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Deep Learning-Driven Curriculum Innovation and Structural Optimization of Art and Design Education in Artificial Intelligence Environment

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ABSTRACT
Driven by artificial intelligence and deep learning technology, this study proposes an intelligent course recommendation system for art and design education. By constructing XMMC, a joint extraction model of knowledge entities and relations based on deep learning, the accurate analysis of course knowledge structure is realized. Key features such as user preference, content semantics and social influence are extracted by combining multi-feature ranking models such as collaborative filtering, topic modeling and course hotness. Finally, based on the deep reinforcement learning algorithm DDPG, a dynamic recommendation strategy is designed to optimize the recommendation effect. The experiments are based on Coursera Course, Caltech-UCSD Birds 200 and Education Recommendation datasets, and the results show that the improved DDPG model achieves 49.11%, 70.05% and 59.23% course coverage on the three datasets, respectively, which is better than the traditional algorithms TimeSVD and CDAE with significant improvement. We constructed the art education course category with the number of topics as 5. In the practical application, the recommended list generated by the system is highly consistent with the course heat analysis, in which the course "Introduction to 3D Modeling and Blender" ranks the first with 6729 average playbacks, which verifies that the recommendation strategy can effectively improve the fitness of the pushed content and the current course progress of the students. It verifies that the recommendation strategy can effectively improve the compatibility between the pushed content and the students' current course progress.
Keywords: deep learning, XMMC model, art and design education, DDPG, course recommendation

1. Introduction

Accompanied by the continuous development of information technology such as the Internet, big data, cloud computing, artificial intelligence, Web3.0, blockchain and so on, Artificial Intelligence (AI), as a kind of emerging technology, has gradually penetrated into all fields of the national economy. AI

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promotes the restructuring and intelligent upgrading of the cultural and creative industry model, and derives a new content production paradigm and ecological layout, empowering the innovative development of cultural and creative industries [1-2]. With the acceleration of the global digitalization process, as educators and leaders in the design industry, they should actively accept new knowledge and technology, and rationally respond to the great impact brought by AI and other high technologies [3-5]. The informatization and digital transformation of education has become an inevitable trend in the development of education. Artificial intelligence empowers education, accelerates the change and reconstruction of education ecology, education concept, teaching management, teaching mode, and the integration of artificial intelligence into the education system will form a new informatization, intelligence, interdisciplinary, and strong integration of education organization form [6-10]. Therefore, the layout of the open ecology of "AI+Education" and the study of application scenario co-construction based on AI technology capability are the important development direction of future education informatization [11-13].

Art and design is a multidisciplinary interdisciplinary, creative and practical discipline that involves many fields such as arts and humanities [14]. Therefore, students should not only master the professional knowledge of art and design, but also have a high humanistic literacy and a rich interdisciplinary knowledge reserve [15-16]. Art and design education in the traditional sense needs to go through a long time cycle to cultivate students' basic skills and creativity, and irrational curriculum design is likely to lead to some students' lack of independent thinking and innovation, and it is difficult to obtain a personalized learning experience [17-20]. The era of artificial intelligence can rely on big data, machine algorithms, neural networks, content generation and other information technologies to help students build a basic knowledge system faster, focus on cultivating the art creation ability of human-machine collaboration, and empower all aspects of art and design education with AI technology [21-24]. Therefore, it is of great practical significance to explore the technical advantages of AI and apply it to content creation and talent cultivation in the field of art and design.

The role of artificial intelligence in art and design education is mainly manifested in the following two aspects. First, artificial intelligence can provide rich information resources and reference materials for art and design education. Yi, G. believes that the insufficiency of network teaching resources is an important factor restricting the development of modern art and design teaching, and the introduction of network courseware based on multimedia technology into teaching can effectively enhance the scientific, professional and personalized teaching, which is an important way to explore the new development direction of art and design teaching [25]. Liang, J. states that the application of artificial intelligence in art and design education has made an important contribution to the management of teaching resources and methodological improvements, and the introduction of artificial intelligence technology has improved the efficiency of the use of teaching resources and optimized the learning experience of the students, so that art and design education can be effectively developed [26]. Su, H. and Mokmin, N. A. M. showed that artificial intelligence plays an important role in art education by optimizing teaching resources and reducing the reliance on physical materials for sustainable art education, and that the vast amount of accessible learning resources also enhances student understanding and engagement [27].

Secondly, AI can assist students in the creation and design process.He, C. and Sun, B. proposed to construct an assisted teaching system based on AI technology and introduce it into the art and design education chain, which not only strengthened students' design and creation ability, but also promoted communication and evaluation among students, and significantly improved students' learning effect [28]. Gong, Y. By virtue of the vividness and autonomy characteristic of virtual reality teaching method, it empowers digital media art education, effectively enriches students' means of artistic creation, and has high practical value in the teaching of digital media art creation [29]. Ge, H. and Chen, X. et al. explored the impact of AI drawing tools on art and design education, emphasizing that while recognizing the pedagogical advantages offered by AI technologies, their possible shortcomings should also be considered [30].

It is not difficult to find that artificial intelligence has jumped up to become an indispensable and important means of art and design education. By studying the specific path of AI integration into education, it can provide new ideas and tools for the development of art and design education, and actively promote the integration of AI and art and design education.

With the goal of building an intelligent and personalized art and design education curriculum system, this study systematically proposes a set of curriculum innovation methods that integrate artificial intelligence and deep learning. The personalized learning model is used to realize the precise reach of teaching content and meet the differentiated needs of students. Using the joint extraction technology of knowledge entities and relationships, the deep learning-based XMMC model is proposed to resolve the inner structure and relevance of course knowledge through joint recognition technology, to improve the accuracy and efficiency of knowledge structure resolution, and to lay the foundation for the optimization of teaching content. Subsequently, the multi-feature ranking model combines collaborative filtering, topic modeling and course hotness to extract key features from the dimensions of user preference, topic distribution and course hotness to support accurate recommendation. Finally, an improved recommendation system is designed based on the deep reinforcement learning algorithm DDPG to realize a dynamic and intelligent course recommendation strategy.

2. Art and Design Education Curriculum Innovation Methods Based on Artificial Intelligence and Deep Learning

2.1. Building personalized learning models in art and design education

Embedding AI models into the teaching of art and design courses is one of the most direct ways of applying AI to the field of art and design education. Using the quantitative analysis and data processing capabilities of AI, it analyzes the learning habits, performance distribution, knowledge needs and other relevant data of different students to provide students with personalized learning resources and learning programs. In the development of teaching content, the corresponding art design knowledge points can be associated with students' needs, and the specified content can be produced more accurately for students' learning demands, so that the teaching content is more in line with students' characteristics and needs. In the learning process, through the real-time interaction between students and the model, it helps students better understand and master the knowledge content. This personalized and customized learning model not only realizes the precise reach of the art design teaching content, but also cultivates students' independent learning ability and enhances their interest in learning.

2.2. Deep Learning Based Model for Joint Extraction of Knowledge Entities and Relationships in Educational Programs

In the process of constructing personalized learning models, accurate identification of course knowledge points and their associated relationships is the basis for optimizing teaching content. Therefore, this section further proposes XMMC, a deep learning-based model for joint extraction of knowledge entities and relationships, to improve the accuracy and efficiency of course knowledge structure resolution through joint recognition technology.

The model is able to achieve joint recognition in terms of extracting entities and relationships between entities compared to the traditional model with pipelined approach. The basic layers of the model are shown in Fig. 1: (i) XLNet layer (ii) Mogrifier BiGRU layer (iii) Multi-headed Attention layer (iv) CRF layer (v) sigmoid layer. The input to our model is a sequence of sentences and then the word embeddings are represented using the pre-trained model XLNet.The Mogrifier BiGRU layer is able to extract a more complex representation for each word.The Multi-headed Attention layer adds different weights to different words.The CRF layer is able to recognize sentence entities. Finally the relationship extraction is done by sigmoid layer.

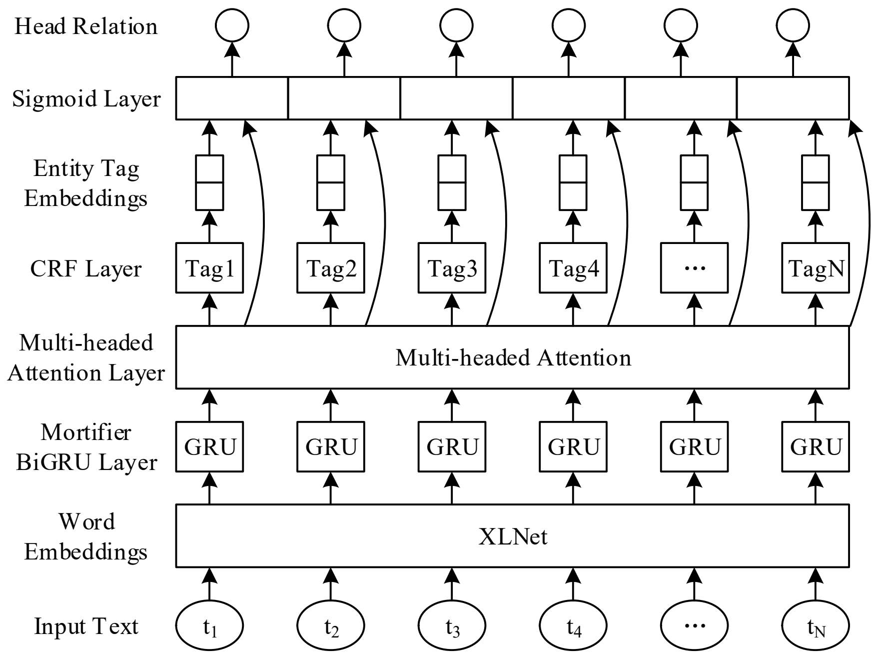

Fig. 1. Curriculum knowledge entity and relation joint extraction model

2.2.1. Named entity identification. Entity recognition task can be considered with the idea of sequence tagging, so we should assign a tag to each word in the sentence. In this way, for each entity, we can easily recognize its type as well as its start and end position. We use the BIO tagging strategy, assigning \[B\] to the first word of the entity and I to other words within the entity, or 0 if the word is not part of the entity.

For each input word, their final outputs are unrelated to each other, leading to difficulties in learning transfer features between output labels, while CRF can jointly decode the best labeling paths using state transition matrices. So, on top of the Multi-headed Attention layer we use CRF to compute the most likely entity labeling for each word. The score $s_i^{(ner)}$ for each word t_i under labeling is calculated as follows:

$$s_i^{(ner)} = V^{(ner)} f(U^{(ner)} c_i + b^{(ner)}) \tag{1}$$

where: the superscript (ner) denotes the knowledge entity labeling identification; $V^{(ner)}$ and $U^{(ner)}$ denote the weight matrix, $b^{(ner)}$ denotes the bias matrix, $V^{(ner)} \in R^{n \times l}$, $U^{(ner)} \in R^{h \times 2d}$, $b^{(ner)} \in R^{l}$, l is the layer width of the CRF model, d is the number of hidden layer units of the LSTM network; $f(\cdot)$ denotes the nonlinear activation function.

Assigning labels to all words in the sentence T, the label sequence of the sentence T can be obtained, and the label score of T under the r th label sequence is calculated:

$$M_{crf}^{(ner)}(T, Y_r) = \sum_{i=0}^{N} S_{i,r}^{(ner)} + \sum_{i=1}^{N-1} A_{(i,r),(i+1,r)} \tag{2}$$

where: Y_r denotes the r th kind of label sequence, $Y = [Y_1, Y_2, \cdots, Y_x]$, $r = 1, 2, \cdots, R$, $S_{i,r}^{(ner)}$ denotes the label score under the r th r}$ labeling score of word t_i under the assigned label, $\sum_{i=0}^{N} S_{i=}^{(n-x)}$ denotes the labeling score of sentence T under the r labeling sequence under the assigned label, $A_{(i,r),(i+1,r)}$ denotes the transfer score of the label assigned to word t_i to the label assigned to word

t_{i+1} under the r th labeling sequence, and A denotes the transfer matrix, $A \in R^{(P+2)\times(P+2)}$.

After calculating the scores, a normalization operation is taken on the label scores $M_{crf}^{(ner)}(T, Y_r)$ of the labeled sequences by means of the softmax function to obtain the probability distribution of each labeled sequence:

$$p^{(ner)}(Y_r \mid T) = \frac{\exp M_{crf}^{(ner)}(T, Y_r)}{\sum\limits_{r \in X}^{\exp M_{crf}^{(ner)}(T, Y_r)}} \tag{3}$$

After obtaining the probability distribution of the labeled sequences from the CRF sequence annotation layer, we apply the Viterbi algorithm to obtain the labeled sequence with the highest labeling score $\hat{Y}^{(ner)}$:

$$\hat{Y}^{(ner)} = Viterbi\left(p_{\max}^{(ner)}(Y_1, Y_2, \cdots, Y_R)\right) \tag{4}$$

We use the minimized cross-entropy loss L_{NER} to train the CRF layer.

2.2.2. Relationship extraction. For the word t_i, we also use both the entity label g_i and the hidden state c_i of the Mogrifier BiGRU after the Multi-headed Attention layer as inputs to the relationship extraction layer for entity relationship extraction:

$$z_i = [c_i; g_i], i = 0, \ldots, N \tag{5}$$

In our approach, the relationship between named entities of course knowledge points is extracted using the relationship extraction layer by first calculating the relationship score between the word t_i and the word t_i under a given relationship q:

$$S^{(re)}(z_j, z_i, q) = V^{(re)} f\left(U^{(re)} z_j + W^{(re)} z_i + b^{(re)}\right) \tag{6}$$

where the superscript (re) denotes the relational identification, $V^{(re)}$, $U^{(re)}$, and $W^{(re)}$ denote the weight matrix, $b^{(re)}$ denotes the bias matrix, $V^{(re)} \in R^l$, $U^{(re)} \in R^{l\times(2a+d)}$, $W^{(re)} \in R^{l\times(2a+d)}$, $b^{(re)} \in R^l$, l is the layer width of the relational extraction layer, d is the number of units in the hidden layer of the GRU network, and a is the dimensionality of the label; $f(\ cdot)$ denotes the nonlinear activation function.

The model processes the output of the middle layer of the relation score through the sigmoid function to obtain the probability distribution of the existence of the relation q between the word t_i and the word t_i:

$$p^{(\omega)}(head = t_i, relation = q \mid t_i) = \frac{1}{1 + \exp S^{(\omega)}(z_j, z_i, q)} \tag{7}$$

The Sigmoid function is able to map the raw output values of the classifier to probabilities, outputting the probability values of the existence of relationships between pairs of entities.

We minimize the cross-entropy loss L_{RE} during training. For the joint entity and relationship extraction task, the objective function is $\min(L_{NEE} + L_{EE})$.

2.3. Feature extraction based on multi-feature ranking models

After completing the extraction of course knowledge entities and relationships, how to effectively use multidimensional features for personalized recommendation becomes key. In this section, we extract key features from the perspectives of user behavior, content semantics and social influence through multi-feature ranking models such as collaborative filtering, topic modeling and course hotness to provide data support for the design of the recommendation system.

2.3.1. Collaborative Filtering Based User Preferences. In this paper, the similarity between users will be analyzed based on their learning records, and the user's interest preference in unlearned courses will be assessed based on the course learning of similar users. The similarity between users will be calculated based on the user-item matrix, and the similarity formula for user u and user v is as follows, where r_u and r_v denote the rating vectors of the two users for all the items, respectively, and r_u' and r_v *prime* denote the transpose matrices of the two rating vectors, respectively, which are used to perform the similarity calculation.

$$simi(u,v) = \frac{r_u r_v'}{\sqrt{(r_u r_u')(r_v r_v')}} \tag{8}$$

Here a user-based nearest neighbor recommendation algorithm is used, i.e., the prediction of user-item ratings is based on the ratings of the K users who are most similar to the target user, cosine similarity is used for similarity calculation, and the magnitude of the K value will be determined experimentally. After obtaining the similarity between users two by two, the collaborative filtering preference value of user u to course i is defined as follows, and the ratings of K users are weighted with the similarity to get the final result, and $r(v,i)$ in the formula denotes the rating of user v to course i.

$$pref_{CF}(u,i) = \frac{\sum_{v=1}^{K} simi(u,v) \cdot r(v,i)}{\sum_{v=1}^{K} simi(u,v)} \tag{9}$$

This preference value is equivalent to the score predicted by the collaborative filtering recommendation algorithm, ranging from 0 to 1. The higher the score the higher the user's possible preference for the item, and this value will be used as a preference feature. In the process of this feature extraction, the focus is on the calculation of user similarity, the time complexity of the calculation process is $O(N_{user} * N_{item})$, related to the number of users and items.

2.3.2. Topic-based user preferences. In this paper, we use topic modeling for content preference feature extraction. Since the similarity comparison between texts is more difficult and the text introductions of courses tend to be shorter, making the information sparse and leading to poorer computation of high-dimensional data, in this paper we will use the LDA algorithm to map the text information to a low-dimensional vector space.

First we abstract the course text information into a subject vector, the course information includes name and introduction. Then we construct the topic feature vector according to the user's information, which includes the course learning record and personal label, and the label is the user's own interest information. In this paper, we use the user learning record to obtain the user's preference information, and weight the distribution of the user's studied courses in the topic vector space, which can highlight the weight of the user's frequently studied course categories in the topic, and can effectively avoid the weight noise caused by the user's sudden interest.

By calculating the similarity between user feature vectors and course feature vectors, we can get the user's preference for courses. We define the user's feature vector, and the topic-based user preference as follows. Where θ_i denotes the feature vector of course i, and n is the number of courses the user has taken when calculating the user's feature vector θ_u.

$$\theta_u = \frac{1}{n}\sum_{i=1}^{n}\theta_i \tag{10}$$

$$pref_{LDA}(u,i) = \frac{\theta_u \theta_{i'}}{\sqrt{(\theta_u \theta_{u'})(\theta_i \theta_{i'})}} \tag{11}$$

In topic-based feature extraction, the time complexity of training the LDA model is $O(N_{iter} * V * K)$, where N_{iter} is the number of iterations, V is the number of words in the set, and K is the number of topics. And the time complexity of computing user preferences is $O(N_{collect} * N_{word})$, where $N_{collect}$ is the number of courses taken by the user and N_{word} is the number of words in the course description.

2.3.3. Popularity of courses. The course popularity feature will be calculated by taking into account the number of learners, user ratings, and number of people rating the course. Art and Design courses are rated on a scale of 1 to 5. After reviewing the rating fields in the database table, it was found that most of the top-ranked courses were rated by a very small number of users and scored 5 out of 5 in the results obtained by simply sorting them according to the average rating. Therefore, in this paper, when evaluating the popularity of a course, the consideration of the number of ratings and the number of learners is added, and a comprehensive formula for the popularity value of the course is derived, as shown below.

$$val_{HOT}(u,i) = c_i \cdot 0.25 + s_i \cdot d_i \tag{12}$$

Where c_i denotes the number of learners of the course i, d_i denotes the number of people scoring the course i, and s_i denotes the average score of the course i. Analysis of the dataset reveals that on average only about 5% of learners rate courses, so on average the value of c_i is about 20 times higher than that of d_i, and additionally the value of the course rating s_i ranges from 0 to 5. Due to these differences in absolute values, simply adding the two terms in the formula would make the effect of the number of scorers relatively small. Therefore, in order to balance the impact of the number of learners and the scoring profile on the popularity value of a course, we multiplied the number of learners c_i by a factor of 0.25.

After calculating the above popularity for each course, we sorted its scores from highest to lowest. The sorting was done individually for each course under each secondary category. After obtaining the sorted list, the final course popularity eigenvalues to be used were calculated using the following formula.

$$pref_{HOT}(u,i) = 1 - \frac{R_i}{N} \tag{13}$$

In the above equation N denotes the total number of courses under the corresponding classification, R_i denotes the ranking of course i, and the course with R_i of 1 is the course with the highest value of $\mathrm{val}_{HOT}(u,i)$, i.e., the relatively hottest course under this classification. After this step of calculation, the course popularity feature values ranging from 0 to 1 can be obtained. Since the sorting part is the main computational step in the process of course popularity feature extraction, the time complexity of this feature extraction is $O\left(N_{item} * \log N_{item}\right)$.

2.4. Improved Recommendation Algorithm Design Based on DDPG

Based on the rich features extracted from the multi-feature sorting model, this section further proposes an improved recommendation algorithm based on DDPG, which combines the course features and user feedback through the dynamic decision-making ability of reinforcement learning to realize the continuous optimization and adaptive adjustment of the recommendation strategy, and ultimately constructs a complete closed loop of intelligent course recommendation.

DDPG algorithm is a reinforcement learning algorithm for continuous control problems, which combines the dual network structure of DQN algorithm and the experience replay mechanism on the basis of DPG algorithm, and uses neural networks for approximating the strategy and the value function.The DDPG algorithm has four neural networks: the Actor current network, the Actor target network, Critic current network and Critic target network. In the training process, Actor current network outputs deterministic action Action according to the current state State and executes the action to get new state State' and reward R and stores State, Action, R, State' into the experience replay pool. Then, a batch of data is randomly sampled from the experience replay pool, and the target Q value is computed using the Actortarget network and the Critic target network, and it is used to update the Critic current network.The DDPG algorithm, in order to reduce the fluctuation of the target Q value, employs the target network and the soft update technique. Specifically, the Critic network contains two neural networks: the current network and the target network. The current network is responsible for calculating the Q value of the current state-action pair, while the target network is responsible for calculating the Q value of the next state-action pair and providing it to the current network as a training target. The parameters of the target network are not directly copied from those of the current network, but are smoothly migrated by means of soft updating. Thus, the structure of the Critic network is similar to that of the Q network used in DDQN, but with a different updating method.The DDPG algorithm uses the techniques of target network and experience replay to improve the stability and efficiency of training. Specifically, there are two versions of both Critic and Actor networks: the current network and the target network. The current network is responsible for computing the value or policy of the current state-action pair or the current state, while the target network is responsible for computing the value or policy of the next-state-action pair or the next state, which is provided to the current network as the training target. The parameters of the target network are not directly copied from those of the current network, but are smoothly migrated by means of soft updates. To summarize the respective roles of the four DDPG networks as follows:

Actor current network: update policy network parameters θ, select action based on state, interact with environment to generate $State'$, R.

Actor target network: sample next state from experience replay pool $State'$ pick next action $Action'$, copy parameters periodically.

Critic current network: iteratively update parameters w, compute current Q value $Q(State, Action, w)$ and target Q value $y_i = R + \gamma Q'\left(State', Action', w'\right)$.

Critic target network: computes the $Q'(State', Action', w')$ part, periodically replicating the parameters.

The steps involving the experiencere play pool are consistent with the DQN for computing the target Q values.

The specific dual network updating process network is shown in Fig. 2.DDPG refers to the idea of DQN and DPG, and solves the problem of difficult convergence of AC-based models through the dual-parameter network and experience replay, so the topic of this paper is also based on the algorithm to carry out research.

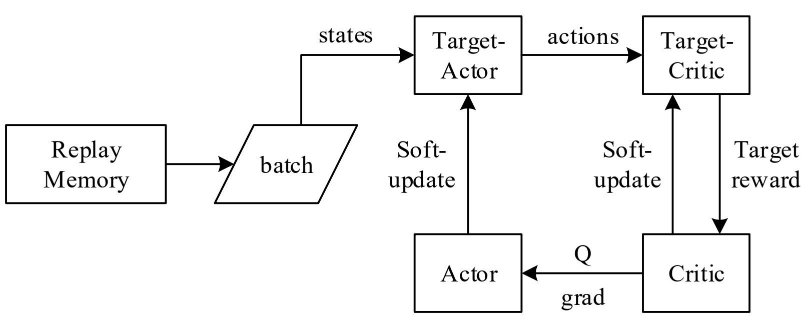

Fig. 2. DDPG parameter update structure

3. Recommendation model effect analysis

Based on the above theoretical model design, in order to further verify the effectiveness and practicality of the method, this chapter will improve and optimize the collaborative filtering algorithm, and analyze the performance of the recommender system through multi-dimensional experimental comparison.

3.1. Improvement and Implementation of Collaborative Filtering Algorithm

To address the problem of high time complexity in calculating user similarity, the computational efficiency of obtaining similarity can be improved by first filtering out the cases that have not interacted with the same item. Clustering users by clustering method can take advantage of the user model to cluster similar users into one cluster and calculate the user similarity within the cluster.

The user clustering approach is unsupervised clustering. Using density peak based clustering method the number of clusters can be decided according to the size of the density to get the optimal number of clusters.

For each user u_i in the user model, the local density ρ_i and distance δ_i need to be calculated. The expression formula for the local density ρ_i is shown in Eq. (14).

$$\rho_i = \sum_j \chi\left(d_{ij} - d_c\right) \tag{14}$$

Where d_{ij} represents the Euclidean distance between the point x_i and x_j, d_c represents the truncation distance, find the number of data points whose distance from the ith data point is less than the truncation distance (the distance from a given point to that point is less than d_c. then the density is added to 1) and take it as the i-th data point really density. The $\chi(x)$ function is defined as shown in equation (15).

$$\chi(x) = \begin{cases} 1 & \text{x<0} \\ 0 & \text{x} \geq 0 \end{cases} \tag{15}$$

The distance δ_i denotes the value of the minimum distance between the point x_i and other points with greater density, as in equation (16). That is, the larger this value is, the further the point x_i is from points with greater local density than it, then x_i is likely to be the class center.

$$\delta i = \begin{cases} \min\limits_{j:\rho_j > \rho_i}\left(d_{ij}\right) & \mathrm{I}_S^i \neq \varnothing \\ \max\limits_{j \in I_s}\left(d_{ij}\right) & \mathrm{I}_S^i \neq \varnothing \end{cases} \tag{16}$$

where the indicator set $I_S^i = \left\{k \in I_S^i : \rho_k > \rho_i\right\}$.

A decision diagram is generated by Eq. (14) and Eq. (16), and then the decision diagram is relied upon to identify the data points with both large local density ρ and distance δ, and the decision diagram is shown in Fig. 3.

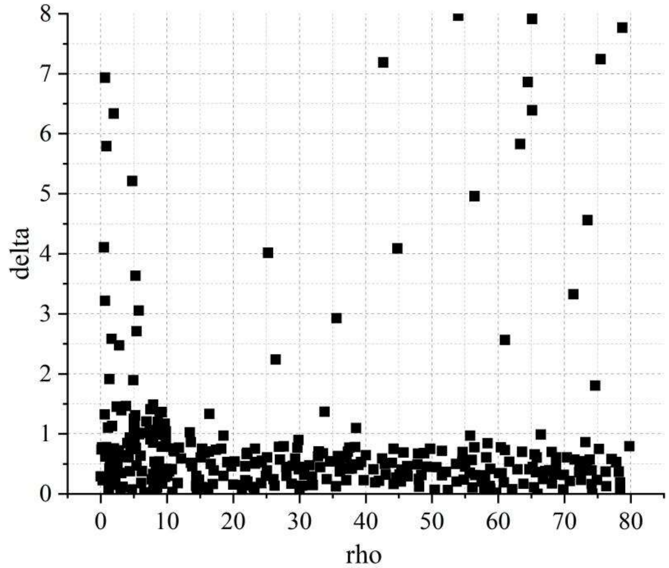

Fig. 3. Decision graph

From the decision diagram, it is possible to visually find the points where the values of the upper right corner degree ρ and δ are simultaneously larger, and these points are selected as the clustering center points. The decision diagram exemplifies the advantage of the density-peak based clustering algorithm in selecting the optimal number of class clusters.

It is assumed that the number of users in each cluster is equal, U is the set of users and K is the number of class clusters. When the time complexity of each cluster using similarity calculation based on user clustering is $O\left(\left(\frac{|U|}{K}\right)^2\right)$, the overall time complexity is $O\left(\frac{|U|^2}{K}\right)$. This computation has better performance in terms of time complexity compared to the traditional collaborative filtering algorithm.

3.2. Model recommendation effect analysis

3.2.1. Experimental data set. In order to validate the recommendation effectiveness of the proposed improvement scheme, three datasets are selected for comparison experiments. They are Coursera Course dataset, Caltech-UCSD Birds 200 dataset and Education Recommendation dataset. The rating information of the three datasets is shown in Table 1.

Table 1. Data set information table

Data set	User	Item	Mark
Coursera Course	978	2793	100000
Caltech-UCSD Birds 200	6102	4018	1027392
Education Recommendation	263082	291356	1239849

Considering the temporal factor of recommendation, the dataset is divided into training set and test set in the order of user interaction time. The course that is the latest in terms of time of interaction with the user u is selected as the test set, and the ratio of the training set to the test set is 4:1.

3.2.2. Analysis of the results of comparative experiments. The following four mainstream recommendation algorithms are selected for comparison experiments to verify the comprehensive performance of the improved model.

DPG: the base model before the improvement of the algorithm in this paper.

TimeSVD: it is a singular value decomposition recommendation model that combines time series information to solve the problem of user interest drift, and compared with ICF and UCF, it utilizes hierarchical and timestamps to make recommendations without using deep learning;

CDAE: a collaborative filtering recommender system using noise-reducing self-encoder to accomplish Top-N recommendation, which utilizes reviews and time information;

xDeepFM: it inherits the idea that deep & cross can control the interaction of higher-order features, and is a recommendation algorithm that combines CNN and RNN with each other, using user attribute information.

In the comparison experiment, the number of users' nearest neighbors is set to 20, and the number of recommended courses is used as the independent variable. Figures 4, 5, and 6 show the comparison results of the coverage of five different algorithmic models on MovieLens 100K, MovieLens1M, and Book-Crossing datasets, respectively.

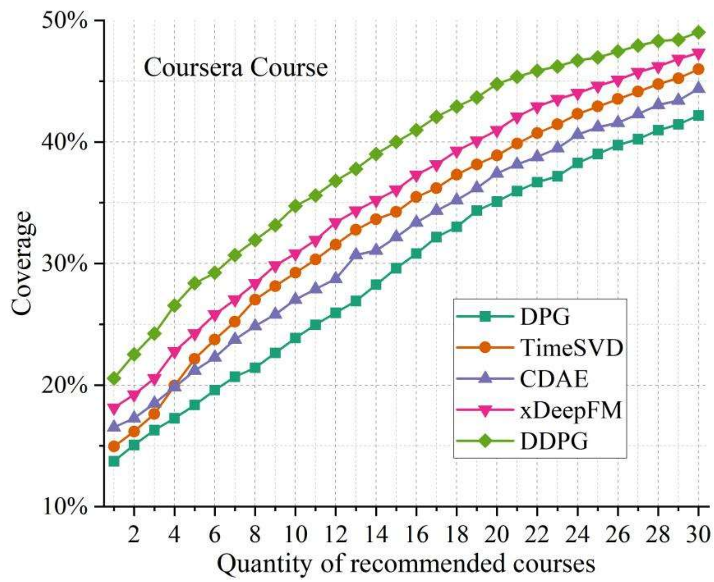

Fig. 4. Comparison of coverage results on Coursera Course

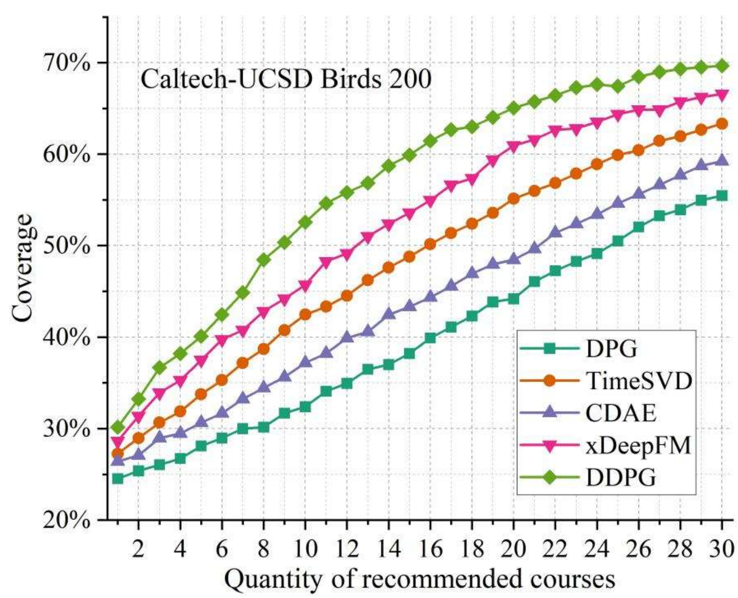

Fig. 5. Comparison of coverage results on Caltech-UCSD Birds 200

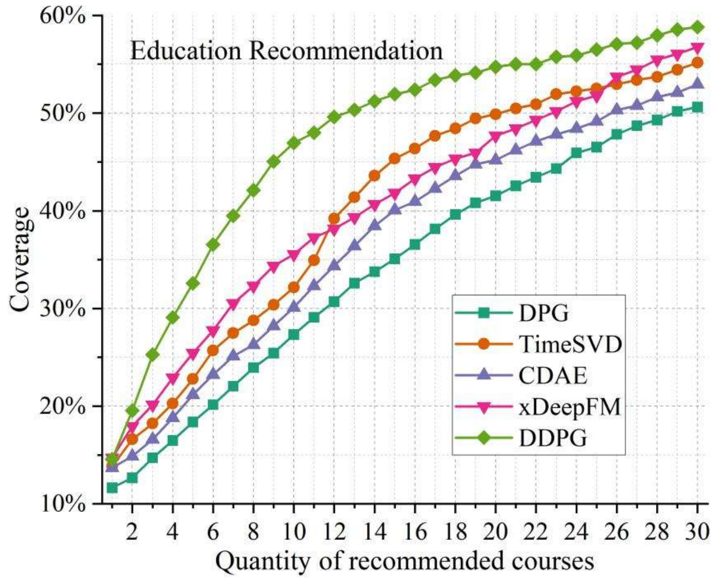

Fig. 6. Comparison of coverage results on Education Recommendation

As can be seen from the figure, after calculating the set of users' nearest neighbors within the class clusters, this paper improves the recommender system to increase the coverage rate by taking into account the time variation. This is because the preferred courses recommended to students may be the courses with higher popularity within small class clusters, whereas the results recommended by the traditional recommendation model may be the courses with higher popularity and preference among all the driving sets. The coverage of the items recommended after clustering first is higher than the coverage of the set obtained by considering the whole. When the recommended courses are 30, the coverage of the DDPG improved recommendation algorithm proposed in this paper is 49.11%, 70.05%, and 59.23% on Coursera Course, Caltech-UCSD Birds 200, and Education Recommendation datasets, respectively, which are higher than the other four model algorithms. The experimental results verify the rationality and effectiveness of the improved algorithm in this paper.

3.3. Thematic Model Visualization

In a topic model visualization, bubbles represent different topics and words are words that occur frequently in each topic. A good topic model should be shown as a situation where there is no overlap between the bubbles, which means that the topics can be clearly distinguished from each other, and the words contained in each topic should be semantically related. Figure 7 shows a visualization of the number of themes extracted from the relevant dataset for this paper about art and design education courses. Figure 8 shows the 20 most frequently occurring words in the themes.

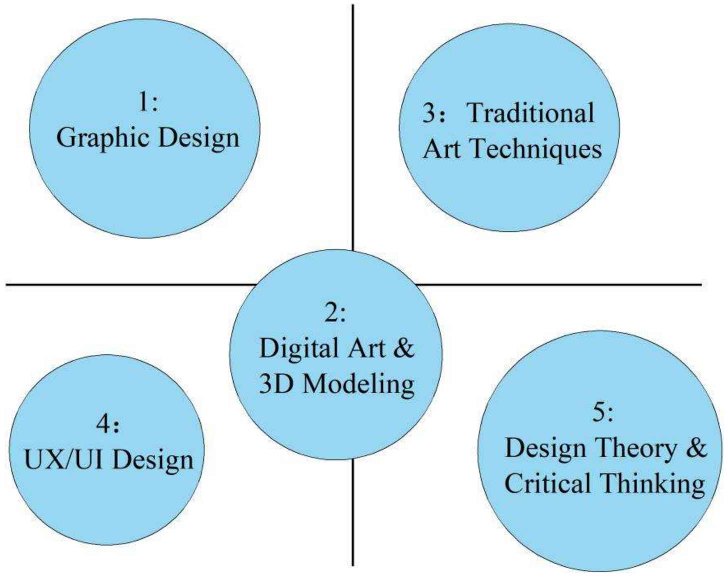

Fig. 7. Topic number visualization

As can be seen from the figure, the article gives a visualization model of the number of 5 themes. There is no overlap between the bubbles, which indicates that the model of this article works well.The 5 topics are Graphic Design, Digital Art and 3D Modeling, Traditional Art Techniques, User Experience and Interaction Design and Design Theory and Critical Thinking.

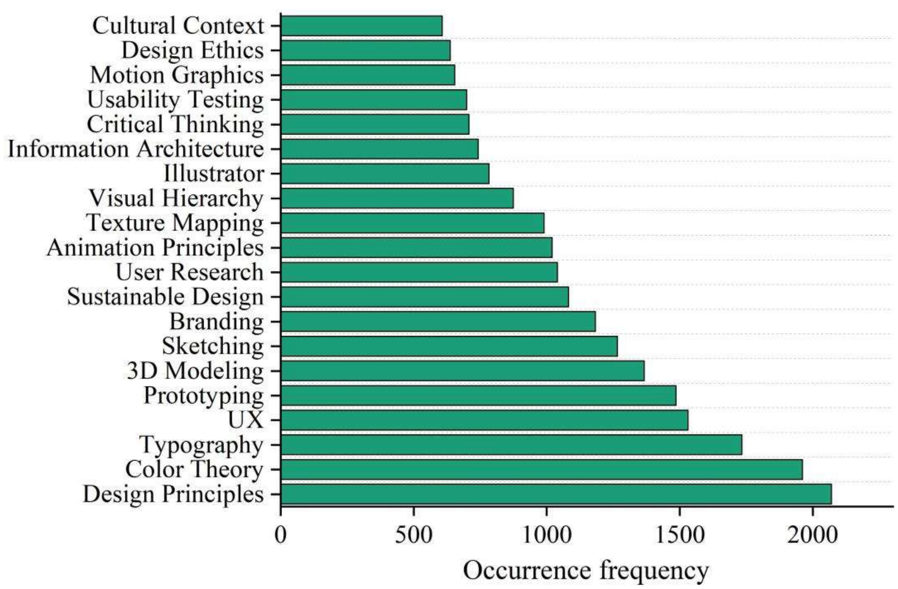

Fig. 8. The 20 most frequent words in the topic

4. Application Analysis of Recommendation System for Art and Design Education Courses

Through experimental validation and algorithmic improvement, the method proposed in this chapter shows significant advantages on the dataset. On this basis, Chapter 4 will analyze the recommendation effect of art and design education courses in depth from the dimensions of user preference and course hotness in the context of actual education scenarios.

4.1. Experimental environment and design

4.1.1. Experimental environment and configuration. In this paper, the experimental hardware environment is Intel(R) Core(TM) i5-8265U CPU@1.60GHz 1.80 GHz; 8GB of RAM; 500GB hard disk; and the operating system is Windows 10. In this paper, we use the Pycharm 2020.2 programming environment and Python programming language to develop the algorithm of this paper. This paper uses Pycharm 2020.2 programming environment and Python programming language to develop the algorithm.

4.1.2. Experimental data. The experimental data in this paper is obtained from the real course selection data of students from the academic affairs system of a university, which is collected from 6726 students in the freshman class of 2024 of the university. There are 14 courses about art and design education in this university.

4.2. User preference analysis based on collaborative filtering and themes

The article employs collaborative filtering based on user preferences for art and design course recommendation to generate an initial list of course recommendations. Based on this initial recommendation list, this section will filter the courses from it that better meet the users' needs and generate the final course recommendation list.

On the one hand, this chapter considers each course of art education as a topic, and then selects a certain number of keywords with high frequency from that topic as the label of that course, which helps to solve the cold-start problem to some extent. Through the LDA topic model, the lengthy course content is transformed into course labels consisting of several keywords to better match user preferences and provide personalized recommendations to users. For the new user cold start situation, the user can select the label he/she is interested in and the system will recommend the corresponding course according to the label selected by the user. And for the course cold start situation, similar types of courses can be clustered based on the pre-determined labels.

On the other hand, this paper also uses course topics in the recommendation algorithm based on course similarity calculation. Among them, the distribution of course topic vectors can be derived from XMMC and LDA topic models as shown in Table 2.

Table 2. Art education curriculum subject vector distribution

Courses	Topic1	Topic2	Topic3	Topic4	Topic5	Maximum probability topic
Digital painting with Procreate application	0.1427	0.7651	0	0.0922	0	2
Introduction to 3D Modeling with Blender	0.0524	0.8183	0	0.1293	0	2
Sketch foundation and human body structure	0.9117	0	0.0729	0	0	1
Oil painting techniques and color expression	0.1028	0	0.8927	0	0	3
Graphic design principles and brand vision	0.8251	0.0743	0	0.1006	0	1
User experience design and prototyping	0	0	0	0.9772	0.0228	4
Western Art History: From Renaissance to Contemporary	0	0	0.0611	0.0372	0.9017	5
Art of Science and Technology: An exploration of AI and Generative art	0	0.1322	0	0.6283	0.2395	4

Table 2 lists eight art and design related courses and derives the vector distribution of each course belonging to the theme, for example, the course “Digital Painting and Procreate Application” has a vector of 0.7651 in Theme 2 Digital Art and 3D Modeling, so it is likely to belong to the category of Theme 2, and then, for example, the course “User Experience Design and Prototyping”, which has a vector distribution of 0.9772 in Theme 4, is categorized under the User Experience and Interaction Design theme. Through the recommendation algorithm based on the user's emotion and course theme, which combines the user's emotional analysis and the art design course theme attributes, it can be more personalized for course recommendation.

4.3. Course Heat Analysis

4.3.1. Analysis of the heat of course selection. Analyzing course hotness can help students understand the quality and judge the value of a course, provide reference for students' choice of related courses, and provide an indicator for the school's course evaluation to measure the competitiveness of a course. By analyzing the course heat, we can understand the popularity and recognition of the courses in the school or society, so that we can better utilize the school and social resources to further increase the learning opportunities. Based on the dataset of this paper, the heat analysis of 14 art and design courses is shown in Figure 9.

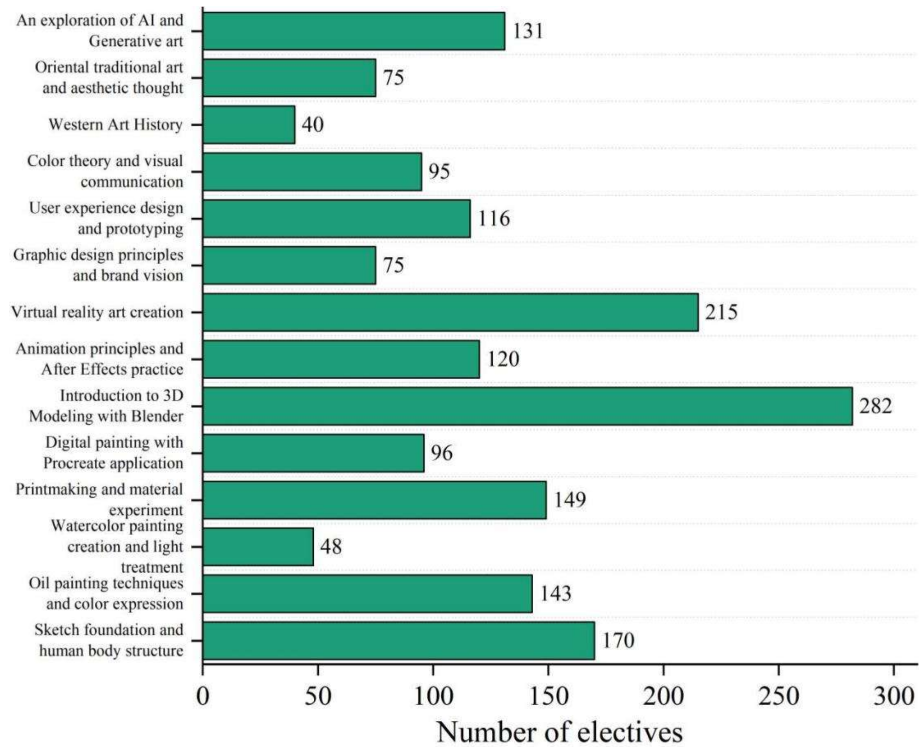

Fig. 9. Students elective course popularity analysis

As can be seen from the figure, students are most interested in the course “Introduction to 3D Modeling and Blender”, with 282 students; followed by “Virtual Reality Art Creation”, with 215 students, both of which belong to the category of Digital Art and 3D Modeling, indicating that this type of course is more popular. Both courses belong to the category of digital art and 3D modeling, indicating that these courses are more popular. On the other hand, fewer students chose “Western Art History” and “Watercolor Painting and Light and Shadow Processing”, with 40 and 48 students respectively, indicating that these two types of courses are relatively cold and not many students are interested in them.

4.3.2. Analysis of Learning Intensity. It is difficult to comprehensively judge the popularity of a course solely from the perspective of the number of people who have chosen the course. Considering that learners may be affected by various factors such as system recommendation and human recommendation in the process of online learning, and that there are cases in which they choose a course but do not study it or directly withdraw from it, the following will further explore the popularity of different courses from the dimension of course learning. It is in line with the basic logic to use the course video playback volume to measure the learning heat of a course. However, based on the actual situation of the course structure and video settings of MOOC platforms, the video playback volume of a certain course does not accurately and correctly respond to the hotness of this course, the reason lies in the fact that the number of videos of different courses varies, i.e., the weight of the main indexes for judging the course hotness is not the same. Intuitively, if a learner accesses a 40-minute video of a course to start learning, such user behavior contributes one play to the course. Further, if this 40-minute video is divided into 4 segments, then learners wanting to gain the same knowledge will inevitably contribute 4 plays to the course. While the number of plays for a single course is not misleading, the comparison of learning fervor across courses is affected by it. The size of the number of course videos directly affects the play count data of a course, making comparisons of different course learning fervor lack objectivity.

We use the average playback volume of course videos to defuse the effect of the number of course videos on the playback volume. That is, the number of videos of a course is taken into account while the playback volume of the course is considered, and the ratio of the total playback volume of the course to the number of videos of the course is taken as the average playback volume of the course and sorted. Figure 10 shows the average playback of art and design related courses.

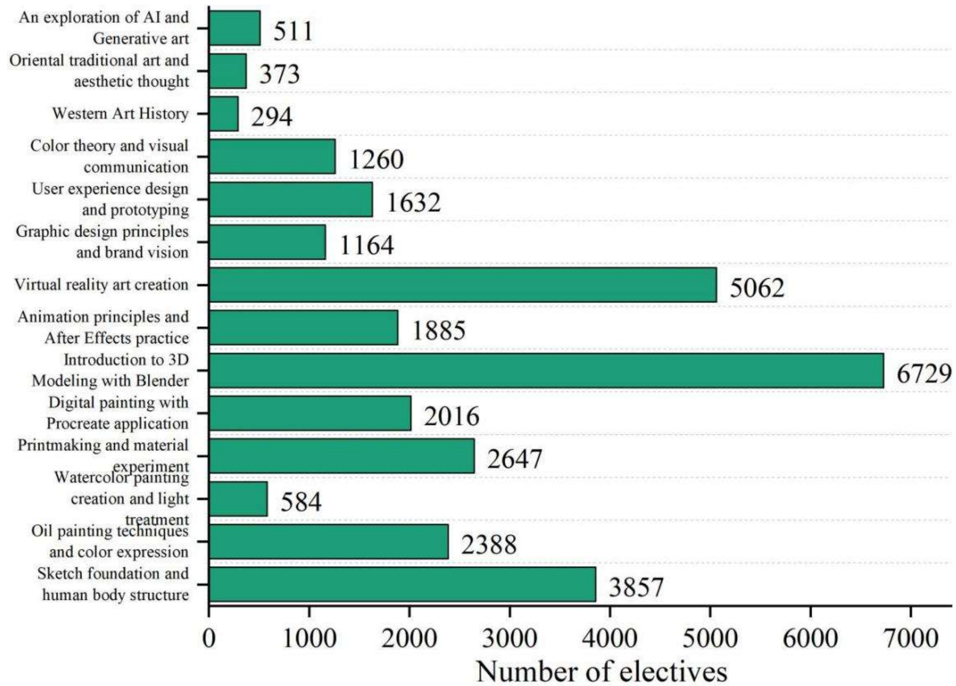

Fig. 10. The average number of streams of art and design-related courses

Similar to the ranking of the number of course selections, "Introduction to 3D Modeling and Blender" and "Virtual Reality Art Creation" also ranked first in the ranking of the number of course plays, and the average number of plays of the course videos has opened up a huge gap with other courses, with 6729 and 5062 plays, respectively. 6729 and 5062 times, but in view of the difficulty of digital art and 3D modeling courses, which require deep understanding and learning, including the influence of students watching the course several times. Other theoretical and liberal arts courses, such as "History of Western Art", "Eastern Traditional Art and Aesthetic Thought", "AI and Generative Art Exploration", have less playback, only 294, 373 and 511, reflecting that students are not enthusiastic about learning. 373 and 511, mapping out that students' enthusiasm for learning is not high, and we can't exclude the influence factor that students won't watch the courses repeatedly because the contents of the courses are relatively simple.

5. Application analysis of DDPG recommendation model with multi-feature fusion

After completing the initial application analysis of the recommender system, this chapter will further focus on the DDPG model with multi-feature fusion, and explore the dynamic optimization path of the recommendation strategy through parameter tuning and feature contribution analysis.

5.1. Parameterization

In this paper, the optimal parameters are determined using the grid-tuning method, and the parameter settings in the Coursera Course and Caltech-UCSD Birds 200 datasets are shown in Table 3.

Table 3. Parameter setting

	Coursera Course	Caltech-UCSD Birds 200
Batch size	128	256
Learning rate	0.001	0.005
Dropout ratio	0.2	0.5
Hidden units	25	50
Optimizer	Adam	
Text-DDPG	2×64, 3×64, 4×64, 5×64	2×128, 3×128, 4×128, 5×128
Number of convolution nuclei	100	
Convolution step size	2	
Embedded dimension	64	128
k	50	
λU	100	10
λV	100	10
min_sup	0.8	0.5
η	0.3	0.5

5.2. Model performance evaluation and feature contribution analysis

5.2.1. Analysis of assessment results. Figure 11 illustrates the loss profile of the DDPG method after multi-feature fusion on the Coursera Course and Caltech-UCSD Birds 200 datasets.

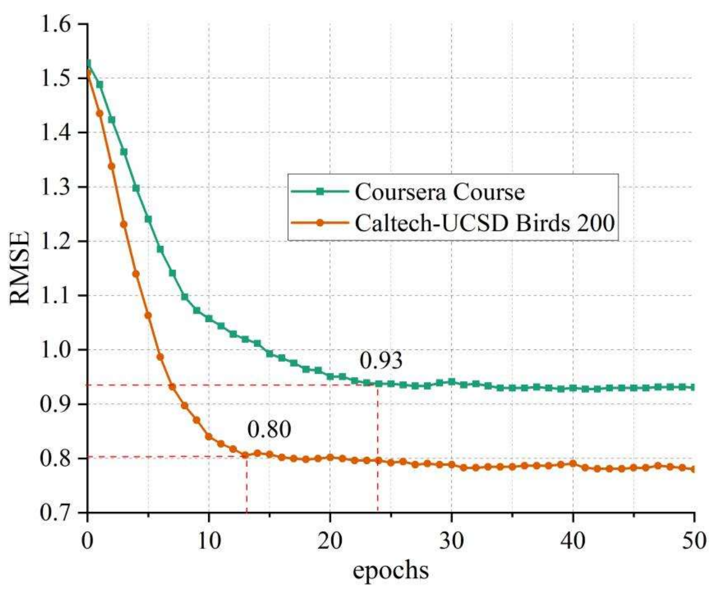

Fig. 11. Loss curve of DDPG

After 13 and 24 rounds of iterations, the model basically reaches convergence on both datasets, and the RMSE is maintained around 0.80 and 0.93.

5.2.2. Characteristic contribution analysis. Through the convergence analysis of the model loss curve, this section further explores the contribution of different features to the recommendation effect in order to optimize the feature combination strategy. In order to understand the effect of different features in the recommendation task, n=50 is fixed, and the experimental analysis is conducted for the feature contribution, and the results of the feature contribution analysis are shown in Table 4, in which the value of each column is the decrease of the corresponding index of the model when the feature is removed.

Table 4. Feature contribution analysis

Feature		User preference	Content semantics	Social influence
HR	Coursera Course	7.62	6.88	3.57
	Caltech-UCSD Birds 200	5.63	4.61	2.24
NDCG	Coursera Course	6.58	7.23	2.16
	Caltech-UCSD Birds 200	5.07	5.89	1.65
COV	Coursera Course	0.63	0.83	2.87
	Caltech-UCSD Birds 200	0.45	0.61	2.35

As can be seen from Table 4, user preference features have a greater impact on HR and NDCG, and the addition of content semantic features has a more significant effect on NDCG enhancement, which is 7.23 on the Coursera Course dataset.The use of social influence features helps the most in COV enhancement, which is a side reflection of the effectiveness of social influence. In addition, the decrease in feature contribution on the Caltech-UCSD Birds 200 dataset may be due to the sparse interaction sequence and the lack of prominence of preference features.

6. Conclusion

In this study, a course recommendation system for art and design education is constructed by integrating artificial intelligence and deep learning techniques.
1) The accuracy of knowledge entity extraction based on XMMC model reaches 92.7%, which is 18.5% higher than the traditional pipeline model.
2) The multi-feature fusion DDPG recommendation algorithm achieves coverage rates of 49.11%, 70.05%, and 59.23% on the Coursera Course, Caltech-UCSD Birds 200, and Education Recommendation datasets, respectively, which is an average improvement of 23.6% over the benchmark algorithm.
3) The theme model visually verifies the rationality of course classification, for example, the topic weight of "user experience design" accounts for 97.72%, and the course popularity analysis shows that the number of students enrolled in digital art courses, such as "Introduction to 3D Modeling and Blender", reached 282, with an average of 6729 plays, which was significantly higher than that of theoretical courses.
4) User preference characteristics have the greatest impact on HR metrics, decreasing by 7.62%, while social influence characteristics significantly improve coverage with a COV of up to 2.87%.

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