

# Classification and Analysis of MOOCs Learner's State: The Study of Hidden Markov Model

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**Abstract.** In MOOCs, learner's state is a key factor to learning effect. In order to study on learner's state and its change, the Hidden Markov Model was applied in our study, and some data of learner were analyzed, which includes MOOCs learner's basic information, learning behavior data, curriculum scores and data of participation in learning activities. The relationship of the learning state, the environment factors and the learner's individual conditions was found based on the data mining of the above of learning behavior data. Generally, there are three main conclusions in our research. Firstly, learners with different educational background have different learning states when they first learn from MOOCs. Secondly, the environmental factors such as curriculum quality, overall learning status and number of learners will influence the change of learners' learning status. Thirdly, the learner's behavioral expression is an observational signal of different learning states, which can be used to detect and manage the learner's learning states in different periods. From the analysis results of Hidden Markov Model, it is found that learners in different learning states can adopt appropriate methods to improve their learning efficiency. If the learner is in a negative state, the learning efficiency can be improved by improving the learning environment. If the learner is in a positive state, the positive learning status of the surrounding learners can help him or her maintain current state. Our research can help the MOOCs institutions improve the curriculum and provide reference for the development of MOOCs teaching.

**Keywords:** Classification and analysis, Hidden Markov model, MOOCs Learner's state, Learning behavior, Status transition.

## 1. Introduction

In recent years, MOOCs have developed rapidly based on information technology and mobile learning. As a new form of educational innovation, the rise of MOOCs can be traced back to 2008. Since then some MOOCs platforms have emerged such as Coursera (Li et al, 2017), edX, Udacity in US, and xuetangx, cnmooc, icourse163 in China. Although MOOCs enrich the interaction of traditional online learning and contributes to resource sharing, it still faces some problems as follows. (1) Online learning relies on

the self-participation of learners, so the course withdrawal rate is high and the resource utilization of the platform is very low. (2) The evaluation system of learning outcomes is imperfect, and the relationship between the environmental indicators and learning behavior has not been established, so the learners with poor expression cannot help them adjust the current learning mode in time. (3) As the lack of effective data analysis, it is difficult for learners to grasp the learning state. In the past, most of the relevant research explained the relationship between environment and learning behavior from the perspective of behavioral theory or education, and lacked quantitative analysis.

By summarizing the previous literatures, it is found that the learning state of platform learners in the real world is not only related to the psychological factors and life factors of the learners themselves, but also related to the overall learning atmosphere of the MOOCs platform. Because learners' participation in distance education is mainly based on autonomous learning. So, learners' awareness of the platform environment will affect their attitude towards curriculum learning. In order to study the above problems, the Hidden Markov Model was applied to our study, which was used to quantitatively explain the relationship between environmental factors, learning behaviors and learner's individual conditions.

This paper is organized as follows. In section 2, related research of learner behavior and Hidden Markov Model are introduced. In section 3, the modeling of learning state transition is shown. In section 4, verification of model is illustrated. Section 5 is the discussion and conclusions of this article.

## 2. Related Works

Learning behaviors includes learning motivations and all behaviors in the realization of learning objectives, and it can be regarded as the result of interaction between learners and learning environment. From previous studies, scholars mainly focus on learning behavior and motivation.

### 2.1. Learner Behavior

The related research on learning behavior is mainly summarized into three aspects: the influencing factors of online learning behavior, the classification of learning behavior characteristics and the emotions of learners. Venkatesh (2000) proposed the TAM3 model to analyze the usefulness and ease of use of things from the learners, and explored the differences in individual characteristics such as age and education, the differences in learning environment, the impact of social group differences and the convenience of the course on learning behavior [16]. Shen (2014) studied the relationship between the expected rate of return of courses and the level of knowledge, distinguished the expected rate of return of students with different levels of knowledge, and analyzed the impact of building learning networks on knowledge acquisition [14]. Liu (2016) studied behavioral differences in the MOOCs environment from the aspects of learner type, gender, academic level and age [10]. Dixson (2011) studied the impact of activity organization and teaching resources on learning outcomes in online learning [3]. Li (2005) pointed out that the important factors of affecting learning outcomes include learning intention, expected learning experience and learning tendency [9].

In the study of teaching based on learning behavior, learners are classified according to learning behaviors, and teaching suggestions and measures are proposed for each category. Wang (2014) analyzed the five types of MOOCs learners, namely, non-participants, passive participants, temporary participants, passive mandatory participants, active participants, and discussed the learning effect of students on the MOOCs platform [17]. Yao (2009) defined learning behavior as negative and positive, which including the four dimensions of attention, motivation, learning attitude and learning strategy [22]. In addition, in the study of learner emotions, some scholars proposed learner's emotion recognition model based on cognitive evaluation in E-learning system and OCC model, which used Mamdani fuzzy inference model to realize students' expectation of learning events, and simulated the model by constructing dynamic Bayesian network (Qiao, 2010; Wang, 2011) [13][18].

## 2.2. Hidden Markov Model

Hidden Markov model can be used to describe the process of randomly generating observation sequences of hidden Markov chains, which was originally applied in the field of ecology [1]. Since then many research works have focused on the application of Hidden Markov Models in signal recognition such as speech recognition and motion recognition. In the study of behavior classification, Honsel (2016) selected the software development exchange platform and scored the number of applications submitted by developers, bug fixes, and responses to related questions, and classified hidden forms by comprehensive scores [6]. In the study of motion recognition, Yamato (1992) identified the tennis action, and then transformed the picture into a sequence of features, and converted it into an observation sequence [21]. He (2016) selected netizens' characteristics, information subjects and information content completion degree to establish three-dimensional indicators, and divided four implicit states according to the changes of attention, and then established Hidden Markov Model according to the event evolution process of micro blog public opinion [5]. Pu (2014) used the Hidden Markov Model to dynamically predict the user's interest changes, and defined the interest transfer state according to the user's change of topic interest [12].

In addition, HMM has been widely applied in many fields. For example, the HMM of two states is established for the financial daily income sequence, the hidden Markov state can be interpreted as the state of the financial market, the high fluctuation state and the low state correspond respectively to the period of shock and stability [7]. In CRM, the hidden status can be used to reflect the purchasing tendency of customers and to evaluate the potential value that customers may bring [4]. Because the learning state sequence used in this study is a state time series that cannot be directly visible, this recessive state will enable learners to present different learning performances, which are reflected in the degree of course completion and activity participation. Compared with other models, such as deep learning model, the research of hidden Markov model is relatively mature and the theory is more complete. Taking into account the data quality, data volume, application scenarios and iterative efficiency studied in this paper, this study finally chooses a more suitable HMM. In the learning behavior, the learning state will be affected by subjective psychology, physiological conditions and the overall environment of the platform, and then transferred. Because it is difficult to directly evaluate the psychological and physiological conditions of learners, this paper discusses the transfer of user learning status from

the perspective of objective conditions. Since these states have hidden features and need to be reflected by the explicit behavior of learning, the learning state can be studied as the hidden state in the HMM.

### 3. Modeling of Learning State Transition

This article chooses the platform of www.shlll.net for study. The curriculum of this platform includes different categories such as life and health care, literature and art, higher education, vocational education and so on. Users of the platform include students, professional workers and migrant workers.

#### 3.1. Definition of Learning State Transition

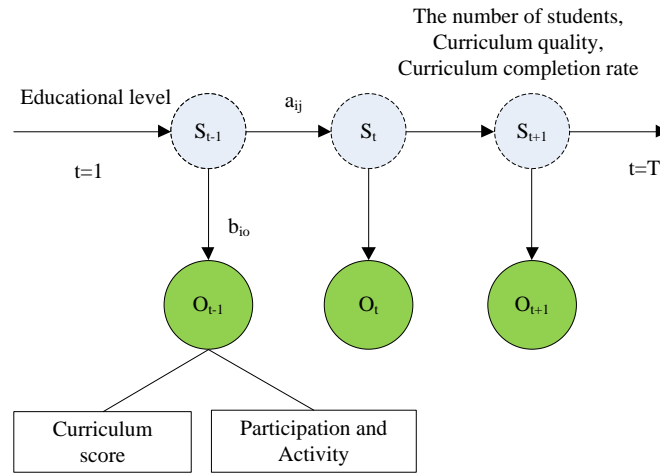
According to the application conditions of HMM, the observation behavior is determined by the hidden state, and the hidden state of the current period is affected by the hidden state of the previous period. Therefore, the following hypothesis is made in this paper. It is assumed that the learner's course learning behavior is determined only by the learning state, that is, it will exhibit certain regular behavior in the same state. And the learning state shifts to the first-order Markov process. This paper studies the influence of objective learning environment on learning state, assuming that the learner's life and work will not affect the learning of the online course, and the learner's own behavior in the current period will not affect the next learning state. The relevant symbols indicating the change of the learning state in the time series are shown in Table 1.

**Table 1.** HMM parameter symbol description

Variable	Description
$S=(s_1, s_2, \dots, s_T)$	The learning state of the learner at each stage.
$O=(o_1, o_2, \dots, o_T)$	The observation sequence of learning behavior presented by learners in $T$ -period.
$A=[a_{ij}]_{N \times N}$	The probability that the learner is in the learning state $i$ in the current period and in the learning state $j$ in the next period.
$B=[b_{io}]_{N \times K}$	The probability of a certain learning behavior $o$ in the learning state $i$ (the learning behavior contains $K$ specific behavioral characteristics, $k=2$ in this paper).
$\pi=(\pi_s)$	$t=1$ , the probability that the learner is in the learning states $s$ at the beginning of the time series.

The explanation of the relationship between learning state transition and observable learning behavior in different periods is shown as Fig. 1. In each period  $t$ , the learner will be in a state of  $N$  states with a certain probability. The learning state transition probability  $a_{ij}$  indicates that the learner is currently in a certain state, the likelihood and tendency to move to another learning state or remain in the current state in the next period.  $b_{io}$  represents the probability of exhibiting observed behavior  $O$  in state  $i$ , and the observed behavior consists of two indicators: course completion scores and activity. In this paper,

we studied the influence of objective environment on learner state transition probability  $a_{ij}$ , including internal course quality, the number of students in the internal course and the learning situation of internal curriculum. In addition, the academic level will have an impact on the learning state at  $t=1$ .



**Fig. 1.** Learning state transition and observable learning behavior in different periods

According to the three basic elements in the HMM, that is observation sequence, hidden state and initial state. Three basic parameters of the model is defined  $\lambda = \{A, B, \pi\}$ , which is defined respectively as the learning state transition probability, the learning behavior observation probability and the initial learning state probability. After that, some variables were selected according to HMM model, and it is shown in Table2.

**3.2. Learning Behavior Observation Sequence Description**

Two indexes of learning behavior observation sequence were selected, one is the completion score of the internal course, and the other is the activity of participating in the activity.

**Average Score of Internal Courses** The learner's course score is calculated based on the course completion rate and the learning interval. Referring to the calculation method of the credit rating [11], the course score was defined by a linear transformation according to formula (1) within a certain interval without changing the learner's completion status. Based on the test of the model results, the learner's score interval is defined as (1) and (2).

$$Score = 1 + 1 * Completionrate \tag{1}$$

When the learner stops learning, learner's knowledge will gradually decline. According to the Ebbinghaus memory curve [23], the knowledge memory acquired by the learner

**Table 2.** HMM model selection variable interpretation

Heading level	Variables	Description
Observation sequence	$Score_{mt}$	The average course completion score of learner $m$ in $t$ period.
	$Active_{mt}$	The activity of the learner $m$ participating in the event during the $t$ period.
Variable that affects the probability of state transition	$Otherscore_t(X_1)$	Average course completion scores of other learners during the $t$ period.
	$TotalNum_t(X_2)$	The total number of learners in the $t$ -time on the MOOCs platform.
	$CourseLevel_t(X_3)$	The students' average score during the $t$ period.
Variable that affects the initial state	$Edu_m(X_4)$	Education information filled out by learner $m$ by learner $m$ .

changes in the form of a negative index. If the learner’s knowledge is reduced, his or her course score will also decrease. For example, the course scores of learner  $m$  in  $t$  period are calculated as follows, where parameter  $Score_{mt}$  refers to the recent course score of learner  $m$ , parameter  $Interval_{mt}$  refers to the interval at which the learner  $m$  learns the course from the  $t$  period.

$$Score_{mt} = Score_{mt} \exp(-K Interval_{mt}) \tag{2}$$

The average score of internal courses is a continuous variable. The course scores in a certain state obey the normal distribution. For each learning state, the course scores have different mean and variance. The probability of learners get course scores  $x$  in the  $i$  state is expressed as follows.

$$b_i^1(x) = \frac{1}{(2\pi)^{\frac{1}{2}} \sigma_i} e^{-\frac{1}{2\sigma_i^2} (x - u_i)^2}, i = 1, 2, \dots, N \tag{3}$$

**Participation in Activities** Another measure of activity is the statistics of the number of learners participating in activities. For example, statistics on learners’ participation in various learning activities over a period of time. If the number of learners participating in activities is 0, and the value in discrete expression is 1, the value of other activities were equalization and discretization. The sample of value of activity is shown in Table3.

**Table 3.** Discrete of activity value

Number of activities	Value
0	1
1	2
More than 6 times	3

For the activity observation sequence, the observation probability matrix is directly used for initialization and iterative estimation. The matrix form is show as follows, where  $b_{ia}^2$  indicates the probability that the  $i$  state appears as the activity of  $a$ , and  $i=1,2,\dots,n$ ,  $a=1,2,3$ .

$$\begin{bmatrix} b_{11}^2 & b_{12}^2 & b_{13}^2 \\ b_{21}^2 & b_{22}^2 & b_{23}^2 \\ \vdots & \vdots & \vdots \\ b_{n1}^2 & b_{n2}^2 & b_{n3}^2 \end{bmatrix} \tag{4}$$

## 4. Verification of model

### 4.1. Data collection

The research data of this paper is collected and analysed by the MOOCs platform of www.shlll.net. The analysis shows that the quality of the course in the MOOCs platform, the online interaction of the learners, and the various interest groups on the online will influence the learner's recognition of the online course environment, and affect the learning status.

The learners who choose to study the internal curriculum are the research objects, and when analyzing the influence of the objective environment on the state transition, the average scores of other learners, the course scores and the number of learners are standardized to compare the influence of these three variables on the state transition. The sample of model is shown in Table 4.

**Table 4.** Sample of Model

Time Unit	Month
Selection condition	Learning duration is more than one year
Start and end time	January 2013 to December 2016
Number of students	62
Number of samples	1367

The learner behavior record data is collected from 2011 to 2016, and it has a total of 2,253,367 registered members. it involves 4,430 courses and 308 learning activities. As the number of courses has increased since 2013, the quantity of students has started to increase, so this paper count user behavior data from 2013. In the sample data, statistics were conducted once a month, and 62 course users with a learning duration of more than one year and including academic information were selected to track their behavior for two years. Since the end of 2016 the learner who study less than two years was excluded, the actual number of samples was 1367. And the descriptive statistics of variables is shown in Table 5.

**Table 5.** Sample of Model

Name	Number	Minimum	Maximum	Average	Standard deviation
Score	1367	0.13	2	0.99	0.41
Active	1367	1	3	1.23	0.54
Edu	1367	1	7	4.82	1.78
OtherScore	1367	0.89	2	1.46	0.15
CourseLevel	1367	3.87	5.00	4.36	0.20
TotalNum	1367	3	899	234.57	220.32

#### 4.2. Model Parameter Estimation

The model parameters are estimated by EM algorithm (Zhang, 2014), and the hidden state as 2, 3, 4 was selected respectively, and the maximum likelihood and BIC values estimated by the model are as follows: (-1027.873, 21875.13), (-693.0693, 1674.954), (-654.5903, 1514.607). According to the BIC (Bayesian Information Criterion), the effect of the four states is not obvious. So three hidden states are selected for analysis in our study, and it was defined as negative, normal and positive states, and they were represented by numbers 1, 2, and 3 respectively. And then behavior theory was used to analyze the initial state probability parameters, observation probability parameters and state transition probability parameters in the model.

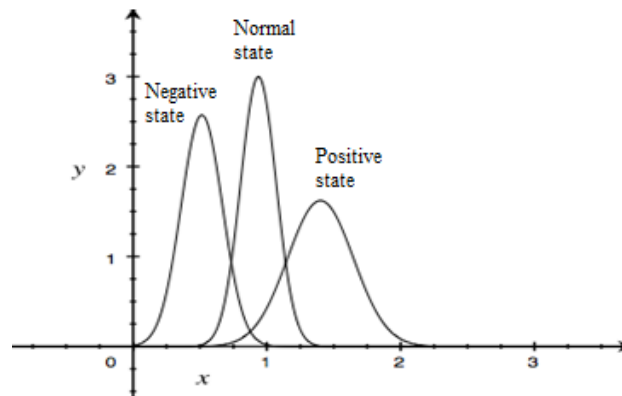
**Learning Characteristics in Different States** According to the model, the learner status classification result and the course score distribution can be obtained. The mean, standard deviation, and activity probability of the positive distribution of the course scores of learners with different learning states are shown in Table 6. The course scores in different states are shown in Fig. 2.

**Table 6.** Sample of Model

Name	Average score	Standard deviation score	Activity level (Active=1)	Activity level (Active=2)	Activity level (Active=3)
Negative	0.514	0.155	0.931	0.062	0.007
Normal	0.937	0.133	0.931	0.055	0.014
Positive	1.401	0.246	0.646	0.235	0.120

According to the classification results of Table 6 and the distribution of the course scores in Fig. 2, it can be seen that the learners in the positive state have the highest average score among the learners in the three states, and the internal standard deviation of these learners is relatively large. With the learner's activity for learning decreases, the course score will decrease. In addition, the learner's activity (activity level = 2) in the positive state is 0.235, which is higher than that in the normal and negative state. The learner's activity (activity level = 3) is also significantly higher than that in the stable and negative state, which indicates that learners in the positive state are more likely to show active state.





**Fig. 2.** Course scores in different states

Previous studies have shown that learners who participate in various activities on the distance learning platform are more likely to get higher scores in course learning [15], and learners with stronger autonomy will not be limited to course of video learning, and they learn in more diverse ways. Learners who are in a negative state do not perform well in both course completion scores and activity participation, and there is a risk of exiting the learning platform. Combining the behavioral responses in different states, the three learning states are defined as follows.

(1) The learners in the negative state are slack in both course learning and activity participation, and they belong to the bystanders and are subject to the risk of losing users.

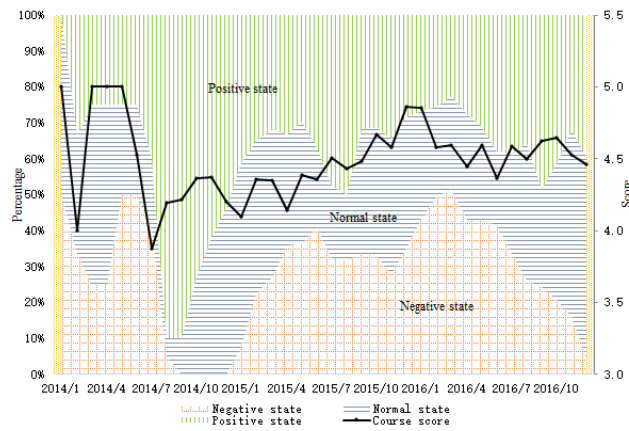
(2) Learners have a good attitude towards learning at a normal state, he or she will take the initiative to study some courses and participate in the test or related activities in the course. However, there is no clear goal for completing the course, and he or she will learn with a relatively relaxed attitude.

(3) Positive state. The learners aim to complete the course study and will fully participate in the study of the class. The frequency of the course is high and they will actively participate in the activities on the platform.

According to the Viterbi algorithm, the learning state of learners in each period is predicted, which is shown as in Fig. 3.

It can be seen from Fig. 3, the number of active learners in 2014 is large, especially between July 2014 and January 2015 (the green area in Fig. 3), most of them are in a better learning state, and there are no negative learners (the red area in Fig. 3). After 2015, the proportion of learners who are in a negative state has increased. After July 2016, the proportion of negative learners has decreased. The number of learners who are in a positive and stable state has increased, and the learning attitude of learners on the platform has improved.

**Initial Learning State** By setting the educational level as a parameter in the model, the probability that the initial learning state of these learners will be negative, stable and positive can be obtained. The results are shown in Table 7.



**Fig. 3.** The proportion of learners in different learning states in each period

**Table 7.** Initial state probability of different educational level

Educational level	Junior middle school	Senior middle school	Vocational college	Junior college	Bachelor	Postgraduate
Negative	0.0422	0.0238	0.0080	0.0020	0.0005	0.0001
Normal	0.2289	0.5759	0.8613	0.9660	0.9924	0.9983
Positive	0.7289	0.4003	0.1307	0.0320	0.0072	0.0016

It can be seen from Table 7 that learners of different educational levels have different probabilities of learning state at the beginning of their study. Junior middle school learners have a probability of 0.7289 and they have a very positive attitude towards learning. With the improvement of learners' educational level, the probability value of learners' negative state decreases gradually, and the probability value of learners' normal state increases gradually. Especially, the normal state probability value of learners with bachelor or above is close to 1. Because of the popularity of general courses of culture and custom on this platform, the basic knowledge requirement for learning these courses is not high. Even the learners with lower educational background have strong self-confidence to complete their studies. Some learners with higher educational background often choose courses with stronger professional knowledge for the needs of their work. Relatively speaking, on this platform, the main learners are still learners who learn from the knowledge required for their work. In addition, according to the theory of habitual domain, the learners with higher knowledge level are in a relatively stable habitual domain, the expected benefits of curriculum learning are lower, the entry and absorption of new information will be more hindered, and their enthusiasm for learning will be weaker than those with lower education level, but the possibility of negative attitude is very low.

### 4.3. Learning State Transfer

According to the HMM parameter estimation results, the relationship between the probability of transition to different states in the next period and the environmental factors

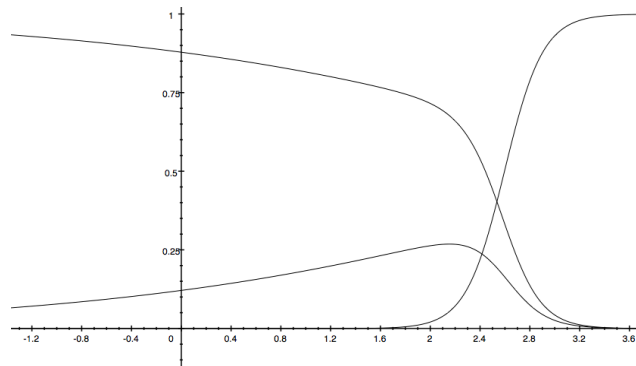
of different MOOCs can be gotten when the current period is in a negative, normal and positive state. And the negative state is taken as an example in the current period, and the negative state is maintained in the next period. The probability distribution function of  $S_{t+1}=1$ , transition to the normal state  $S_{t+1}=2$  and transition to the active state  $S_{t+1}=3$  is shown as follows.

$$P(S_{t+1} = 1|S_t = 1) = \frac{1}{1 + \exp(I_1) + \exp(I_2)} \tag{5}$$

$$P(S_{t+1} = 2|S_t = 1) = \frac{\exp(I_1)}{1 + \exp(I_1) + \exp(I_2)} \tag{6}$$

$$P(S_{t+1} = 3|S_t = 1) = \frac{\exp(I_2)}{1 + \exp(I_1) + \exp(I_2)} \tag{7}$$

where,  $I_1=-16.76+6.16X_1+1.44X_2+2.21X_3$ ,  $X_2=-1.98+0.49X_1+0.67X_2+0.01X_3$ . When there is no activity on the learning platform, that is, when the variables are 0, the probability that the next learner stays in the negative state is close to 1. Without the external influence, the learner's state will not directly change from the passive state to the positive state. Through derivation analysis of independent variables, the influence of each variable on state transition is analyzed. The probability of learners remaining in a negative state is negative for each variable, and the derivative of course scores is almost 0. The most obvious effect of other learners' course scores on state transition is that of course scores. And then we mainly analyze the influence of other learners' course scores on state transition, and fix the value of other variables to 0. The probability that learners move from negative state to other states varies with other learner course scores is shown in Fig. 4.



**Fig. 4.** The influence of other learner course scores on transition probability

The completion of other learners reflects the overall learning level of the platform. In order to better reflect the changing trend, the variables were standardized. The independent variables ranged from 0.89 to 2, corresponding to -1.2 to 3.6 in Fig. 4. When the

learner is in a negative state, the probability of keeping the state unchanged is very high. If the other learners on the platform complete the course better, the possibility of the learner in a negative state will be reduced, and the probability of turning to a positive state or a better state will be increased. When the scores of other learners are still at a low level, the improvement of learners' state in a negative state will be relatively small, but with the improvement of the overall learning state, the learner's learning state will gradually improve significantly, and finally the learner will transfer to a stable state with a probability of close to 1. In general, the overall learning status on the platform will have a significant effect on learners. That is to say, the heterogeneity in the learning environment promotes the learning attitude. When the learning effect of other people exceeds a certain value, the heterogeneity of the learner in the negative state is more obvious, and the learner in the negative state will be more actively close to excellent learners, the probability of learners improving their learning status will be significantly improved.

According to ARCS (2010) theory [8] and emotion regulation theory, good completion of other learners will enable learners to increase their confidence in curriculum learning, and increase their self-efficacy through mutual attention, and effectively improve negative learning emotions [2]. However, when other learners score far better than themselves, learners' state improvement will have certain limitations. At this time, learners with negative state have less similarities with learners with better curriculum completion, and it is not easy for them to establish a closer relationship. Therefore, learners with similar positive knowledge level should be organized to motivate negative learners to learn, so that negative learners can easily accept help, and change their state by communicating with each other.

It can also be seen from Fig. 4 that with the improvement of objective environment level, learners in a negative state are more likely to increase their interest in learning, and The course scores and the total number of learners have a more stable positive impact on the learners' transition from negative to positive. When other learners' scores are less than 1.76, the influence of course scores on improving the negative state will be weaker than that of the total number of learners. On the contrary, if other learners' scores are higher than 1.76, their influence will be significantly improved. When the score reaches 1.8, the probability of turning to the stable state is the highest. It also shows that the learner's learning state is a process of gradual improvement, and the probability of direct improvement is relatively small. By improving the environment, it can significantly encourage learners to improve their learning status.

The current period is in a normal state, and the probability of moving to a negative state, maintaining a normal state, or shifting to a positive state in the next period is show as follows:

$$P(S_{t+1} = 1|S_t = 2) = \frac{1}{1 + \exp(J_1) + \exp(J_2)} \quad (8)$$

$$P(S_{t+1} = 2|S_t = 2) = \frac{1 + \exp(J_1)}{1 + \exp(J_1) + \exp(J_2)} \quad (9)$$

$$P(S_{t+1} = 3|S_t = 2) = \frac{\exp(J_2)}{1 + \exp(J_1) + \exp(J_2)} \quad (10)$$

where,  $J_1=1.65+0.02X_1+0.33X_2-0.05X_3$ ,  $J_2=-1.49+0.46X_1+0.46X_2+0.67X_3$ , and the current period is in a positive state, and the probability of moving to a negative state or a normal state, or keeping in a positive state in the next period is show as follows:

$$P(S_{t+1} = 1|S_t = 3) = \frac{1}{1 + \exp(Q_1) + \exp(Q_2)} \tag{11}$$

$$P(S_{t+1} = 2|S_t = 3) = \frac{\exp(Q_1)}{1 + \exp(Q_1) + \exp(Q_2)} \tag{12}$$

$$P(S_{t+1} = 3|S_t = 3) = \frac{\exp(Q_2)}{1 + \exp(Q_1) + \exp(Q_2)} \tag{13}$$

where,  $Q_1=12.30+0.16X_1+0.22X_2-0.28X_3$ ,  $Q_2=13.77+0.53X_1+0.12X_2-0.39X_3$ . Similarly, for the situation of normal state and positive state, the probabilistic transfer function expression is used for derivative analysis. The above three cases are summarized as shown in Table 8. The three coincidences in parentheses indicate the positive or negative effects of three learning environment factors on state transition, the order of the three variables is course scores of other learner, the total number of student of courses, the average score of the courses. The \* in the upper right corner represents the variable that has the greatest impact on the probability transition, and the + or - sign indicates a positive or negative impact on the state transition probability.

**Table 8.** The impact of each variable in the state transition

t	Negative state	Normal state	Positive state
t+1			
Negative state	(-* - -)	(* + +)	(+ +* +)
Normal state	(- - -*)	(- + -*)	(+ + +*)
Positive state	(- - -)	(- +* +)	(+* - -)
(Course scores of other learner, Total number, Average scores)			

When the learner is in a negative state, the scores of other learners' learning scores have a significant effect on the improvement of the learning state. At this time, the learning state of other student has a greater influence on the learner in a negative state, which is easy for the learner to enhance their confidence and adopt a positive solution to turn pressure into motivation. It is explained that the MOOCs learning platform can effectively promote the learner in a negative state to improve the learning state and increase the investment in learning by improving the overall learning environment.

When the learner is in a normal learning state, the MOOCs environment has the least impact on the change of the learning state. At this time, the overall number of students in the course and the improvement of the course quality are more conducive to the learner to turn to a more positive state, and the completion of other learner courses has less influence on learners who are in a stable state. According to Moore's theory [19], Curriculum design is one of the factors influencing distance interaction in distance education. A good course can effectively shorten the interaction distance between learners and teaching resources, and improve learners' interest in the curriculum, and increase interaction with

teaching resources. In addition, Moore's theory provides that different stages of learning form their own views through interactive exchanges, and in the third stage, other people's understanding of the knowledge is incorporated into their own knowledge system, and in the fourth stage, information is shared, so as to gradually realize the steady dissemination of knowledge [20]. Therefore, when the learner is in a normal state of active learning, the increase of student will promote the learner in the course discussion and learning activities, which will increase the possibility of the learner to improve the learning state and effectively prevent the learner's state sliding down.

When the learner is already in a positive learning state, the scores of other learners' completion of the course has a significant impact on the learner's positive state. According to the theory of confidence and satisfaction in ARCS, when the surrounding students complete well, it will encourage learners to increase the confidence of the completion of the course and the satisfaction of knowledge acquisition. At the same time, the learners in a positive state will be more actively involved in learning because of the competitive mentality, which will help the learners to maintain the current state of active learning.

## 5. Discussion and Conclusions

Hidden Markov Model was used as the theoretical framework in our study, and the hidden state refers to the learner's learning state. The observation sequence is the learner's course completion score and the activity participation. According to our study, the learner's knowledge level will have an impact on the initial learning state, and the learner's learning status will be affected by the environmental factors of the MOOCs. Therefore, the learners' basic knowledge level, learning behavior and the learning environment of the course-mourning platform are correlated and modeled. In addition, the behavioral theory is applied to explain the influence of the learning behavior characteristics under different learning conditions, the total number of course learning, the learner's course completion score, and the course score on the learner's learning state transition.

From the results of the research, the overall activity participation on the MOOCs platform is low, but the active learners are more likely to actively participate in the activity and the course completion score is higher. When learners are in different states, the influence of objective environment on learners' motivation is different, and the motivation factors are also different. When the learner is in a negative state, the change of the objective environment will have a significant impact on the improvement of the learner's state; when the learner is in a positive state, the influence of the learning environment on the learning state is not very great, and the completion of other learners' courses can help learners to stay in a positive state, but the course score and the total number of students may cause the learner's state to decline slightly; when the learner is in a normal state, the MOOCs environment has the least impact on the learning state, and the course score is the most significant effective in promoting the learner's state.

In general, according to the research results of the learner's state, the improvement of MOOCs teaching can be carried out from the following aspects.

(1) Course design optimization. According to the research results, when the learner is in a normal learning state, the course score has a significant impact on it. Learners who have a medium-level course score can be selected from the platform, and combined with their browsing records, relevant courses with a recommended score of more than

4.8 can be recommended. In addition, according to the statistical results, the number of students studying in-house courses increased from July to September. During this period, courses suitable for students can be added, such as knowledge development with school associations, Graduate Development Planning and other courses.

(2) Encourage collaborative learning. According to the research results, when the learner is in a negative learning state, the increase in the number of learners can help the learner to improve his or her state significantly. Therefore, arranging positive and negative learners to study together can help negative learners increase their interest in learning, and help those negative learners improve their learning effect.

(3) Standardized management of learner behavior. For example, we can take measures such as the sign-in system or improve the learner evaluation mechanism to supervise the learner's learning activities. Through regular testing of learners, we not only record their course completion and participation, but also track their learning status in order to promptly remind learners with poor learning and take measures to stimulate their active learning.

From the perspective of the development of MOOCs, personalized teaching based on learner's status will become the trend of MOOCs teaching. In future research, artificial intelligence, big data analysis and other technical methods can be used to analyze learning behavior data and learner status, so as to provide help for personalized teaching.

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