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Estimation of Test Scores based on Questionnaire and Video Viewing Behavior in the Programming MOOC Course

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Abstract

The Massive Open Online Courses (MOOCs) offer various types of learners the opportunity to attend university-level lectures. However, since many learners drop out during the learning process, the average MOOC completion rate is usually as low as 10%. For future improvement, MOOCs must grasp the learners' features in the earlier stage and provide appropriate support to each learner. This paper investigates the relationship between learners' characteristics and test scores in the programming MOOC course to recognize different types of learners. Video viewing behavior and the questionnaire information at the beginning of the lecture, i.e., age, programming skill, and keywords in the free description, are analyzed to characterize learners. As the results, it was observed that the repeated learning behavior and later join to the course relates to the higher and lower score, respectively. The information from the questionnaire improves the accuracy of pass/fail estimation before the third week. The characteristic cluster of learners, who could be rescued by offering appropriate support, was also obtained by multiple regression analysis results.

Keywords: MOOC, Learning Analytics, Test Score, Video Viewing Behavior, Multiple Regression Analysis

1 Introduction

The attractive point of the Massive Open Online Courses (MOOCs) is to provide university-level lectures to various types of massive participants. The Japan Massive Open Online Courses Promotion Council (Hereinafter, JMOOC), which started in 2013 [1], offers 340 courses in total as of 2019 and produced more than one million learners. Universities and laboratories introduce their strong and famous aspects via courses, and the National Institute of Informatics also developed an introductory programming course, "*Hajimete no P* (The first step of programming)" [2]. In such MOOC courses, even though many participants join initially, many participants drop out in the middle of the course without completing it. The typical completion rates are as low as 10%, which is a negative aspect of the MOOC and is recognized as a problem to be solved in the MOOC operations [3][4].

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Learning analytics (Hereinafter, LA) aims to solve problems in the learning process and improve education by collecting and analyzing learning logs stored in the learning management systems. The research themes of LA include estimation of learners' skills, trials to provide teaching materials according to the learners' interests and abilities, and various other researches on educational improvements [5]. MOOCs' dropout problem is one of the targets of LA, and various studies have been conducted.

Khalil et al. investigated the causes of dropouts in MOOCs and clarified that the causes are lack of time, lack of learners' motivation, feelings of isolation, lack of interactivity in MOOCs, insufficient background and skills, and hidden costs [6]. Lee et al. reviewed research papers related to online course dropout in post-secondary education and found that the factors that affect dropouts can be categorized into student factors, course/program factors, and environmental factors [7]. They also showed that the strategies to overcome the dropout are understanding each student's challenges and potential, providing quality course activities and well-structured supports, and handling environmental issues and emotional challenges. Tan et al. tried to predict student dropouts [8]. They used variables such as the student's age, major, number of subjects learned, average test score, and so on, and compared classification methods such as naive Bayes, random forest, logistic regression, and k nearest neighbor. The results showed that logistic regression outperformed other classifiers, and the accuracy was nearly 90%. Gitinabard et al. estimated dropouts using learning behaviors such as access to teaching materials and features extracted from discussions [9]. They developed a social network and extracted structural and behavioral features, such as whether learners played an important role in the discussions.

Regarding the representation of learner features, Manrique et al. proposed three different student representations: Global Feature-Based, Local Feature-Based, and Time Series [10]. They found that the Local Feature-Based approach, such as the grades of registered courses, was more effective in estimating dropouts than global features, such as the number of registered courses and the average grade. They also found that the temporal aspect of the data increased the computational cost but did not contribute to the prediction accuracy. On the other hand, Ye et al. showed that finer-grained temporal information increased the accuracy of prediction in the early phases of the MOOC course on Pattern-Oriented Software Architectures [11]. The purpose of these studies is to predict dropouts, but the approaches are very different. This is due to the significant differences in the characteristics of the target group of learners and the functions of the LMSs [12].

Considering the low completion rate of MOOCs, it is unrealistic to assume that all MOOC learners will complete the courses. To reduce the dropout in MOOCs, LA needs to consider which type of learners could be rescued. Rather than just estimating the pass/fail of the course in advance, it requires providing more granular supports, such as sending support e-mails, to a particular type of learners at appropriate opportunities. Grasping the types of learners in the earlier stage is essential to realize such a process. We succeeded in estimating learners' differences by investigating the relationship between learners' video viewing behavior and test scores in the programming MOOC course [13]. This previous study analyzed video viewing behavior in detail and applied the multiple regression analysis to get insight into the characteristics of learners. In this paper, we improve the accuracy of the estimation by using the video viewing behavior and the information obtained from the questionnaire at the beginning of the lecture, i.e., age, programming skill, and keywords in the free description.

The academic and social contributions of this paper is as follows. By comparing the learner's behavior and determining whether or not a learner can complete a course, it is shown based on the actual MOOC course that instructors do not have to worry about course completion of learners who actively watch videos, but they need to pay attention to learners who do not actively watch the videos. Next, by the results of the multiple regression analysis, the groups of learners who may complete the course with appropriate support are identified. These results will lead to effective learning support. Although the results of this paper are for the field of education, the proposed method could be applied to other fields such as marketing, where sales promotions are made to consumers who stop buying.

2 The Programming MOOC Course

The target of analysis is the introductory programming course "*Hajimete no P* (The first step of programming)" developed by the National Institute of Informatics. This course was developed on gacco [14], one of the JMOOC platforms. This course started on August 9, 2016 and lasted 70 days. The lecture was given by three assistant professors and one navigator. The content of the course is shown in Table 1.

Table 1: Content of the Course

Unit	Title	Description of the content
1	Become a Programmer - Learn the fascination of programming!	The attractiveness of programming and learning methods are introduced based on the experience of the lecturers. Learn basic programming knowledge (variables, assignments, arithmetic operations, types of variables, and arrays).
2	ABC of programming - Let's tinker with Bit's tweet!	By inputting a simple JavaScript program on a Web browser, the tweet of *Bit-kun* is modified. Learn the basics of programming (statement, loop, conditional branch, and function).
3	Getting Started with Programming - Let's Complete Bit's Game!	Through *Bit-kun*'s game (get home without hitting a car), help learners feel that they can do programming. Learn case statement and function by changing the game program.
4	An Introduction to Algorithms - Learn the Theory of Programming by Experience!	Using familiar subjects, learners learn the essence of the mathematics behind computers. Learn selection sort and merge sort, right-hand search and breadth-first search, the binary system, and XOR.

In the first unit, along with basic programming knowledge, three lecturers introduced the attractiveness of programming and the learning methods based on their experiences. In the second unit, the tweets of *Bit-kun*, the mascot character of the laboratory, are modified by JavaScript. In the third unit, the Racket [15] game was modified to learn a little more complicated programming elements such as case statements. In the fourth unit, algorithms behind computers and programming were introduced. Each unit consists of 3-5 short videos and confirmation quizzes. A discussion board and a forum were set up for discussion and mutual help. In addition, a web-based questionnaire was conducted at the beginning of the course. Regarding the completion conditions, if the overall score of the confirmation quizzes is 70 or higher, the learner passes the course and gets a certificate of completion.

The number of learners who participated in the course was 6,859, and the number of discussion threads reached 210. These were above the gacco average. The completion rate of this course was 18%, which also exceeded the average completion rate of gacco.

3 System Environment of Log Storage

Figure 1 shows the learning analytics platform that was used in the analysis [16]. The system's base is Learning Locker [17], which is an open-source log store application, and MongoDB is used as a database. The gacco platform is developed based on Open edX [18], an open source MOOC platform, and the learning log data extracted from the gacco platform are stored in MongoDB in the xAPI format [19]. The xAPI is one of the standards related to learning log store, and 90 kinds of events, such as "logged in" and "viewed," are defined in our study. To protect personal information, personally identifiable data such as user names and user IDs are anonymized using hash algorithm. The analysis can be carried out using Python and R, which are often used for statistical analysis.

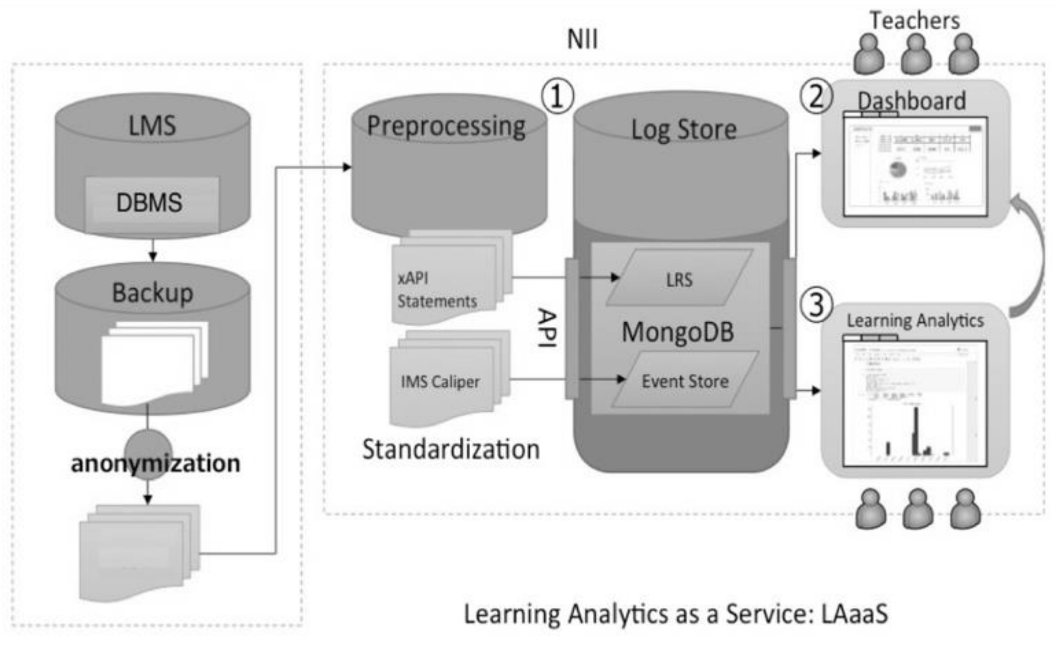


Figure 1: System Environment for Learning Log Analysis

4 Analysis of Questionnaire

In this online course, the web-based questionnaire was conducted at the beginning of the course to understand the learners' attributes. The obtained information can be used for LA. Among the total 6,859 learners, 2,415 learners answered the questionnaire, and the data was used for the following analysis.

Figure 2 shows the relationship between ages and scores. The horizontal axis shows the scores, and the vertical axis shows the composition ratio of scores. The age was calculated from the year of birth in the questionnaire. The 24 unnatural cases, such as over 100 years old, were eliminated from the figure. In this figure, A, B, and C show the classes 0-24, 25-49, and 50-74 years old, respectively, whereas D shows 75 years old and over. The number of learners of A, B, C, and D is 134, 1097, 1069, and 91, respectively. The average score of A, B, C, and D is 29.6, 32.7, 51.3, and 55.0, respectively. The figure shows a large percentage of learners scored less than 10 (mostly 0) or over 90 (mostly complete). In the full score (100 points), relatively young A and B are lower than C and D. On the other hand, it is the opposite if the score is low (less than 10 points). This course was developed primarily as a programming course for younger people, but the result shows that scores tend to higher with age.

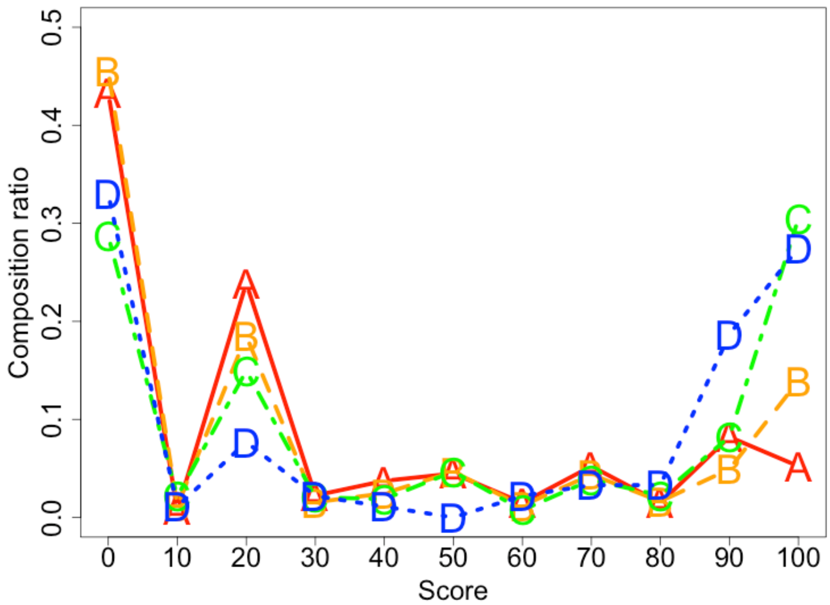


Figure 2: Composition Ratio of Scores for Each Age

In the questionnaire, the programming skills were selected from the four categories shown in Table 2. The number of learners of skill level 1, 2, 3, and 4 is 1309, 597, 391, and 118, respectively. The number of learners decreased as the skill level increased.

Figure 3 shows the relationship between programming skills and the scores. The horizontal axis shows the scores, and the vertical axis shows the composition ratio of the scores. The average score of skill level 1, 2, 3, and 4 is 35.3, 47.3, 52.2, and 47.0, respectively. The average score of skill level 4 is slightly lower than that of skills 2 and 3, but the scores of skills 1-3 increase as the skill level increases. In addition, the figure shows that, in the skill level 1, the percentage of full scorer is low and the percentage of low scorer (less than 10 points) is high.

Table 2: Definition of Skill Levels

Skill level 1	No programming experience
Skill level 2	Have studied programming through introductory books or websites
Skill level 3	Have experience creating programs
Skill level 4	I do programming daily

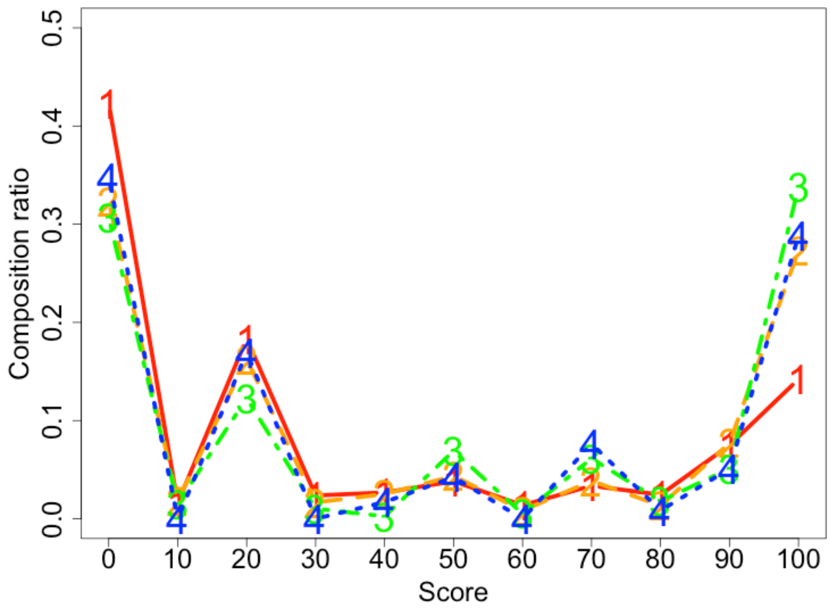


Figure 3: Composition Ratio of Scores for Each Skill Levels

The learners answered as free description to a questionnaire “If you have any expectations for this course, please write freely”. The free description may contain keywords related to the score. Since the questionnaire is obtained in the early learning stage of the course, it will help to estimate the future result if the correlation exists.

For the analysis of free description, we calculated TF-IDF and extracted important keywords. TF (Term Frequency) indicates the frequency of words. Words that appear more frequently are considered to be more important. IDF (Inverse Document Frequency) is an index that considers words in a smaller number of documents to be more important. It is calculated by dividing the total number of documents by the number of documents containing the target keyword and taking the logarithm. TF-IDF is the product of TF and IDF, and words with larger TF-IDF values can be considered to be more important keywords.

To select important keywords, first, morphological analysis was performed on the free description, and each sentence was divided into words. Then, only nouns were extracted from these words. Finally, TF-IDF values were calculated for each word, and 60 words were selected in descending order of the value. As a result, the following 60 words were extracted:

programming, understanding, expectation, program, course, introduction, beginner, content, request, self, knowledge, fundamentals, language, attendance, learning, lecture, study, easiness, interest, enjoyment, body, trigger, level, mastery, explanation, creation, thinking, experience, amateur, skill, class, future, person, job, now, start, method, introduction, last, technology, clarity, continuation, up, me, practice, step, application, term, concept, anxiety, explanation, self-study, education, specialization, degree, computer, recentness, frustration, app, and end. We use the number of these words in each free description as the characteristics of each learner.

5 Analysis of Learning Behavior

The analysis of learning behavior is the same as in our previous study [13]. Since video viewing behavior stored in the log storage is thought to reflect the amount of learning and enthusiasm for learning, it was used as one of the learners' characteristics. As in the analysis of the questionnaire, learning logs of 2,415 learners who answered the questionnaire at the beginning of the course were analyzed.

To get the number of video views, we extracted the *play_video* events from the learning log data. However, due to playback errors, the *play_video* events were sometimes counted more than the actual video views. To eliminate error data, the number of video views was counted as one if any videos in each unit were viewed more than once a day. This means that we use the number of days each unit is viewed as the number of video views. The number of videos in each unit is different, and the length of each video is also different. However, each unit was designed to have the same amount of learning, so the number of video views was counted this way. This counting method allows us to analyze the data from a macroscopic point of view. The learning materials are composed of four units, so the number of video views of each learner increases up to four times a day.

Figure 4 shows the heat map of video viewing behavior. The vertical axis denotes elapsed time throughout the course. The 1st day when the course started is displayed on the top, and the 70th day when the course ended is displayed on the bottom of the figure. One vertical line corresponds to one learner, and all 2415 learners are shown in this figure. The horizontal axis is sorted so that learners with high scores become on the left. In this figure, white color means 0 views, gray means one view, and black means more than two views. As a general tendency, it can be seen that left of the figure is darker, meaning that the learners will get a higher score watched the videos more frequently than the learners will get a lower score (FEATURE 1). The figure's left part is dark every week interval, and gradation can be seen more clearly than the right part of the figure. This difference reflects the tendency that the learners with high scores learn the course regularly (FEATURE 2). The right top part of the figure is white, and the dark part appears lower. From this dark point, learners started to take the course. The fall of the dark line from left to right reflects the tendency that many learners with low scores started the course late (FEATURE 3).

To investigate FEATURE 1, Figure 5 shows the number of video views. (a) shows the results one week after the first access to the course, (b) shows the results three weeks after the first access to the course, and (c) shows the results ten weeks after the first access to the course. As same as Figure 4, the horizontal axis is different learners sorted by the score. One vertical line corresponds to one learner. The four lines from top to bottom correspond to the number of video views of units 1 to 4. In this figure, white means 0 views, whereas black means four or more views.

From (a), it can be seen that the learners mainly watched unit 1. After three weeks (b), especially in high score learners, they watched unit 2 and unit 3 repeatedly. However, low score learners do not have a similar tendency. This repeated behavior happens because unit 2 and unit 3 are the main content of this course and relatively difficult to understand. After ten weeks (c), the higher the score, the more learners watched unit 4. In this course, if the overall score is 70 or higher, the learner passes the course. Among the 2,415 learners shown in this figure, 833 learners passed the course. They are almost 1/3 of the figure and almost consistent with those who repeatedly watched unit 4. However, even in learners who will not pass the course, there is a high gray level between 20 to 70. In the case of unit 2, the dark part exists beyond 70 (α). In addition to that, some learners are losing contrast while progressing the course (β). There is a possibility that this type of learner could be rescued by offering appropriate supports.

To investigate FEATURE 2, Figure 6 shows the video viewing intervals. (a) shows the results one week after the first access to the course, (b) shows the results three weeks after the first access to the course, and (c) shows the results ten weeks after the first access to the course. The horizontal axis is different learners sorted by the score. One vertical line corresponds to one learner, and the intervals are arranged from top to down as 0 to 19 days. The interval is counted as 0 days when a learner watches multiple units of videos on the same day and one day when a learner watches videos one day and the day before. The contrast has 4 gray levels: white means 0 views, and black means three or more views. The figure shows that the gray level of 0 days intervals becomes dark after one week (α). After three weeks (b), gray gradation becomes more apparent. The high score learners watch video more than one-day interval (β). This is due to the repeated viewing of unit 2 and unit 3 videos. After ten weeks (c), as denoted by (γ), seven days interval becomes apparent, especially in high score learners, showing that high score learners viewed videos in their weekly procedure. They are almost 1/3 of the figure and almost consistent with those who passed the course. In contrast, the weekly procedure could not be observed in learners who took lower than 70.

To investigate FEATURE 3, Figure 7 shows when learners started to view videos. The vertical axis shows days elapsed after starting the course. The 1st day is on the top, whereas the 70th day is on the bottom. Black point for each learner indicates the first day of the video view. The result shows that learners with exceptionally high scores take the course from the first day (α). These learners must have obtained the course information in advance. Therefore, they could access the course from the first day. On the other hand, many learners with low scores tend to start later (β). Between (α) and (β), the black line falls repeatedly. This shows that even in the same score, some learners are starting from a later date. We can see several different types of learners in this figure. In particular, learners with scores between 20 and 70 are similar to learners with scores above 70, and these learners could be rescued. On the other hand, as shown in (β) of the figure, learners who start learning after seven days from the beginning of the course will have difficulty passing the course.

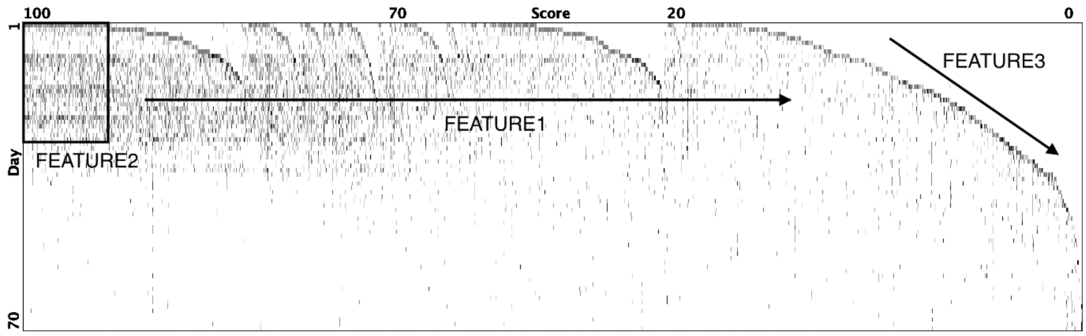
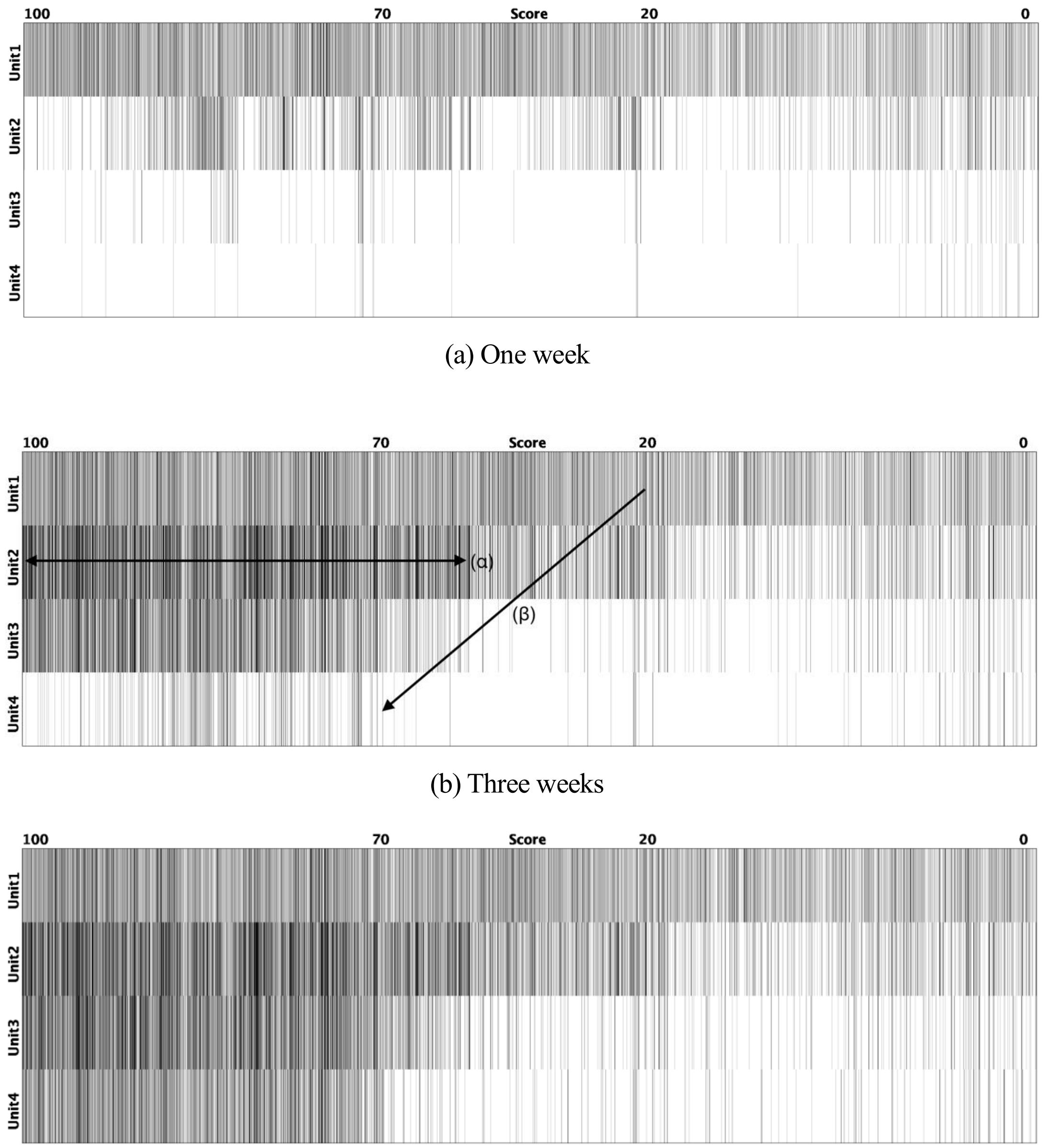


Figure 4: Heat Map of Video Views

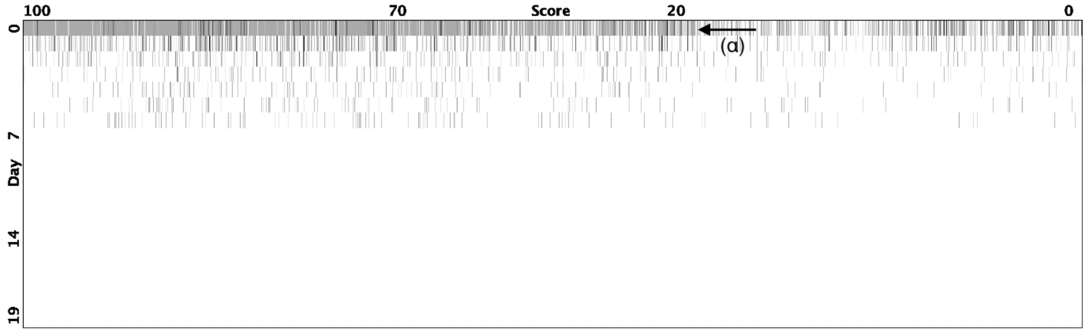


(a) One week

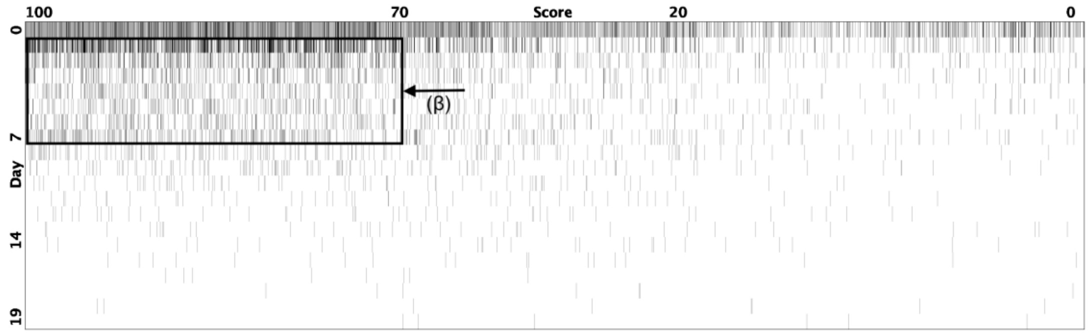
(b) Three weeks

(c) Ten weeks

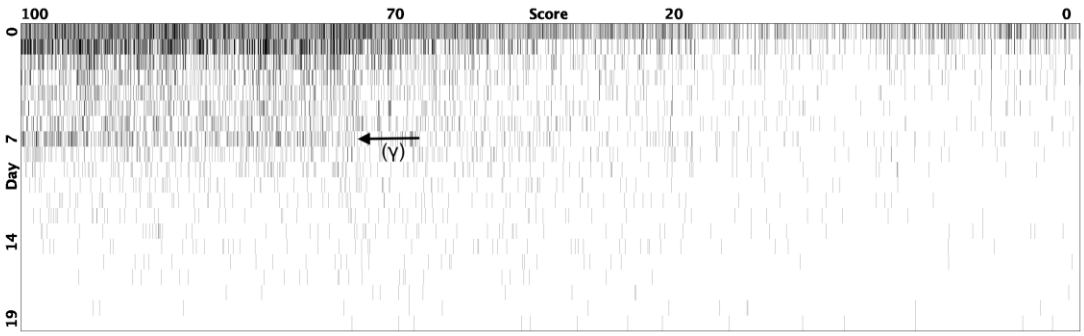
Figure 5: Number of Video Views



(a) One week



(b) Three weeks



(c) Ten weeks

Figure 6: Intervals of Video Views

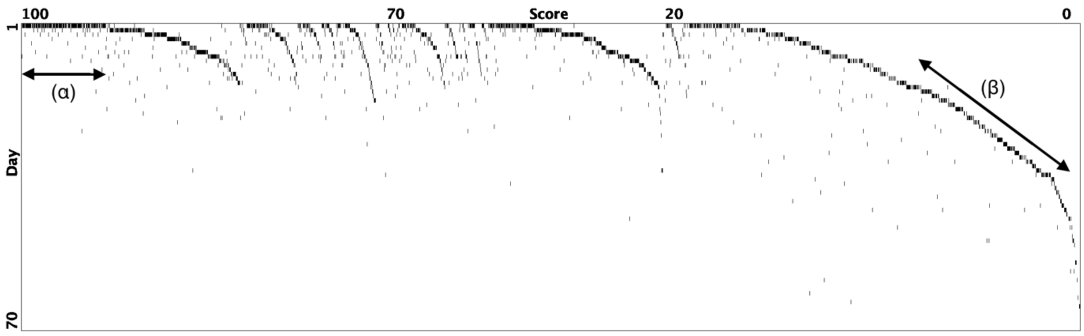


Figure 7: First Access to Videos

6 Score and Pass/Fail Estimation

This section aims to develop the model that predicts each learner's test score based on the information obtained from the questionnaire and video viewing behavior. Following parameters after N weeks are used for the estimation.

1) Age

The age of the learners was obtained using the method described in section 4. The 24 learners whose ages were unnatural values outside the range of 0-100 were treated as 46 years old, the average of the ages.

2) Programming experience

Regarding programming experience, skill level 1 to 4 mentioned in section 4 were quantified from 1 to 4. The larger value, the more the learner has programming skills.

3) Keywords in free description

The 60 words with large TF-IDF values were extracted from the questionnaire's free description as described in section 4. We computed the 60-dimensional vector of word frequencies, and these values were used as the features of each learner.

4) Number of video views

Since the learning material is composed of 4 units, the number of video views becomes 4-dimensional data. The number of video views was counted as one if any videos in each unit were viewed more than once a day.

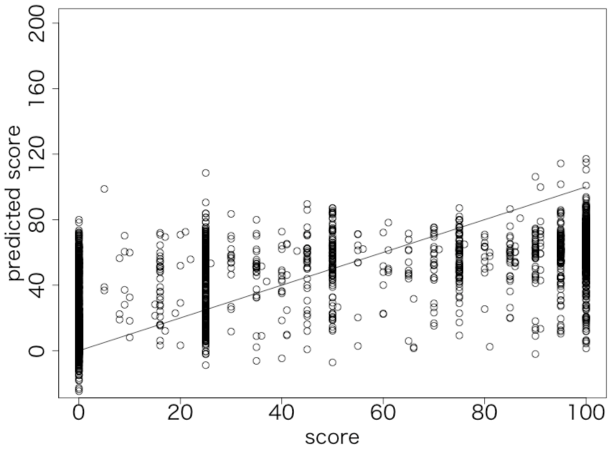
5) Intervals of video views

Typically, high score learners view videos intensively at short intervals, and low score learners do not. Since the intervals of video views more than 20 days are almost 0, 20-dimensional data from 0 to 19 days are used as the features of video viewing intervals.

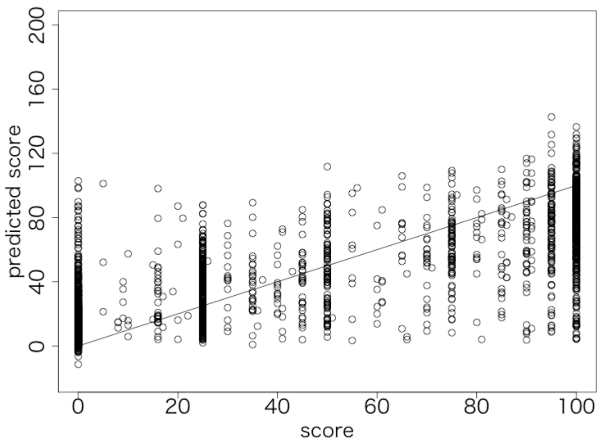
6) First access to videos

This parameter corresponds to the value obtained in Figure 7. It is one-dimensional data, and if there was no video access, the value was set to 71.

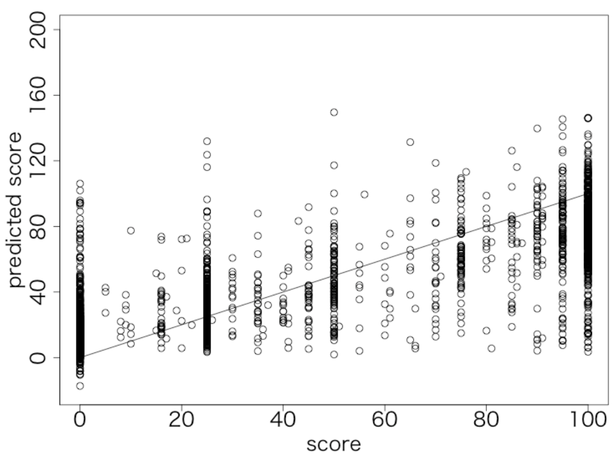
To predict the test scores, multiple regression analysis is used. The input data are 87-dimensional data that are the sum of the above features. The weights of these input data are determined to reproduce the test scores. Figure 8 shows the relationship between actual scores and predicted scores. (a), (b) and (c) show the results after one week, three weeks, and ten weeks, respectively. The horizontal axis is the actual score, and the vertical axis is the score predicted by the multiple regression analysis. If the scores are entirely predictable, the points will lie on a straight line between (0, 0) and (100,100). The circle is the predicted score versus each learner's actual score, which means that there are 2,415 circles in this figure. The correlation between the actual scores and predicted scores becomes more stronger as time passes.



(a) One week



(b) Three weeks



(c) Ten weeks

Figure 8: Correlation between Score and Predicted Score

Figure 9 shows the coefficient of determination (square of the correlation coefficient R, which is a measure of the strength of correlation) calculated by the multiple regression analysis. The “+” markers indicate the case where only the video viewing behavior features are used. The “◯” markers indicate the results when the information obtained from the questionnaire is added. It can be seen that the coefficient of determination before the third week is improved by using the information obtained from the questionnaire at the beginning of the course.

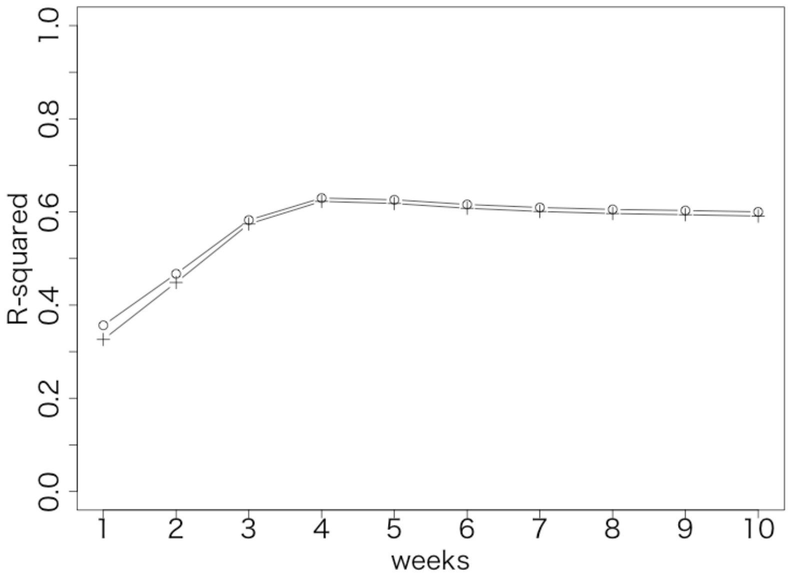


Figure 9: Square of the Correlation Coefficient R

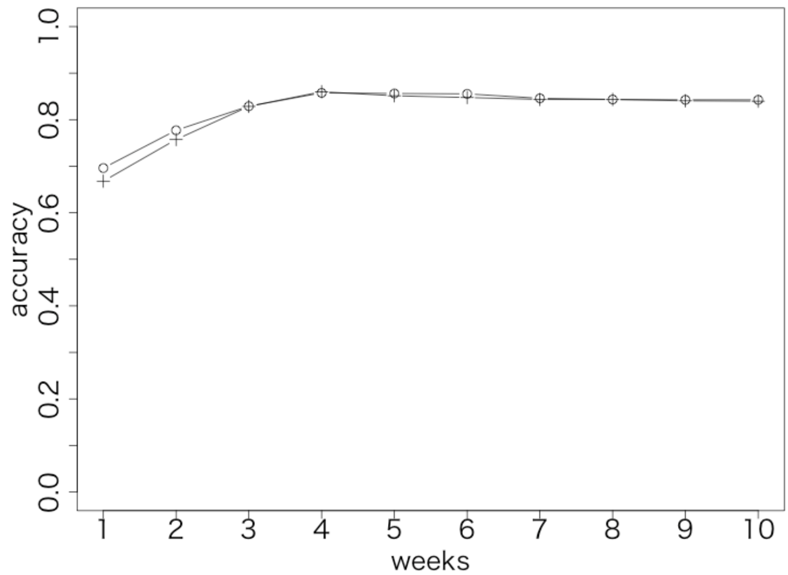


Figure 10: Prediction of Pass/Fail

Figure 10 shows the accuracy of the prediction of pass/fails using multiple regression analysis. The "+" markers indicate the case where only the video viewing behavior features are used. The "◯" markers indicate the results when the information obtained from the questionnaire is added. In this online course, learners whose scores are 70 or higher pass the course. The accuracy was calculated by whether the model could predict the actual pass/fail. This figure shows that pass/fail estimation can be performed with an accuracy of 80% or more after three weeks. This figure also shows that the accuracy was improved using the information from the questionnaire before the third week, indicating that the questionnaire's information is helpful for estimating pass/fail at a relatively early stage when sufficient information on learning behavior cannot yet be obtained.

Looking at the results in Figure 5(a), in unit 1, learners scoring 20-70 and scoring 70-100 watched the video to the same extent. In unit 2, learners scoring 20-70 and learners scoring 70-100 also watched the video to the same extent, and some of the learners scoring 20-70 watched the video more intently than learners scoring 70-100. Looking at the results in Figure 6(a), it can be seen that learners scoring 20-70 and the learners scoring 70-100 have 0 days intervals to the same extent, i.e., they watched a similar number of videos on the first day. On the other hand, in Figure 8 (a), the predicted score for the actual score of 50 tends to be higher. From these results, it can be seen that the learners with the final score of around 50 worked hard at the beginning of the course but could not get a score over 70. Thus, the learner cluster in this range has the potential to learn and can pass the course with appropriate supports.

7 Conclusions

In this paper, to recognize different types of learners, we investigated the relationship between learners' features and test scores in the programming MOOC course. As the learners' features, in this paper, video viewing behavior and the questionnaire's information at the beginning of the lecture, i.e., age, programming skill, and keywords in the free description, are used. As the results, it was observed that the repeated learning relates to the higher score, later learning relates to the lower score, and the information from the questionnaire improves the accuracy of pass/fail estimation before the third week. The characteristic cluster of learners, who could be rescued by offering appropriate support, was also observed in the results.

As support for learners, for example, we can send support e-mail to the cluster of learners who have low expected scores and may drop out. We can recommend appropriate learning materials to learners whose expected scores are medium in order to promote better understanding. On the forums, we can promote interaction between learners who may drop out and learners who have a good understanding of the course content. Also, if we have data on the differences in learning behavior among learners, we can help learners by saying that those who passed the test watched this video many times.

However, the results of this study are limited because they are based on a particular MOOC course. The relationship between learning behavior and scores may change depending on the composition of the learning materials and the conditions for completion. Also, learners with the same score do not necessarily have the same characteristics, so the clustering method need to be able to identify finer-grained differences among learners. Therefore, extending this study by using data from other courses will be a future work.

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