Design of Push Algorithm for Individualized Course Content of College Public Art Education Online Education

Fang Li[1(✉)] and Jie Li[2]

[1] Wuhan University of Technology, Wuhan 430070, China
fangdancing@163.com
[2] International Business School, Xi'an Fanyi University, Xi'an 710105, China

Abstract. In order to improve the adaptability of online education personalized course push resources and user demand resources, and reduce the push time, a new push method is designed for online education personalized course content of Public art education courses in colleges and universities. A collaborative filtering algorithm is introduced to determine the target content to be pushed. Through screening similar users, we can master the demand directions of different types of users for course content, and realize the calculation of user preferences. We introduce convolution neural networks to train the data information in the convolution layer of convolution neural networks, obtain the characteristic parameters of course content, and conduct directional extraction of course content of public art education. We introduce a weighted fuzzy calculation method to determine the recommendation levels of course content in combination with the spatial expression of course content, and realize the active recommendation of course content. Experimental results show that the proposed method can reduce the discrepancy between the content of push-forward course and user's demand, and ensure a higher adaptability between the content and user's demand.

Keywords: Convolution Neural Network · Fuzzy Weighting · Collaborative Filtering Algorithm · Resource Push · Teaching Resources · College Education · Public Art Education

1 Introduction

The public art education in colleges and universities refers to the public art courses set up in colleges and universities to improve students' artistic quality, aesthetic quality, cultural taste and understanding and understanding of art forms under different cultural backgrounds. Public art education in colleges and universities is different from professional art education in that it provides students with basic knowledge and skills of art literacy for all subjects. The development of public art education in colleges and universities can not only improve students' aesthetic ability and cultural quality, but also enhance their creativity and imagination. Public art education can make students more

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open-minded and broadened horizons, but also can promote students' emotional experience and enhance students' mental health [1]. However, college public art education is facing some difficulties. Public art education is generally not the major of a student, and students may have limited time and energy to learn, so it is difficult to gain as much artistic culture and experience as possible in a short period of time. Online art education in colleges and universities refers to art-related learning activities through online platforms under the network environment. Online public art education in colleges and universities can learn independently according to individual needs and time without time and space constraints. Compared with the traditional public art education in colleges and universities, online public art education in colleges and universities is more convenient and flexible [2]. With the popularization and development of modern Internet technology, large-scale online open courses have become a new and popular trend in the field of education. With the characteristics of openness, free and accessibility, online teaching platform provides learners with diversified and high-quality online courses, which are not limited by time and place. Compared with the traditional teaching, the large-scale online open course provides a more flexible learning style for learners. Learners can learn according to their own schedule and requirements. In addition, the online teaching platform has no limit on the number of participants, and provides interactive, multimedia and other forms of online learning experience for learners through various teaching methods and forms, so as to enhance students' participation and learning enthusiasm, and enhance the quality and effect of courses. In a word, the large-scale online open course is an innovative form of education, which is loved by many learners with its flexibility and universality.

In today's globalization and informationization, online education has become the mainstream trend in the future. With the improvement of people's life quality, the demand for art is higher and higher. With college public art online education, students can learn art-related knowledge and skills to meet their needs and interests. The significance of online education of public art in colleges and universities lies in solving the limitation of time and space under the traditional education mode. College public art online education can improve people's learning enthusiasm and self-learning ability, and make learning more personalized and customized, attract more students to participate in art education. However, there are some difficulties in public art online education in colleges and universities. Because of the large amount of tedious steps and the complexity of information, the traditional scientific research elective system faces great challenges. Choosing courses not only needs time and energy, but also may bring stress and bad experience to students. The problem of information overload and difficult screening also makes it difficult for students to find valuable learning resources they need. These problems greatly hinder the improvement of students' academic performance and learning experience. Therefore, the accurate search and recommendation of online teaching resources has become a significant research topic.

Some scholars have proposed the use of cloud computing technology to build an e-learning resources recommendation system, featuring the use of Google cloud services to recommend learning resources based on students' needs and an incentive module to urge students to enhance learning [3]. Some scholars propose to use machine learning technology to provide a new Dirichlet framework for online teaching platform, which

can provide users with curriculum suggestions according to their preferences and behaviors. Using Latent Allocation to mine text, using decision tree to generate decision rules, using Self Map to evaluate courses, and using rule-based fuzzy system to predict user preferences. In addition, the feature selection method is used to select important criteria for forecasting user preferences [4]. Another proposal is to design an enhanced e-learning hybrid recommendation system that adaptively matches learners' learning patterns and rules according to their behaviors and semantic relationships. Semantic extension methods including DBpedia and WordNet ontology are used to expand terms, and various mood analysis models are introduced to improve the accuracy and effectiveness of recommendation system. Text reviews in e-learning resources are classified into fine-grained emotional categories and applied to rating forecasts [5]. The methods mentioned above put forward different application techniques for searching and recommending learning resources, but when they are applied to public art education courses in colleges and universities, the problems such as frequent collapse of use, great time consumption and loose relevance of recommended contents are likely to occur due to the complexity of resource types and the large number of users concurrent [6], which brings great trouble to users. According to the market users' experience feedback, the existing recommendation systems have the characteristics of large deviation between recommendation resources and users' individual needs.

In order to solve the problem of poor application of traditional method in the process of individualized content push of college public art education courses, an algorithm is designed. Based on the calculation of user preferences based on Collaborative filtering algorithm, the Convolutional neural network method is used to achieve the directional extraction of Public art education curriculum content in colleges and universities. The personalized course content of online education was actively pushed through weighted fuzzy calculation, and the effectiveness of this study was verified through experiments. The main innovations of this approach are as follows:

(1) According to the personalized demands of college students, the user preferences are calculated based on the information such as the user's web browsing history and search history. The collaborative filtering algorithm is used in this process to preliminarily delineate the user's resource push resources and reduce the calculation amount.
(2) Using the convolution neural network algorithm to extract the resources within the user's preference range, through the cycle training related keywords, the course content resources with similar content are traversed and extracted, and a complete set of related resources is obtained.
(3) The weighted fuzzy algorithm is used to rank the weight of the course contents in the resource set, determine the relevance importance of the content resources, and give priority to the content resources with the highest relevance to users' interests and preferences, thus realizing the personalized recommendation of online education resources for public art education courses in colleges and universities.

This method can provide learners with more personalized art education curriculum resources, and also provide new ideas and methods for the research of adaptive recommendation algorithm.

2 User Preference Calculation Based on Collaborative Filtering Algorithm

In order to accurately push the individualized course content of public art education online in colleges and universities, this paper introduces collaborative filtering algorithm [7]. In this process, it is necessary to identify the target group of public art education curriculum content push, through the screening of similar users in the group, to master different types of users' demand for public art education curriculum content. Collect user's personal information, through the analysis of information, generate a user demand resource score matrix [3]. The matrix expression is as follows.

$$\mathbf{S} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mn} \end{bmatrix} \tag{1}$$

In formula (1): **S** means the matrix expression of the grading of the curriculum contents required by users; s_{mn} means the scoring indicators of the curriculum contents required by users. By using the scoring matrix, the users who push the course content are screened, and the users with the same needs are classified into a same category. At the same time, the use of collaborative filtering algorithm to classify resources [8]. Randomly push the content of a public art education course for one user, and calculate the user's preference for the pushed content. According to the calculation results, master the user's demand for public art education curriculum content. The formula for calculating user preference is as follows.

$$B = \frac{L(X)^2}{J \times k} \tag{2}$$

In formula (2): B represents user preference; L represents course content category; X represents collaborative filtering algorithm; J represents automatic clustering parameters; and k represents recommended capacity within courses. According to the above formula, the user preference based on collaborative filtering algorithm is calculated.

3 Orientation Extraction of Course Content Based on Convolution Neural Network

On the basis of the above design contents, convolution neural network [9] is introduced to conduct directional extraction of the contents of online teaching courses of public art education in colleges and universities. Considering the large amount of content resources of online teaching course of public art education in colleges and universities, the initial course content is input on the network interface. In the convolution layer of convolution neural network, the data information is trained to get the characteristic parameters of the course content. This process is illustrated by a formula.

$$w = \frac{r(c) - f(a)}{\|y\|^2} \tag{3}$$

In formula (3): w represents the characteristic parameters of course contents; r represents the convolution layer in convolution neural network; c represents the training processing of data information; f represents distributed fusion; a represents reorganization model; and y represents characteristic attributes. On the basis of the above contents, using the semantic representation tool in convolution neural network [10], the course contents are divided into several categories, and the course contents with the same characteristics are clustered in space, so as to make the transition from high-dimensional data to low-dimensional data and ensure the uniformity of data format in the terminal. This process is illustrated by a formula.

$$G = \frac{\overline{N}^j}{K\sqrt{HN}} \tag{4}$$

In formula (4): G represents the unified processing of data format in the terminal; $\overline{N}$ represents high-dimensional data; K represents semantic representation tools; H represents the number of course contents with the same characteristics; N represents low-dimensional data; and j represents cluster centers. After finishing the treatment, we set up the content reorganization model of online teaching course of public art education in colleges and universities. At the same time, the design of directional extraction target function [11], so that users have the demand for curriculum content, the terminal can provide users with real-time curriculum content push services. The expression of the extraction objective function is as follows.

$$F = \vartheta_k \sqrt{\frac{\sum [v + c]^2}{M_k}} \tag{5}$$

In formula (5): F represents the expression of the extraction objective function; ϑ_k represents the fusion of parameters; M_k represents the directed set; and v represents the hash table. According to the calculation formula, the content of the course is extracted from the nodes of convolution neural network to meet the real-time demand of college students for the content of public art education online course.

Based on the preference of college students, this paper constructs a model of course content extraction, and obtains the sample statistical regression analysis result as shown in Fig. 1.

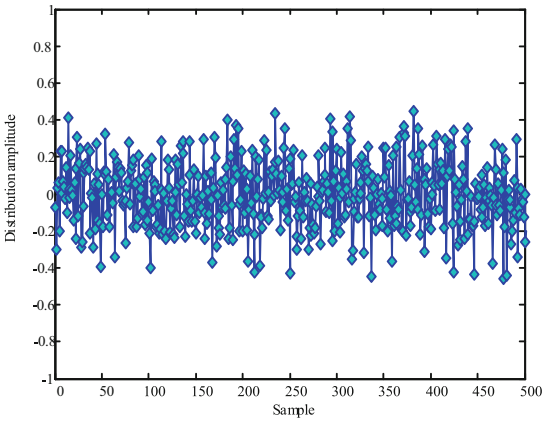

Fig. 1. Sample statistical regression analysis

4 Active Push of Course Content Based on Weighted Fuzzy Computation

After completing the above research, the weighted fuzzy calculation method [12–14] is introduced to calculate the recommended level of the course content. The formula is as follows.

$$\alpha = \left(AA^T + \partial D\right)^2 + \|\delta\|_{2,1}^{z} \tag{6}$$

In formula (6): α represents the recommended level of course content; A represents the amount of access control; δ represents the position of nodes in space; D represents the associated attributes of course content; and z represents weighted fuzzy coefficients. On this basis, the proposed boundary data range of fitness matrix is designed to determine the corresponding data processing accuracy. According to the different categories of curriculum content and the attributes of corresponding curriculum content, the subordination degree is assigned, and then the feasibility of pushing curriculum content is analyzed through the adaptation of pushing curriculum content and user demand curriculum content. [15]. Through this way, improve the university public art education curriculum content of comprehensive push ability, realize the initiative to recommend the curriculum content. Design this process as shown in the following formula.

$$\mu = \sum_{q>1}^{q} \frac{1}{\gamma \times \omega} \tag{7}$$

In formula (7): μ means active recommendation of course content; γ means fitness matrix; ω means suggested range of boundary data; q means precision of data processing. In accordance with the above method, the active recommendation of curriculum content based on weighted fuzzy calculation is realized, and the individualized curriculum content push algorithm is designed.

5 Experiment and Result Analysis

5.1 Experimental Preparation

But this method is still at the stage of theoretical research. In order to popularize this method in colleges and universities or relevant institutions in the education market (Fig. 2), we should evaluate its comprehensive performance on the basis of the existing work. Therefore, the following will take the design of comparative experiments to test the effectiveness of this method.

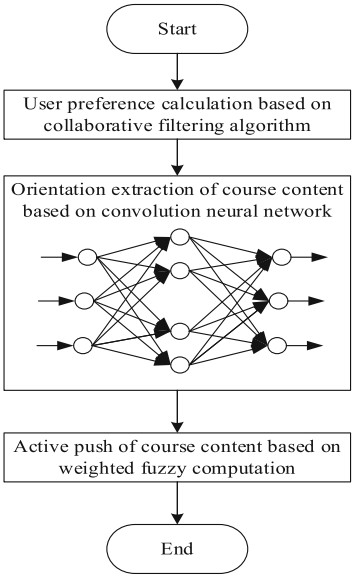

Fig. 2. Algorithm Flow

In order to ensure the authenticity of the test results and the objectivity of the data, the public art education majors in a key university in a certain area are selected as experimental sites to recommend online education courses. According to a university official, the school launched a comprehensive public art education program last year, and set up special subjects to give students special guidance on public art education 3–5 h a week. But public art is closely related to personal tastes and interests. The effect of ordinary education is not ideal. Students are not only weak in learning consciousness, but also poor in art identification. Therefore, after signing the relevant agreement with the person in charge of the college, it is decided to carry out the test of the application effect of the design method in the college. To test the application performance of the individualized content push algorithm of online art education courses designed in this paper.

Before carrying out the experiment, the public art education resources of the public art education course of the university in the past half a year shall be collected together with the online resources of the public art education course of the university obtained

through the network to form a data set, and the data sources are various, including the development data of the relevant majors and market- related industries, the public art education course resources of the university, the art performance resources, etc. Statistical data samples are divided into two categories: value resources and general resources. The statistical data are collected and sorted as the test data in the comparative experiment. As shown in Table 1 below.

Table 1. Comparative Experimental Sample Data

Data volume (piece)	Data Properties
200000	Total number of data
140000	Value resources
600000	General resources
175000	test data
25000	contrasting data

The university's public art education curriculum resource data set includes more than a dozen art projects, each with 30 to 50 courses, with art appreciation, drama appreciation, drama and dance as an example. Some online teaching resources are shown in Fig. 3 below.

Fig. 3. Example diagram of online instructional resources

After the statistics of the experimental test samples is completed, the method designed in this paper is used to recommend the contents of public art education courses for students participating in the experiment. In the process of recommendation, collaborative

filtering algorithm is introduced to extract users' history learning behavior and web browsing data, and user identity model is established to calculate user preference. On this basis, convolution neural networks are introduced to conduct directional extraction of university public art curriculum resources (existing resources). Through the weighted fuzzy calculation of the recommended resources, the active and accurate push service of public art resources is provided for users.

5.2 Push Performance Verification

Taking a college student user as an example, through the analysis of information such as history learning behavior and web browsing data, it is found that the user's main interest is oil painting, among which Richard Schmid is the most frequent keyword search. In this case, the push interface of this method is as follows:

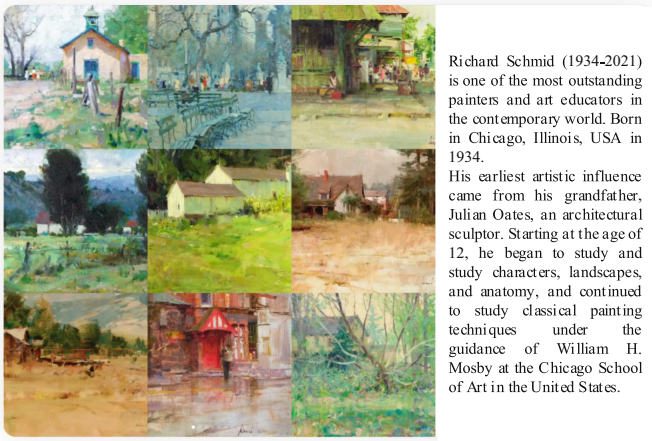

Fig. 4. Push interface

Figure 4 shows that this method can effectively push the personalized content of public art education online teaching. The content pushed is closely related to the user's interests, and more push content can meet user needs.

5.3 Verification of Fitness

In the process of pushing the individualized course content of public art education courses online in colleges and universities, the probability distribution density of the content resources of public art education courses that college students click on or actively retrieve is calculated as follows:

$$Q = \sum_{i>1}^{\infty} e(t) + \frac{1}{\sqrt{c}\exp\left[R(t)^2\right]} \tag{8}$$

In the formula (8): Q shall mean the probability distribution density of the recommended resources clicked or actively retrieved by the user; e shall mean the number of times searched by the user; t shall mean the valid range of probabilities; R shall mean the number of iterations; i shall mean the number of times of data mining. When the result is close to 1.0, the probability of students to click or retrieve the personalized course content resources is higher, and the adaptability of the proposed method is higher. Randomly select a college student user to participate in this experiment, according to the background record data, statistical experimental results, as shown in Fig. 5 below.

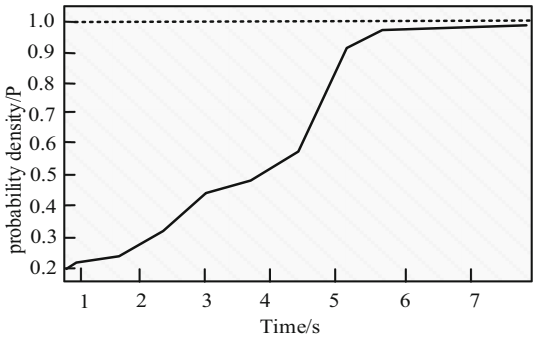

Fig. 5. Trend of probability distribution density for proactive retrieval of push resources

Based on the experimental results shown in Fig. 5 above, it can be seen that as the time of browsing the Web increases, the data of user behavior obtained by the terminal increases, and the probability distribution density of users clicking or actively retrieving the push resources of public art education personalized curriculum content increases. When the time of browsing the Web reaches 6 s, the probability distribution density of users clicking or actively retrieving the push resources tends to 1.0, that is, the fitness between the push resources of personalized curriculum content and the user demand resources tends to 100%. It can be proved that the algorithm designed in this paper is effective in practice, and can improve the adaptability between the public art education personalized course content and the user resources.

5.4 Difference Degree Contrast

On the basis of the above design contents, literature [3] method, literature [4] method and literature [5] method are introduced, and these methods are compared with the push algorithm designed in this paper. Using the method of this paper and the traditional method, we push the individualized course content of public art education to different users. The difference between push resource and user demand is used as evaluation index to calculate the evaluation index. The formula is as follows.

$$P = \frac{\sum_u |a_1 - a_2|}{n} \tag{9}$$

In formula (9): P represents the difference between push resources and user needs; a_1 represents push resources; a_2 represents user needs resources; n represents push times; and u represents average errors. According to the above formula, the smaller the value of P is, the smaller the difference between the public art education personalized curriculum content push resources and the user's demand is, the better the push effect is; the greater the value of P is, the greater the difference between the public art education personalized curriculum content push resources and the user's demand is, the worse the push effect is. The statistical results are shown in Fig. 6 below.

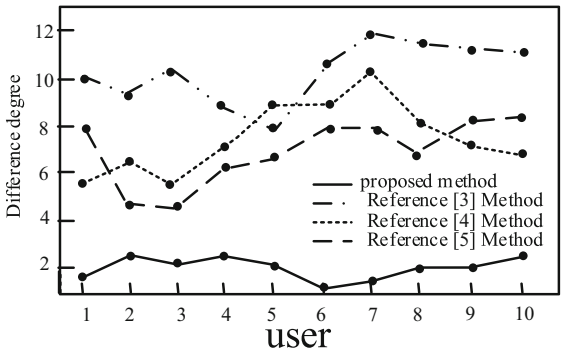

Fig. 6. Comparison of the difference between push resources and user requirements

Based on the experimental results shown in Fig. 6 above, it can be seen that the difference of the proposed method between the public art education personalized curriculum content push resources and users is small, with an average of 2.1. On the other hand, literature [3] method, literature [4] method and literature [5] method have significant differences in the average of 9.5, 7.8 and 6.1. It shows that the method can push the similar public art education personalized curriculum content, which makes the user experience of college students better, and is conducive to promoting the public art education curriculum.

5.5 Push Time Comparison

In order to further verify the application performance of the personalized course content push algorithm designed in this paper, five experiments were repeated to test the keywords of 10 different public art education courses by using the methods of document [3], document [4] and document [5] as the comparison methods. The results are shown in Table 2 below:

Table 2. Push Resource Time/ms

group	The method of this paper	Reference [3] Methods	Reference [4] Methods	Reference [5] Methods
1	146	501	387	586
2	251	533	339	688
3	188	496	376	641
4	267	467	540	689
5	207	528	486	643
mean value	211.8	505	425.6	649.4

From the Table 2, we can see that the speed of pushing the individualized curriculum content of public art education courses varies greatly among different methods. Under the application of this method, the pushing resource consumption is the shortest, averaging 211.8 ms, while the pushing resource consumption of document [3] method, document [4] method and document [5] method is high and fluctuating, averaging 505 ms, 425.6 ms and 649.4 ms respectively. The results show that this method can get the individualized course content of public art education with high response speed, and enhance the satisfaction of college students.

Compared with other methods, the proposed algorithm can reduce the difference between the push resource and the user's requirement, and ensure the higher adaptability between the push resource and the user's requirement.

6 Concluding Remarks

In this paper, we design an algorithm to push the individualized content of online art education courses in colleges and universities, and use convolution neural network to extract the content. After completing the design, the experiment proves that the method can reduce the difference between the personalized course content resources and the needs of college students, ensure the adaptability between the personalized course content resources and the needs of users, and reduce the overall push time. The purpose of this study is to provide some technical guidance for the rapid implementation of public art education in colleges and universities, and to enhance students' awareness of public art. In future research, multiple methods can also be considered for combination and integration to further improve the accuracy and effectiveness of personalized course content push algorithms. At the same time, attention should also be paid to issues such as privacy protection and data security to ensure that students' personal information is appropriately protected.

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