Predicting Learners' Performance Using MOOC Clickstream

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Abstract. Massive Open Online Courses (MOOCs) have gradually become a dominant trend in online education. However, due to the large number of learners participating in MOOCs, teachers usually cannot accurately know the learning outcomes of each MOOC user. In addition, many learners did not take the corresponding quiz after watching the MOOCs' videos, and some MOOC videos even did not contain a quiz, which makes it difficult to evaluate the learners' performance. In the absence of learners' test scores, how to evaluate learners' performance has become a huge challenge. In this paper, we build a MOOC platform and collect user clickstream data in course videos, and propose a novel approach for predicting learners' performance based on MOOC clickstream. We use MOOC clickstream data to define handcrafted features and embedding features of user learning behavior, which are used to infer learners' performance. Experimental results show that the performance of the proposed method exceeds that of the state-of-the-art methods.

Keywords: Learners' performance · Learning outcome · Clickstream · MOOC · E-learning

1 Introduction

With the popularization of online education, more and more people acquire knowledge through the Internet. Massive Open Online Courses (MOOCs) [9] are also gaining popularity as an important online learning resource. MOOC refers to the establishment of learning communities through unrestricted participation and readily available online courses. In the MOOC platform, students are

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not limited by time and place, and can flexibly arrange their own study plans. Especially, in traditional classrooms, if students are distracted, they will miss what the teacher taught, and they will have to spend a lot of time reviewing after class. MOOC is different from these traditional courses. If students do not understand the content of the course, they can understand the knowledge by playing the course video repeatedly. In general, in the MOOC learning process, there is no teacher supervision, no entry threshold, and no need to pay expensive fees, which is very convenient for students to carry out personalized learning. Currently, MOOC platforms such as Coursera [13], edX [1], and XuetangX [18] have registered more than 10 million people.

However, the MOOC learning mode also faces some problems. On the one hand, learning in MOOC is mainly based on watching course videos. The number of students participating in a MOOC is much higher than that of a traditional course. It is difficult for teachers to take care of each student. Many students do not continue to participate in the study after enrolling in the course, and the low course completion rate is a common problem faced by MOOC platforms [8,11].

On the other hand, there are many learners who just watch the course video of a MOOC without taking the quiz in the course, and some MOOCs even do not provide a quiz, which made it difficult for MOOC users to know the effect of their learning. Since many MOOCs lack student test scores, it is obviously impossible to directly evaluate their learning outcomes. How to accurately evaluate the learning outcomes of MOOC users has become an urgent problem to be solved in the current MOOC research. Some researchers try to predict the learning outcomes of MOOC users by analyzing the learning history records left by users, and provide early guidance for the users who need help [2,3,5,10].

In fact, it is not easy to obtain the learning history information of students from each MOOC platform, because it is the private data of each platform after all. In this study, we built a MOOC platform using open source code, and collected the learning history information of students, i.e. clickstream data, from the MOOC platform to support the task of prediction of learning outcomes of MOOC users. By analyzing the characteristics of MOOC users' clickstream actions and combining them, we define the handcrafted features of user learning behaviors; in addition, we also input the clickstream data into recurrent neural networks according to time series, and extracted the embedding features of user learning behaviors. Both of the two types of features are used to predict the learning outcomes of MOOC users. Experimental results on four datasets demonstrate effectiveness and robustness of the proposed approach on predicting learning outcomes. Additionally, our approach also significantly outperforms the state-of-the-art methods.

Our main contributions include:

- A novel approach that leverages MOOC users' clickstream data to predict their learning performance. This is useful for assessing student performance in MOOCs that lack student test scores.

- A MOOC platform and four clickstream datasets. The datasets come from four videos of a MOOC and contain all the clickstream actions of MOOC users when watching videos.

The remainder parts of this paper are organized as follows: Sect. 2 discusses related work. In Sect. 3, we introduce the MOOC platform and the process of collecting user clickstream data. We present the architecture of our approach and the definitions of user learning behavior features in Sect. 4. Detailed experimental results and analysis are given in Sect. 5. Section 6 summarizes our work with a brief discussion of future work.

2 Relate Work

In the beginnings of MOOC growth, related researches primarily focused on the quality of MOOC videos such as the length of the video and presentation [7,17]. Later, researches on online learning analytics centered on creating a predictive model to predict dropout rate by examining their participation in MOOC course video events [8,11]. Recently, researchers are beginning to focus on how to evaluate students' performance in MOOCs. Sinha et al. [14] presented the first study that describes usage of detailed clickstream information to form cognitive video watching states that summarize student clickstream.

Brinton et al. [2] studied student behavior and performance in two MOOCs. They presented two frameworks by which video-watching clickstreams can be represented: one based on the sequence of events created, and another on the sequence of positions visited. With the event based framework, they extracted recurring subsequences of student behavior, and they found that some of these behaviors were significantly associated with whether a user would be Correct on First Attempt (CFA).

Chu et al. [3] developed a methodology for predicting student performance on in-video quizzes from their associated video watching behavior. They modelled student video-watching behavior through deep learning operating on raw event data. They developed a clustering guided meta-learning-based training procedure that optimizes the prediction model based on inferred similarities within student behavioral clusters.

Crockett et al. [4] focuses on analysis of clickstream data from the textbook in search of viewing patterns among students. It was found that students typically fit one of three viewing patterns. These patterns can be used in further research to inform creation of new interactive texts for improved student success.

Aouifi et al. [6] analyzed how learners interact with the pedagogical sequences of educational videos, and its effect on their performance. In their study, the video courses were segmented on several pedagogical sequences. They focalized on the interpretation of the path followed by a learner watching an educational video, and the way they navigate the pedagogical sequences of that video, in order to predict whether a learner can pass or fail the video course.

Mubarak et al. [12] exploited a temporal sequential classification problem by analyzing video clickstream data and predicted learner performance by addressing their issues and improving the educational process. They employed a LSTM network on a set of implicit features extracted from video clickstream data to predict learners' weekly performance and enable instructors to set measures for timely intervention.

Yu et al. [15] established a series of learning behaviors using the video clickstream records of students of a MOOC platform to identify seven types of cognitive participation models of learners. They subsequently built practical machine learning models by using KNN, SVM, and ANN algorithms to predict students' learning outcomes via their learning behaviors. Besides, their approach of combining basic clickstream actions into user learning behavioral features has given us great inspiration.

Yurum et al. [16] focuses on the study which is to investigate the predictive relationship between video clickstream behaviors and students' test performance with two consecutive experiments. The first experiment was performed as an exploratory study with 22 university students using a single test performance measure and basic statistical techniques. The second experiment was performed as a conclusive study with 16 students using repeated measures and comprehensive data mining techniques. The findings show that a positive correlation exists between the total number of clicks and students' test performance.

Some of the above methods are similar to our proposed approach, but they only rely solely on handcrafted or embedding features of user learning behavior to predict learners' performance. In this article, we will combine both of the two types of features to predict their learning outcomes.

3 MOOC Platform Construction

We built a MOOC website using the source code provided by the EduSoho[1] platform. Then we upload the video files of courses such as "Software Design and Architecture", "JAVA Application Development", "PHP Technology" of a software engineering major in a Chinese university to the platform. These courses are taught in Chinese, and there are corresponding quizzes in each course video. In this paper, we only choose the data of the MOOC "Software Design and Architecture" for the experiment. Compared with other courses on the MOOC platform, this course has the largest number of students. The number of students currently enrolled in other courses is not large, so the clickstream data of these courses was not used.

In this MOOC platform, various clickstream actions of users watching course videos will be recorded in real time, such as the start play action, the pause action, the forward skipping action, the backward skipping action, accelerating the playrate action, decelerating the playrate action and the ending action. By recording these actions, it will help us analyze the learning behavior of MOOC users, and then predict their performance based on learning behavior.

[1] https://www.edusoho.com/open/show.

4 Proposed Approach

The work of this research is to serve the online education platforms such as various MOOC platforms. Generally speaking, students' performance are evaluated through quizzes. This study uses students' learning behaviors to evaluate their learning outcomes. No matter for the students who did not take the quizzes in videos or the students who have not finished watching the videos, our proposed method can be used to evaluate their performance, so that teachers can provide help to the students with poor learning effect as soon as possible. Furthermore, we define both handcrafted features and embedding features of MOOC users' learning behaviors to predict their learning performance. Handcrafted features can better reflect the intention of learners' clickstream actions when watching videos, while embedding features can better reflect the time-series characteristics of clickstream data. The combination of the two can help us more accurately infer learners' performance. The architecture of the proposed approach is shown in Fig. 1.

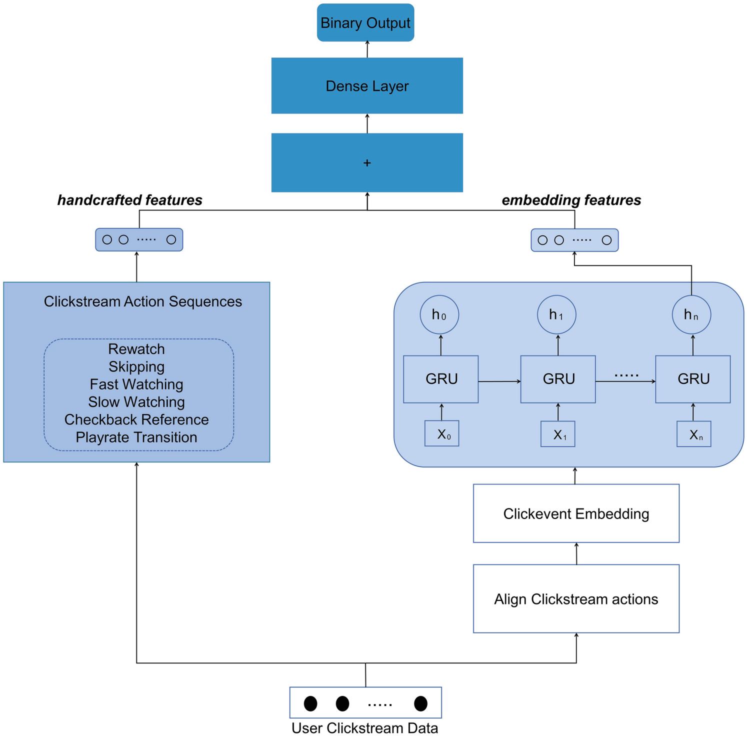

Fig. 1. The architecture of the proposed approach.

4.1 Handcrafted Features

Inspired by [15], our MOOC platform records seven types of clickstream actions: the start play action of the video (Pl), the pause action of the video (Pa), the forward skipping action of the video (Sf), the backward skipping action of the video (Sb), accelerating the playrate action of the video (Rf), decelerating the playrate action of the video (Rs) and the ending action of the video (St).

Most clickstream actions are recorded directly, but Rf and Rs are not. When MOOC users change the playback speed, we only record the action and the changed speed. Then, we know whether the playback speed has increased or decreased by comparing it with the speed before the action occurred.

However, a single clickstream action often cannot reflect the current intention of a MOOC user. Only by observing his or her continuous multiple clickstream actions, will we know what the user wants to do at the moment. Therefore, we define six handcrafted features for user learning behavior, each feature is composed of three clickstream actions. Each feature represents an event that occurs while the user is watching the video, and also reflects the intention of the MOOC user at that time. The six features are as follows.

(1) Rewatch: It is the number of times the user rewatches any part of the video. If a MOOC user wants to replay a part of a video, they usually perform two actions: Sb action and Pl action. In other words, when a user clicks the start play button after performing the backward skipping action, it means that the user wants to rewatch the part of the video at the moment. Here, we define the event rewatch as a clickstream action sequence of Sb and Pl, such as "PlSb*". Besides, "*" can represent any clickstream action.
(2) Skipping: It is the number of times the user skips forward in the video. The event skipping usually indicates that the MOOC user has already mastered the knowledge of the current part of the video, and he or she looks forward to the correct time point of a video they want to watch. Moreover, it usually requires multiple forward skipping actions (Sf) to find an accurate position. Therefore, we define the event skipping as a combination of multiple Sf actions.
(3) Fast watching: It is the number of times the user watches any part of the video at a faster speed. The event fast watching may indicate that a MOOC user has already watched the current part of a video. If the user skips forward directly, it may not be possible to accurately locate the correct position at once. Consequently, we define the event fast watching as a sequence composed of Pl action and Rf action.
(4) Slow watching: It is the number of times the user watches any part of the video at a slower speed. The event slow watching may suggest that the MOOC user wants to watch the current part of the video carefully. This may be because the current content is more important, so users need to watch this part slowly. We define the event slow watching as a sequence of Pl action and Rs action.
(5) Checkback reference: It is the number of times the user skips backward in the video. The event checkback reference is similar to the event skipping.

The MOOC user may want to find an accurate playback point backwards. So, we define this event as a combination of multiple Sb actions.

(6) Playrate transition: It is the number of times the user chooses the playback speed when watching a video. The event playrate transition indicates that a MOOC user is selecting the optimal playback speed for the video. Accordingly, we define this event as a sequence of Rf action and Rs action.

Table 1 shows the details of grouping clickstream action sequences to form MOOC user behavioral features.

Table 1. Grouping clickstream action sequences to form user behavioral features.

Features	Clickstream action sequences
Rewatch	*SbPl*, *SbPl, PlSb*, *PlSb, Sb*Pl, Pl*Sb*
Skipping	*SfSf*, *SfSf, Sf*Sf*
Fast watching	*PlRf*, *PlRf, RfPl*, *RfPl, Pl*Rf, Rf*Pl*
Slow watching	*Pl*Rs, Rs*Pl*
Checkback reference	*SbSb*, *SbSb, Sb*Sb*
Playrate transition	*RfRf*, *RfRf, Rf*Rf, RfRs*, *RfRs, Rf*Rs, RsRs*, *RsRs, Rs*Rs, RsRf*, *RsRf, Rs*Rf*

It should be noted that Pa and St did not appear as key elements in the above-mentioned action sequences. They may appear in the action sequences as non-critical factors denoted by "*".

4.2 Embedding Features

When we use the above handcrafted features, we only record the number of occurrences of corresponding feature events, such as when users watch course videos, their Rewatch times and their Fast Watching times, etc. However, the clickstream data generated by MOOC users while watching videos is a typical time series data. Analyzing the time series data directly can also help predict students' performance. The above mentioned handcrafted features only reflect the number of times of the of certain feature events, and do not reflect the characteristics of this time series.

In order to make full use of the hidden information in MOOC users' clickstream data, we use recurrent neural network (RNN) to extract user learning behavior features from user clickstream data. Derived from feedforward neural networks, RNNs can use their internal state (memory) to process variable length sequences of inputs. However, due to the gradient exploding problem and vanishing gradient problem, RNNs can only learn short-term dependencies, and it is difficult to model long-distance dependencies. In order to solve these problems, a better solution is to introduce a gating mechanism to control the accumulation speed of information, including selectively adding new information and selectively forgetting previously accumulated information. Two typical variants of Gated RNN are Long Short-Term Memory Network (LSTM) and Gated Recurrent Unit (GRU). LSTM uses three gates to control the path of information transmission, namely input gate, forget gate and output gate. Among them, the input gate and the forget gate are complementary and have certain redundancy. The GRU network directly uses a gate to control the balance between input gate and forget gate, i.e. reset gate. In addition, GRU also uses an update gate to control how much information the current state needs to keep from the historical state, and how much new information needs to be accepted from the candidate state. In this paper, we will choose the GRU network to extract user learning behavior features from MOOC clickstream data.

In a course video, the number of clicks performed by different users is usually not the same. Taking the video "Introduction to the Unified Modeling Language" in the course "Software Design and Architecture" as an example, the average number of clicks in this video by users is 31. Among them, 91% of the users have no more than 100 clicks. The user with the most clicks made 494 clicks. In addition, there are very few users who have less than 3 clicks. To solve this problem, we only selected the first 100 clicks of each user in a video for the analysis of user learning behavior. For each click operation, we will use one-hot encoding to generate its vector. If the user clicks less than 100 times in a video, the insufficient part is treated as all-zero. If the user clicks less than 3 times in the video, the learning record of the user will be discarded.

The vector sequence of these clickstream actions will be sequentially input into a GRU network to generate the user's embedding feature vector. The generated embedding features are a 64-dimensional vector. After the handcrafted features and embedding features are concatenated, they will be input into a dense layer to predict the MOOC users' performance. The activation function is sigmoid.

5 Experiments

5.1 Datasets

We selected four course videos from the course "Software Design and Architecture" to build user clickstream datasets, including "Introduction to Unified Modeling Language" (D1), "Object-Oriented Design Principles" (D2), "Factory Patterns" (D3), "Decorator Pattern" (D4). The "Factory Patterns" contains three design patterns: simple factory, factory method and abstract factory. The code and data are available at https://github.com/PxYAN/Clickstream.

We provide ten exercises in each video, all of which are one-choice questions. If a MOOC user answers 9 out of 10 questions correctly, we consider the user to have passed the quiz and mastered the knowledge of the video; otherwise, the user is considered to have failed the quiz and not mastered the knowledge of the video. The test scores of these students will be used as the ground truth for our experiments to evaluate the performance of the proposed approach. Table 2 shows the statistics of the four datasets.

Table 2. Statistics of the four datasets.

	D1	D2	D3	D4
Total number of users	223	194	172	127
Number of users who passed the quiz	111	69	61	85
Number of users who failed the quiz	112	125	111	42
Clicks per capita	31.0	42.5	84.1	48.1
Most clicks	494	779	3138	1637
Number of users with more than 100 clicks	18	20	28	13
Average study time of students (min)	65.27	123.32	169.73	113.07

5.2 Experimental Settings

The evaluation is performed using a 5-fold cross validation. The latent embedding dimension in our model is set to k = 64. During training, the batch size is set to 512, the learning rate to 0.001, and the weight decay to 0.03. We train the proposed model using the Adam optimizer for 100 epochs. And our model is implemented with keras.

To evaluate the performance of the proposed approach, we apply two commonly used classification metrics: prediction accuracy (ACC) and F1 score. ACC measures the average accuracy of students' performance on the test datasets. The F1 score is the harmonic mean of precision and recall.

5.3 Baselines

We compare our approach with the following state-of-the-art methods:

1) kNN model: Aouifi et al. [6] focalized on the interpretation of the path followed by a learner watching an educational video, and the way they navigate the pedagogical sequences of that video, in order to predict whether a learner can pass or fail the video course. They applied educational data mining technique using K-nearest Neighbours and Multilayer Perceptron algorithms to predict learner's performance. In our experiments, we represent the baseline as "kNN".
2) n-gram model: Jeon and Park [8] presented a binary classification model that encodes clicking events as n-gram vectors of event types and uses them as input to GRU networks. In our experiments, we use n = 3 and denote the baseline as "3-gram".
3) HFs model and EFs model: We also use the proposed handcrafted features and embedding features separately to predict the learning outcomes of MOOC users, and name these two models "HFs" and "EFs" respectively.

5.4 Comparison with Baselines

Table 3 lists the performance comparison of different methods on accuracy, precision, recall and F1 score. We can see that the performance of the HFs, EFs, and the proposed method (HFs + EFs) on the four datasets is generally better than that of the 3-gram and kNN models. All three proposed models perform better than 3-gram and kNN except that HFs perform slightly worse than kNN on the dataset "Factory Patterns" (D3) in terms of accuracy and F1. Closer observation shows that the performance of proposed method and EFs is significantly better than that of HFs and kNN, while the performance of HFs and kNN is significantly better than that of 3-gram.

Among all the methods, the proposed method beats others with best accuracy and F1 across all four datasets. Its average accuracy outperforms 3-gram, kNN, HFs and EFs by 21.94%, 20.47%, 16.48% and 0.56%, respectively. Also, its average F1 outperforms the four state-of-the-art methods by 17.16%, 12.24%, 7.92% and 0.81%, respectively. It suggests that using GRU to analyze time-series clickstream data is of great help in predicting the performance of MOOC users.

Table 3. Comparison proposed approach with baseline methods.

		D1	D2	D3	D4
3-gram	Acc	60.21	50.34	48.73	59.82
	P	68.21	60.34	51.42	70.14
	R	74.39	52.98	50.00	71.47
	F1	70.64	54.27	50.31	70.26
KNN	Acc	61.68	58.45	56.45	70.14
	P	**87.21**	76.26	65.00	**91.32**
	R	65.80	62.01	57.88	72.47
	F1	74.84	67.86	61.17	80.72
HFs	Acc	65.67	61.48	53.42	70.94
	P	65.84	62.72	53.94	73.25
	R	**99.26**	85.09	70.00	92.50
	F1	79.16	71.87	60.70	81.44
EFs	Acc	81.59	75.19	74.34	79.49
	P	83.25	77.10	75.26	81.00
	R	90.09	80.64	**77.50**	92.57
	F1	86.27	78.76	75.82	86.32
Proposed method	Acc	**82.15**	**80.74**	**75.08**	**81.27**
	P	82.95	**81.40**	**77.15**	83.27
	R	91.71	**87.13**	76.25	**92.72**
	F1	**87.08**	**83.98**	**76.31**	**87.30**

5.5 Discussion

Let's go back to the question of greatest concern: what kind of learning behaviors do MOOC users have that are more likely to pass the quiz in a course video? From the experimental results, we can see that there are two types of learners who are more likely to pass the quiz in a video. The first type of people are those who learn faster than normal, and the second type of people are those who learn slower than normal.

For the first type of people, during their learning process, there are usually events such as "Skipping" or "Fast watching". In other words, when they watch a MOOC video, they skip forward multiple times, or play fast multiple times. We suppose that these MOOC users have already learned relevant knowledge in traditional classrooms or textbooks before watching the videos. Watching the video is just a review of previously learned knowledge for them, so they watch the video faster than normal.

For the second type of people, when they start watching a course video, there will always be multiple pause actions (Pa), or the decelerating the playrate action (Rs) and then the pause action (Pa). In our opinion, these learners may not have learned the knowledge in the video before, but they feel that the knowledge at the beginning of the video is more important. Once they miss it, the later knowledge will be difficult to understand, so their learning speed at the beginning of the video is very slow. These learners can watch the course videos with a very humble attitude, and the learning outcomes will naturally be very good.

6 Conclusions and Feature Work

Early prediction of the performance of MOOC users will help teachers and educational experts analyze and understand the learning behavior of the users. It is very difficult to identify the learning outcomes of MOOC users without knowing their quiz scores. In this paper, we build a MOOC platform and propose a clickstream based approach that predicts the performance of MOOC users through their learning history records. On the one hand, we combine basic clickstream actions into handcrafted features of users, and on the other hand, we input clickstream data into the GRU network to generate embedding features. Experiments on four datasets show that the performance of the proposed method is significantly better than the state-of-the-art methods.

As for future work, we want to increase the number of courses in the MOOC platform and the number of learners participating in the experiment. In addition, we will also analyze the amount of time learners spend watching each course video and the difficulty of the content. We believe that these factors will help improve the accuracy of MOOC user performance prediction.

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