RESEARCH ON MOOC CURRICULUM RECOMMENDATION MODEL OF HIGHER VOCATIONAL ENGLISH BASED ON IMPROVED INTENSIVE LEARNING NETWORK

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Abstract. With the development and maturity of the Internet education industry, more and more vocational colleges have opened English teaching courses based on massive open online courses courses. However, there are many English-related courses on the massive open online courses course platform, and the use of scientific recommendation models can improve the teaching quality of such courses. Therefore, this research attempts to design two improved attention mechanisms and user-based embedded expression using meta-path technology. At the same time, these two are combined with reinforcement learning technology to design an improved massive open online courses English course recommendation model. The test results show that the hit rate of the model designed in this study is 89.84%, 74.28%, 70.81% and 71.35% respectively when the rank number is 20 and the parameter is 10. At this time, the cumulative income of normalized discount is 48.24%, 34.58%, 25.96% and 28.69% respectively. However, when the number of calculated samples reaches the maximum value of 1158609, the calculation time of the improved reinforcement learning recommendation model is 1867 seconds, which is also higher than the comparison model. The experimental results show that the curriculum recommendation accuracy of the massive open online courses recommendation model designed in this study is higher and the recommendation results are more reasonable. The results of this research have a certain application potential in the field of the construction of online education in colleges and universities.

Key words: Reinforcement learning; Metapath; Massive open online courses: Recommended model; Embedded expression; Attention mechanism

1. Introduction. After entering the 21st century, with the rapid development of computer technology, the online education industry has been recognized by more and more schools and teachers and students. In this context, a large number of vocational colleges have opened English teaching courses based on massive open online courses (MOOC). Moreover, MOOC, as one of the largest online education platforms in the world, has strong application value. It was also used by a large number of educational institutions at home and abroad during the COVID-19 epidemic [1, 2]. However, there are a variety of English courses on the MOOC platform. Even in some subdivisions of English education, such as oral English teaching, there are a large number of relevant courses to choose from. Too many choices have brought great difficulties to teachers who carry out teaching [3]. Teachers with less teaching experience cannot quickly select the appropriate curriculum design courseware and teaching process from a large number of courses [4]. Moreover, the self-study ability of students in higher vocational colleges is weaker than that of students in ordinary colleges [5]. Therefore, when they are faced with a large number of admirers, they may also have negative emotions such as confusion and helplessness. This may discourage students from learning. At the same time, in the process of self-study, if students choose inappropriate courses, it will greatly increase the learning difficulty and extend the learning hours, especially if they choose advanced courses with higher learning threshold [6]. It can be seen that the combination of higher vocational colleges and universities in English teaching has certain teaching value. However, it is necessary to use the MOOC recommendation model in the teaching system to recommend courses suitable for students' learning ability and learning stage for teachers and students. By this way, it can help teachers carry out teaching according to their aptitude and interest, and improve the learning effect of students. Under this background, this research attempts to combine attention mechanism, user embedded expression based on meta-path, and reinforcement learning (RL) technology. Based on this, a course intelligent recommendation model is designed. The model can more clearly extract key information such as learning interests and learning habits of users of

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English courses on the Moor platform.

2. Related Work. At present, online education is one of the key points of teaching reform in colleges and universities at home and abroad, and a large number of courses exist on the platform. This made experts realize the application value of the course recommendation model. Some experts have carried out relevant research on curriculum recommendation and general recommendation. Rabiu I and others believe that the recommendation system depends on the historical data purchased by users and their feedback to describe their preferences and make future recommendations [7]. Most of these systems usually use collaborative filtering models to analyze user ratings. At the same time, they infer the potential factors that show the characteristics of users and projects in the k-dimensional potential space. However, the historical rating data used for recommendation is usually sparse and unbalanced. Therefore, a new emotional scoring model based on long-term and short-term memory is proposed in the study. In order to alleviate the sparsity and imbalance of the data set, a combination function is designed in the experiment to capture the emotional bias between user ratings and comments. The test results of the design model using Amazon data show that the proposed model is superior to the existing static and dynamic models. Statistical tests show that all performance gains differ significantly. Roozbahani and others found that the current knowledge content on most mainstream knowledge sharing platforms is too complex. It is necessary to design a more intelligent recommendation model to help users quickly select knowledge content that is more in line with their needs. Therefore, the research team designed a recommendation model based on improved collaborative filtering algorithm. The test results show that the model can effectively improve the accuracy of content recommendation on the knowledge platform [8]. Zeng et al. found that the way of extracting information from the user's history is widely used to define the user's fine-grained preference to build an interpretable recommendation system. Because these aspects are extracted from the historical records, it is impossible to identify the aspects that represent the negative preferences of users. However, these potential aspects are also as important as the information representing the user's positive preference for building a recommendation system [9]. Choi et al. believed that the web-based courses used to teach the maintenance methods of mechanical components needed a more targeted recommendation system. The system can be recommended to engineers who need such services. For this reason, the research team has built a recommendation model for mechanical component maintenance course recommendation. The model combines K-means clustering algorithm and random forest classifier. The test results show that the recommendation results of this recommendation system are better than those of traditional methods [10]. Yang and others found that some commodity recommendation methods used by e-commerce platforms are designed based on traditional collaborative filtering algorithms. These recommendation methods have the shortcomings of data set reduction and coefficient matrix filling, and can't meet user needs well. Therefore, this study proposes an improved hybrid algorithm for online handicraft recommendation. The test results show that the model can effectively improve the effectiveness and exemption of online recommendation of handicrafts, and reduce the item score of candidates set users, which has certain application value [11]. Dat NV believes that the content-based recommendation algorithm has the problem of probability similarity calculation, so he proposes a recommendation algorithm based on Gaussian mixture model. The test results show that the recommended accuracy of the model is significantly higher than that of the comparison model. In practical application projects, the response time is shorter, the calculation speed is increased by 24.37% on average compared with the four comparison models, and the calculation results are the most stable and reliable [12].

To sum up, although many former scholars and scientists have designed a lot of improved recommendation systems to improve the efficiency and accuracy of online recommendation systems. However, at the same time, it is quite rare to consider more user interest characteristics and apply reinforcement learning to improve recommendation quality. Both of them have strong potential application value for more detailed mining of user information.

3. Design of MOOC Curriculum Recommendation Model Based on RL and Improved Attention Mechanism.

3.1. User Embedding Expression Mode and Node Layer Design Integrating Meta-path. This research is to design a recommendation model of MOOC that pays more attention to auxiliary information and user habits. On the one hand, it uses courses, knowledge points, and user data to build heterogeneous
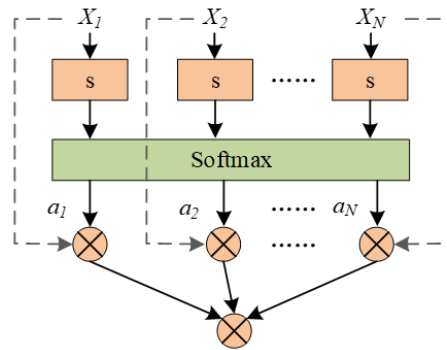
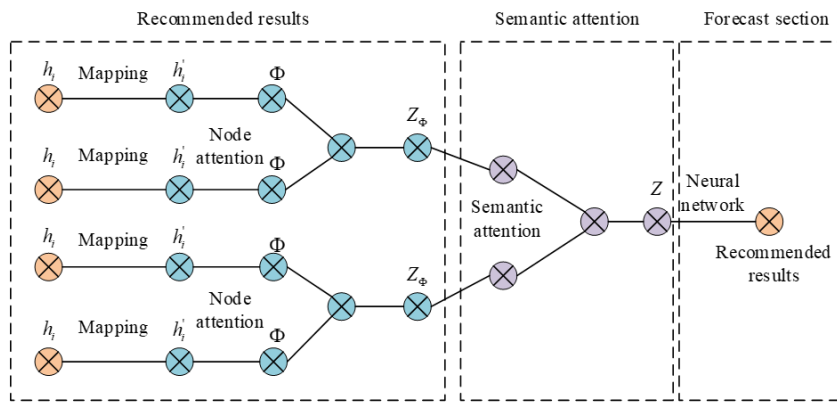Fig. 3.1: General Calculation Mode of Attention Mechanism

Fig. 3.2: Typical Structural Model of HAN

information networks, so as to use the two-level attention mechanism and meta-path sampling method to embed and express user data [9, 10]. On the other hand, RL is integrated into the recommendation model, which makes the model capture the user's interest features more accurately.

The improved MOOC recommendation model designed in this study is based on the attention mechanism and graph network. The general calculation model of the attention mechanism is shown in Figure 3.1. Figure 3.1, $\alpha_1, \alpha_2, \ldots, \alpha_N$ is the attention distribution, $X_1, X_2, \ldots, X_N$ is the input data, and is the data characteristics after query transformation [11]. As shown in Figure 3.1, the attention mechanism can make the neural network have the ability to focus computing resources on the specified feature subset, thus improving the feature extraction and expression ability of the neural network. The information with rich semantics and heterogeneity is the difficulty of graph representation in heterogeneous networks. The heterogeneous graph attention network (HAN) algorithm proposed by the predecessors has a higher precision in processing this data because it integrates semantic attention and node attention structure. The typical structure is shown in Figure 3.2 [12, 13]. As shown in Figure 3.2, the initial node feature h_i is first linearly mapped to h_i, and then fused through the node attention module composed of meta-path Φ , and then the node level attention embedding calculation is completed through the embedding expression Z_Φ of each meta-path [14]. The next step is to use the semantic layer attention to get the weight values under the embedded expression conditions of different meta paths, so as to calculate the final embedded expression for future calculation.

However, the spatial semantic information of the HAN model needs to be mined, and the user data in the MOOC recommendation model is complex and not applicable [15, 16, 17]. Moreover, HAN model can
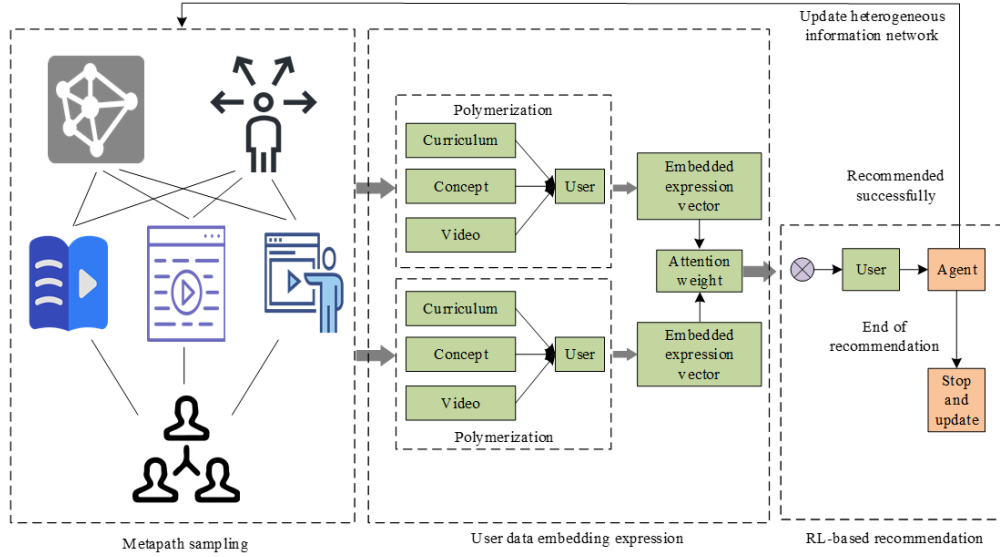
Fig. 3.3: RL-HAN Neural Network Model Calculation Framework

only learn data expressed by fixed heterogeneous information network at present. Its learning effect on non-fixed heterogeneous information network needs to be determined [18]. In view of the above shortcomings of HAN model, this research has designed a reinforcement learning combined with heterogeneous graph attention network (RL-HAN) model that is more suitable for the recommendation work of MOOC. The calculation framework of this model is shown in Figure 3.3. The RL-HAN model includes user embedded representation, meta-path sampling and enhanced knowledge point recommendation [19, 20]. In the meta-path sampling section, the algorithm will build a heterogeneous information network based on the concept of knowledge points, courses and user data. At the same time, the heterogeneous information network is sampled according to the random walk method, and the sampling is carried out according to the meta-path method [21, 22]. In the user embedded expression section, this research innovatively maps the obtained meta-path to the feature space through the hierarchical attention network. Subsequently, the self-attention mechanism is used to calculate the user's neighbor nodes and obtain the corresponding feature vector [23]. Then in the path layer, this research applies another attention level to fuse various semantic expressions and output the user's embedded expression features [24, 25]. In the strengthened knowledge recommendation module, this study referred to the enhanced learning technology to carry out user course recommendation. The following describes the meta-path sampling method first. After building a heterogeneous information network according to the MOOC data set, the same meta-path is sampled using the random walk method for the purpose of searching the network structure of the graph. Suppose that all users in user set U need to take N paths, so we can get $|U| \times N$ paths, put them into set M, and then complete the meta-path sampling.

As mentioned above, RL-HAN model calculates according to two attention mechanisms: node layer and path layer, and designs node layer attention mechanism. If a user has been assigned a meta-path type, because there are many corresponding nodes of user data in the heterogeneous information network. And the corresponding feature space of different types of nodes is also different. Therefore, a linear mapping is designed to map the corresponding nodes of user information to the same unified feature space. Suppose there is a type transfer matrix M_ϕ for each node type ϕ_i, and equation 3.1 shows the mapping method.

$$h_i' = M_{\phi_i} \cdot h_i \tag{3.1}$$

h_i' and h_i represent the characteristics of node i after and before mapping in equation 3.1. Since the user embedded expression of each node under the same meta path corresponds to different contribution weight

values, here we choose to use the self-attention mechanism to learn the weight values of different types of nodes, and calculate according to equation 3.2.

$$\alpha_{ij}^{\Phi} = \text{softmax}(e_{ij}^{\Phi}) = \frac{\exp(\sigma(a_{\Phi}^{T} \cdot [h_i' \& h_j']))}{\sum_{k \in N_i^{\Phi}} \exp(\sigma(a_{\Phi}^{T} \cdot [h_i' \& h_k']))} \tag{3.2}$$

σ represents the activation function, $\&$ is the calculation symbol defined in this study, which means the matrix splicing operation in equation 3.2. (a_{Φ}^{T}), h_i' and h_j' represent the transposition of the attention vector of the node layer corresponding to the $\phi-$element path, the feature vector of the center node that completes the mapping, and the feature vector of the leader node after the mapping. In equation 3.3, the meta path embedding expression of node i can also be obtained through the fusion operation of adjacent nodes.

$$u_i^{\Phi} = \sigma \left(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot h_j' \right) \tag{3.3}$$

u_i^{Φ} represents the corresponding embedded expression of the node learned by the algorithm from the meta path in equation 3.3. And each embedded expression is related to the adjacent node representation. Considering the scale-free characteristics of heterogeneous graphs, the data variance may become large. Therefore, the attention mechanism of the node layer is adjusted to the multi-head attention mechanism to improve the robustness of the network training process. Therefore, it is necessary to copy the node layer attention K times to obtain different mapping features. And then splice these embedded expressions as the final user embedded expression vector, as shown in equation 3.4.

$$U_i^{\Phi} = \mathop{\&}_{k=1}^{K} \sigma \left(\sum_{j \in N_i^{\Phi}} \alpha_{ij}^{\Phi} \cdot h_j' \right) \tag{3.4}$$

Assuming that the meta-path set is $\Phi_0, \Phi_1, \ldots, \Phi_P$, the embedded expression $U_{\Phi_0}, U_{\Phi_1}, \ldots, U_{\Phi_p}$ of node elements containing P specific meta-paths can be obtained by following the above operations.

3.2. Attention Mechanism of Fusion Path and Design of Recommendation Model Based on RL. After the input data set of the recommendation model is processed by the node-level attention mechanism, the embedded expression of the meta-path node is output. But the expression scale of this information is still limited, because the user's preferences on different meta-path are different. Therefore, the attention mechanism of the path layer is also designed here. Assuming that there is an embedded expression matrix of P specific meta-path nodes, the corresponding weight value $\beta_{\beta_0}, U_{\beta_1}, \ldots, U_{\beta_p}$ can be calculated according to equation 3.5.

$$(\beta_{\Phi_0}, \beta_{\Phi_1}, \ldots, \beta_{\Phi_P}) = \text{att}_{path}(U_{\Phi_0}, U_{\Phi_1}, \ldots, U_{\Phi_P}) \tag{3.5}$$

att_{path} is the path-level attention in the neural network structure in equation 3.5, which is used to learn different types of deep semantic information in heterogeneous information networks. Assuming that is the attention matrix of the path layer, the embedded expression vector needs to go through nonlinear mapping and internal product calculation with q, and equation 3.6 shows the calculation method of normalized output weight w_{Φ_i}.

$$w_{\Phi_i} = \frac{1}{|\nu|} \sum_{i \in \nu} q^T \cdot \tanh(W \cdot u_i^{\Phi} + b) \tag{3.6}$$

W and b respectively represent the parameters that need to be trained and optimized in equation 3.6. They are shared in all meta-paths and path-level attention. So far, the corresponding weight coefficients of each meta-path are obtained. The next step is to normalize all weights according to the softmax function. See equation 3.7 for the calculation method.

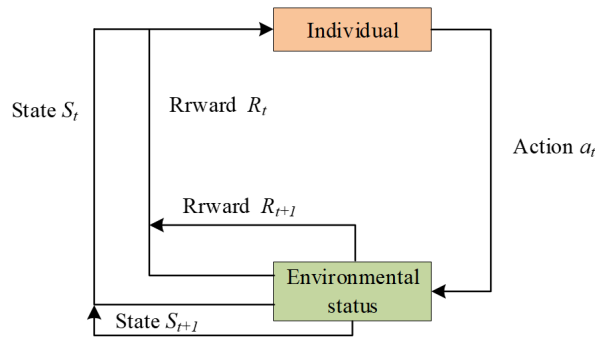$$\beta_{\Phi_i} = \frac{\exp(w_{\Phi_i})}{\sum_{i=1}^{P} \exp(w_{\Phi_i})} \tag{3.7}$$

Fig. 3.4: Schematic Diagram of Traditional RL Calculation Process

β_{Φ_i} represents the weight vector obtained after normalization. This indicator can be used to show the importance of meta-path in formulation. Specifically, the larger the value, the more important it is to represent this meta path. The final user embedded expression can be obtained by support, see equation 3.8.

$$U = \sum_{i=1}^{P} \beta_{\Phi_i} \cdot U_{\Phi_i} \tag{3.8}$$

Traditional recommendation systems often build a model to minimize the distance between the quantitative data of users' real behavior and the prediction results [26]. The optimization process is realized by loss function. However, this recommendation model does not take into account the long-term interest of the recommended person. At the same time, the user's interest will also change with time and the observed behavior. Even in some cases, displaying or hiding specific items can be used to guide users' interests. However, in this case, the recommendation results are often unsatisfactory. Therefore, this study designed a recommendation model based on RL. Because the model better considers the long-term interests of users and the dynamic embedded expression characteristics of users, it has the potential to improve the recommendation performance. The typical overall task flow of RL is shown in Figure 3.4. Since this structure has been more commonly used, details will not be described here.

The optimization purpose of reinforcement learning is to find a strategy that can maximize the expectation of cumulative rewards, as shown in equation 3.9.

$$L_{\mathrm{RL}}(\theta) = \mathbb{E}_{\pi_\theta(C_t \,|\, u)} \sum_{t=1}^{T} r_t(c_t \,|\, u) \tag{3.9}$$

In equation 3.9, π_0 and r respectively represent optimization strategies and immediate rewards. Considering that the recommended task in the study has no RL environment, the self-designed method is selected to obtain the environment. Take 1 and -1 as the reward points, which respectively represent the output of the environment when the model prediction result is user behavior or prediction recognition. And when the recommended course is correct, the model will modify the heterogeneous information network to connect the recommended course c_t with user u. After the modification of the heterogeneous network, the new embedded information expression u_{t+1} can be obtained. If the recommended course is reasonable, the RL-HAN model can continue to recommend until the guidance recommendation fails. The model uses the embedded expression information of user as the input state of the reinforcement learning module. If the recommendation result is wrong, the predicted Q_{t+1} network will become consistent with Q_t, which is not suitable for the MOOC recommendation task. Therefore, the strategy gradient method is selected as the optimization strategy of reinforcement learning. According to
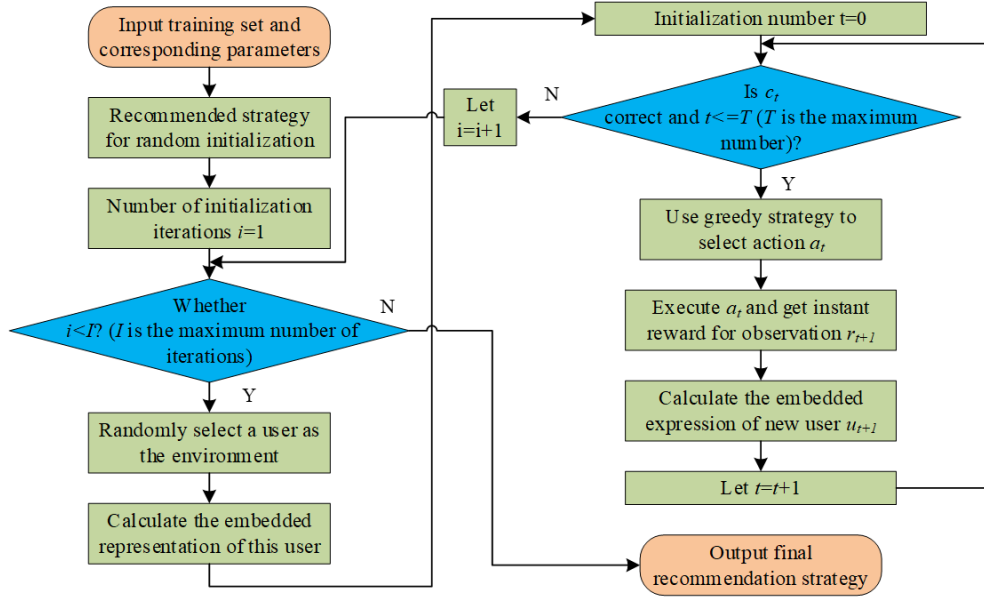
Fig. 3.5: Calculation Flow of English MOOC Recommendation Model Based on RL-HAN Algorithm

equation 3.10, its cumulative reward expectation gradient $(\nabla_\theta L_{\mathrm{RL}}(\theta))$ is calculated.

$$\nabla_\theta L_{\mathrm{RL}}(\theta) = -\sum_{t=1}^{T}[\nabla_\theta \log \pi_\theta(c_t \,|\, u_t)] \cdot r_t \tag{3.10}$$

To improve the learning speed and quality of recommendation model and improve its global search ability, entropy regularization is used as the regularization term $(H[\pi_\theta(c_t, |, u_t)]$ of the optimization index. See equation 3.11 for the calculation method.

$$H[\pi_\theta(c_t, |, u_t)] = -\sum_{t=1}^{T}\sum_{c_i \in C} \log(\pi_\theta(c_t \,|\, u_t))\pi_\theta(c_t \,|\, u_t) \tag{3.11}$$

Therefore, according to equation 3.12, the objective function of the recommended model can be calculated.

$$E_{c \sim \pi_\theta(c\,|\,u)}L_{\mathrm{RL}}(\theta) + \lambda H[\pi_\theta(c\,|\,u)] \tag{3.12}$$

λ represents the regularization coefficient in equation 3.12. The design of the English MOOC recommendation model based on RL-HAN algorithm is completed, and its overall calculation process is shown in Figure 3.5. The contents in Figure 3.5 have been shown completely and have been repeatedly mentioned, and it will not be repeated here.

Subsequent tests will be carried out to verify the performance of the design model. In the test, the hit rate $HR\#K$ with rank k, the normalized discount cumulative income $NDCG\#K$, and the mean reciprocal ranking MRR are used as evaluation indicators. Their calculation methods are shown in equation 3.13 to equation 3.15.

$$HR\#K = \frac{\mathrm{Num\_Hits}K}{|GT|} \tag{3.13}$$

Table 4.1: Detailed information of the test experiment dataset.

Node No	Entity node	Number of nodes	Node edge number	Node edge type	Number of node edges
#01	Video	98552	*01	Concept+Video	12846
			*02	User+video	54185142
#02	Curriculum	7424	*03	Video+course	852654
			*04	User+course	17564281
			*05	Concept+course	70154
#03	Concept	2588	*06	Course+concept	22512
			*07	Video+concept	12404
#04	User	3862031	*08	Course+user	16538410
			*09	Video+user	16538410

$$NDCG\#K = \frac{1}{Q} \sum_{q=1}^{|Q|} Z_{kq} \sum_{j=1}^{k} \frac{2^{r(j)} - 1}{\log(1 + j)} \tag{3.14}$$

$$MRR = \frac{1}{Q} \sum_{q=1}^{|Q|} \frac{1}{\text{rank}_i} \tag{3.15}$$

Num_{HitsK} and $|GT|$ respectively represent the sum of elements belonging to the test set and the size of the test set in the TOP-K recommendation list of each user in equation 3.13. In equation 3.14, Z_{kq} is the regularization factor. In equation 3.15, $|Q|$ and $rank_i$ represent the size of the candidate set and the corresponding ranking.

4. Performance Test of Improved MOOC Course Recommendation Model.

4.1. Test Experiment Scheme Design and Model Parameter Setting. To verify the performance of the recommended model designed in this study, a test experiment is designed here. The data required for the experiment is from the MOOC platform of Tsinghua University in China, which includes 7424 courses, 98552 teaching videos, 2588 concepts, 3862031 users and 154266250 edges connecting information entities. For details, see Table 4.1. The data set is divided into training sets and test sets according to the 7:3 ratio.

The improved Neural Architecture Search with Reinforcement Learning (NASR) algorithm based on the Gated Recurrent Unit (GRU) neural network, the Multilayer Perceptron (MLP) algorithm based on the shallow neural network, and the Batch-material Requirement Planning (BRP) algorithm based on Bayesian estimation were selected as the comparative recommendation model. The hit rate $HR\#K$ of the evaluation index specifically selects $HR\#3$, $HR\#5$, $HR\#10$, $HR\#15$ and $HR\#20$. The evaluation index of normalized discount cumulative income $NDCG\#K$ is specifically selected as $NDCG\#3$, $NDCG\#5$, $NDCG\#10$, $NDCG\#15$ and $NDCG\#20$. In addition to the hit rate $HR\#K$ with rank k, the normalized discount cumulative income $NDCG\#K$, and the mean reciprocal ranking MRR, the study also selected Area Under Curve (AUC), loss function, and calculation time as evaluation indicators.

5. Analysis of test results. First, the change rule of the loss function of each recommended model in the training process is compared. See Figure 6 for the statistical results. The horizontal axis represents the number of iterations, and the vertical axis represents the loss function value. In Figure 5.1, with the increase of the number of iterations, the loss function of each recommended model decreases rapidly and gradually converges. However, their convergence rate and the value after convergence are different. Specifically, the convergence speed of BRP recommendation model and MLP recommendation model is relatively fast, but the loss function value after convergence is large. RL-HAN and NASR recommended models have a slow convergence rate, but the loss function value after convergence is low. When the number of iterations exceeds 300, all model's complete convergence. The loss functions of RL-HAN, BRP, MLP and NASR models are 1.28, 5.74, 3.42 and 1.35 respectively.
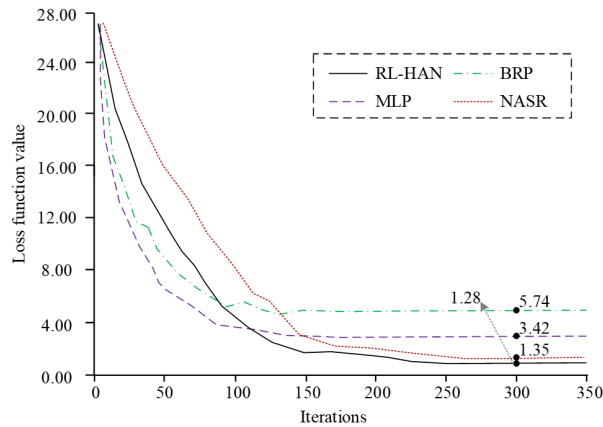
Fig. 5.1: Change law of loss function during training

Table 5.1: Calculation Results of Various Indicators for Each Recommended Model

Evaluating Indicator	RL-HAN	BRP	MLP	NASR
NDCG#3	47.08%	27.55%	15.77%	20.36%
NDCG#5	46.93%	29.51%	16.82%	22.40%
NDCG#10	48.24%	34.58%	25.96%	28.69%
NDCG#15	49.85%	36.72%	29.07%	31.75%
NDCG#20	52.91%	38.49%	31.48%	33.48%

In the following experiment, the quality of the recommended results of each model after the training is analyzed. The calculation results of various indicators are shown in Table 2. The larger the selected rank, the higher the hit rate, which is also consistent with the calculation logic of hit rate. The horizontal comparison shows that when the rank number is the same, the RL-HAN recommendation model has the highest hit rate, followed by the BRP model. For example, when the rank number is determined as 20, the hit rates of RL-HAN, BRP, MLP and NASR recommended models are 89.84%, 74.28%, 70.81% and 71.35% respectively.

Then in the experiment, the normalized discount cumulative income *NDCG#K* index is used to evaluate each model, and the statistical results are shown in Table 5.1. The larger the parameter k, the higher the corresponding normalized discount cumulative income. Through horizontal comparison, with the same parameter , the of RL-HAN recommended model is still the highest, and the corresponding value of MLP model is the lowest. For example, when parameter is 10, the normalized discount cumulative income of RL-HAN, BRP, MLP and NASR recommendation models is 48.24%, 34.58%, 25.96% and 28.69 respectively.

In the following experiment, the index *MRR* of mean reciprocal ranking is used to evaluate each model, and the statistical results are shown in Figure 5.2. The horizontal axis in Figure 5.2 is used to show different recommended models, the vertical axis represents the *MRR* value, and the different icons represent different scale test data sets. On the whole, the stability of the model recommended by NASR is the best. Because this model has the smallest numerical difference in different scale test data sets, and the stability of MLP and BRP models is poor. From the perspective of MRR value, the RL-HAN recommended model has the largest MRR value as a whole. For example, when using 100% test data set, the values of RL-HAN, BRP, MLP and NASR recommended models are 0.3756, 0.3086, 0.2069 and 0.2024 respectively.

The statistical results of AUC values of each recommended model are shown in Figure 5.3. The horizontal axis represents the false positive rate and the vertical axis represents the true positive rate in Fig. 8. The curves of different styles in the figure represent different recommended models. All curves in the figure are receiver
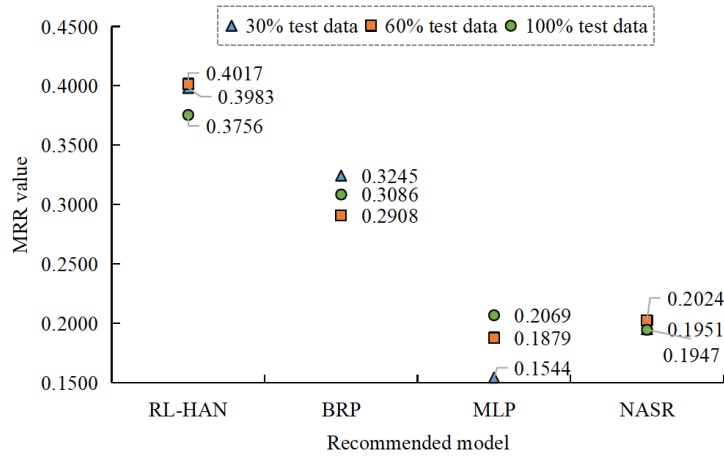
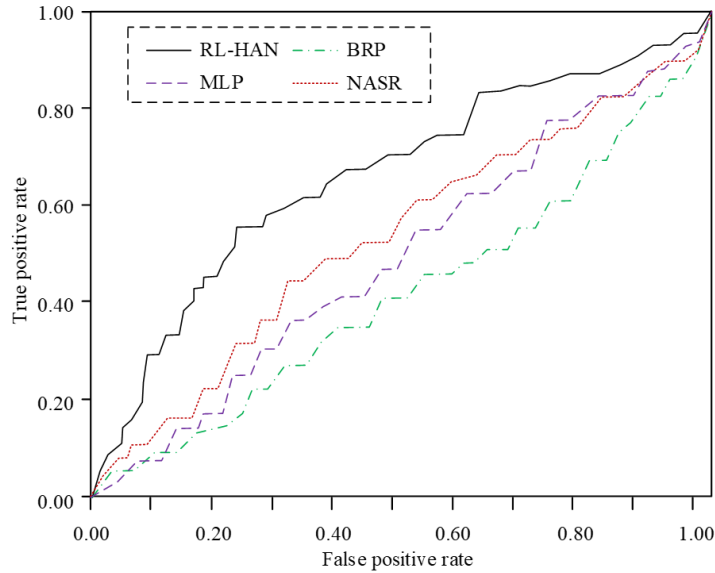Fig. 5.2: Statistical Results of Index of Each Model

Fig. 5.3: Statistical Results of AUC Indicators of Each Model

operating characteristic curve (ROC) curves. The area under the ROC curve and enclosed by the coordinate axis is AUC. According to Figure 5.3, the ROC curve of RL-HAN recommended model is always above the ROC curve of other models, and this model's AUC area is the largest. The AUC values of RL-HAN, BRP, MLP and NASR recommended models are 0.681, 0.463, 0.517 and 0.586 respectively.

Finally, the recommendation efficiency of each recommendation model is analyzed in the experiment, and the calculation time is used to evaluate the performance in Figure 5.4. The horizontal axis represents the number of samples participating in the test, and the vertical axis represents the calculation time, in seconds. Different icons represent different recommended algorithms, and different linetypes represent different fitting curves. With the increase of calculation samples, the calculation time of each model increases. However, the calculation time of NASR model shows an exponential growth trend, and the calculation time of other models
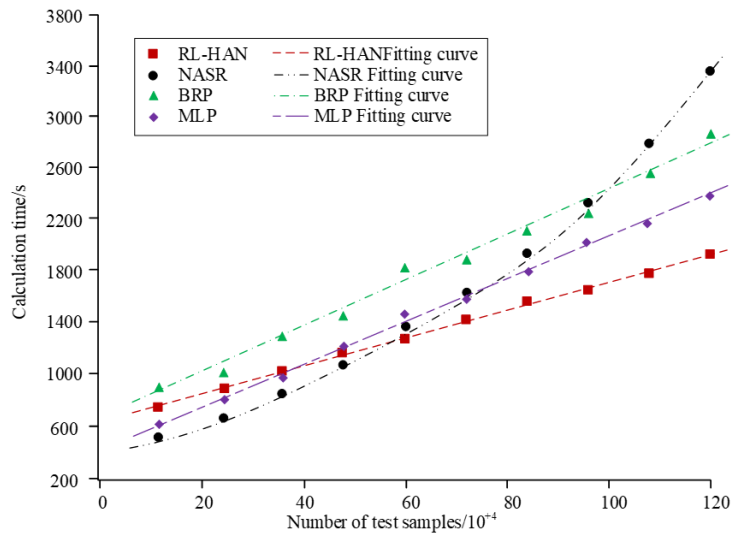
Fig. 5.4: Comparison of Calculation Time of Each Model

increases according to a linear rule. When the calculation sample is small, the efficiency of the model designed in this study is low. When the calculation sample is large, the calculation efficiency of the design model in this study is the highest. When the number of calculated samples reaches the maximum of 1158609, the calculation time of RL-HAN, BRP, MLP and NASR recommended models is 1867 s, 2866 s, 2349 s and 3980 s respectively.

6. Conclusion. Aiming at the inaccurate problem of curriculum recommendation in higher vocational education, this study designed an improved recommendation model integrating meta-path and reinforcement learning technology. When the number of iterations exceeds 300 in the training process, all model's complete convergence. The loss functions of RL-HAN, BRP, MLP and NASR models are 1.28, 5.74, 3.42 and 1.35 respectively. When the rank number is the same, the RL-HAN recommendation model has the highest hit rate. When the rank number is determined as 20, the hit rates of RL-HAN, BRP, MLP and NASR recommended models are 89.84%, 74.28%, 70.81% and 71.35% respectively. With the same parameter , the of RL-HAN recommended model is still the highest, and the corresponding value of MLP model is the lowest. When parameter is 10, the normalized discount cumulative income of RL-HAN, BRP, MLP and NASR recommendation models is 48.24%, 34.58%, 25.96% and 28.69% respectively. From the perspective of MRR value, the RL-HAN recommended model has the largest MRR value as a whole. When using 100% test data set, the AUC values of RL-HAN, BRP, MLP, and NASR recommended models are 0.3756, 0.3086, 0.2069, 0.2024. The AUC values of RL-HAN, BRP, MLP, and NASR recommended models are 0.681, 0.463, 0.517, and 0.586, respectively. Moreover, when the number of calculated samples reaches the maximum of 1158609, the calculation time of RL-HAN, BRP, MLP and NASR recommended models is 1867 s, 2866 s, 2349 s and 3980 s respectively. This shows that the recommendation accuracy of the improved MOOC recommendation model designed in this study is higher than that of the common models. However, its disadvantage is that its computational efficiency is not excellent, which is also an aspect that can be further improved in subsequent research.

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