

## Retraction

# Retracted: Recommendation Algorithm of Web-Based Learning Resources considering Timeliness and Popularity

### Advances in Multimedia

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] X. Han, "Recommendation Algorithm of Web-Based Learning Resources considering Timeliness and Popularity," *Advances in Multimedia*, vol. 2022, Article ID 2584890, 6 pages, 2022.

## Research Article

# Recommendation Algorithm of Web-Based Learning Resources considering Timeliness and Popularity

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The optimized learner evaluation matrix and similarity model are essential methods to deal with the challenges of “data sparsity” and “cold start” in the process of learning resource recommendation on the online learning platform. Accordingly, an improved collaborative filtering algorithm (TRCP) is proposed to improve the accuracy of learning resource recommendation. The TRCP algorithm generates the learner evaluation matrix for recommended projects by classifying learning resources. It comprehensively considers the influence of learners’ online learning behavior, learning time, and popularity of learning resources on learners’ interest and optimizes the sample data in the evaluation matrix. The experimental results on the school online teaching platform verified that this method has achieved obvious and effective results in both the accuracy and satisfaction rate of learning resource recommendation.

## 1. Introduction

Due to the popularization of the Internet, various online education platforms develop rapidly, which provides learners with rich learning resources and convenient learning conditions [1–3]. Unfortunately, in the absence of clear goals, it is difficult for traditional classification retrieval and popular recommendation to guide learners to obtain the required high-quality learning resources quickly and accurately. Personalized recommendation is a popular intelligent technology recently [4–7]. Specifically, it judges learners’ potential interests and hobbies by analyzing learners’ historical behavior data on the learning platform and predicts the learning contents that they may be interested in in the future, so as to provide learners with a list of learning resources and thus supporting learners to quickly and accurately obtain a catalog of valuable learning resources.

Traditional recommendation algorithms [8, 9] mainly involve content-based recommendation, collaborative filtering-based recommendation (CFR), and hybrid recommendation [10–12]. Compared with the other two recommendation algorithms, the advantage of CFR is that it

assists users to discover new interests. Collaborative filtering can identify potential interest preferences different from the known interests of users, avoid the incompleteness and inaccuracy of content analysis by sharing the experiences of others, and filter based on complex concepts (such as personal taste). In addition, it is capable of speeding up personalized learning through feedback from other similar users. All these enable collaborative filtering to develop into one of the most extensively applied and successful recommendation techniques today [13–16].

Based on the existing research and practice, this work analyzes the scenarios and challenges faced by collaborative filtering recommendation technology in learning resource recommendation on the online education platform and puts forward a set of collaborative filtering recommendation algorithm TRCP based on time series and popularity and validates and compares it with the actual data of the school online education platform. TRCP incorporates two elements of online learning resource recommendation, namely, the time for learners to operate on learning resources and the popularity of learning resources, and constructs the time decay model (TDM) and interest capture model (ICM),

respectively, which alleviates the problem of data sparsity, captures changes in learners' interest in learning content, and improves the accuracy of recommendation.

## 2. A Brief Introduction to Collaborative Filtering Algorithms

The user-based collaborative filtering algorithm calculates the similarity between users in the system and predicts the project according to the similar patterns between them [17–19]. This method is recommended by the “user-project score matrix” [20]. The steps of the algorithm are as follows:

Step 1 Build a user rating matrix

Define the user collection and the project collection  $I = \{i_1, i_2, \dots, i_{n-1}, i_n\}$ . Build the user rating  $U = \{u_1, u_2, \dots, u_{m-1}, u_m\}$  matrix  $R_{m \times n}$  and complete the filling. If the user  $U_m$  does not score the project  $i_n$ ,  $r_{m,n} = 0$ .

$$R_{m \times n} = \begin{bmatrix} r_{1,1} & r_{1,2} & r_{1,3} & \dots & r_{1,n} \\ r_{2,1} & r_{2,2} & r_{2,3} & \dots & r_{2,n} \\ \dots & \dots & \dots & \dots & \dots \\ r_{m,1} & r_{m,2} & r_{m,3} & \dots & r_{m,n} \end{bmatrix}. \quad (1)$$

Step 2 Calculate the user similarity matrix

Based on the user score matrix constructed in Step 1, the user similarity matrix is calculated through the user similarity. The commonly used standard cosine similarity matrix formula is shown as follows:

$$Sim(a, b) = \frac{\sum_{c \in I_{a,b}} r_{a,c} r_{b,c}}{\sqrt{\sum_{c \in I_a} r_{a,c}^2} \sqrt{\sum_{c \in I_b} r_{b,c}^2}}. \quad (2)$$

The user similarity matrix is the matrix of  $m \times m$  and is defined as  $S_u$ .

$$S_u = \begin{bmatrix} 1 & sim(1, 2) & sim(1, 3) & \dots & sim(1, m) \\ sim(2, 1) & 1 & sim(2, 3) & \dots & sim(2, m) \\ sim(3, 1) & sim(3, 2) & 1 & \dots & sim(3, m) \\ \dots & \dots & \dots & \dots & \dots \\ sim(m, 1) & sim(m, 2) & sim(m, 3) & \dots & 1 \end{bmatrix}. \quad (3)$$

Step 3 Identify a collection of user neighbors

According to the user similarity matrix obtained in Step 2, several users with the highest similarity to the target user  $a$  are determined to form the neighbor set  $U_k$ .

Step 4 Predict the score and generate a set of recommendations

After obtaining the nearest neighbor set  $U_k$ , predict the rating score  $P_{a,c}$  of the project  $c$  by user  $a$ , as shown as follows:

$$P_{a,c} = \bar{r}_a + \frac{\sum_{b \in U_k} (r_{b,c} - \bar{r}_b) \times sim(a, b)}{\sum_{b \in U_k} |sim(a, b)|}. \quad (4)$$

For the recommendation way to return the recommendation list, it is generally necessary to generate the candidate item set when considering the real-time performance of the recommendation and the length of the recommendation list, then predict the score of the candidate items by the active users, and finally generate the Top-N recommendation list according to the prediction score.

**2.1. System Model.** Figure 1 provides the overall architecture of the TRCP recommendation [21–24] algorithm. In this method, the matrix decomposition model with time factors is used to calculate the implicit relationship between learners and classified learning resources from the behavior records of learning resources and the learners' preferences for all kinds of learning resources are obtained. This solves the problem that learners' learning preferences change dynamically over time [25, 26]. Considering the contribution weight of popular learning resources in the calculation of score similarity, learning resources are divided into popular resources and unpopular resources and different score similarity contribution weights are set in these two types of projects to optimize score similarity. Then, the learner preference considering the time factor and the learner preference considering the popularity of learning resources are combined with the logical regression method to get the score of learners' preference for a certain type of learning resources to ensure the accuracy of task recommendation. Subsequently, the cosine similarity calculation method is used to calculate the user similarity, the K neighbor readers who are most similar to the target learners' preference for learning resources are determined, and the categories of learning resources that the nearest neighbor learners like and the target learners have not borrowed are obtained. Finally, the score of the target reader on the classification of learning resources in the set is predicted and the popular learning resources in the first N position in the learning resource category are recommended to the target reader as the recommendation result according to the predicted score.

The main parameters used are described as follows: the set of  $n$  learners is denoted as  $R = (r_1, r_2, \dots, r_n)$ , the set of  $m$  learning resource categories is denoted as  $B = (b_1, b_2, \dots, b_m)$ , and each learner's behavior record of learning resources is represented as  $H_i$ , where  $H_i$  contains all kinds of learning resources browsed, downloaded, collected, and shared by learners  $r_i$ , and all sets of learning resources for each type of learning resources are represented as  $Z_j$ , while  $Z_j$  includes the numbers of all learners who browse, download, bookmark, and share  $j$  types of learning resources. Therefore, an effective method is proposed to accurately calculate each learner's score matrix  $Y$ ;  $y_{i,j}$  refers to all kinds of learning resources, which represents the learner  $r_i$ 's score for a certain type of learning resources  $b_j$ , and generates a list of favorite learning resources for each learner.

### 2.2. Learner Rating Matrix for Categorized Learning Resources

**2.2.1. Classification of Learning Resources.** Conventionally, the learning resource recommendation system generally

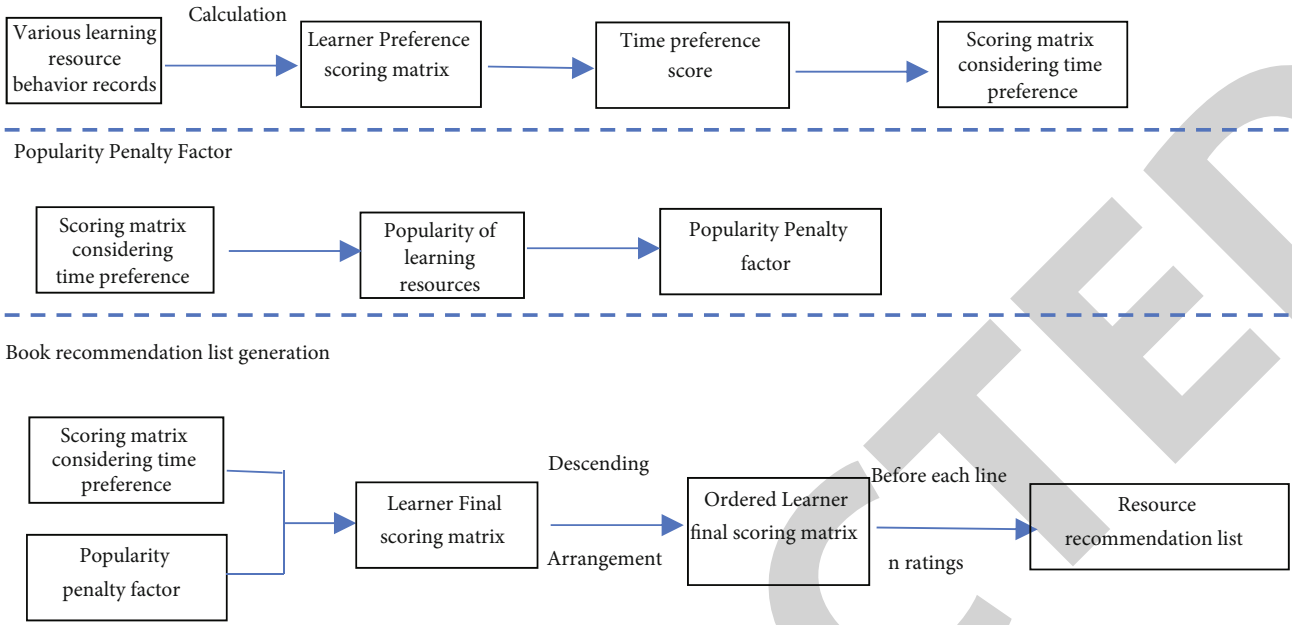


FIGURE 1: Book recommendation system of university library considering timeliness and popularity.

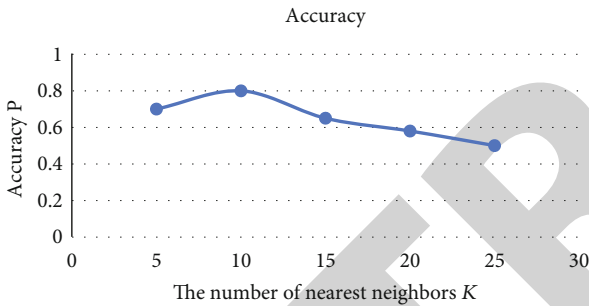


FIGURE 2: Accuracy of learning resource recommendation results.

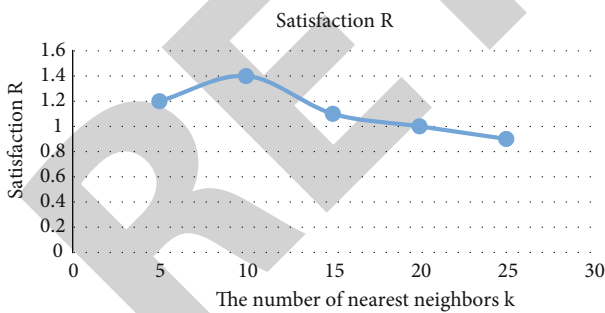


FIGURE 3: Satisfaction value of learning resource recommendation results.

directly scores the learning resources browsed, downloaded, saved, and shared by the learners [27–29]. However, learners have less learning resources for online operations and a huge number of learning resources on learning platforms, which are vulnerable to sparse data and inaccurate scoring. For example, both students have browsed the e-book of calculus but the authors and publishers of the two e-books may be different. According to the conventional grading algorithm,

the similarity between the two students is 0, but in fact, the learning preferences of the two students are very similar. In order to solve the problem of sparse data and inaccurate scoring, the book classification number is used to calculate the learners’ preference for a certain kind of learning resources. The *Chinese Library Book Classification* stipulates the classification of books collected in Chinese libraries, in which there are 22 first-level categories, and there are second-level subcategories under each category. For example, the “T Industrial Technology” category is divided into 16 secondary subcategories: “TB General Industrial Technology, TD Mining Engineering, ..., TV Water Conservancy Project”, and there are three and four subcategories under the second-level subcategory. Considering the amount of computation, solving the problem of sparse data and the accuracy of recommendation, the method of “learner-learning resource four-level classification” is adopted to combine the learner  $r_i$ ’s score of learning resource category  $b_j$ .

**2.3. Learners’ Rating on Learning Resource Behaviors.** Learners’ routine operation of web-based learning [30–32] can be divided into four types: browsing, downloading, collecting, and sharing. These operations reflect the user’s interest in learning resources. According to the user learning behavior log data, the learning behavior data can be converted into the corresponding interest score of learning resources. The four operating behaviors of browsing, collecting, downloading, and sharing are given different scores of 1, 2, 3, and 4, respectively, by the way of expert scoring. If a variety of behaviors are produced at the same time, the scores of each behavior are added to get the final score. For example, if a user has two browsing and one download of a learning resource in a day, the score is  $1 \times 2 + 3 \times 1 = 5$ . By analogy, the behavior score formula of learner  $r_i$  for a

certain type of learning resource  $b_j$  on a certain day is as follows:

$$a_{i,j} = \sum n_1 + 2n_2 + 3n_3 + 4n_4, \quad (5)$$

where  $n_1$ ,  $n_2$ ,  $n_3$ , and  $n_4$  represent the number of times that learners  $r_i$  browse, save, download, and share, respectively, a certain type of learning resource  $b_j$  on a certain day.

**2.4. Learners' Time Rating on Operation Behaviors of Various Learning Resources.** Considering the time dynamic characteristics of learners' preference for learning resources, the learning resources that learners have operated recently are more representative of learners' preferences. The weight of rating information is decayed exponentially with time through the exponential decay function  $e^{-\lambda(t-t_{i,j})}$ , where  $t$  represents the current moment,  $t_{i,j}$  represents the time of learners  $r_i$  to operate on a certain kind of learning resource  $b_j$  (accurate to daily),  $\lambda$  represents time attenuation factor, and  $\lambda > 0$ , and the larger  $\lambda$  is, the lower the importance of the historical preference is. On this basis, the time scoring matrix  $YT$  for learning resources is established. Each child element  $yt_{i,j}$  in  $YT$  is calculated by the following formula:

$$yt_{i,j} = \sum_1^n e^{-\lambda(t-t_{i,j})} a_{i,j}, \quad (6)$$

where  $n$  is the number of days for learners to operate on the same type of learning resources.

**2.5. Reader Score Calculation Method Integrated into Book Popularity.** The traditional collaborative filtering score calculation method ignores a problem, that is, learning resources with different popularity have different effects on similarity in the learner-learning resource scoring matrix. For example, both readers have read *Newsweek*, which does not show that their reading preferences are similar, perhaps because the journal is more popular. But if both readers have read *Discrete Mathematics*, a professional e-book, it is more likely that their preferences will be closer. Therefore, if readers have common operating behavior on unpopular learning resources, they can better reflect the convergence of their interests and preferences. The lower the popularity of learning resources, the higher the preference weight distribution value of the learners who are interested in it. The popularity coefficient  $\beta_j$  of a certain type of learning resource  $j$  can be expressed by the formula as follows:

$$\beta_j = \frac{\max(cn) - cn_j}{\max(cn) - \min(cn)}. \quad (7)$$

Among them,  $\max(cn)$  and  $\min(cn)$  represent the maximum and minimum of the number of times operated in all kinds of learning resources, respectively, and  $cn_j$  represents the number of times that a certain type of learning resource  $j$  is operated. The greater the popularity coefficient of learning resources, the more unpopular resources, the greater the

impact on the similarity of learners' preferences. On the contrary, the smaller the popularity coefficient of the learning resources is, the more popular the resources are and the smaller the influence on the similarity of readers' preferences is.

After comprehensively considering the operation mode, operation time, and popularity of learning resources, the learner scoring matrix  $Y$  is established. Each child element  $y_{i,j}$  in  $Y$  represents the reader  $j$ 's rating of a certain type of learning resource  $II$ , which is calculated as follows:

$$y_{i,j} = \beta_j \cdot yt_{i,j}. \quad (8)$$

**2.6. Calculation Method of Learner Similarity.** The calculation of learner similarity is the core of the recommendation algorithm, which is aimed at determining the  $k$  users who are most similar to the target learners' preferences and form a set of nearest neighbors. Collaborative filtering algorithms usually use the cosine similarity calculation method to calculate learners' similarity. Cosine similarity is evaluated by calculating the cosine value of the angle between two vectors in space. The smaller the angle is, the higher the similarity is. The formula for calculating user similarity is as follows:

$$\text{Sim}(u, v) = \frac{\sum_{i \in I(u) \cap I(v)} (y_{ui} - \bar{y}_u) \cdot (y_{vi} - \bar{y}_v)}{\sqrt{\sum_{i \in I(u) \cap I(v)} (y_{ui} - \bar{y}_u)^2} \cdot \sqrt{\sum_{i \in I(u) \cap I(v)} (y_{vi} - \bar{y}_v)^2}}. \quad (9)$$

In the formula,  $\text{sim}(u, v)$  represents the similarity of the two learners  $u, v$ .  $I(u)$  and  $I(v)$  represent all the categories of learning resources involved in the four types of learning behaviors of the two learners'  $u, v$  browsing, downloading, collecting, and sharing and  $y_{ui}$  and  $y_{vi}$  indicate that the two learners  $u, v$  scores the purpose of the learning resources.

**2.7. Generate Recommendation Results.** The recommendation result is to generate a personalized learning resource recommendation list with the length of  $n$  for the target learners, which enables the list to meet the preferences of the target learners as much as possible. According to the preference similarity between computing learners, it is clear that the  $k$  learners who are most similar to the target learners can get a set of learning resources that similar learners browse, download, collect, and share but the target learners have not been involved. Then, the score of the learning resources in the set is predicted by the target learners and the popular learning resources in the category of learning resources are recommended to the target learners as the recommended results according to the predicted scores. Among them, the score prediction is the core of the recommendation system research. Based on the user's neighborhood algorithm, the prediction formula of the user's score on the item is as follows:

$$\hat{P}_{ui} = \bar{y}_u + \frac{\sum_{v \in S(u,K)} \text{sim}_{uv} (y_{vi} - \bar{y}_v)}{\sum_{v \in S(u,K)} |\text{sim}_{uv}|}, \quad (10)$$

where  $\hat{P}_{ui}$  represents the predicted score of the recommended learning resource category  $i$  by the target user  $u$ ,  $S(u, k)$  represents the  $k$  neighbor users of the user  $u$ ,  $\text{sim}(u, v)$  represents the similarity between the target user  $u$  and the neighbor user  $v$ ,  $y_{vi}$  represents the interest score of the user  $v$  in a certain kind of learning resource  $i$ , and  $\bar{y}_u$  and  $\bar{y}_v$  represent the average score of each learning resource category scored by the target user  $u$  and the neighbor user  $v$ , respectively.

**2.8. Implement Personalized Recommendation of Learning Resources.** Each functional module of the system is realized through the analysis and design of learning resource recommendation, and the user-based CFR algorithm is used to complete the learning resource recommendation. When the learner initiates a request to generate a recommendation, the system forwards the request to the server background. The background will generate the recommendation results according to the real-time requests sent by the learners combined with the algorithm and then push the results to the foreground user interface for display to quickly guide learners to obtain learning resources that they may like or be interested in.

### 3. Experiment and Analysis

**3.1. Sources of Experimental Data and Evaluation Criteria.** The experimental data use the background management data of the AHZY university network teaching platform, which includes 1284 courses and 24521 student users, including e-books, courseware, lesson plans, cases, assignments, examination questions, and other text teaching resources and video, image, audio, and animation and other multimedia teaching resources. All learning resources are classified and coded according to the *Chinese Library Book Classification* and the types of learning resources. A total of 500 students were randomly selected as recommended subjects, including 20, 60, and 40 students in the first, second, and third grades, respectively. The evaluation criteria of the experimental effect are book recommendation accuracy  $P$  and satisfaction rate  $R$ , where  $P$  and  $R$  are defined as follows:

$$P = \frac{\sum_{i=1}^m b_i}{N}, \quad (11)$$

$$R = \frac{\sum_{j=1}^n y_j}{N}, \quad (12)$$

where  $b_i$  represents the  $i$ th recommended learning resources approved by students,  $m$  represents the number of learning resources approved by students,  $N$  represents the total number of recommended learning resources, and  $y_j$  represents readers' satisfaction with the  $j$ th recommended learning resources. The corresponding values of the three options of "satisfied, basically satisfied and dissatisfied" are 2. The recommended results communicate with the students by email and push the recommended list of learning resources to the interviewed students. The email contains a link to learning resources and an evaluation form of learning resources,

and the interviewed students are required to evaluate the recommended learning resources and send back the evaluation form. The recommended scores for learning resources are shown in Figures 2 and 3:

### 4. Conclusions

In order to solve the problem of sparse data in the evaluation matrix of learning resources on the online learning platform, the automatic evaluation is realized from the perspective of learning resource classification by using learner behavior records and the evaluation criteria are unified. Specifically, this work employs a user-based collaborative filtering algorithm, calculates the similarity between learners by constructing a learner book score matrix on the basis of considering the timeliness and popularity of learner behavior data, defines the neighbor users who are close to the learners' interests, and predicts the learners' preference for the learning resources involved in the neighbor users' network learning behavior to generate learning resource recommendations. The experimental results conclude that learning resource recommendation can achieve high accuracy and user satisfaction, and the overall recommendation effect is affirmed by learners. In the future research, we will focus on how to use the scientific research information of teachers and students, learners' individual interest discovery strategies, and learner clustering information to improve the quality of recommendations.

### Data Availability

The dataset can be accessed upon request.

### Conflicts of Interest

The author declares that there are no conflicts of interest.

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