Method of Online Teaching Resource Recommendation Towards International Communication Based on.NET Platform

Qian Jiang[1](✉) and Lin He[2]

[1] International Cooperation Exchange Center, Chongqing Vocational College of Transportation, Chongqing 402260, China

[2] College of Information Engineering, Fuyang Normal University, Fuyang 236041, China

Abstract. According to the status quo of personalized recommendation of education and teaching resources, combined with the current main recommendation model, and according to the characteristics of education and teaching resources, a recommendation model of international exchange online teaching resources based on the .NET platform is constructed. First obtain user data, then use the frequency of user use of tags and the time factor of user use of tags to mine user interests and preferences, and then conduct unified management and classification of teaching resources, build teaching resource models, and finally implement user-based collaborative recommendation algorithms Teaching resource recommendation. The results show that compared with the recommendation model based on association rules and content, under the application of the established recommendation model, the MAE is lower, the accuracy and the recall rate are higher, which proves the recommendation quality of the model.

Keywords: NET platform · Teaching resources · Collaborative recommendation · Internet+ · Education

1 Introduction

Nowadays, when network technology and information technology are highly developed and popularized, online teaching of international exchanges has become an important way to cultivate talents and promote the development of scientific research and education [1]. However, to make the network and information technology really serve the teaching and realize the optimization of the teaching process and teaching resources, it must be supported by rich teaching resources. Therefore, the prerequisite for our development of distance teaching is to build a complete and substantial network teaching resource system [2]. Most of the current international exchange online teaching resource database systems only provide the functions of uploading, querying and downloading teaching resources. They still stay at the level of 'material-oriented' and fail to reflect the 'people-oriented' idea, a particularly prominent problem It is that most of the current teaching

W. Fu et al. (Eds.): eLEOT 2021, LNICST 389, pp. 110–121, 2021.
https://doi.org/10.1007/978-3-030-84383-0_10

resource database systems do not have the characteristics of individualization and intelligence, which has led to the contradiction between the massive teaching resources and the individual needs of users, which has become a microcosm of 'the lack of knowledge in the information explosion era' [3]. The long-term existence of this contradiction not only greatly reduces the effective utilization of teaching resources, but also creates huge difficulties for users to find and use required teaching resources, and directly hinders the role of international exchange online teaching resources in teaching. In this era, the personalized recommendation system came into being. It is currently one of the most effective tools to solve the problem of 'information overload'. It uses existing users by establishing a binary relationship between users and information products. Behavioral information and some similarity relationships to mine each user's potentially interested objects, and then make personalized recommendations for them, is essentially a process of information filtering. Personalized recommendation technology and recommendation system provide the possibility to fundamentally solve the contradiction between massive resources and the personalized needs of users. To this end, based on the NET platform, research, design and implement a feasible international exchange online teaching resource recommendation model to improve the personalization and intelligence of the teaching resource library system, and to a certain extent solve the user's difficulty in finding the required teaching resources. The problem of low utilization.

2 Recommendation Model of Online Teaching Resources for International Exchanges

The rapid development of the Internet and computer software and hardware technology has brought huge development space to the education field. The rapid rise of remote online teaching breaks the limitations of traditional learning methods in terms of time, space, and environment, and sharing learning resources has become a powerful supplement to traditional teaching methods [4]. Therefore, an online teaching platform for international exchange based on NET was designed. NET is Microsoft's new generation technology platform, that is, the Microsoft ML Web services platform. It can be used to agilely build standards-based, interconnected, stable and high-performance interconnected application systems that adapt to changes. XML. Web services allow applications to communicate and share data via the Internet, regardless of the operating system, device, or programming language used. The Microsoft .NET platform provides what is needed to create WML Web services and integrate these services together. From a technical point of view, a .NET application is an application running on the .NET Framework. (To be more precise, a .NET application is an application written using the .NET Framework class library and running on the Common Language Runtime).

The design and application of the NET-based international exchange online teaching platform can easily add and modify courseware subjects and content, thus avoiding repeated development, not only saving manpower and material resources, but also bringing greater convenience to the production and upgrading of online courseware. However, there is also a big problem, that is, the lack of some personalized and intelligent functional design, which brings many problems and inconveniences to the management and use of teaching resources. Because learners have individual differences in learning starting points, styles, expectations, etc., the contradiction between massive teaching resources and the individual needs of users has prevailed. The long-term existence of this contradiction not only greatly reduces the effective utilization of teaching resources, but also brings great difficulties for users to find and use the required teaching resources.

2.1 User Data Collection

User models are generally completed in two stages: user data collection and model characterization. The user data frequently used can be roughly divided into two categories:

Explicit Data
Explicit data refers to the fact that users directly give out their preference information for the project according to the guidance of the system. Such data can be directly stored in the database as the basis for the next user modeling. The advantage of explicit data input is that it can simplify the data preprocessing process, and the data obtained is highly reliable and usable, which can improve the operating efficiency of the system; but obtaining explicit data requires user intervention, and the degree of automation of the system is not high. In addition, the data is obviously subjective and lacks judgment standards, so the data has accuracy and authenticity problems. At present, the commonly used explicit data includes that the system requires the user to actively fill in the pre-set questions to submit the part of interest to the system, but the system cannot track and understand the changes in user interest [5]. In addition, the user's rating data for items is often used as explicit data input in the modeling of collaborative filtering systems. Because explicit data input can quickly obtain user preference information for items, most recommendation systems use explicit data as System input.

Implicit Data
Modeling users' interests is also a learning process, and constantly clarifying the needs of users. The user's demand information will be reflected in the browsing behavior when interacting with the system. The implicit data is to use information technology to find the user's various activity clues in an indirect way, and transform it into the user's interest and preference data. For example, the combination of pages that users frequently visit, the user's click stream, favorite records, browsing time, and the number of times the scroll bar is pulled up and down. The research conclusions of behavioral science prove that this kind of data often reflects the current interests of users, and plays a very critical guiding role in online recommendation. In the traditional e-commerce recommendation system, the user's historical transaction data is also used as implicit data. It is believed that every customer who has purchased a product represents the user's interest in the product, which is an estimate of historical preference. The advantage of implicit data is that the data is automatically obtained, and the user does not need additional work when accessing the system, but the process of data preprocessing is more complicated, and the data is noisy.

The collection of user data is the process of obtaining relevant information that can reflect user characteristics, preferences and needs. According to different data sources, it can be roughly divided into explicit collection methods and implicit collection methods. The display collection is mainly through the questioning requirements presented manually, and directly obtains the user's rating, options, and clear statement evaluation information. This method collects Data has obvious pertinence and is relatively easy in reality. It has been widely used in collaborative filtering recommendation technology. However, a single display collection method has problems with the authenticity of the data, and even negative data may be generated due to subjective factors and privacy reasons.

The invisible collection method mainly refers to the process of collecting Log signs and various Web resources from the system's Web server. The data acquisition process actually uses Web mining methods, among which Web content mining and Web usage mining are the main methods for data preprocessing. Web content mining involves characterizing Web pages and extracting knowledge from page content; Web application mining can discover user access patterns and provide a reliable basis for the next step of mining users' potential interests. The main techniques included are path analysis., Association rules, sequence patterns and clustering techniques. Since the invisible collection method can obtain the user's current interest preferences and reflect the timeliness of information needs, some Web recommendation systems use the log log of the user's access to the server to analyze and predict the user's pages of interest to form recommendations, such as Recommendation systems for large websites such as LOGSUM, SUGGEST 3.0 and WebPersonalizer [6].

2.2 User Interest Model

User interest is the core step of personalized recommendation. To recommend personalized resources that meet their interests and needs for people with different backgrounds, different needs, and different preferences, we must first accurately perceive and express user interests. User interest modeling is the process of mining and acquiring knowledge related to user interests, needs and usage habits, and generating a user interest model that can express the user's specific background knowledge and hobbies is the final result of user interest modeling. A good user interest model should not only be able to obtain, express, and store user interest preferences, but also understand user characteristics and user categories, capture users' long- and short-term interests, and understand the different needs of users in different periods [7]. From this point of view, user interest modeling should include two aspects: user interest mining and user interest expression. In the social tagging system, the tags used by users when tagging resources express users' interests. For example, the higher the frequency of tag usage, the more users like the resources related to the tag; the usage time of the tag also reflects the user's interest. Long-term and short-term interests, the tags recently used by users can reflect the user's recent interests; considering that in reality, user interests change dynamically over time, the user's interest is mined by combining the frequency and time factors of the user's use of tags. In terms of user interest model representation, according to the results of the tag network clustering, the final user interest model is represented by the user's preference vector for tag clusters.

The user's interest preference is mined by comprehensively considering the frequency of the user's use of tags and the time factor of the user's use of the tags, that is, the user's interest preferences are mined through the combination of frequency-weighted label preferences and time-weighted label preferences, and after calculating the user's interest preferences for tags, Then according to the tag clusters generated by the tag clustering, calculate the user's interest preference for each tag cluster, and finally express the user interest model in the form of an n-dimensional vector. Each component of the vector is the user's interest preference for each tag cluster [8]. As shown in Fig. 1:

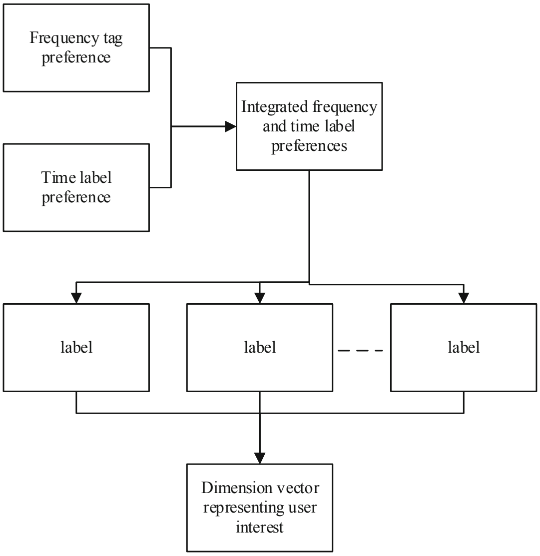

Fig. 1. User interest model

The vector space model was originally proposed by Gerard Msalton and others in the 1970s and was successfully used in the field of information retrieval. The basic idea of the space vector model is to express resources or search content in the form of feature vectors, thereby converting the processing of text data into matrix vector operations in the vector space, and using the similarity of vectors to reflect the similarity between resources. Usually the TFIDF value represents the feature weight, and the cosine function is used to measure the similarity between vectors.

2.3 Construction of Teaching Resource Model

Teaching resources refer to all resources used by users for teaching in the intelligent teaching system and E-learning environment, including information, personnel, materials, equipment, and technology. Learning resources can be divided into hardware resources and software resources according to their different forms of performance. Hardware resources mainly refer to equipment resources used for teaching design; software resources refer to multimedia resources for online teaching design, such as textbooks and videos., Audio teaching materials, etc. With the development of education informatization, the emerging online learning communities, education blogs, and online teaching platforms for learning resources have shared and reused learning resources online, breaking the traditional teaching. Therefore, the unified management and classification of teaching resources and the semantic relationship between teaching resources, subject knowledge and knowledge points are the main work of this chapter [9].

In view of the characteristics of teaching development at this stage, before personalized teaching resource recommendation, the resources must be classified first, which can improve the accuracy of teaching resource recommendation and better provide users with personalized learning services. In the mobile autonomous school, the teaching resource classification strategy is divided into: subject classification, grade classification, content classification and knowledge point classification strategies. These classifications are in a progressive relationship.

Subject classification: At present, the application of subject classification in actual teaching has been very mature, and the subject classification of teaching resources is distinguished by coding.

Grade classification: According to the different levels of knowledge and level of learning in different grades, learning resources need to be classified according to the syllabus and grade information. Teachers have a strong ability to control educational resources. Teachers can classify resources based on teaching experience and user development requirements. In the self-developed mobile autonomous school platform, learning resources are mainly classified from the teaching stage.

Content type classification: Teaching resources are presented in a variety of forms. The teaching resources are classified according to different formats, and finally resources of text, video, audio, courseware, animation and other types are obtained.

Knowledge point classification: mainly analyze the content of teaching resources, extract the attribute characteristics of the content, and build the knowledge point ontology. Knowledge point classification is a further decomposition and refinement of learning resources, so that users can search for teaching resources more accurately.

By analyzing the construction of the teaching resource model, it mainly includes several modules such as learning resource classification, classification coding, classification coding binding, and resource use subject.

2.4 Teaching Resource Recommendation Algorithm

Personalized recommendation refers to those who can first analyze and identify user interest preferences based on the user's background information and historical behavior, and then match user interests with resource characteristics through certain recommendation models and algorithms, and then actively meet user needs and interests A system that recommends information resources to users to meet the individual needs of each person [10]. Such a system not only enables users to easily obtain high-quality information resources, but also greatly reduces the time and energy cost of users to obtain information [11]. Due to the academic value and practical value of personalized recommendation, personalized recommendation has become a research hotspot in the fields of information science, computer science, and data mining. Teaching resource recommendation generally includes six steps:

Step 1: Data collection, see chapter 1.1.

Step2: Learning data analysis: Use educational data mining technology to analyze user data, perform data preprocessing, data cleaning, data integration and data specification. In order to achieve accurate recommendations, it is necessary to filter missing data, noise data, and redundant data.

Step3: By analyzing the user's behavior data in the learning process, extracting the three characteristic attributes of the user's knowledge level, cognitive ability and learning preference to construct the user model; among them, in order to realize the accurate recommendation of personalized teaching resources, the focus is on the user For preference information, use ontology technology to establish semantic relationships between user preferences, and use OWL ontology description language to describe user preference models.

Step4: Construction of learning resource model: through online editing by users, online creation by teachers, and semantic representation of the media form of the resource and learning content, using ontology and knowledge structure diagrams to represent the structure of teaching resources, and using Ontology to build knowledge of resources, courses, and chapters The relationship between points.

Step5: Personalized teaching resource recommendation: After the user model and the learning resource model are successfully constructed, a recommendation algorithm is selected to recommend high-quality educational resources, courses, knowledge points and similar user partners for the target users.

Step6: Multi-format presentation: After the personalized teaching resources are formed, they will be adaptively presented to users in multiple formats, so that users can accurately match resources no matter they use smart terminals such as pc, ipda or iphone, which can perform high Effective learning.

Finally, after accurately matching the teaching resources, the user automatically updates the teaching method, and re-does the teaching diagnosis and evaluation. In this way, a Step 1-Step 2-Step 3-Step 4-Steps-Step 1…continuous cycle process is formed. The user generates data and again According to the analysis results, the teaching enthusiasm and learning efficiency can be improved, so that the data in the model can be updated iteratively.

Recommendation algorithm is the core module of the recommendation system, which directly affects the efficiency and quality of recommendation. Researchers have proposed various recommendation algorithms based on the characteristics of recommendation systems in different fields. Many of these methods combine research results in the field of data mining. The mainstream recommendation algorithms currently in use include: association rules, content-based recommendation algorithms, and collaborative filtering recommendation algorithms [12].

Among the three methods, the most widely studied and applied is the collaborative filtering algorithm, so the collaborative filtering algorithm is selected for resource recommendation. Recommendation based on collaborative filtering is the earliest recommendation method proposed. Different from content-based recommendation, the main point of collaborative filtering is to generate recommendations for new users through the understanding of existing users. In this process, some of the existing users Past behavior records will be of great help to recommendations, not just a study of new users' behavior and preferences. Its main idea lies in collaboration, which is more reflected in the role of the group. The recommendation based on collaborative filtering mainly uses the nearest neighbor technology to calculate the distance through some historical preferences of the user, and then uses the weighted evaluation value of the target user's nearest neighbor user to evaluate the teaching resource to add the target user's preference for the specific teaching resource It is expected to recommend teaching resources to target users. According to the different recommended principles, they are divided into two categories:

Based on User Recommendations
Finding neighbor users with the same preference of the target user, recommend the target user according to some preference information of the neighbor users.

Project-Based Recommendations
Mainly focus on the relationship between information, match and associate resources between resources for a single user, and push resources and projects with a high degree of correlation to users. Collect all users' evaluations of resources or projects, analyze based on users' overall preference characteristics, calculate the similarity between resources or projects, and recommend corresponding resources or projects with high similarity to current users.

The specific process of user-based recommendation: Based on the user's preference vector for the tag cluster, construct the user's tag cluster-interest matrix, replace the user's scoring matrix for the item with the tag cluster-preference matrix, and perform personalized recommendation through collaborative filtering [13]. Collaborative filtering recommendation includes three basic steps: the construction of the user's tag cluster-preference matrix, the search for similar neighbors, and the generation of personalized recommendation resources.

(1) Construction of user interest matrix.
User interest is the basis of personalized recommendation. Only by understanding the user's interest can we recommend resources that meet the user's interest. This article builds a user interest matrix based on the user's interest vector for tag clusters that integrates frequency and time factors, also called It is the user's tag cluster-interest degree relationship matrix [14].
(2) Neighboring user set construction.
The selection of neighbor users is the core step of the collaborative filtering recommendation algorithm based on users. The construction of the neighbor user set mainly includes two steps: the calculation of user similarity and the selection of neighbor users.
Calculation of user similarity. User similarity calculation refers to calculating the similarity degree of user interest through a certain similarity calculation method according to the user's tag cluster and interest degree relationship. Commonly used user similarity calculation methods mainly include cosine similarity, Pearson similarity and Jaccard coefficient method [15].
Selection of neighbor users. The selection of neighbor users refers to selecting a set of users with the same or similar interests as the target user based on the calculation result of the similarity between users in the previous step. There are two main methods currently selected: Threshold setting method and K nearest

neighbor method (KNN). This paper uses the K nearest neighbor method to select neighbor users. This method sorts the similarity between the target user U0 and all other users Sim (U0, U1) in order from high to low, and selects the top K users. That is, the K users with the highest similarity to the target user U0 are regarded as the set of neighbor users. The value of K will affect the effect of the recommendation. Therefore, the selection of the K value generally has to go through many trials. Neighbor users who are not very similar will bring 'noise' to the prediction and affect the accuracy of the system recommendation. When K is too small, the number of prediction items will be too small, which will affect the recall rate of the recommendation system.

(3) Generation of personalized recommendations.
The result of tag clustering is to group tags with similar semantics into a cluster. These different clusters represent different themes. Therefore, using tag clusters as an intermediary can more clearly reflect the interests of users and the themes of resources. The resources collected by the neighbor users of the target user are used as the basic resource collection, and the user's interest in these resources is calculated using the tag cluster as an intermediary according to the user's interest in the tag cluster and the correlation between the resource and the tag cluster. Among them, the user's tag cluster-interest degree relationship matrix has indicated the user's interest in the tag cluster; and the correlation between the resource and the tag cluster can be calculated based on the tag set used by all users to label the same resource; finally, the tag cluster is Intermediary, which calculates the degree of interest of specific users in specific resources. The user's interest in resources is predicted based on the resources collected and marked by neighbor users and the correlation between resources and tag clusters.

The correlation between the resource and the tag cluster is equal to the ratio of the frequency of all users using tags in the tag cluster to annotate the resource to the frequency of users using tags in all tag clusters to annotate the resource, as shown in formula (1):

$$R_{jk} = \frac{\sum_{T_l \in C_k} \mathrm{Count}\left(RT_{jl}\right)}{\sum_{T_l \in T} \mathrm{Count}\left(RT_{jl}\right)} \tag{1}$$

Indicates the degree of relevance between the resource R_j and the tag cluster C_k, C_k represents the tag set in the k tag cluster, $C_k\left(RT_{jl}\right)$ indicates the number of times that all users use the tag T_l to mark the resource R_j, and T indicates the tag set used when the resource R_j is marked by all users.

The user's interest in resources is equal to the sum of the user's interest in each cluster multiplied by the relevance of the resource to the corresponding cluster. As shown in formula (2), n represents the number of label clusters after clustering.

$$I_{ij} = \sum_{k=1}^{n} U_{ik} \times R_{jk} \tag{2}$$

In formula (2), U_{ik} represents the user U_i's interest in the tag cluster C_k.

Finally, the user's interest in the resources in the basic resource set is sorted from largest to smallest, and the top N resources are recommended to the user, namely TOP-N.

3 Simulation Experiment Analysis

Randomly select 100 users as target users, analyze the average recommendation effect for these 100 users, and number the selected 100 target users from 1 to 10. The data in the selected data set is divided into five parts, and the five-fold cross-validation method is adopted for the experiment. 20% of each is used as the test set, and the remaining 80% is used as the experimental data to implement the recommended algorithm. In order to reflect the superiority of the recommended model studied, the recommendation model based on association rules and content is used as a comparison method. The experiment process is divided into three parts: database establishment, preference model establishment, learning model establishment, and algorithm evaluation.

3.1 Experimental Environment

The experimental operating system is Windows Microsoft SQL Server 2010, Windows10, CPU frequency is 2.79GHz, 8G memory, the development environment is Eclipse, and the programming language is JAVA.

3.2 Evaluation Criteria

Aiming at the recommendation performance of learning resources, the average absolute deviation MAE (Mean Absolute Error), which is commonly used in statistical accuracy measurement methods, is used as the metric to evaluate the recommendation quality of the recommendation system to intuitively measure the recommendation quality. The calculation formula is defined as:

$$MEA = \frac{\sum_{j=1}^{N} \left|P_{ij} - R_{ij}\right|}{N} \tag{3}$$

Among them, N is the number of resources that the target user has learned in the recommendation result set, R_{ij} is the user's actual score for teaching, and P_{ij} is the recommendation degree between the resource and the user predicted by the recommendation algorithm.

In addition, in order to better compare and evaluate the accuracy and accuracy of the recommended results, recall and precision are used as evaluation indicators for comparative analysis. Since the data set has been divided into the training set and the test set for comparison during system testing, the intersection of the calculated recommendation result and the training set can be used as the data result for calculation. This calculation method can also be used for accuracy. Formulas such as (4), (5):

$$\text{Precision} = \frac{1}{M} \sum_{n} \frac{|R_u \cap T_u|}{R_u} \tag{4}$$

$$\text{Recall} = \frac{1}{M}\sum_{n}\frac{|R_u \cap T_u|}{|T_u|} \tag{5}$$

In formula (4) and formula (5), M is the number of users in the test case, R_u is the recommended list of teaching resources, and T_u is the set of teaching resources actually selected by the user in the recommended list.

3.3 Result Analysis

Table 1. Recommended quality comparison table

Method	Mean absolute deviation	Accuracy rate/%	Recall rate/%
Research method	0.85	96.55	93.50
Recommendation model based on association rules	1.26	88.36	81.23
Content-based recommendation model	1.54	90.54	82.58

It can be seen from Table 1 that the researched NET platform-based international exchange online teaching resource recommendation model shows a better recommendation effect. The average absolute error of the prediction score MAE is significantly lower than the other two comparison recommendations, while the precision and recall rates are Relatively high, proving the effectiveness of the research.

4 Conclusion

With the rapid development of information technology and data science, as well as the 'Internet +' innovative concept, the pace of development of education informatization has been accelerated. The development of education informatization has accumulated a large amount of teaching resources, and users cannot accurately find information that suits them when facing these resources. Therefore, personalized learning in the online learning environment has become an important issue of current research. The research on personalized teaching resource recommendation model has solved the problem of inaccurate resource recommendation to a large extent, and achieved good results, but there are still many shortcomings:

In the process of constructing the user preference model, the method of obtaining content preference and media preference information is further studied, and experimental verification is performed.

The application of personalized teaching resource recommendation model is further explored.

Fund Projects. Jiangsu Province Tong Brand Professional Construction Project (Z215015002).

References

1. Liu, S., Sun, G., Fu, W. (eds.): eLEOT 2020. LNICSSITE, vol. 339. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-63952-5
2. Zhu, T.: Empirical research on the application of online teaching in chinese colleges and universities under the situation of novel coronavirus pneumonia prevention and control. Int. J. Emerg. Technol. Learn. (iJET) **15**(11), 119 (2020)
3. Liu, S., Li, Z., Zhang, Y., et al.: Introduction of key problems in long-distance learning and training. Mobile Netw. Appl. **24**(1), 1–4 (2019)
4. Harlow, S.: Online teaching and learning: a practical guide for librarians. Tech. Serv. Q. **35**(4), 412–413 (2018)
5. Gupta, M., Kumar, P.: Recommendation generation using personalized weight of meta-paths in heterogeneous information networks. European J. Oper. Res. **284**(2), 660–674 (2020)
6. Shi, C., Liu, J., Zhang, Y., et al.: MFPR: a personalized ranking recommendation with multiple feedback. ACM Trans. Soc. Comput. **1**(2), 1–22 (2018)
7. Le, D.D., Lauw, H.W.: Stochastically robust personalized ranking for lsh recommendation retrieval. Proc. AAAI Conf. Artif. Intell. **34**(4), 4594–4601 (2020)
8. Liu, T., Liao, J., Wang, Y., et al.: Collaborative tensor–topic factorization model for personalized activity recommendation. Multimedia Tools Appl. **78**(12), 16923–16943 (2019)
9. Xiao, H., Lukas, F., Karsten, B.: Kernelized rank learning for personalized drug recommendation. Bioinformatics **34**(16), 2808–2816 (2018)
10. Li, H.J., Yang, L., Zhang, P.W.: Method of online learning resource recommendation based on multi-objective optimization strategy. Pattern Recognit. Artif. Intell. **32**(04), 306–316 (2019)
11. Balasubramanian, C., Sekar, J.R., Devi, M.S.: A personalized user recommendation based on attributes clustering and score matrix. Int. J. Pure Appl. Math. **119**(12), 13751–13756 (2018)
12. Wang, C.Y., Wang, Y.C., Chou, S.C.T.: A context and emotion aware system for personalized music recommendation. J. Internet Technol. **19**(3), 765–779 (2018)
13. Aliannejadi, M., Crestani, F.: Personalized context-aware point of interest recommendation. ACM Trans. Info. Syst. **36**(4), 1–28 (2018)
14. Bingzhuan, P.: Intercultural communicative competence teaching and assessment based on modern information technology. Int. J. Emerg. Technol. Learn. (iJET) **16**(7), 175 (2021)
15. Zhao, Y., Luo, Y.: Autonomous learning mode based on a four-element teaching design for visual communication course. Int. J. Emerg. Technol. Learn. (iJET) **15**(19), 66 (2020)