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S.I. : EMERGENCE IN HUMAN-LIKE INTELLIGENCE TOWARDS CYBER-PHYSICAL SYSTEMS

Intelligent learning system based on personalized recommendation technology

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Abstract
With the continuous development of networks, web-based e-learning is changing the way people acquire knowledge. An increasing number of learners are eager to acquire more knowledge through personalized and intelligent means. Based on content recommendation and collaborative filtering recommendation algorithm, this paper proposes a hybrid recommendation algorithm which can improve the efficiency of traditional recommendation algorithm. The presented research introduces the whole process of user interest model and teaching resources model, which also designs and implements the personalized network teaching resources system prototype. Finally, in comparison with the traditional recommendation algorithm, the improved hybrid recommendation algorithm has more advantages in personalized intelligent educational resources recommendation system.

Keywords Smart education · Learning resource · Collaborative filtering · SVM

1 Introduction

With the continuous development of the network technology, web-based e-learning [1, 2] is changing the way people acquire knowledge; more and more learners are eager to acquire more knowledge through more personalized and intelligent way. In e-learning environment, with the rapid expansion of teaching resources and information, the "information overload," "resources lost" and other problems appeared one after another. How to push out the most suitable resources information for students from the huge information is the important problem to be solved as an integral part of information technology; teaching resources play an important role in education. The existed network teaching resources system cannot meet users' personalized needs. Therefore, in order to achieve the goal of personalized service to meet users' demands, personalized recommendation technology is applied to the system of online teaching resources.

(1) At present, it is difficult for users to meet their special demands using the myriads of teaching resources. To address this problem, personalized recommendation is introduced to the network

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teaching resource system, providing personalized service to learners with difference background and interest.

(2) Personalized recommendation [3] is impossible without determining user interest. A user interest model is proposed by combining explicit and implicit user tracking. First, user's background is collected from their registration data. Next, user's interest model is established by extracting user's interest from their system behavior. Finally, the model is updated with changes of user's behavior.

(3) Relevant personalized recommendation technologies are described. Considering the characteristics of the traditional teaching resources and the network-based teaching resource system, a new algorithm that combines content-based and collaborative filtering-based recommendation methods is proposed to recommend resources for the user. An intelligent education platform is implemented that supports customization of network teaching resources. Feasibility and effectiveness of the proposed algorithm is demonstrated.

2 Related theories

2.1 Personalized recommendation of teaching resources

Rapid advances in the Internet technology and the exponential increase in the amount of data available from the Internet highlight the need for personalized service. In this context, service customization has become a major issue of research on intelligent information processing and network techniques. Despite years of progress, personalized service recommendation is not very mature until now, but it has penetrated into our daily life. Currently, personalized recommendation service has been widely used in various industries, including e-commerce and search engine. In addition, it has been incorporated into the education websites to provide users with resources that they want.

According to the students' characteristics, personalized learning makes a set of personalized learning process for the students to improve their knowledge level and enable them to achieve the purpose of the learning. The radical goal of personalized learning is to develop individual students and advocate personalized learning. Personalized learning focuses on the adjustment of students' own learning state. Without the participation of the teachers, the students can still learn according to their own characteristics and needs. In this case, the development of individualized learning system needs to pay more attention to the problems existing in the learning process and guide students to improve their learning efficiency.

The so-called personalized learning refers to the implementation of educational activities according to students' personality characteristics, giving full consideration to the students' initiative, and promoting the development of the students' personality on the basis of promoting the students' comprehensive, free and coordinate development. In fact, personalized learning is an exploratory, practical and creative learning.

In essence, the personalized recommendation system involves various websites or other application systems (e.g., information retrieval) collecting user interests, analyzing user information, constructing user interest model, updating the model in real time and dynamically providing the user with contents that address their needs .

Compared with the traditional network teaching resource system, the personalized resource system has the following two advantages.

(1) Simplify retrieval of wanted information

For learners who have clear purposes, it is easy to identify their wanted resources using the retrieval system [4, 5]. But for those who browse the website randomly, it is a challenge to find the resources of their interest from the exponentially increasing information database. Incorporating personalized recommendation into the network teaching resource system makes it possible to recommend wanted resources for users based on their registration and system behavior, switching the user from a passive browser to an active learner.

(2) Motivate learners to retrieve information

Quick and convenient access to interested resources will increase learning desire and motivate them to access the system more frequently. Moreover, more records of user behavior will be accumulated in the system to improve recommendation accuracy.

2.2 User interest profile

User interest profile is a calculable description about the information of the user interest. It builds a model to record and manage the user's interest, describe the user's potential interest requirement, and record the user's behavior.

The main purpose of the user interest profile is to predict the user's intention in a certain environment, and to provide active help to the user, so that the user can quickly and accurately find the needed resources from the massive information resources.

The key of personalized recommendation is to establish user interest profile. Only by accurately describing user's interest, we can provide personalized teaching resources recommendation service according to user's interest. User interest profile firstly needs to attract user's interest, which can be done through user registration information, download, collection, evaluation as well as other behaviors to collect user interest-related behavior information. The appropriate method is then adopted to establish the user interest model. Finally, the user interest profile is updated with the change of user interest preference.

2.2.1 Obtaining user's interest

The process of a user's interest tracking involves obtaining user's interest. This process generally includes two aspects: explicit tracking and implicit tracking.

Explicit tracking refers to the user filling out the form by entering personal information or answering the questions raised by the system, taking part in the modeling process directly (e.g., personal information and the evaluation of resources that the user filled when registered).

Implicit tracking does not require users to provide information. All tracking is done automatically by the system. Users browsing the web, clicking the mouse, marking bookmarks, dragging scrollbars and other behavior records can indicate the potential interest of the user. The research shows that browsing pages, marking bookmarks and dragging scroll bars can effectively reveal the interests of users, while simple actions (such as clicking the mouse) cannot effectively do so.

2.2.2 Representation of user interest profile

The representation of user interest model needs to reflect the real information of the user and be computable, but it also restricts the choice of user modeling methods to some extent. There are many representations based on different requirements of personalized recommendation systems. Few of such examples are representation based on vector space model, representation based on evaluation matrix and so on.

(1) Representation based on vector space model

At present, vector space model [6, 7] is a popular representation method of user interest model. VSM is the spatial representation of text document and most commonly used in representation methods. In this model, a text is regarded as a set of feature items, and the text is represented as an n dimension of vector space. Each dimension corresponds to a feature item in the whole text set. The advantage of vector space model is that the text is represented as a vector by feature terms and weights, so that the calculation of the correlation between texts can be transformed into the operation of the correlation between vectors. The user interest model using this method is expressed as an n-dimensional feature vector. In this method, the user interest model is expressed as an n-dimensional feature vector $\{(k_1,w_1), (k_2, w_2),\ldots (k_n, w_n)\}$. Each dimension of the n-dimensional eigenvector is composed of a keyword and a corresponding weight. Weights may be real or Boolean values, indicating whether the user is interested in a resource including the degree of the interest. Vector space model uses user interest feature words combination to describe user interest and express the importance of each feature word in user interest model.

(2) Representation based on evaluation matrix

The method of representing the user–item evaluation matrix is a $R_{m\times n}$ matrix to express the user interest model, where m is the number of users in the system and n is the number of items. Each element r_{ij} in the matrix represents user i' evaluation of item j and generally an integer value in a real range (such as 1–5 min, and the larger the score is, the higher the user's preference for the item is; a null value indicates that the user did not rate the item). Most of the systems based on evaluation matrix are personalized recommendation systems based on collaborative filtering.

3 System design

The proposed system for customized recommendation of teaching resources serves students, teachers and other staff, providing them with multimedia resources that they need.

3.1 The construction of user interest model

Determining user interest is a process of collecting feedback about user's interest. This process is either explicit or implicit. In order to accurately determine user's interest, the proposed system collects static data on user's interest through explicit feedback and dynamic data on user's interest through implicit feedback. The constructed user interest model is shown in Fig. 1. During registration, the new user manually inputs their basic information and interest, which is stored in the database table of user information. The user interest model is initialized using user registration data.

The system collects and tracks the characteristics of the registered users through implicit feedback. In detail, the characteristic words that can represent resources of user's interest are determined based on downloading. These words can be treated as the source of user's interest to initialize the original user interest model.

For the teaching resource system, user interest in some subjects is stable, and it is also possible for the user to become interested in other subjects due to additional needs. Hence, the proposed system keeps updating the user

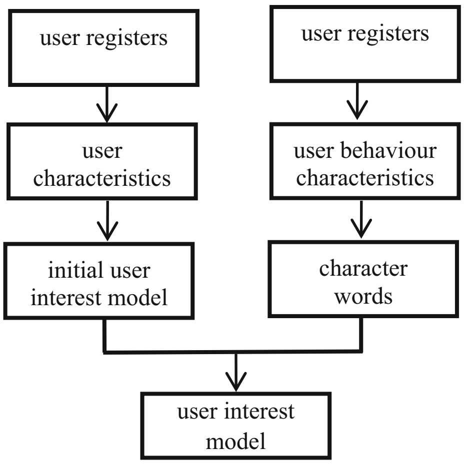

Fig. 1 The user interest model

interest model based on downloading, resource evaluation and other user behaviors. The accuracy of the user interest model is thus improved.

3.2 Personalized recommendation algorithm

Comparison of various recommendation algorithms [8–10] indicates that the item-based CF method is more suited for the proposed system. The core of the customized network teaching resource system is the recommendation module, which largely determines system performance. The recommendation module is dependent on the choice of an appropriate recommendation algorithm, which is expected to be incorporated into the application, reduce possible problems, improve recommendation quality and alleviate system complexity. Collaborative filtering is the most extensively studied and used recommendation technique. It is very efficient and based on the interest of neighbors. That is, user similarity is determined considering the extent to which the resource is liked by other users. The evaluation score of user for a resource is determined considering the extent to which the resource is liked by similar users. With these data, the system is able to make customized recommendation accurately. The CF recommendation method can be classified into three categories: user based, item based and model based.

In order to address the sparsity problem of the item-based CF method, we combine it with content-based recommendation. That is, the level of user interest in the non-evaluated resource is first computed through content-based recommendation. The calculation result is defined as the predicted evaluation score of user for the non-evaluated resource, constituting a user–resource evaluation matrix. Finally, the evaluation matrix is used to compute the item-based similarity, generating the top-N recommendations.

(1) Input user–resource evaluation matrix

The input user–resource evaluation matrix R $(m,\ n)$ is derived from the user's evaluation of resource and the system-generated user interest in resource, where the row denotes the m users, column denotes the n resources, and the element $R_{i,j}$ denotes the score of user i for resource j. The user allocates an appropriate rank to the resource, and this determines the contribution of resource to the user. The higher the rank, the more interested the user is in the resource.

$$R(m,n) = \begin{bmatrix} R_{1,1} & R_{1,2} & \ldots & R_{1,n} \\ R_{2,1} & R_{2,1} & \ldots & R_{1,n} \\ \vdots & \vdots & \vdots & \vdots \\ R_{m,1} & R_{m,2} & \ldots & R_{m,n} \end{bmatrix} \tag{1}$$

The list of resource evaluation scores and the list of predicted scores need to be updated whenever the user assesses a new resource or changes assessment of an old resource. First, the list of resource evaluation scores is retrieved to check whether the resource has been evaluated. If so, the new assessment will replace the old one. Otherwise, it should be inserted as the user's evaluation of resource. Afterward, the new assessment is used to recompute user interest in non-evaluated resources. In this way, the list of evaluation scores is updated to guarantee the accuracy of the user–resource evaluation matrix.

(2) Compute the nearest neighbor

The Pearson correlation coefficient is used to compute the correlation between items i and j.

$$\mathrm{Sim}(i,j) = \frac{\sum_{u \in I_{ij}} \left(R_{u,i} - \vec{R_i}\right)\left(R_{u,j} - \vec{R_j}\right)}{\sqrt{\sum_{u \in I_{ij}} \left(R_{u,i} - \vec{R_i}\right)^2} \sqrt{\sum_{u \in I_{ij}} \left(R_{u,j} - \vec{R_j}\right)^2}} \tag{2}$$

where I_{ij} denotes the set of users who have assessed items i and j, $R_{u,i}$ denotes the evaluation score of user u for item i, and $\vec{R_i}$ and $\vec{R_j}$ denote the average score of items i and j. An appropriate value of k is then selected to extract the most similar k items as the set of nearest neighbor [11–13] of i.

(3) Make recommendation

The predicted score of the target user u for the item $P_{u,j}$ is:

$$P_{u,j} = \frac{\sum_{j=1}^{k} \mathrm{Sim}(i,j) \times R_{u,j}}{\sum_{j=1}^{k} \mathrm{Sim}(i,j)} \tag{3}$$

where k denotes the set of resources in the list of nearest neighbor which are most similar to the item i, $Sim(i,\ j)$ denotes the similarity between items i and j, $R_{u,j}$ denotes the evaluation score that the content-based algorithm predicts using the existing evaluation score of u for j.

After the predicted evaluation score of u for different items is computed, the top N items with the highest scores are defined as the top-N recommendation set.

4 Analysis and design of recommendation strategy

The improved algorithm of personalized recommendation based on mixed recommendation is built upon traditional collaborative filtering algorithm and content-based recommendation. This algorithm introduces user's existing interest model, potential user's interest, fusion interest and so on. Next, the implementation of the improved personalized recommendation algorithm based on hybrid recommendation algorithm will be described in detail.

(1) Establishing the Existing User Interest Model (EUIM)

For any user in the system, the key words $(f_1, f_2\ldots\ldots f_k)$ of the user's information of interest resources F, where k represents the k keywords of the resource, are calculated by text vectorization and obtain the weight vector F_1. The mathematical formula can be expressed as follows:

$$\mathrm{EM} = (w1_1, w1_2\ldots\ldots w1_j\ldots\ldots w1_k) \tag{4}$$

where $w1_j$ denotes the weight of the keyword f_j in the EUIM.

(2) Building Potential User Interest Model (PUIM)

For the users in the system, the related interest resources in the neighbor set with high correlation degree are pushed to the target users by the collaborative filtering recommendation algorithm, and then, the weight vector of the resource keywords is obtained. The mathematical formula can be expressed as follows:

$$\mathrm{PM} = (w2_1, w2_2\ldots\ldots w2_j\ldots\ldots w2_k) \tag{5}$$

where $w2_j$ denotes the key words f_j of F in the PUIM.

(3) Building Fusion User Interest Model (FUIM)

For the user in the system, the EUIM and PUIM are computed to form a new weight vector and finally establish the FUIM. The mathematical expression of the model is as follows:

$$\mathrm{FM} = (w3_1, w3_2\ldots\ldots w3_j\ldots\ldots w3_k) \tag{6}$$

where $w3_j$ represents keyword f_j weight of F in FUIM.

4.1 Construction method of user's existing interest model

We take text vectorization of the given set of educational resources $D = \{d_1, d_2\ldots d_i\ldots d_n\}$ and the resources key word $f = \{f_1, f_2\ldots f_i\ldots f_k\}$. Key word matrix sequence and resource d_i in educational resource set correspond to each other to form spatial vector model. $d_i = \left(w_{i1}, w_{i2}\ldots w_{ij}\ldots w_{ik}\right)$, where w_{ij} represents the weight of the key word f_j in resources of d_i. In the case of $w_{ij} = 0$, f_j does not exist in resource d_i. The mathematical formula of the resource set weight matrix is as follows:

$$DM = \begin{bmatrix} w_{11} & w_{12} & \ldots & w_{1k} \\ w_{21} & w_{22} & \ldots & w_{2k} \\ \ldots & \ldots & \ldots & \ldots \\ w_{n1} & w_{n2} & \ldots & w_{nk} \end{bmatrix} \tag{7}$$

The common methods of weight expression are: frequency representation, TF-IDF representation and Boolean representation. This paper mainly adopts the method of TF-IDF.

4.2 Construction method of user's potential interest model

The potential user interest model is different from the existing user interest model. It cannot be retrieved through the previous user comments or history. Because of the large number of educational resources, the recommended list contains not only the relevant resources in the user interest model, but also the potential interest resources of the user. In this paper, a collaborative filtering method is proposed to recommend the interest of similar user groups to target users, which can be used to represent the potential interests of target users.

In the traditional collaborative filtering and the hybrid similarity calculation, the users only use the users to score the resources, which cannot fully explain the similarity of the users.

For example, in an educational resource recommendation system, the description or type of a possible file for the same resource is different. Several users are interested in the resource, but the resource number is not the same. In collaborative filtering algorithms, these users who browse different resources can hardly be classified as similar users. In view of the above problems, this paper uses a form degree calculation method of mixed behavior and content. The user similarity is extended to two parts: score similarity $(\mathrm{sim}(_{\mathrm{grade}}(u, v)))$ and content similarity $(\mathrm{sim}(_{\mathrm{content}}(u, v)))$.

Suppose user u's resources rating set is shown as follows:

$$D_u = \{d_{u1}, d_{u2}, \ldots, d_{ui}, \ldots d_{um}\}$$

$$\mathrm{EM}_u = \left\{w1_{u1}, w1_{u2}, \ldots, w1_{uj}, \ldots w1_{uk}\right\}$$

Resources rating set for user v is shown as follows:

$D_v = \{d_{v1}, d_{v2}, \ldots, d_{vi}, \ldots, d_{vm}\}$

$\mathrm{EM}_v = \{w1_{v1}, w1_{v2}, \ldots, w1_{vj}, \ldots, w1_{vk}\}$

The score similarity of users u and v is as follows:

$$\mathrm{sim}_{\mathrm{grade}}(u,v) = \frac{\sum_{i \in D_u \cap D_v} \frac{1}{\log(1+|U(i)|)}}{\sqrt{|D_u||D_v|}} \tag{8}$$

where U(i) denotes the user set that commented on the resources d_i.

The content similarity calculation formula of users u and v is shown as follows:

$$\mathrm{sim}_{\mathrm{content}}(u,v) = \frac{EM_u \cdot EM_v}{|EM_u| \cdot |EM_v|} \tag{9}$$

The mixed formula of this paper is shown as follows:

$$\mathrm{sim}(u,v) = \beta \mathrm{sim}_{\mathrm{grade}}(u,v) + (1-\beta)\mathrm{sim}_{\mathrm{content}}(u,v) \tag{10}$$

The coefficient β is a weighting factor determined by experiment, which is a similarity percentage parameter, and its value range is 0–1.

When $\beta = 0$, the similarity calculation only considers the content feature data, and when $\beta = 1$, the similarity calculation only considers the score feature data. The score behavior similarity and content similarity of users u and v are calculated, and then, the weighted factor β is used to combine the two similarity degrees to obtain the mixed user similarity. The similarity between the target user and all other users is obtained, and the most similar user and h user are selected as the similar user group; and the similar user group is recommended to the target user by collaborative filtering. The potential interest model of the target user is obtained.

Let the similar user group be $U_u = \{v_1, v_1, \ldots, v_i, \ldots, v_k\}$ of user u, and the similarity between user u and any user v_i in the similar user group is $\mathrm{sim}(u, v_i)$. The existing user interest model of v_i is $\mathrm{EM}_{v_i} = \{w1_{v_i1}, w1_{v_i2}, \ldots w1_{v_ij}, \ldots w1_{v_ik}\}$. Calculate the weights of the feature term f_i of the user's model of potential interest using the following formula:

$$w2_{uj} = \sum_{v_i \in U_u} \frac{\mathrm{sim}(u, v_i)}{\sum_{v_i \in U_u} \mathrm{sim}(u, v_i)} \cdot w1_{v_ij} \tag{11}$$

4.3 A method of constructing mixed user interest model

After obtaining the existing interest model (EUIM) and the potential interest model (PUIM) of the target user, the weights of the feature words of the two interest models are merged, and the mixed interest of the target user can be obtained. Then, we calculate the similarity between the weight vector of the main feature words of candidate educational resources and FUIM, and compare the calculated results with the set threshold; that is, the final recommended results are obtained.

Set the EUIM of user u: $\mathrm{EM}_u = \{w1_{u1}, w1_{u2}, \ldots w1_{uj}, \ldots w1_{uk}\}$, set the PUIM of user u: $\mathrm{PM}_u = \{w2_{u1}, w2_{u2}, \ldots w2_{uj}, \ldots w2_{uk}\}$, set the FUIM of user u as follows: $\mathrm{FM}_u = \{w3_{u1}, w3_{u2}, \ldots w3_{uj}, \ldots w3_{uk}\}$, candidate resource $d = \{wd_1, wd_2, \ldots wd_j, \ldots wd_m\}$.

$$w3_{uj} = \max(w1_{uj}, w2_{uj}) \tag{12}$$

In Eq. 12, the max function represents the selection of a large value of $w1_{uj}$ and $w2_{uj}$ that is recommended to the user.

5 Experimental result and discussion

5.1 Experimental data source

The data used in this experiment are provided by the web learning platform (http://evaluate.guoshi.com/publishg/). We use 1-month log file once again and extract the data of scholars' access behavior, achieving the number of scholars 540, the number of online data 2780, and nearly 160,000 records. In order to better evaluate the results, 80% of the data set is taken as the training data set and the other as testing data set, respectively.

5.2 System evaluation metrics

In order to evaluate feasibility and effectiveness of the recommendation algorithm used in the customized network teaching resource system, the proposed hybrid recommendation method is compared with the traditional item-based model and the collaborative filtering model. Evaluation metrics include recall, precision and F measure.

Mean absolute error (MAE) refers to the mean of the absolute value of the difference between the actual user score of resource and the predicted score.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |q_i - p_i|}{n} \tag{13}$$

where p_i denotes the user-predicted evaluation score, q_i denotes the actual user score, and the set is $\{q_1, q_2, q_i, \ldots, q_n\}$.

5.3 Experimental results and analysis

In formula (12), the parameter β is a similarity proportional parameter based on time weight function, and its size of gathering will directly affect the effect of recommendation.

Therefore, repeated experiment is needed to determine the best value, to ensure that the recommendation result is optimal, and the value interval of β is [0–1]. In this experiment, the values of β are set from 0 to 1, and the growth value is 0.1. The experimental results are shown in Fig. 2.

As can be seen from the above figure, when β is 0.6, we can obtain the smallest recommendation error *MAE* value and the highest accuracy of recommendation. When gathering is 0 and 1, it represent, respectively, that the similarity calculation only considers the content feature data and the rating feature data. But the recommendation performance is not best, so we take β 0.6 in the following experiment.

The data obtained in this section are applied, respectively, to common collaborative filtering algorithms, item-based collaborative filtering algorithm, collaborative filtering algorithms based on K-means and MRP algorithm proposed in this paper and analyze experimental results. The effectiveness of the new algorithm is verified by comparing several common collaborative filtering algorithms. The MAE values of various filtering methods are obtained by selecting different nearest neighbor numbers. The experimental results are shown in Fig. 3.

From Fig. 3, we can see that the collaborative filtering algorithm based on hybrid recommendation strategy is better than the traditional ones in MAE performance. And when the number of nearest neighbors is about 30, the value of MAE will not change. It is proved that the algorithm will reach the best state when the number of nearest neighbors is about 30. It is proved by comparison that the new proposed algorithm plays a certain role in improving the accuracy of recommendations.

In order to verify the accuracy of this algorithm, the precision values of these algorithm are compared with those of the above algorithms. The results of the experiment are shown in Fig. 4.

The experimental results show that the accuracy of the proposed algorithm is higher than that of the traditional

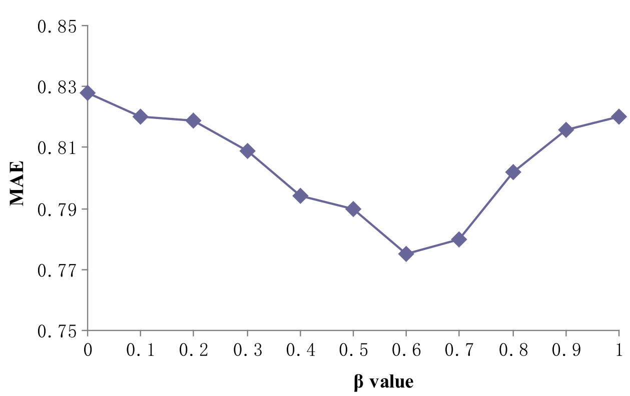

Fig. 2 The experimental results parameter β

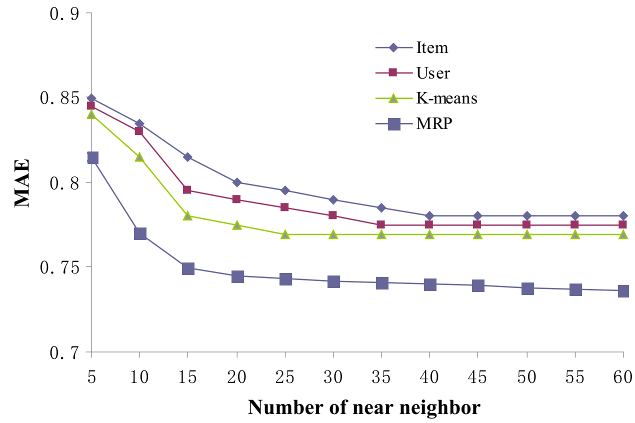

Fig. 3 The experimental MAE result

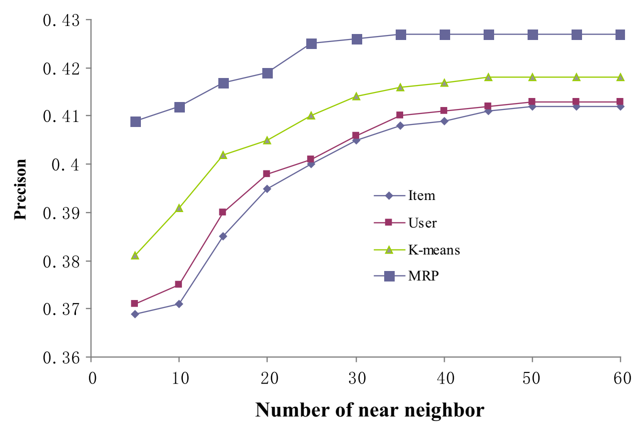

Fig. 4 The experimental precision result

collaborative filtering algorithm, and the validity of the algorithm is verified.

6 Conclusion

With the rapid development of the Internet and science and technology, more and more people acquire knowledge and skills to through the network. “Information overload” has become an important factor restricting the development of online learning. In this paper, we studied a popular personalized recommendation technology and introduced the principle, flow and strategy of collaborative filtering in detail. On the basis of extensive research on the literature of recommendation technology, we studied the existing problems in collaborative filtering recommendation technology according to teaching resources and the characteristics of users, and put forward some solutions.

Personalized recommendation service of teaching resources has wild prospects. Although this paper has done some research on the personalized recommendation, in spite of the limitations of time and conditions, there are still some problems that have not been solved. The main following work includes: the recommendation algorithm only makes improvement in the aspect of cold start, and the new project problems remain unsolved. The system can only be recommended to users through the latest resources, with low personalized degree, and the further research is needed in the following work.

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