, 2019). Learning pattern analysis using an LMS or e-books involves collecting and analyzing data on learning behaviors, such as page back-and-forth movements, highlighting, underlining, and commenting (Mouri et al., 2019). Studies to detect outliers are also being conducted in the field of education. In a study of a massive open online course (MOOC), Gitinabard et al. (2018) predicted who would drop out based on student access to materials and forum logs. They were able to quickly identify individuals who were at risk of becoming unsuccessful learners, and they showed that their approach was useful for early learner intervention and guidance (Gitinabard et al., 2018).

Research is likewise being conducted on the efficacy of student support systems that integrate LMS data with student management and grading management systems. Course Signals, developed at Purdue University, is an early-intervention system that provides real-time student feedback based partly on student records accumulated in Blackboard and past learning logs (Arnold & Pistilli, 2012). A system called E2Coach at the University of Michigan sends messages to learners based on their course score data. These messages motivate learners to take the actions necessary for success, reminding them, for example, to ensure that they have sufficient time to prepare for their next exam (McKay et al., 2012). In recent years, research on data mining and dashboards that analyzes LMS learning logs has been active (Slater et al., 2017). For example, Estacio et al. (2017) used a vector space model in Moodle's learning logs to analyze the relationship between learning behavior and the final grade. They developed a method to monitor learners' behavioral levels and showed that they could find learners who are struggling in class (Estacio et al., 2017). All these studies aim to obtain useful knowledge for class management and the improvement of teaching materials.

3. Course Outline and Teaching Material

This study was tested with a class taught at Aichi University in Japan. Moodle learning logs were collected from the course "Introduction to Social Data Analysis," of which the first author was in charge at the university. Learning logs were collected from September 18, 2019 to January 8, 2020. Learners from freshman to senior can enroll in the course. There were 55.0% and 45.0% male and female undergraduates, respectively, and the age range for most of the learners was 18 to 22 years; a total of 47 learners participated in this class. The content of the class was an introduction to statistics using Excel. In the actual class, learning was undertaken over 15 weeks, starting with learning the basic use of Excel, including representative value, variance, standard deviation, simulation, frequency distribution and pivot tables, attribute correlation, covariance, correlation analysis, and regression analysis. The course materials for reading were mainly created in PDF files, comprising 12 chapters, 112 sections, 10 external URLs, and the entire material of 154 pages. The materials were divided into 112 files, and they were then uploaded to Moodle, which was set to "topic" mode.

All lessons were conducted according to the teacher's instructions; learners accessed the materials according to the instructions and learned about data processing using Excel. In the first half of the class, while reading the materials on Moodle, the learners have their Excel screens open at the same time, and they operate their personal computers to study. In the second half of the lesson, the learners carried out each exercise and were asked to submit a work file of all the exercises in Excel that they had completed. In the classroom, one material presentation monitor was prepared for every two learners, and the learners could see the materials and a demonstration of computer operations. They can also open materials from the Moodle screen on their computers at home or on their classroom computers and freely browse and download them. In this study, the number of downloads is therefore included in the material clickstream. In the first lesson of the semester, the first author explained to all learners that Moodle collects student learning logs 24 hours a day.

The clickstream in this study refers only to the number of times the course material on Moodle is opened, not to all the clickstreams for operating a personal computer. The clickstream of materials by chapter, corresponding to the question range of the quiz, is also tabulated. The clickstream of materials covered the period from the first lesson of the semester to the end of the quiz in each chapter. This log included in-class and out-of-class activity. The quizzes were conducted a week from the learning start time of each chapter. Aggregating the individual learners' material clickstreams for each learning period corresponding to the quiz was necessary, so we adopted the framework of time-series cross-section (TSCS) analysis. Excel Pivot Table can be used to aggregate the frequency distributions of multiple discrete data to generate a 2D cross-table. As the Moodle learning log contains time-stamp data, creating the TSCS table and aggregating clickstreams are possible.

Quizzes were created for each chapter using the materials that were on Moodle. We decided to adopt fill-in-the-blank-type quiz questions (i.e., complete the sentence), with five alternative answers for each question. An average of 12 quiz questions were created for each chapter, totaling 146 questions. The classes covered in this study were conducted once a week. To confirm the degree of the learners' comprehension of the lesson content in a given week, a quiz was administered the week after completing the lesson. At the beginning of the lesson, we used the quizzes on Moodle and gave 12 quizzes from weeks 3 to 15. For the weekly quizzes, learners were given five minutes to answer five questions. These questions were randomly chosen from the questions for the chapter learned in the previous week. During the final lesson of the semester, a 30-question final quiz was given. The final quiz integrated the 12 weeks of quizzes, with 30 of the 146 questions created for the weekly quizzes being randomly selected, to assess the learners' level of comprehension of the various lessons.

4. Experimental Results

4.1 Classification of Learning Patterns

This section describes how to anticipate any relationships between Moodle material clickstreams and quiz scores and how to classify learning patterns that could potentially lead to obstacles to learning. In the proposed method, the deviation between the clickstream and the quiz score is calculated; this is then classified into four learning patterns based on the characteristics of those values and plus or minus signs. The four patterns classified here can be easily visualized through the creation of a scatter-plot graph. In addition, the scattered learning patterns increase the likelihood of identifying learners who should achieve excellent grades and those who are likely to fail the course. Here, the deviation is D_i, the observed value is x_i, and the average is $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, calculated by the following equation:

$D_i = x_i - \bar{x}$.

The first quiz was held in the third week of the fall semester of 2019. Table 1 (Week 3, Chapter 1, October 2, 2019) shows an example in which four learning patterns are classified from the deviation between the material clickstream and the quiz score at that time. In the work file in Table 1, the first column student shows the names of the anonymized learners, the second column Click shows the number of clickstreams of the materials in the chapter corresponding to the quiz range, the third column Quiz shows the quiz score, the fourth column Devi.click shows the deviation of the clickstream, the fifth column Devi.score shows the deviation of the quiz score, and the sixth column Learning Pattern shows the corresponding learning pattern. Patterns 1 to 4 correspond to the first to fourth quadrants on the scatter plot.

4.2 Learning Pattern by Deviation

As mentioned above, the learning pattern is considered to indicate behavioral engagement, so it is assumed that this affects the clickstream and the quiz score accumulated in the learning log of Moodle. Therefore, the number of outliers that appeared in the final quiz scores and the clickstream for the entire semester was examined. If a correlation exists between the number of occurrences of each learning pattern and the outliers, it is considered that the classified learning patterns can play a role similar to that of the outliers. This means that the visualization of learning patterns can help identify anomalous learners based on their final quiz scores and clickstreams, or learners who are struggling in class.

Table 1. *Example of the deviation calculation results and learning pattern classification for Week 3 (Chapter 1).*

	Click	Quiz	Devi.click	Devi.score	Learning Pattern
Student01	12	10	-17.09	2.72	P2
Student02	36	2	6.91	-5.28	P4
Student03	52	8	22.91	0.72	P1
Student04	22	10	-7.09	2.72	P2
Student05	24	8	-5.09	0.72	P2
Student06	11	6	-18.09	-1.28	P3
Student07	44	8	14.91	0.72	P1
Student08	21	4	-8.09	-3.28	P3
Student09	49	10	19.91	2.72	P1
Student10	15	8	-14.09	0.72	P2
Student11	32	4	2.91	-3.28	P4
Student12	27	8	-2.09	0.72	P2
Student13	24	8	-5.09	0.72	P2
Student14	27	8	-2.09	0.72	P2
Student15	22	4	-7.09	-3.28	P3
Student16	37	6	7.91	-1.28	P4
Student17	22	6	-7.09	-1.28	P3
Student18	15	2	-14.09	-5.28	P3
Student19	22	6	-7.09	-1.28	P3
Student20	20	8	-9.09	0.72	P2
Student21	24	6	-5.09	-1.28	P3
Student22	30	10	0.91	2.72	P1
Student23	21	8	-8.09	0.72	P2
Student24	29	6	-0.09	-1.28	P3
Student25	37	8	7.91	0.72	P1
Student26	35	8	5.91	0.72	P1
Student27	28	8	-1.09	0.72	P2
Student28	20	10	-9.09	2.72	P2
Student29	35	10	5.91	2.72	P1
Student30	31	6	1.91	-1.28	P4
Student31	27	8	-2.09	0.72	P2
Student32	29	10	-0.09	2.72	P2
Student33	31	8	1.91	0.72	P1
Student34	24	4	-5.09	-3.28	P3
Student35	47	10	17.91	2.72	P1
Student36	22	6	-7.09	-1.28	P3
Student37	32	8	2.91	0.72	P1
Student38	40	6	10.91	-1.28	P4
Student39	25	8	-4.09	0.72	P2
Student40	27	6	-2.09	-1.28	P3
Student41	40	10	10.91	2.72	P1
Student42	19	8	-10.09	0.72	P2
Student43	39	10	9.91	2.72	P1
Student44	34	4	4.91	-3.28	P4
Student45	24	8	-5.09	0.72	P2
Student46	49	4	19.91	-3.28	P4
Student47	34	10	4.91	2.72	P1
AVERAGE	29.085	7.277	0.000	0.000	
STDEV.S	9.717	2.223	9.717	2.223	
MAX	52	10	22.915	2.723	
MIN	11	2	-18.085	-5.277	
Data(N)	47	47	47	47	

Table 2. *Accumulation of learning patterns for weeks 1 to 15. "abs" = absent. Colored cells for click and quiz indicate outliers.*

	Clickstream(Week1-15)			Final Quiz	Learning Patterns					Hotelling's T2 theory			
										Outliers		P-value	
	In class	Out of class	Total	Week 15	P1	P2	P3	P4	Abs	Click	Quiz	Click	Quiz
Student01	316	2	318	22	0	8	5	0	0	2.972	0.001	0.005	1.000
Student02	412	128	540	21	4	5	4	0	0	0.029	0.039	0.977	0.969
Student03	268	26	294	15	0	1	9	0	3	3.580	2.324	0.001	0.024
Student04	442	133	575	27	2	2	4	2	3	0.006	1.275	0.995	0.208
Student05	477	63	540	24	1	5	1	3	3	0.029	0.217	0.977	0.829
Student06	478	49	527	20	4	6	1	1	1	0.068	0.175	0.946	0.862
Student07	354	194	548	24	5	3	4	0	1	0.013	0.217	0.990	0.829
Student08	521	205	726	27	7	2	1	3	0	1.285	1.275	0.205	0.208
Student09	330	51	381	21	0	2	9	0	2	1.645	0.039	0.107	0.969
Student10	521	148	669	22	6	2	0	4	1	0.539	0.001	0.592	1.000
Student11	254	33	287	21	0	4	4	0	5	3.767	0.039	0.000	0.969
Student12	568	189	757	22	7	2	0	3	1	1.824	0.001	0.074	1.000
Student13	447	111	558	26	4	3	4	2	0	0.002	0.825	0.999	0.414
Student14	419	253	672	27	8	2	2	1	0	0.571	1.275	0.571	0.208
Student15	360	116	476	24	1	5	4	1	2	0.381	0.217	0.705	0.829
Student16	389	4	393	14	0	3	8	2	0	1.437	3.048	0.157	0.004
Student17	550	45	595	24	5	4	3	1	0	0.047	0.217	0.963	0.829
Student18	302	41	343	17	0	5	7	0	1	2.399	1.171	0.020	0.247
Student19	339	111	450	22	0	3	7	1	2	0.639	0.001	0.526	1.000
Student20	490	218	709	21	2	3	2	5	1	1.029	0.039	0.309	0.969
Student21	412	22	434	10	0	0	11	2	0	0.831	6.919	0.410	0.000
Student22	469	159	628	22	8	2	2	1	0	0.200	0.001	0.842	1.000
Student23	540	31	571	17	1	3	5	4	0	0.002	1.171	0.998	0.247
Student24	407	69	476	24	2	4	4	1	2	0.381	0.217	0.705	0.829
Student25	466	250	716	19	9	0	0	4	0	1.131	0.410	0.264	0.684
Student26	404	16	420	23	3	7	3	0	0	1.019	0.060	0.313	0.953
Student27	453	49	502	24	2	8	3	0	0	0.189	0.217	0.851	0.829
Student28	393	147	540	22	0	7	4	2	0	0.029	0.001	0.977	1.000
Student29	432	181	613	22	7	3	1	2	0	0.117	0.001	0.907	1.000
Student30	497	111	608	28	4	3	4	2	0	0.094	1.824	0.925	0.075
Student31	408	37	445	9	0	2	11	0	0	0.696	8.131	0.490	0.000
Student32	424	391	815	20	4	2	1	3	3	3.086	0.175	0.003	0.862
Student33	572	187	759	27	10	1	0	2	0	1.862	1.275	0.069	0.208
Student34	432	139	571	16	0	1	11	1	0	0.002	1.699	0.998	0.096
Student35	662	211	873	24	12	0	1	0	0	4.679	0.217	0.000	0.829
Student36	460	76	536	18	2	3	6	2	0	0.039	0.742	0.969	0.462
Student37	494	59	553	25	3	4	3	0	3	0.006	0.472	0.995	0.639
Student38	562	154	716	28	8	2	0	3	0	1.131	1.824	0.264	0.075
Student39	399	60	459	25	1	7	5	0	0	0.542	0.472	0.590	0.639
Student40	361	170	530	21	1	5	6	1	0	0.057	0.039	0.955	0.969
Student41	480	199	679	27	11	2	0	0	0	0.647	1.275	0.521	0.208
Student42	344	30	374	25	0	8	3	0	2	1.773	0.472	0.083	0.639
Student43	438	231	669	28	11	1	0	1	0	0.539	1.824	0.592	0.075
Student44	474	55	529	16	4	2	4	3	0	0.061	1.699	0.952	0.096
Student45	558	61	619	17	2	6	2	3	0	0.148	1.171	0.883	0.247
Student46	574	270	844	26	11	0	0	1	1	3.841	0.825	0.000	0.414
Student47	490	187	678	25	7	2	2	2	0	0.636	0.472	0.528	0.639
AVERAGE	443.4	120.7	564.1	21.9	3.8	3.3	3.6	1.5	0.8	0.979	0.979	0.558	0.576
STDEV.S	86.7	86.1	142.8	4.5	3.7	2.2	3.1	1.4	1.2	1.214	1.581	0.382	0.373
MAX	662	391	873	28	12	8	11	5	5	4.679	8.131	0.999	1.000
MIN	254	2	287	9	0	0	0	0	0	0.002	0.001	0.000	0.000
0 (zero)					12	4	8	15	29				
Exclude 0					35	43	39	32	18				
Data(N)	47	47	47	47	47	47	47	47	47	47	47	47	47

Therefore, the number of occurrences of each learner from patterns 1 to 4 was aggregated from weeks 3 to 15, and correlations with the final quiz score and clickstream outliers were verified (Table 2, columns the eleventh to the fourteenth, Hotelling's T^2 theory). Table 2, columns the sixth to the tenth Learning Patterns shows the corresponding patterns 1 to 4 and the absenteeism data for each learner, as well as the calculated results for detecting outliers in clickstreams and quizzes. Specifically, the Pearson correlation coefficient was calculated using the data from columns the fourth to the ninth in Table 2. The detection of an outlier is based on Hotelling's T^2 theory, and the following equation is used, where the outlier is a, the observed value is $x_1, x_2, \dots, x_n$, the average is $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, and the standard deviation is $s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$, calculated by the following equation: $a(x_i) = (x_i - \bar{x})^2/s^2$

4.3 Pearson’s Correlation Coefficient between the Learning Log and the Four Patterns

In each learning pattern shown in Table 2, the data in which the number of occurrences is zero are included. Therefore, excluding those with zero occurrences, the Pearson’s correlation coefficient was obtained for each learning pattern and final quiz score, as well as between each learning pattern and clickstream; the level of correlation was investigated. The following relationships for each pattern were clarified. Regarding absenteeism, the correlation coefficient was omitted because the number of data points was small.

Pattern 1 tends to exhibit both material clickstreams and quiz scores that are higher than average because of the opening of materials and reading them, and it is expected that the opening of materials will affect quiz scores. The Pearson’s correlation coefficient between the final quiz scores of the learners who belonged to pattern 1 was $r = 0.396$ ($p = 0.009$, $p < 0.05$), indicating a weak positive correlation. The Pearson’s correlation coefficient between the material clickstreams of the learners who belonged to pattern 1 was $r = 0.747$ ($p = 0.000$, $p < 0.05$), indicating a strong positive correlation. Learners who maintain this pattern at all times are expected to have good results and tackle their classes well. Another feature of this learning pattern is that it rarely exhibits pattern 3 (Table 2, students 33, 38, 41, 43, and 46).

Pattern 2 has a lower number of material clickstreams, but the quiz scores are higher than the average value. The Pearson’s correlation coefficient between pattern 2 learners’ final quiz scores and the pattern’s number of occurrences was $r = 0.055$ ($p = 0.362$, $p > 0.05$), indicating no correlation. The Pearson’s correlation coefficient between the clickstreams of material and the number of occurrences corresponding to the pattern was $r = -0.469$ ($p = 0.001$, $p < 0.05$), indicating a negative correlation. This means that learners who show pattern 2 tend to reduce the number of times they fall into this pattern if they open the material and read it carefully. Learners belonging to this pattern tend to have higher quiz scores without opening materials. Therefore, it is assumed that they have prior experience of learning content similar to that of the material; it is also assumed that some learners simply do not read the material. Furthermore, by listening carefully to the commentary while watching the teacher’s monitor during class, some learners highly likely decided that they did not have to read the materials (Table 2, students 01, 09, 11, 19, 26, and 42).

Learners who exhibit pattern 3 have a relatively lower than average material clickstream and a lower than average quiz score. The Pearson’s correlation coefficient between pattern 3 final quiz scores and the number of occurrences was $r = -0.689$ ($p = 0.000$, $p < 0.05$), indicating a negative correlation. The Pearson’s correlation coefficient between the clickstream of the materials and the number of occurrences corresponding to the pattern was $r = -0.579$ ($p = 0.000$, $p < 0.05$), indicating a negative correlation. Learners who exhibit pattern 3 are assumed to have the tendency to be uninterested in the lesson content. It is expected that some of these learners will fall into the category of unsuccessful learners (Table 2, students 03, 16, 18, 21, and 31).

Learners who exhibit pattern 4 have more material clickstreams than average, but their quiz scores are lower than average. The Pearson’s correlation coefficient between pattern 4 learners’ final quiz scores and the group’s number of occurrences was $r = -0.327$ ($p = 0.036$, $p < 0.05$), indicating a weak negative correlation. The Pearson’s correlation coefficient between the clickstream of the materials and the number of occurrences corresponding to the pattern is $r = 0.328$ ($p = 0.033$, $p < 0.05$), indicating a weak positive correlation. This pattern includes learners who have not read the materials even though they have opened them and learners who cannot understand the materials even if they have read them. It is expected that those who are not interested in the class, as well as pattern 3 learners, fall under pattern 4. Giving priority to the learners who belong to this group and encouraging them to carefully read the materials and to concentrate and participate in the lessons are necessary (Table 2, students 20, 25, and 32).

5. Discussion

It is assumed that a correlation is established between learners’ clickstream of the materials and their proper learning of the materials, as reflected by their weekly quiz and final quiz scores. When a positive correlation exists, it is assumed that the learner opened the materials and properly understood the lesson content. Conversely, there could be several causes for a negative correlation, such as inappropriate reading of the materials by the learners, insufficient understanding of the lesson content, use of inappropriate teaching methods, and inappropriate content of the materials.

However, during each lesson in this study, the course materials were displayed on the teacher's monitor screen, the content was explained to the learners as they read it, and the related Excel operations were demonstrated. Therefore, it is presumed that the learners—without having to open the materials on their own computer, often understood the lesson content from watching their teacher's explanations and demonstrations. This seemed to be true for learners who exhibited pattern 2. Therefore, if there are many learners who exhibit pattern 2, the relationship between the clickstream and the quiz score tends to be weakly correlated or uncorrelated.

6. Conclusion

A method was proposed to classify learning patterns using the deviation between the teaching material clickstream and the quiz score. The proposed method not only identified those learners who were struggling in the lesson but also showed the level of the learners' engagement in learning and their reaction to their teacher's teaching. It was found that few learners have a constant learning pattern, and many tend to change their learning patterns every week. However, learning patterns categorized from the Moodle course log can be used by teachers to identify and improve their approaches to better teaching and learning.

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