Research Article
Discrete Dynamic Modeling Analysis Based on English Learning Motivation

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With the popularization of the Internet, various online learning platforms have developed rapidly, providing users with abundant learning resources, and realizing personalized resource recommendation has become the development trend of online learning platforms. In this paper, a personalized learning recommendation model based on improved collaborative filtering is proposed. Firstly, a multilayer interest model of learners is established to accurately describe learners’ interest in knowledge topics, courses, and knowledge areas; then, in view of the sparse scoring matrix and cold-start problems of traditional collaborative filtering recommendation algorithms, an improved collaborative filtering-based personality is proposed. The personalized learning recommendation model is used to improve the similarity calculation of users by introducing user initialization tags and solve the cold-start problem of new users. Finally, the effectiveness of the algorithm is proved by experimental comparison, and the improved algorithm improves the recommendation effect of personalized learning.

1. Introduction

In recent years, consumers’ interest in mass-produced undifferentiated commodities has gradually decreased, and they have pursued personalized and customized products that can reflect their own interests and preferences. However, full customization will consume a lot of time, manpower, material resources, etc., and the cost is high [1–4]. How to effectively solve the contradiction between the high cost of complete customization and the pursuit of personalized and differentiated products by consumers has become a difficult problem for many companies, especially manufacturing companies [5, 6]. In this context, mass customization emerges as the times require [7]. The basic idea of mass customization is to better meet the needs of consumers by providing users with ever-increasing product categories and personalized products, and to meet their personalized characteristics, while retaining the efficiency and cost of the original mass production [8–11]. Whether in business or academia, the research on mass customization is increasing, but most of them focus on the definition, characteristics, customization mode, acquisition of customer needs, supply chain management, and marketing of mass customization. How to help users quickly and efficiently find their own product solutions from massive data. There are not many research studies on recommendation algorithms. At present, people have entered the era of big data. One of the important features of the era of big data is the huge amount of data, and information overload has become an objective phenomenon that has to be faced. For customers who want to customize products to meet their own interests and preferences and face for a large amount of product configuration information, how to quickly form one’s own personalized customization plan has become a top priority, and the emergence of the recommendation system has effectively solved this problem [12–14].

With the continuous increase of online education applications, online education platforms have become an important platform and space for multiple learners to jointly create, share, and acquire knowledge. There are many different learners involved in an online education platform, each with different interests and hobbies, and it is dynamic. In order to label and manage learners’ interests, online education platforms usually provide learners with a way to
customize their interests by labeling topics. However, it is difficult for learners to describe their interests in detail, and the interest labels are not necessarily updated with the change of interests. In addition, there are many learners who do not actively mark their interests. Therefore, how to automatically discover the learning interests of learners in an open learning environment is a problem worthy of research.

The user-based collaborative filtering algorithm is user-centric, which is more suitable for the field of personalized learning recommendation [15, 16]. In the face of massive learning resources, how to implement personalized resource recommendation according to users’ learning interests, habits, and abilities is the development trend of online learning platforms. Personalized recommendation is widely used in the field of e-commerce, and scholars at home and abroad have carried out relevant researches on the recommendation of personalized online learning resources [17]. Chen Jiemin summarized the current personalized recommendation algorithms for learning resources and concluded that there are mainly content-based filtering, association-rule-based, collaborative filtering, and hybrid-based models. Liang Tingting established a learning resource filtering model through content vector space filtering; multidimensional correlation analysis is carried out on learners, resources, situations, etc., to achieve personality matching between resources and learners; Shen Miao designs a collaborative filtering algorithm based on student attribute classification to realize the intelligence and personality of the student course selection system [18]. Resource recommendation: Lei W first obtains association rules through data mining to establish preference matrix and then mixes it with collaborative filtering algorithm for personalized recommendation [19].

In this paper, a personalized learning recommendation model based on collaborative filtering algorithm is proposed. Through knowledge modeling of learning users and learning resources, collaborative filtering algorithm is used to introduce users’ learning behavior logs [20–23]. Sharing, collection, browsing, downloading: Potential features such as educational background and interests can alleviate the user’s cold-start problem. The improved collaborative filtering algorithm can achieve more accurate personalized network learning resource recommendation and effectively alleviate the data sparseness and cold-start problems existing in traditional recommendation technology [24, 25].

2. Multidimensional Learner Model Construction

The learner is the main body of online learning and has static and dynamic personalized characteristics. The learner model is used to describe the characteristics of the learner. The construction of this model is the core of improving the recommendation performance of online learning resources, optimizing the recommendation accuracy, and realizing personalized recommendation. When constructing a learner model, the first choice is to determine the individual characteristics of the learner. Based on the CELTS-11 learner information model specification, this paper divides the learner characteristics into static characteristics and dynamic characteristics under the guidance of learning style theory and educational goal classification theory. There are two parts, in which the static features include the learner’s basic information, learning style, and static interest preferences, and the dynamic features include cognitive level and dynamic interest preferences. Static features are the initial features of learners, which cannot change with the deepening of learning during the entire learning process and cannot represent the degree of individualized features of learners, but as basic features can solve the cold-start problem of initial users in the recommendation process. Dynamic features refer to the gradual emergence of some implicit features of learners with the occurrence of learning behavior, such as learning cognitive status and learning evaluation of certain resources, which will change over time. Therefore, dynamic features are to build a learner model. The static and dynamic data of learners are collected through the acquisition layer, and the information is classified in the data layer. The data analysis layer will further data mine the classified information, which is the learning style, cognitive level, and static and dynamic of the presentation layer. Interest preference features provide a data basis. The learner model building process is shown in Figure 1.

2.1. Data Collection. The learner’s initial static data and dynamic behavior data are the data basis for constructing the learner model. The basic information, learning style, static interests and preferences, and other characteristic information of the learner model can be obtained through the questionnaires and scales filled in by the learners during registration and obtain the learner’s cognitive level and dynamic interest preference characteristics. The acquisition and collection of basic data are realized through the data collection layer, which lays the foundation for the next step of classification, analysis, mining, and feature representation.

2.2. Feature Representations for Learning Styles. The concept of learning style was first proposed by Salem in 1954. It is a concept that reflects the needs of learners’ physical and psychological needs. The study of learning style provides a basis for the individual requirements of the learner model. Based on the Felder–Silverman-style model and using the Solomon Learning Style Questionnaire (ILSQ) as a means, the learners’ learning style is quantified from four dimensions of perception, input, processing, and understanding. Each learner has to fill in the learning style questionnaire, send the obtained ILSQ scale results to the data layer and analysis layer, and construct learning style features in the presentation layer.

The specific process of learning style feature quantization is as follows:

(1) The learning style quantization result is represented in the form of a quadruple \(<L_i, V_i> (i = 1, 2, 3, 4)\), \(L_i\) represents the four dimensions of ILSQ, and \(V_i\) represents the four dimensions of ILSQ.
represents the learning style in the $L_i$ dimension $A$ quantified value of propensity.

(2) When the learner fills in the ILSQ scale, there are 44 questions in total, each question contains two options A and B, and the value of the answer result is defined as $P_j$, where $j$ represents the question number.

(3) Screening and processing according to the results of $P_j$, classification, and accumulation, and the final accumulation results are represented by $a$ and $b$.

(4) Judging the size of $a$ and $b$ values, if $a > b$, then $V_i = (a − b)a$; if $a < b$, then $V_i = (b − a)a$.

(5) The test result of the learning style feature quadruple $L_i$ is the quantification result of the learner's learning style feature.

2.3. Feature Representation of Interest Preference. The learner's interest preference features are divided into static interest preference features and dynamic interest preference features. Part of the learning resources in the dataset is manually marked, and the remaining resources are automatically marked by similarity calculation, nearest neighbor sorting, etc., and finally checked through the manual query-related feedback mechanism to ensure the accuracy of the feature representation of learning resources. Using the normalized label set composed of learning resource features as an option, construct a static interest and preference questionnaire. In the data collection layer, each learner must fill in the static interest and preference questionnaire, and the obtained results are sent to the data layer and the analysis layer, and are constructed in the presentation layer. Static interest preference features.

The learning process of a learner is a dynamic changing process. Various operations in the learning process will generate corresponding behavior information, which reflects the current learner's interest preference. In this paper, the interest preference generated over time is called dynamic interest. Preference, the specific quantification process is as follows.

2.3.1. Learner Behavior Classification and Weight Calculation. Learner behaviors are mainly divided into five categories, namely, browsing behavior, collection behavior, sharing behavior, downloading behavior, and evaluation behavior. Different behaviors represent different implicit preferences of learners. Here, weights are introduced to represent different learning behaviors. There are many ways to determine weights. Expert evaluation or empirical weights are subject to a certain degree of subjectivity. In this paper, the entropy weight method is used to determine the weight learner's behavior classification, weight distribution, and the final weight value used in this paper, as shown in Table 1, where $w_i$ indicates the weight distribution occupied by the $i$th behavior.

2.3.2. Learner-Learning Resource Scoring Matrix Construction. According to the learning behavior and its weight distribution, the learner-learning resource scoring matrix $P_{mn}$ is constructed. This matrix can be used as the basis for learners' evaluation of learning resources. $P_{mn}$ is
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Table 1: Learner behavior classification and weight distribution.

<table>
<thead>
<tr>
<th>Behavior classification</th>
<th>Weight distribution</th>
<th>Numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Browsing behavior</td>
<td>( u_i )</td>
<td>0.176</td>
</tr>
<tr>
<td>Collection behavior</td>
<td>( u_i )</td>
<td>0.193</td>
</tr>
<tr>
<td>Sharing behavior</td>
<td>( u_i )</td>
<td>0.195</td>
</tr>
<tr>
<td>Download behavior</td>
<td>( u_i )</td>
<td>0.212</td>
</tr>
<tr>
<td>Evaluate behavior</td>
<td>( u_i )</td>
<td>0.224</td>
</tr>
</tbody>
</table>

Each value in the \( P_{mxn} \) matrix represents the behavioral weight of the learner \( u_i \) to the resource \( j \). If \( s_{ui} = 0 \), it means that the learner \( u_j \) does not have any action on \( t_k \). If the matrix elements are all 0, it means that the learner \( u_j \) did not start learning.

2.3.3. Learning Resources-Learning Label Matrix Construction. In order to establish a direct relationship between learners and learning resources, we first construct a learning resource label matrix to represent the characteristics of learning resources:

\[
P_{mxn} = \begin{bmatrix} S_{11} & S_{12} & \ldots & S_{1n} \\ S_{21} & S_{22} & \ldots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{m1} & S_{m2} & \ldots & S_{mn} \end{bmatrix}
\]  

(1)

The element \( r_{jk} \) in the \( Q_{mex} \) matrix indicates whether the resource \( r_{ij} \) has the label \( t_{jk} \). If \( r_{jk} = 1 \), it indicates that the label \( t_{jk} \) labels the resource \( r_{ij} \), and \( r_{jk} = 0 \) indicates that it is not labeled, so the matrix \( Q_{mex} \) is a matrix composed of 0 and 1.

The learner-label matrix \( T_{mxl} \) is constructed according to the learner-learning resource scoring matrix \( P_{mxn} \) and the learner-learning resource label matrix \( Q_{mex} \):

\[
T_{mxl} = \begin{bmatrix} g_{11} & g_{12} & \ldots & g_{1l} \\ g_{21} & g_{22} & \ldots & g_{2l} \\ \vdots & \vdots & \ddots & \vdots \\ g_{ml} & g_{m2} & \ldots & g_{ml} \end{bmatrix}
\]  

(3)

In the formula, \( g_{jk} = \sum_{c=1}^{n} s_{jk} r_{ck} T_{mxl} \), the element \( g_{jk} \) in the \( T_{mxl} \) matrix represents the behavioral weight of the learner \( u_j \) accumulated on the learning resource label \( t_k \) and \( T_{mxl} \) is used to represent the dynamic interest preference matrix after the learner produces behavior.

2.3.4. Representation of Learner’s Dynamic Interest Preference Behavior Feature. The accumulation of different behaviors of learners on learning resources can be represented by the dynamic interest preference matrix \( T_{mxl} \). The degree of preference of learners to resources reflects the difference between learners, which is the characteristic attribute of learner’s behavior that is an increasing function, and its calculation formula is

\[
F^{op}_{utk} = \exp \left( \frac{g_{utk} - \lambda}{v_{utk}} \right), 1 \leq k \leq l.
\]  

(4)

In the formula, \( g_{utk} \) \((1 \leq k \leq l)\) is the cumulative value of the learner’s interest preference on the learning resource and is the sum of the continuous accumulation of the learner’s behavior on the tag \( t_k \) of the associated resource; \( v \) is the learner’s average interest preference value; \( \lambda \) is the minimum value of the cumulative sum of learner behavior, which is used to eliminate the bias of interest and preference among different learners.

2.3.5. Time Factor Adjusts the Offset of Dynamic Interest Preference Features. The learner’s interest and preference characteristics will shift with the deepening of learning. The adjustment of dynamic interest and preference characteristics includes the characteristic representation of various behaviors and time factors. The characteristics of the time parameter are calculated using the time decay function. The calculation formula of the learner’s dynamic interest preference characteristic time factor is as follows:

\[
F_{utk}^{\text{time}} = \theta + (1 - \theta) \exp \left[ - (t_{now} - t_{utk}) \right].
\]  

(5)

In the formula, \( 1 \leq k \leq l \), \( t_{now} \) is the current time; \( t_{utk} \) represents the learner, \( u_j \) is labeled, and the latest value in the time set is marked by \( t_k \); the hyperparameter \( \theta \in [0, 1] \) can affect the time factor to dynamic interest features, and the two show a negative correlation.

The behavioral feature and time weight feature are integrated to obtain the learner’s dynamic interest preference feature, that is,

\[
F_{utk} = F_{utk}^{op} F_{utk}^{\text{time}}, \quad 1 \leq k \leq l.
\]  

(6)

2.4. Feature Representation of Cognitive Level. The characteristics of the learner’s cognitive level describe the results of the test after the learner has learned a certain knowledge point.

Based on “Bloom’s Educational Objective Classification Theory,” the learning objectives of the learning resources corresponding to knowledge points are divided into 6 levels, as shown in Figure 2, these 6 levels represent the mastery of different learners’ core knowledge points, the cognitive level. The chapter knowledge test data of the collection layer represent performance information. By analyzing the chapter knowledge points and test questions, the characteristics of the knowledge level can be obtained. Since this indicator is divided into 6 levels, different learners will have different overall cognitive levels, and the same learner will have different level statuses for different knowledge points in different periods, so the cognitive level reflects the individual characteristics of the learner. The characteristics of learners’ cognitive level are expressed as follows:
In the formula, \( k_i \) represents the \( i \) th knowledge point; \( l_i \) represents the mastery of the \( i \) th knowledge point, that is, the cognitive level; and \( n \) is the number of knowledge points that have been learned.

3. Improved User Collaborative Filtering Recommendation Algorithm

The user-based collaborative filtering algorithm establishes a user similarity model according to the user’s historical interest in resources and recommends resources with high predicted scores to users through the predicted scores of users with similar interests; item-based CF establishes resources based on users’ historical evaluation of resources. The similarity model calculates the similarity between resources and then recommends resources similar to the user’s historical preference to the user. In this paper, aiming at the matrix sparsity and cold-start problems of collaborative filtering recommendation algorithm, the learning behavior log and user initialization label are introduced to improve the algorithm. According to the user’s ability, major, interest, and education tags, the user initialization tag is generated; the user similarity is calculated according to the user resource matrix and the user initialization tag; finally, the recommendation result is generated.

The specific algorithm model architecture is shown in Figure 3.

3.1. User Resource Evaluation Matrix. The user’s historical evaluation of resources is converted into a component value matrix to form an \( M \times N \) matrix, as shown in Figure 4.

\[ U_k = [(k_1, l_1), (k_2, l_2), \ldots, (k_n, l_n)], \]

In the formula, \( k_i \) represents the \( i \) th knowledge point; \( l_i \) represents the mastery of the \( i \) th knowledge point, that is, the cognitive level; and \( n \) is the number of knowledge points that have been learned.

3.2. User Resource Behavior Matrix. The user’s operation of network resources is not only the direct acquisition and evaluation, but also learning behaviors such as sharing, collection, browsing, and downloading in the middle. Therefore, by collecting users’ learning behavior logs, analyzing their learning behavior trajectories, and establishing the relationship between behavior trajectories and resource evaluations, mining the similarity of users can improve collaboration to a certain extent. Convert the user’s relevant learning behavior to the resource into the corresponding interest score. The score is obtained through the questionnaire. The questionnaire gives 15 learning behaviors. The resource is just clicked and browsed, indicating that the user may not have a high evaluation of the resource, but the user has browsed + saved + downloaded + shared the resource, indicating that the user should have a high evaluation of the resource. A total of 500 questionnaires were distributed to students in school, and 421 copies were effectively recovered. The average score of each behavior was counted and then reduced to a multiple of 0.5. The final score is shown in Table 2.

The user resource behavior matrix is shown in Figure 5.

3.3. User Resource Matrix. If the user has not evaluated a certain resource, analyze whether the resource has performed relevant learning behavior operations, and calculate the corresponding score according to Table 2. After this process, a user resource matrix is obtained, the density of which is significantly higher than that of the user resource evaluation matrix.
3.4. User Initialization Label. The characteristics of the user’s learning ability, study major, education background, and interests are the direct description of the user. When a new user joins the system, the user’s initial label is used to calculate the similarity of the user. The label representation of the user is shown in

$$T_u = [t_{ua}, t_{um}, t_{ur}, t_{ui}]$$

(8)

$t_{ua}$, $t_{um}$, $t_{ur}$, and $t_{ui}$ represent the learning ability, major, education, and interest of user $u$, respectively.

(1) Learning ability: It is divided into 4 levels, namely, poor, medium, good, and excellent, represented by 1–4. The similarity calculation of the learning ability of users $u$ and $v$ is shown in

$$\text{sim}(t_{ua}, t_{va}) = 1 - \frac{|t_{ua} - t_{va}|}{3}$$

(9)
3.5. User Similarity Calculation. The user similarity uses a linear weighting method to fuse the user resource score similarity and the user initialization label similarity, and its calculation is shown in

\[
\text{sim}(u, v) = \varphi \text{sim}_{i}(u, v) + (1 - \varphi)\text{sim}_{t}(u, v). \tag{14}
\]

\(\text{sim}_{i}(u, v)\) is the similarity of user resource scores, and its user evaluation data come from user resource matrix; \(\text{sim}_{t}(u, v)\) initializes the label similarity for the user, and the calculation is shown in formula (13).

3.6. Output Recommendation Results. After the similarity of users is obtained, they are sorted by size, and the first \(k\) neighboring users are selected as the similar user set \(S_u = \{s_{u1}, s_{u2}, s_{u3}, \ldots, s_{uk}\}\) of the target user \(u\). Find all the resources that the target user \(u\) has not evaluated in the similar user set \(S_u\), and predict the target user \(u\)'s score for the resource. The specific calculation formula is as follows:

\[
\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{v \in S_u} \text{sim}(u, v)(r_{vi} - \bar{r}_v)}{\sum_{v \in S_u} \text{sim}(u, v)}. \tag{15}
\]

4. Experiment Analysis

4.1. Experimental Data. The experimental data come from the school’s high-quality resource online course learning platform. The platform includes 1,015 courses and 38,578 student users. 2,000 users and 400 courses are randomly selected as experimental data. The experimental data include the students’ scores on the course and the behavior records of browsing, collection, download, sharing, etc., as well as the comments and forwarding records between students. 200 user data are extracted from the system for experimental testing.

4.2. Evaluation Indicators. The evaluation standard adopts the MAE evaluation index of the recommendation algorithm, and the average absolute error of the MAE is used to accurately predict the score of the learning user to evaluate the effectiveness of the algorithm. The calculation formula is

\[
\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - x_i|. \tag{16}
\]

Among them, MAE is the mean absolute error, \(y_i\) is the predicted rating of the learning resource by the learning user, \(x_i\) is the actual rating of the learning resource by the learning user, and \(n\) is the number of predicted ratings.

4.3. Experimental Results and Analysis. Set the fusion weight factor \(\varphi\) to 0.7. The value range of the number of adjacent users \(k\) is \([10, 50]\), and the experimental results are shown in Figure 6.

As can be seen from the above figure, the RMSE value is the smallest when \(k\) is 30.

In order to verify the mitigation effect of the improved algorithm on the user’s cold-start problem, a verification experiment of the recommendation effect of new users was carried out, and 200 users were randomly selected as the test data. In order to imitate new users, when finding similar users, the similarity of their resource scores is removed, only
the similarity of user initialization labels is retained, and the experimental parameter $\varphi$ is taken as 0.7. The recommendation effect is measured using the average precision and recall, which are calculated as shown in

$$\text{precision} = \frac{1}{|T|} \sum_{u \in T} \frac{|P_u \cap R_u|}{|P_u|},$$  

(17)

$$\text{recall} = \frac{1}{|T|} \sum_{u \in T} \frac{|P_u \cap R_u|}{|R_u|},$$  

(18)

In formulae (17) and (18), $T$ denotes the test data, $|T|$ denotes the size of the test dataset, $P_u$ denotes the resource set prerecommended to the user with a predicted score $\tilde{r}_u \geq 8$, and $R_u$ denotes the actual user score $r_u \geq 8$ users really like the resource set (in this experiment, the user score $\geq 8$ is set as the user’s favorite resource). In the case of taking different numbers of adjacent users, the results of the average precision rate and average recall rate are shown in Table 3.

It can be seen from the experiments that the algorithm in this paper also has a good effect on the recommendation of new users, avoiding the problem that the collaborative filtering algorithm cannot be recommended due to the cold start of new users.

In order to verify the performance of the improved algorithm in this paper, the algorithm proposed in this paper is compared with four other types of algorithms. The algorithm proposed in this paper is referred to as IT_UCF, and the collaborative filtering algorithm that only introduces user learning behavior logs is referred to as I_UCF. The filtering algorithm is abbreviated as T_UCF, the traditional user-based collaborative filtering recommendation algorithm is abbreviated as UCF, and the traditional item-based collaborative filtering recommendation algorithm is abbreviated as ICF. Measured using RMSE, the results are shown in Figure 7.

Through comparative experiments, it is found that the RMSE values of I_UCF and T_UCF are small, indicating that the introduction of user learning behavior logs or user initialization label similarity can indeed improve the algorithm; the RMSE value of the IT_UCF algorithm is smaller than that of the I_UCF and T_UCF algorithms, indicating that user learning is introduced at the same time. Behavior logging and user initialization tags are better than introducing just one or the other.

### 5. Conclusion

With the popularization of the Internet, various online learning platforms have developed rapidly, providing users with rich learning resources, and realizing personalized resource recommendation is the development trend of online learning platforms. Aiming at the typical problems of traditional collaborative filtering-based recommendation algorithms—cold start and matrix sparseness, this paper proposes a personalized learning recommendation model based on improved collaborative filtering. By introducing user initialization tags, the similarity calculation of users is improved, and the cold-start problem of new users is solved. And the effectiveness of the algorithm is proved by experimental comparison, which improves the recommendation effect of personalized learning. However, the algorithm in this paper also has certain shortcomings. On the one hand, the algorithm has certain limitations. In many other application fields, the user’s operation log of the resource and the user’s initial label are not easy to obtain; on the other hand, over time, the user’s learning Interests, habits, and abilities may change, and historical data are time-sensitive. This phenomenon of user interest drift is not considered in the algorithm proposed in this paper. Further research is needed to address these issues.
**Data Availability**

The dataset can be accessed upon request.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

**References**


