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# Personalized Intelligent Recommendation Model Based on Hybrid Collaborative Filtering Algorithm

**Yujiao Wang[1], Haiyun Lin[2,*], Lina She[3] and Li Sun[4]**

[1] *College of Teacher Education, Kunming University, Kunming 650214, China*
[2] *College of Physical Science and Technology, Kunming University, Kunming 650214, China*
[3] *Science and Technology Management Department, Kunming University, Kunming 650214, China*
[4] *School of Information Engineering, Kunming University, Kunming 650214, China*

In the context of a learning environment, the purposes of this paper are to construct an intelligent learning resource model based on personalized recommendation; improve the efficiency of the current recommendation algorithm; propose a hybrid collaborative filtering recommendation algorithm; establish a push strategy for intelligent learning resources; create a two-way matching mapping strategy; and promote a personalized and intelligent education service. It is anticipated that the realization of these goals will help to address several problems: the overall quality of the recommendation system, the new-user cold start recommendation, the slow convergence of the recommendation algorithm, the system stability and other issues.

Keywords: personalized learning, intelligent recommendation, resource model, recommendation algorithm

## 1. INTRODUCTION

The development of technologies such as Big Data, Artificial Intelligence, Cloud Computing and the Internet of Things has helped to integrate the real world, virtual world and conceptual world, while simultaneously increasing the volume of data and the variety of data modes. The era of big data is now officially established. The cloud computing processing and application model has produced a large number of different types of data sets with complex structures (Ma et al., 2019). Big data is changing the way we work and live, and is also triggering changes in the education domain in terms of thinking, pedagogy, models, evaluation and management. Through intelligent perception devices, students' learning trajectories can be tracked online and offline, the data pertaining to their learning processes learning process data can be obtained, and personalized services and guidance can be provided (Intayoad et al., 2019). The application of big data technology is bound to promote the development of personalized education. Big data offers new potential for ubiquitous learning, can break the "information overload" deadlock, and provide students with timely learning support and services, thus providing new opportunities for personalized education. This can be achieved by constructing an intelligent Personalized Learning Resource Recommendation system, improving the efficiency of the traditional recommendation algorithm, establishing a two-way matching mapping strategy, creating a learning process-oriented learning resource active service strategy, establishing an efficient personalized recommendation service, meeting the individual differences of learners, and providing differentiated and precise teaching (Jiao et al., 2019).

*Corresponding Author E-mail: lhy198@163.com.

**Table 1** Frequency of learners' behavior.

| Learner | Browse number | Collection number | Number of shopping carts added | Purchase number |
|---|---|---|---|---|
| $i_1$ | 3 | 2 | 3 | 2 |
| $i_2$ | 4 | 1 | 2 | 1 |
| $i_3$ | 2 | 0 | 1 | 0 |

## 2. MODEL FRAMEWORK

An intelligent personalized learning resource recommendation system consists of four core modules, according to the system function flow data processing module, recommendation algorithm module, resource filtering module and resource model configuration module.

Of the four business function modules, the data processing module, system recommendation algorithm and resource filtering module are more important, and the resource allocation module is the basic module of the system.

The model configuration module consists of: the administrator that has the authority to upload resources and modify the configuration resources to assess and process the validity and timeliness of resources. The system administrator has the authority to control the number of resources pushed each time (Shi et al., 2019).

The data processing module extracts, preprocesses and models the characteristic attributes of the system-oriented resources and learner objects, and then organises, stores and records the processed resource information in the database.

The resource filtering module uses the predictive scoring results of target learners calculated by the recommendation algorithm module to screen the validity of the resource information, and then recommends the resources to target learners (Al-Hamadi and Soliman, 2006).

As the core of the personalized recommendation system, the recommendation algorithm module is also responsible for determining and analysing learner interest similarity, combine similarity and learner prediction score of the data matrix between resources and learners, and then the processed data results are stored in the database table for other modules to use (Saia et al., 2016; Mohammed, 2020; Yakubu, 2020; Joanna, 2019).

## 3. SYSTEM DEVELOPMENT ENVIRONMENT

MySQL is used in the database. In the data processing module of the recommendation model, data extraction, conversion, calculation and program allocation are done by using Java language and the data mining analysis module written in Python.

The final prototype system recommended by personalized learning resources is deployed on a Tomact's server.

The operating system is Windows 10 Professional Edition, 64-bit operating system.

The technology used for crawling learning resources is a combination of Python + Beautiful data package.

The visual interface of the personalized learning resource recommendation system is displayed with Eclipse integrated development environment used for module configuration. The database operation is realized with Java language coding. The front-end interface is created with JavaScript, and MVC and SSH framework technology are used.

## 4. IMPROVED COLLABORATIVE FILTERING ALGORITHM

The collaborative filtering algorithm is an algorithm used to predict learners' behavior when accessing learning resources. Traditional algorithms rely mainly on the score matrix of learners-learning resources to predict the score for the acquisition of learning resources, that is, the similarity of learners-learning resources can be predicted (Wang and Ma, 2019). The algorithm in this study is a collaborative filtering algorithm based on learner behavior and time-based behavior frequency.

### 4.1 Learner Behavior and Frequency

In the intelligent education environment, the collaborative filtering algorithm is not used to determine the value of particular learning resources for learners (generally evaluated with a range of 1 to 5). The evaluation of learning resources for learners' interest in learning resources is implicit feedback information (Ding et al., 2016). In the research, learners' interest in the learning resources is divided into four kinds of behaviors: browsing, collecting, adding to the shopping cart and purchasing. Because different behaviors of learners have different effects on the degree of preference for particular learning resources, different weights should be given to learners' behaviors when expressing their preference for learning resources, which translates learners' behaviors into learning. The score for the learners' learning resource is the explicit feedback information. The weight values of learner behavior are 1, 2, 3 and 4 respectively.

In the actual learning process, when a learner is considering the purchase of a learning resource, he or she may browse it once or more before engaging in a purchasing behavior (Zhang et al., 2019). Therefore, the frequency of the learner's main behavior indicates that learner's preference for certain learning resources that attract the learner's interest. The behavior frequency regarding resource J is shown in Table 1.

The score vector of learners' behavior is defined as $a = (1, 2, 3, 4)$ (Huangfu and Xiao, 2019). To calculate the score matrix of learners' learning resources through the behavior vector, we need to define a vector to determine whether the learners engage in a behaviour in regard to the learning resources; that is, whether learners' behavior frequency vector $f$ is greater than 0 to determine whether the behavior occurs, which is represented by 0 and 1 respectively. 0 means that no behavior has occurred, and 1 means a behavior has occurred. Then the score matrix of learners' learning resources is calculated. The behavior score matrix of learners' learning resources is as follows:

$$R_{i,j} = \begin{bmatrix} 3 & 2 & 3 & 2 \\ 4 & 1 & 2 & 1 \\ 2 & 0 & 1 & 0 \end{bmatrix} \tag{1}$$

The formula is as follows:

$$R_{i,j} = \sum_{n=1}^{m} A \bullet B^T, \ n \in \{1, 2, 3, 4\} \tag{2}$$

It refers to a certain behavior of learners.

# 5. EVALUATING INDICATOR

## 5.1 Mean Absolute Error (MAE)

The mean absolute error (MAE) is used to measure the performance of the recommendation system, which is used to calculate the mean of the absolute value of the difference between the actual resource score and the predicted value (Shi et al., 2019). The mean absolute error MAE is found with:

$$MAE = \frac{\sum_{i=1}^{n} |q_i - p_i|}{n} \tag{3}$$

where $p_i$ represents the predicted score of learners, and the set can be expressed as: $\{p_1, p_2 \ldots p_i \ldots p_n\}$; $q_i$ represents the actual score of learners, and the set is expressed as $\{q_1, q_2 \ldots q_i \ldots q_n\}$.

The smaller the value of MAE, the more accurate is the score prediction function of the recommendation system, and the better is the algorithm quality of the recommendation system (Zhang, 2020).

## 5.2 Precision

Precision is a kind of classified precision evaluation index, which is the ratio of the number of relevant items in the retrieval results to the total number of items (Yoori and Yoonhee, 2018). This is calculated with:

$$P = \frac{1}{M} \sum_{n} \frac{N_t}{N_t + N_f} \tag{4}$$

where $M$ stands for the total number of test learners, $n$ stands for each learner, $N_t$ stands for the number of items recommended by the system that the learners like, $N_f$ stands for the number of items that the system does not recommend or dislike (Zhou et al., 2018). The precision value is between 0 and 1. The closer the value is to 1, the greater is the precision.

## 5.3 Recall

Recall rate is also a classified evaluation method, and is the ratio of the number of items retrieved to all related items. This is calculated with:

$$R = \frac{1}{M} \sum_{n} \frac{N_t}{N_t + N_j} \tag{5}$$

$N_j$ represents the amount of data that learners like but the system does not recommend.

In the recommendation system, the higher the accuracy and recall rate, the better. But the fact is that there may be discrepancies between the two. For example, there is only one correct search result, where $P$ equals 100%, but $R$ is low (Li et al., 2014). If you adjust the algorithm now and return all the recommended results, when $R$ equals 100%, the accuracy is low. At this time, we need a comprehensive evaluation index to measure the quality of the recommendation system, which we introduce. The mathematical expression for the comprehensive evaluation index is:

$$F = P \times R \times \frac{2}{(P + R)} \tag{6}$$

The *F value in the formula is the harmonic average comprehensive evaluation index of* accuracy and recall rate. *P represents the accuracy rate and R represents the recall rate. The higher the F value, the better and more effective is the algorithm recommendation result returned by the recommendation system.*

# 6. SYSTEM TEST ANALYSIS

## 6.1 Quality Analysis of Resources Recommended to New Users

In the comparative experiment, the experimental data and conditions remain unchanged, and the three experimental systems are tested repeatedly. The experimental results for the quality of resources recommended to new learners are shown in Figure 1.

Based on the experimental design and analysis of an intelligent personalized primary and secondary education recommendation system, the evaluation indexes of recommendation system are introduced, including accuracy, recall and comprehensive evaluation indexes (Xie and Wang, 2018). In the experiment design, we are mainly concerned with the design of the control experiment system. In order to avoid multiple rounds and groups of experiments, we analyze and discuss the experimental results. The results show that the hybrid recommendation algorithm proposed in the personalized primary and secondary school learning resource recommendation system can effectively solve the difficulty of new learners in the traditional recommendation system, the overall recommendation quality is not high, and the recommendation service is not good (Karidi et al., 2018). The problem of instability can be seen from the experiment that the hybrid recommendation system can provide reliable learning resources recommendation services for the majority of primary and secondary school learners.

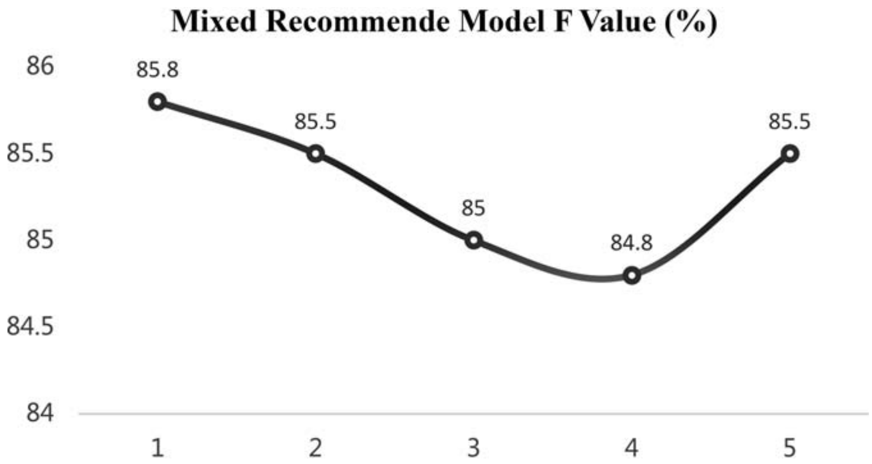


**Figure 1** F-value graph of new learners based on hybrid recommendation algorithm.

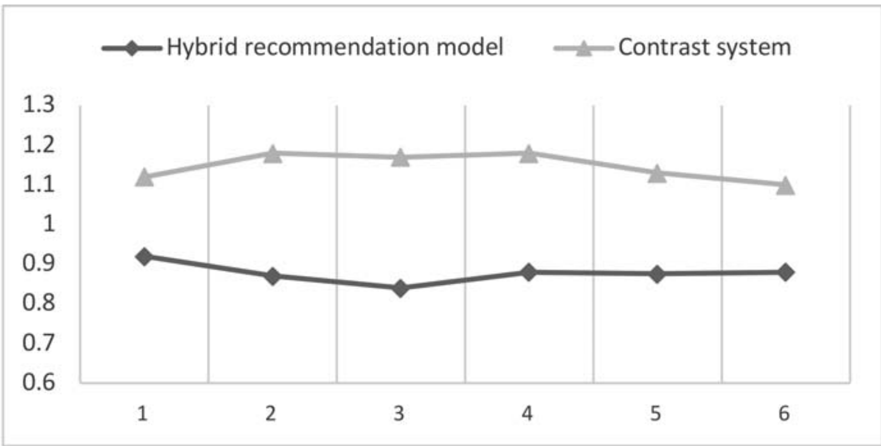


**Figure 2** MAE analysis.

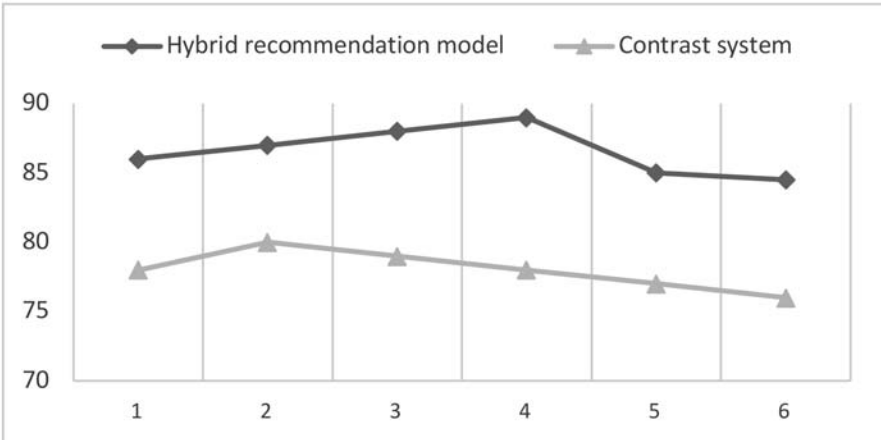


**Figure 3** *F* value of comprehensive evaluation index.

## 6.2 Analysis of Experimental Results of Resource Recommendation Quality

The experimental conditions remain unchanged. Based on the collaborative filtering recommendation model (contrast system) and the hybrid recommendation model, several rounds of experiments are carried out on the two systems. The experimental results are shown in Figure 2.

The $F$ value of hybrid recommendation system is significantly higher than that of the contrast system, which indicates that the test method is effective. The experimental results presented in Figure 2 and Figure 3 show that the MAE of the personalized education resource recommendation system using the hybrid recommendation technology is significantly lower than that of the experimental contrast system; this shows that the hybrid recommendation algorithm has a small recommendation error and an accurate recommendation algorithm. Therefore, the hybrid recommendation algorithm improves the overall quality of the recommendation system (Dong et al., 2017).

## 7. PART CODE OF INTELLIGENT SEARCH MODULE

The intelligent search module is based mainly on the learners' search history records (Zhang et al., 2017). When learners want to search learning resources again, they will automatically find the history in the search box. When learning, learners use search tools to search for keywords, and the system will indicate whether the record is stored. The module part code is as follows.

```
 public Object search (Http Servlet Request req) {
  return ma Service. search Key Words(req);
 }
public String key Word Add (Http Servlet
Request req) {
  String key = req. get Parameter(‘‘search–text’’);
  req. get Session (). get Id ();
  Object obj = req. get Session (). get
  Attribute(‘‘history’’);
public Object search Key Words (Http Servlet
Request req) {
  return req. get Session (). get
  Attribute(‘‘history’’);
}
List<String> history = new Array List<> ();
 If (! history. contains(key)) {
history. add(key);
}
req. get Session (). set Attribute (‘‘history’’,
history);
return ‘‘success’’;
}
Else {
return ‘‘fail’’;
}
If (!  ’’  ‘‘ . equals (key)) {
  If (obj ! =null) {
history = (List<String>) obj;
}
}
```

## 8. CONCLUSION

In regard to personalized education resources that can promote education equity, this paper proposes a recommendation algorithm strategy based on hybrid collaborative filtering, uses high-dimensional association analysis method to mine the complex internal relationship between learners and resources, realizes personalized recommendation of education resources, and provides an integrated solution comprising recommendation and clustering.


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