

## Design of resource matching model of intelligent education system based on machine learning

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### Abstract

Aiming at the problems of cold start and data sparsity in the process of traditional education resource matching, a resource matching model based on machine learning is designed to get the best resource matching result of a better intelligent education system. Firstly, the similarity hierarchical weighting method is used to calculate the user and resource feature similarity by K-means. Then, the target resources and the nearest neighbor are predicted, and the resources with the highest score to match the target user can be selected according to the nearest neighbor score results. The test results show that the recall rate and coverage rate of the matching results of this model are higher than 98% and 96%, which proves that this model can effectively improve the problems of cold start of resource matching and data sparsity.

**Keywords:** Machine learning, Intelligent education system, Resource matching, K-means clustering.

Received on 16 December 2021, accepted on 05 February 2022, published on 10 February 2022

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doi: 10.4108/eai.10-2-2022.173381

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### 1. Introduction

With the rapid development of information technology and the Internet, information resources are growing exponentially. In the face of serious overload of information, it is difficult for users to quickly locate useful information resources, so they spend a lot of time searching for the content they want. This makes the matching method come into being, which can provide personalized recommendation services for different users according to their preferences [1].

In the information age, the contradiction between the mass of educational information resources and learners' rapid access to educational information resources to meet their personalized learning needs has become increasingly prominent. Learners need to spend a lot of time and energy searching and identifying resources, which greatly increases the learning burden of learners, resulting in the evolution of ubiquitous learning into ubiquitous search [2].

Different information literacy leads to different degrees of advantages and disadvantages of educational information resources collected by different learners. Learners with higher information literacy can obtain high-quality resources, while learners with lower information literacy find it more difficult to find resources suitable for themselves, which gradually aggravates "the superior are better and the poor are poorer". Universal resources are difficult to meet the personalized learning needs of all learners. Non-mainstream high-quality resources are often permanently buried due to the prevalence of mainstream resources, resulting in a serious waste of resources [3]. The stereotyped learning path and learning system are easy to ignore learners' cognitive laws, cause learners' cognitive overload and learning loneliness, and have an impact on learners that can not be ignored. The use of information technology makes every learner equally enjoy educational information resources, promotes educational equity, and turns ubiquitous learning into ubiquitous search. Mainstream resources are not applicable to all learners, and non-mainstream educational information resources may only be

some minority learning resources suitable for specific learners [4].

Among the massive educational information resources, it is the demand of modern learners to quickly obtain and effectively use high-quality personalized educational information resources. It is more and more difficult for learners to accurately find target information. When learners' increasingly diverse learning needs are not met, it will inevitably mean the emergence of new information service methods and tools [5]. As an effective means to alleviate the "Information trek" in the era of big data, the matching service of educational information resources has become the research object of many scholars and experts. According to the characteristic information of learners and resources, it should push the appropriate resources to the appropriate learners, realize the intelligent push of resources, and solve the problem of "excess resources" caused by resource pulling. Reasonable educational information resource matching service of intelligent education system can not only save learners' time and energy cost of obtaining resources, but also effectively improve the utilization of educational information resources [6]. Therefore, more and more researchers pay attention to the on-demand active matching service of educational information resources.

At present, the research on active matching service of educational information resources in the field of education has achieved a lot of results. For example, the personalized information push service of the library and the personalized customization of CNKI digital library can push books or learning resources related to their majors or similar interests to learners. However, the application of educational information resources to actively promote services is not extensive and in-depth, and the effect is not ideal [7]. High quality educational information resources are not fully utilized, which is largely due to the blind spots in the selection and push of resources, the ways and means for learners to obtain high-quality resources are hindered, or the resources pushed by the system are not the resources that learners want, which is difficult to meet individual learning needs, resulting in aversion. The matching service in the intelligent education system can not only meet the needs of learners to retrieve information, but also record learners' personal information and behavior information, accurately locate their personalized demand characteristics, push high-quality educational information resources to them, and provide real personalized services [8].

At present, there are many researches on resource matching. Reference [9] believes that educational resources should highlight the core values of "digitization" and "serving education and teaching". In the process of optimal allocation of educational resources, it can draw theoretical support from niche effect, long tail effect, restrictive factors and ecological development chain, and thus construct an optimal matching ecosystem model of educational resources, which highlights the principle of sustainable "evolution" of allocation of educational resources. In

reference [10], the relationship between learners and learning resources is fully considered, and the personalized learning model of resource matching is studied. This resource matching process can meet learners' personalized learning needs, but it has the defect of poor matching accuracy. Reference [11] constructs an online education and teaching resource matching and recommendation model based on subject words. Based on the user's historical learning records, the model extracts the user's main search subject words and matches them with the current query keywords, so as to finally realize resource matching and recommendation. Although the model has high recommendation performance, it does not consider the impact of massive noise in the network.

In addition, reference [12] applies machine learning technology to the learning recommendation process. This method analyzes from the perspectives of learning content, collaborative filtering and knowledge mixing, and realizes the effective matching and recommendation of e-learning resources through intelligent learning, data set construction, intelligent matching and evaluation process. However, this method has the disadvantage of poor recommendation accuracy.

The machine learning technology mentioned in reference [12] takes the computer as a tool and is committed to simulating human learning methods in real time, and divides the existing content into knowledge structures to effectively improve learning efficiency. Machine learning is closely related to computational statistics, focusing on the use of computers for prediction. Data mining is an important content in the field of machine learning, which focuses on exploratory data analysis and unsupervised learning.

In view of the shortcomings of the above traditional resource matching methods, this study designs a resource matching model of intelligent education system based on machine learning, and selects K-means clustering algorithm to process the resources in intelligent education system, so as to achieve accurate and efficient matching of intelligent education system resources. The specific design ideas are as follows:

(1) According to the characteristics of the learners, and the characteristics of the learning resource description, and fusion concept difference functions, the difference of ability and two objective function the design of the final match the objective function, the use of the function of the objective function and small differences in resources combination of search, so as to make the combination of resources is more conform to the requirements of the learners.

(2) The user feature similarity and resource feature similarity are calculated by using the similarity hierarchical weighting method, and k-means clustering is implemented for feature information to form feature cluster.

(3) Predict the nearest neighbor of the target resource and the target user. According to the scoring result of the nearest neighbor, select the resource with the highest score and match it to the target user. Strengthen the relationship

between resources or users to make the final matching result more accurate.

(4) According to the experimental results, when the  $K$  value of the K-means clustering algorithm is 7, the best resource matching result of the intelligent education system can be obtained. The recall rate and coverage rate of the model matching results in this paper are higher than 98% and 96% respectively, which proves that it can effectively improve the problems of cold start of resource matching and data sparsity.

## 2. Design of resource matching model

### 2.1 Question description

#### Description of learner's characteristics

It is assumed that  $K$  different learners study a course together. In order to match different learners with appropriate learning resources in the intelligent education system, the existing knowledge and ability, learning objectives, learning time and other factors of learners must be considered. These characteristics are expressed by the following parameters:

- (1)  $L_i (1 \leq i \leq K)$  stands for a learner;
- (2)  $A_i (1 \leq i \leq K)$  represents the ability level of learners, where  $A_i$  is the ability level of learners  $L_i$ ;
- (3)  $H_i (1 \leq i \leq K)$  represents the learner's preset learning goal, where  $H_i$  is the learning goal of learner  $L_i$ ;
- (4)  $T_{-}L_i (1 \leq i \leq K)$  represents the lower limit of the expected learning time when  $L_i$  is learning a course;
- (5)  $T_{+}U_i (1 \leq i \leq K)$  represents the upper limit of the expected learning time when  $L_i$  is learning a course.

#### Description of characteristics of learning resources

The learning resources of the intelligent education system can include text, video, audio and other digital resources that can be reused. The relevant characteristic parameters of the learning resources of the intelligent education system are defined as follows:

- (1)  $LC_i (1 \leq i \leq N)$  represents a learning resource contained in a course in the intelligent education system, assuming there are  $N$ .
- (2)  $C_i (1 \leq i \leq N)$  represents a learning knowledge point within a learning range in the intelligent education system. It is assumed that there are  $M$  knowledge points in total.

(3)  $D_i (1 \leq i \leq N)$  represents the difficulty of a learning resource in the intelligent education system, and  $D_i$  represents the difficulty of  $LC_i$  this resource.

(4)  $R_i (1 \leq i \leq N)$  represents the learning concept contained in a learning resource in the intelligent education system. Where  $R_i = \{r_{i1}, x_{i2}, x_{i3}, \dots, x_{ij}\}$ ,  $1 \leq j \leq M$ . If  $r_{ij} = 1$ ,  $LC_i$  includes  $C_m$ ; Otherwise,  $LC_i$  does not contain  $C_m$ .

(5)  $T_i (1 \leq i \leq N)$  represents the time required for learning this  $LC_i$  resource in the intelligent education system.

According to the characteristics of learners, learning resources with moderate difficulty can be matched so as to improve learning efficiency by meeting the learning needs of students [13]. This is also the focus of this study.

#### Constructing objective function

Decision variable  $x_{ij}$  is introduced,  $1 \leq i \leq N$ ,  $1 \leq j \leq K$ , and  $x_{ij}$  needs to meet:

$$x_{ij} = \begin{cases} 1, & LC_i \text{ Recommend to } L_j \\ 0, & \text{other} \end{cases} \quad (1)$$

Based on the three tasks in the feature description of learning resources, the following objective functions are constructed:

$$F_1 = \frac{\sum_{n=1}^N \sum_{m=1}^M x_{nk} |r_{nm} - h_{im}|}{\sum_{n=1}^N x_{ni}} \quad (2)$$

$$F_2 = \frac{\sum_{n=1}^N x_{nk} |D_n - A_i|}{\sum_{n=1}^N x_{ni}} \quad (3)$$

$$F_3 = \max \left( T_{L_i} - \sum_{n=1}^N t_n x_{ni}, 0 \right) + \max \left( 0, \sum_{n=1}^N t_n x_{ni} - T_{L_i} \right) \quad (4)$$

$$F_4 = \sum_{m=1}^M h_{im} \left| \sum_{n=1}^N x_{ni} r_{nm} - \frac{\sum_{n=1}^N \sum_{m=1}^M x_{ni} r_{nm}}{\sum_{m=1}^M h_{im}} \right| \quad (5)$$

Where,  $1 \leq i \leq K$ , the function  $F_1$  is called the concept difference function, which is used to calculate the difference between the relevant knowledge points contained in the learning resources in the intelligent education system and

the learners' predetermined learning objectives;  $F_2$  is called the ability difference function, which is used to calculate the gap between the average difficulty of learning resources recommended by the intelligent education system and the ability of learners [14]; The objective function  $F_3$  ensures that the learning resource time recommended by the learning intelligent education system is within the learners' expected learning time; the objective function  $F_4$  is used to balance the proportion of knowledge points contained in multiple learning resources in the intelligent education system. The four functions are integrated to obtain the final fitness function, and the above four objective functions are given different weight values ( $w_1, w_2, w_3, w_4$ ) to obtain the final resource matching model of intelligent education system. The objective function is:

$$\min F(x) = \sum_{i=1}^4 w_i F_i \quad (6)$$

The basic idea of the objective function of the resource matching model for intelligent education system is to find out the resource combination with little difference from the objective function. In this way, the resource combination of intelligent education system is more in line with the requirements of learners.

The above contents according to the characteristics of the learners, and describes the characteristics of the learning resources, on this basis, the fusion concept difference functions, the difference of ability and two objective function the design of the final intelligent education system resources matching model objective function, its aim is to search and target function differences small resources combination, so as to make the combination of resources is more conform to the requirements of the learners.

## 2.2 Similarity calculation

The similarity hierarchical weighting method is used to calculate the user feature similarity and resource feature similarity. The traditional matching algorithm takes less account of the user's feature similarity when calculating the user similarity. Therefore, the traditional personalized matching algorithm is difficult to accurately find the nearest set of target users when the user's historical behavior records are few, resulting in low matching quality. For the above reasons, the user feature similarity is introduced into the user similarity calculation. The user similarity is defined as the weighted sum of the user feature similarity and the user behavior similarity. The user similarity applied to the resource matching model of intelligent education system is expressed as:

$$Sim_c(i, j) = aSim_r(i, j) + (1-a)Sim_h(i, j)_g \quad (7)$$

Where,  $Sim_r(i, j)$  represents the feature similarity between user  $i$  and user  $j$ ,  $Sim_h(i, j)$  represents the behavior similarity between user  $i$  and user  $j$ ,  $a$  is the weight factor, when the user is a new user of the intelligent education system,  $a$  takes 1, representing that the user has no historical behavior data of the intelligent education system, which effectively alleviates the cold start problem during resource matching.

User feature similarity  $Sim_r(i, j)$  is expressed as follows:

$$Sim_r(i, j) = \frac{N_{(u_{ri}=u_{rj})}}{N_{Sum}} \quad (8)$$

Where,  $u_{ri}$  represents the  $r$ -th feature of user  $i$ , and  $Sum$  is the union of feature attributes of user  $i$  and user  $j$ ;  $N_{(u_{ri}=u_{rj})}$  represents the number of elements in the intersection of feature  $r$  between user  $i$  and user  $j$ ;  $N_{Sum}$  represents the number of elements in the union of characteristic attributes of user  $i$  and user  $j$  [15].

User behavior similarity is defined as the weighted sum of resource basic characteristics and resource score, which is expressed as follows:

$$Sim(i, j)_h = \alpha Sim(i, j)_b + \beta Sim(i, j)_g \quad (9)$$

Where,  $\alpha$  and  $\beta$  represent the weights, and  $\alpha + \beta = 1$ .  $Sim(i, j)_b$  represents the similarity of basic resource features between user  $i$  and user  $j$ ;  $Sim(i, j)_g$  indicates the similarity between user  $i$  and user  $j$  in scoring resources.

The similarity of basic characteristics of resources is expressed as follows:

$$Sim(i, j)_b = \frac{E_{(X_{bi}=X_{bj})}}{E_{Sum}} \quad (10)$$

Where  $X_{bi}$  represents the  $b$ -th basic characteristic information of user  $i$  resources;  $Sum$  is the union of basic characteristic information of user  $i$  and user  $j$  resources;  $E_{(X_{bi}=X_{bj})}$  represents the number of attribute intersection elements of user  $i$  and user  $j$  for the same resource;  $E_{Sum}$  represents the number of union elements of user  $i$  and user  $j$  resource attributes [16].

The cosine angle correlation ignores the score difference between different users, and an improved correlation calculation method, the modified cosine angle correlation, is proposed. The modified cosine angle correlation subtracts

the average score of all users on the recommended items based on the angle cosine correlation.

The cosine angle correlation expression is as follows:

$$\begin{aligned} Sim(i, j)_g = \cos(\vec{i}, \vec{j}) &= \frac{\vec{i} \cdot \vec{j}}{\|\vec{i}\| \times \|\vec{j}\|} \\ &= \frac{\sum_{X \in I_{ij}} (r_{i,X} - \bar{r}_X)(r_{j,X} - \bar{r}_X)}{\sqrt{\sum_{X \in I_{ij}} (r_{i,X} - \bar{r}_X)^2} \sqrt{\sum_{X \in I_{ij}} (r_{j,X} - \bar{r}_X)^2}} \end{aligned} \quad (11)$$

Where,  $i$  and  $j$  represent users;  $X$  represents resources;  $I_{ij}$  represents the set of resources scored jointly by user  $i$  and user  $j$ ;  $r_{i,X}$  represents the user  $i$ 's score on resource  $X$ ;  $r_{j,X}$  indicates the user  $j$ 's rating of resource  $X$ ;  $\bar{r}_X$  represents the average score of all users on the resource  $X$  score. If the user has no score,  $X$  is 0.

In the above content, the hierarchical weighting method of similarity is adopted to calculate user feature similarity and resource feature similarity, laying a foundation for subsequent resource matching.

## 2.3 K-means clustering algorithm

K-means clustering is not only the most classical, but also one of the most popular and commonly used clustering algorithms in machine learning. In this algorithm, the minimum square error is used to describe the sample tightness between clusters, and the data set is iteratively divided by the preset cluster number  $k$  to form cluster clusters.

Assuming that the sample data set is represented by  $D = \{X_i | X_i \in R^m, i = 1, 2, \dots, n\}$ , the sample data dimension and sample set size are represented by  $m$  and  $n$  respectively. Assuming that the category of the sample set is represented by  $C = \{c_k | c_k \in R^m, i = 1, 2, \dots, k\}$ , the number of categories and the initial cluster center are represented by  $K$  and  $C^0$  respectively. The distance between samples is generally calculated by European distance [17], and the calculation formula is as follows:

$$Dist(X_i, X_j) = \sqrt{(X_i - X_j)^T (X_i - X_j)} \quad (12)$$

Cluster center expression is:

$$c_k = \frac{1}{n_k} \sum_{x_i \in c_k} x_i \quad (13)$$

The basic idea of K-means clustering is: firstly, randomly select the clustering center according to the preset  $K$  value and algorithm, and repeatedly iterate to select the samples in the class. If the objective function is optimal (i.e. minimizing the square error and minimizing the  $E$  value), the iteration ends. The clustering results obtained by the

algorithm are characterized by small sample distance within the cluster and large sample distance between clusters.

The expression for minimizing the square error is as follows:

$$E = \sum_{i=1}^k \sum_{j=1}^{n_j} Dist(X_j, c_i) \quad (14)$$

The steps of K-means clustering algorithm is:

Input:  $K$ : number of clusters;  $D$ : a dataset containing  $n$  objects.

Output: set and class number of  $K$  clusters;

Methods:

- 1) Select  $K$  random points in  $D$  as the starting clustering centers;
- 2) Calculate a mean value and assign the corresponding objects to the corresponding clusters [18];
- 3) Move the cluster center, and the moving position is at the average value of the cluster set;
- 4) The value of the objective function  $E$  does not change, that is, it reaches the optimum.

In the above process, the resource features and user features are clustered by means of K-means clustering, so that while the distance between samples in the cluster decreases, the distance between samples in the cluster increases, thus forming the feature cluster.

## 2.4 Build resource matching model

By clustering resources, the spatial dimension of nearest neighbor search is reduced, the resource matching efficiency is improved, and the sparsity of user resource scoring matrix and cold start problem are reduced. The similarity calculation method of formula (11) is used to calculate the similarity of resources in resource set  $A[n] = \{a_1, a_2, \dots, a_n\}$ , the resources are clustered by K-means clustering algorithm, and the resources are divided into  $K$  clusters  $\{A_1, A_2, \dots, A_k\}$ , so that  $A_1 \cup A_2 \cup \dots \cup A_k = A$  and  $A_i \cap A_j = \emptyset$ .

If  $i, j \in [1, k]$ , let the resource set  $S_{uv} = A_u \cup A_v$  in which  $u$  is not scored in the union set  $S_{uv} = A_u \cup A_v$  of users  $u$  and  $v$  evaluated resources. For  $i \in N_u$ , if  $i, j \in A_k$ , where  $k \in [1, k]$ , then other resources  $j$  in  $A_k$  are the neighbors of  $i$ ,  $U_{ij}$  represents the user set of resources  $i$  and  $j$  in cluster  $A_k$  that have been jointly scored in  $R$ , and the  $K$  nearest neighbor resource set  $KNN(i)$  of resource  $i$  in cluster  $A_k$  is calculated by using the similarity of resources  $i$  and  $j$ ,  $K$  represents the specified number of fixed neighbors, that is, the first  $K$  users with high similarity are selected as the nearest neighbors of the target resource.

Using the similarity of resource attributes instead of the calculation of historical score similarity [19], the calculation formula of the user's initial predicted value score for non-rated resources can be obtained as follows:

$$P_{ui} = \begin{cases} \frac{\sum_{j \in KNN(i)} sim(i, j) r_{uj}}{\sum_{j \in KNN(i)} sim(i, j) old i} \\ \frac{\sum_{j \in KNN(i)} asim(i, j) r_{uj}}{\sum_{j \in KNN(i)} asim(i, j) new i} \end{cases} \quad (15)$$

The above formula is used to calculate the predicted scores of users  $u$  and  $v$  in resource cluster  $A_k$  for resources  $i \in S_{uv}$ . The summary expression of the initial predicted user  $u$ 's score on  $i$  can be obtained as follows:

$$R_{id} = \begin{cases} r_{ui} & (\text{User } u \text{ has rated item } i) \\ P_{ui} & (\text{User } u \text{ did not comment on item } i) \end{cases} \quad (16)$$

According to the above process, formula (11) is used to obtain the similarity between user  $u$  and its neighbors in the cluster. The first  $K$  users with the greatest similarity are selected as the nearest neighbor set  $KNU(u)$  of the target user; the average score evaluated by a user is used as the benchmark score, and the unpriced resources of  $u$  is used to form the optimized final prediction scoring formula of user  $u$  on resource  $i$ . The expression is as follows:

$$P(u, i) = \bar{R}_u + \frac{\sum_{v \in KNU(u)} sim(u, v) (R_{vi} - \bar{R}_v)}{\sum_{v \in KNU(u)} sim(u, v)} \quad (17)$$

Finally, the resources that the target user did not score are predicted, the obtained prediction values in descending order from high to low are arranged, and the first  $N$  resources are obtained to recommend to the user  $u$ , forming a matching set of Top-N resources [20].

To sum up, the resource matching process of intelligent education system is as follows:

Step 1: Calculate the similarity between different resources, and use k-means clustering method to cluster the resources of intelligent education system according to the resource attributes.

Step 2: Search for the nearest neighbor of the target resource in the resource cluster obtained by the cluster according to the similarity of the score for the initial prediction score. According to the characteristics of users, k-means clustering is used for users.

Step 3: Search for the nearest neighbor of the target user in the user cluster according to the scoring similarity. According to the scoring status of the nearest neighbor, make the final prediction of the original unscored resources of the target user in the cluster, and select the final N scoring

resources to recommend to the target user.

The above process can overcome the problem of cold start in the face of new users or new resources. The initial clustering center can be automatically determined by means of K-means clustering, so that the feature information is evenly distributed without falling into local optimization, thus improving the matching rate and accuracy. At the same time, the above process combined the similarity of attribute characteristics and similarity of score, strengthened the relationship between resources or users, obviously overcame the problem of sparsity of matching, and made the final matching result more accurate.

### 3. Results and analysis

#### 3.1 Experiment design

In order to verify the effectiveness of the resource matching model for intelligent education system based on machine learning, the following experiments are designed.

This model is applied to the intelligent education system of a university, which uses the intelligent education system to provide teaching resources for teachers and students. The data samples of intelligent education system resources are shown in Table 1.

Table 1. Sample data set

Data set type	Dimension	Number of samples/N	Number of categories
Literature	3	1251	3
Science and technology	5	1165	2
Philosophy	3	985	2
Politics	4	854	2
Astronomy	8	754	3
Aerospace	6	1052	6
Environmental science	7	465	4
Agricultural Science	5	852	3
History	10	741	6
Geography	8	694	5

#### 3.2 Results and analysis

This model uses K-means clustering algorithm to process the resources of intelligent education system. When K values are different, the clustering accuracy of clustering using the proposed model is shown in Figure 1.

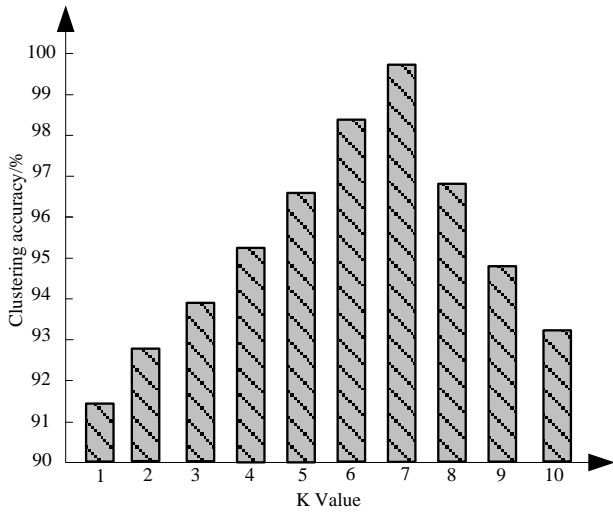


Fig. 1. Clustering accuracy

The model in this paper uses K-means clustering algorithm to process the resources of intelligent education system. When the K value is different, the false positive rate of clustering using the model in this paper is shown in Figure 2.

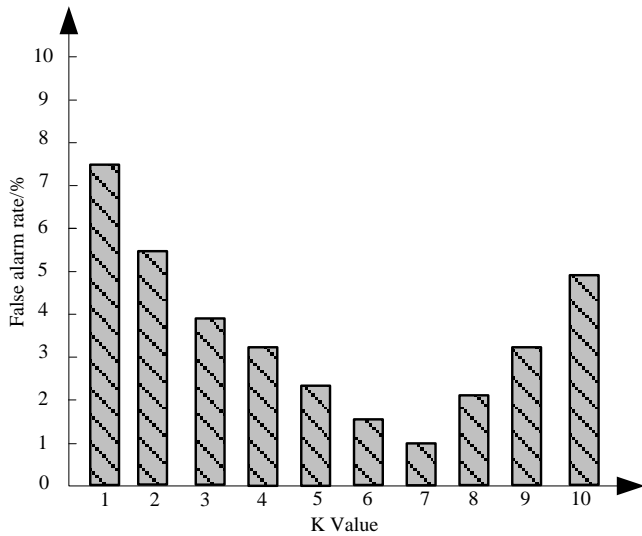


Fig. 2. Clustering false alarm rate

According to the experimental results in Figure 1 and Figure 2, the K-means clustering algorithm used in this model can effectively improve the problems of unstable initial center point, easy to fall into local optimization and difficult to select the optimal cluster number. When K value is 7, the model in this paper has the highest clustering accuracy and the lowest clustering false alarm rate. The experimental results verify that the clustering algorithm used in this model has high clustering performance. The K-means clustering algorithm used in this model has small intra-class distance and high inter-class distance, so it can obtain very high classification effect.

The K value of K-means clustering algorithm is set to 7, and the model in this paper is used to match resources for 10 users of the system. The matching results are shown in Table 2.

Table 2. Resource matching results

User serial number	TOP1 resource	TOP2 resource	TOP3 resource	TOP4 resource	TOP5 resource
A	10512	13548	21054	58451	51284
B	51184	23494	51842	31524	10564
C	31514	21546	35845	68774	81544
D	56485	10546	16154	28545	52394
E	74856	26184	64852	74112	25648
F	64855	13247	56452	12084	53645
G	21611	32845	89742	56152	12364
H	10526	26485	35484	15661	45846
I	23384	56844	25163	38411	22518
J	51690	34687	48645	12636	26487

The experimental results in Table 2 show that the model in this paper can accurately match the resources of the intelligent education system for different users. This model recommends the corresponding resources required by the top five users according to the scoring results. The results in Table 2 verify that the model in this paper has high resource matching performance of intelligent education system. Through high resource matching results, the practical application performance of intelligent education system and learning efficiency of intelligent education system are improved.

Performance evaluation can find the matching quality of the matching model in time, so as to optimize the follow-up work. The commonly used evaluation criteria mainly include accuracy, coverage, diversity, novelty and so on. The measurement accuracy standards mainly include statistical accuracy standards and decision support accuracy standards. The statistical accuracy standard evaluation is obtained by comparing the predicted user's score on the resource with the actual target user's score on the resource.

There are two common methods to match the accuracy of the model: MAE and RMSE. Among them, MAE is the average absolute error, which was earlier used to evaluate the matching performance. If a predicted user  $u$  scores  $P$  for  $n$  resources in turn, and the actual score of user  $u$  for this resource in turn is  $Q$ , the MAE predicted by the user can be expressed as:

$$MAE = \frac{\sum_{i=1}^n |p_i - q_i|}{n} \quad (18)$$

RMSE is another measure of the accuracy of the matching model. The index is calculated as follows:

$$RMAE = \sqrt{\frac{\sum_{i=1}^n (p_i - q_i)^2}{n}} \quad (19)$$

MAE and RMSE are calculated for the degree to which the score prediction results deviate from the real situation. The smaller the value is, the smaller the deviation is, indicating that the score of the intelligent education system for users is closer to the real situation, that is, the higher the accuracy of resource matching is.

In order to further highlight the effectiveness of the model in this paper, the model in reference [10] is compared with the model in reference [11]. The average absolute error and mean square error of matching intelligent education system resources with different models are counted, and the results are shown in Figure 3 and Figure 4.

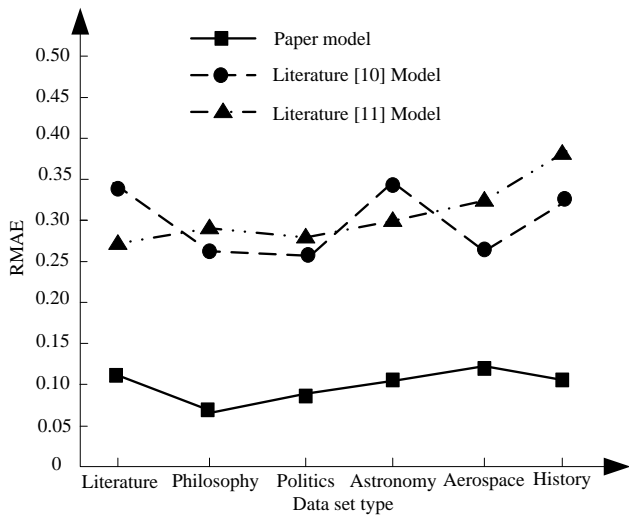


Fig. 3. Comparison of average absolute error of resource matching

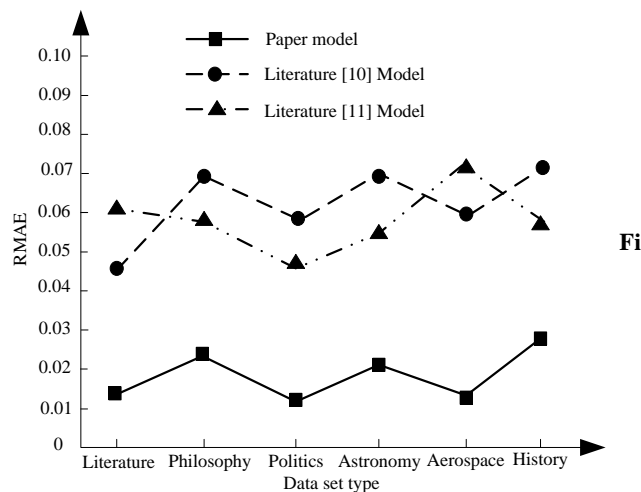


Fig.4. Comparison of mean square error of resource matching

According to the experimental results in Figure 3 and Figure 4, the K-means clustering algorithm is used in the proposed model to cluster the resources of intelligent

education system. Under the optimal number of clusters and neighbors, the average absolute error MAE and mean square error of resource matching are significantly reduced, which proves that the resource matching effect of this model is much better than that of the other two models. It can effectively improve the resource matching performance of intelligent education system.

The accuracy standard of resource matching decision support is used to evaluate the prediction, that is, whether the user likes or dislikes the resource, and whether the recommendation is correct or wrong, so as to facilitate the user to quickly find the resources that meet their interests and preferences. It is a process of assuming that the prediction process is a decision-making process for the user. The recall rate is used to measure the resource matching performance of the intelligent education system. It is assumed that the recommended result set is the favorite item of users in the test set, then:

$$Recall = \frac{\sum_u |R_u \cap T_u|}{\sum_u |T_u|} \quad (20)$$

The above evaluation method takes part of the known historical score data as training data and part as test data to evaluate the matching performance of the matching model.

Coverage is based on the amount of resources matched by the matching model to users. If a matching model is good enough, it will certainly be able to recommend resources of interest to users, and it will not let go of high-quality resources and recommend as many as possible. The basis of matching model coverage is to calculate the proportion of matched resources in all resources in the intelligent education system. If the proportion is too low, user satisfaction may decline. Assuming that the user set is  $U$ , the resource set is  $I$ , and the recommendation result set is  $R_u$ , the formula for calculating the coverage is:

$$Coverage = \frac{|\bigcup_{u \in U} R_u|}{|I|} \quad (21)$$

According to the statistics, the proposed model is used to match the recall rate and coverage rate of intelligent education system resources, and this model is compared with the models in reference [9] and reference [10]. The comparison results are shown in Figure 5 and Figure 6.

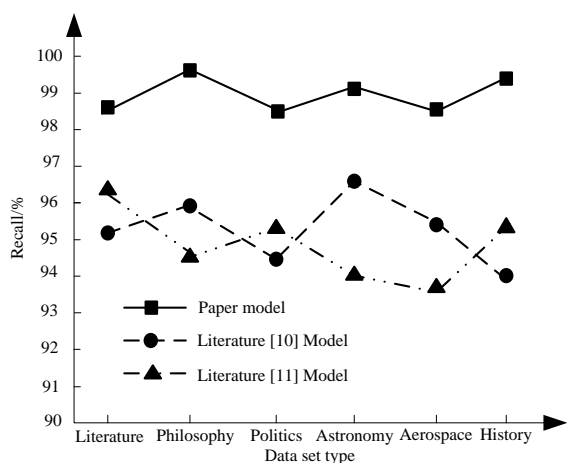


Fig.5. Comparison of recall rates of resource matching

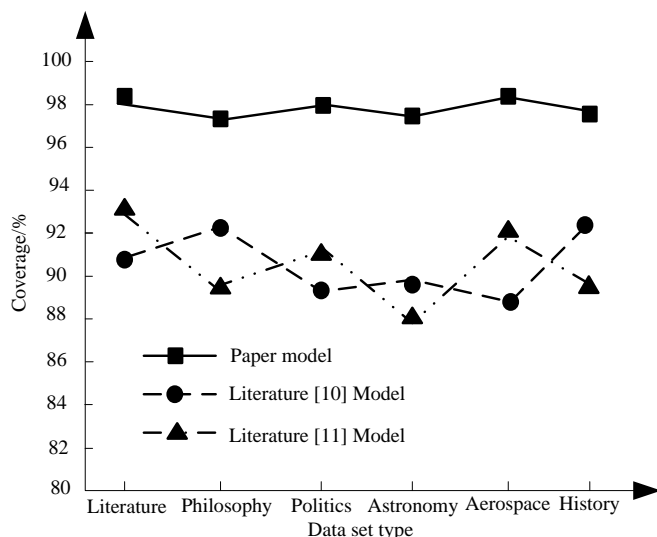


Fig. 6. Comparison of coverage ratio of resource matching

According to the result of contrast figure 5, figure 6 shows that the model presented in this paper the recall rate and coverage rate were significantly higher than that of the other two models, the matching results of the recall rate is higher than 98%, coverage above 96%, shows this model effectively improves the intelligence resources matching quality of education system, to a certain extent, ease the cold start and data are sparse in traditional matching model.

The reason for the above results is that the model in this paper combines attribute feature similarity and scoring similarity, strengthens the relationship between resources or users, obviously overcomes the problem of matching sparsity, and thus improves the accuracy of matching results.

## 4. Discussion

On the basis of fully respecting the subject status and

individual differences of learners, it should accurately grasp the personalized learning needs, and design an efficient resource matching model of intelligent education system according to the characteristic information of learners and educational information resources and their matching relationship and association rules. According to the breadth and depth of learners' knowledge structure, learning needs and needs degree, educational information resources are screened and matched, and educational information resources that meet learners' personalized needs and have a high degree of matching are actively presented to learners. For learners, this resource matching service based on matching relationship can fully reflect the subject status of learners, let them participate in it, participate in screening resources when their own needs are clear, respect learners' needs and individual differences, and meet the personalized learning needs of different users. The resource builders of intelligent education system can also develop and build high-quality educational information resources according to the personalized learning needs of learners in the system, form targeted educational information resources, improve the quality of resources and improve the utilization rate of resources. According to the characteristic information of learners and resources, the intelligent education system matches learners and resources to form a mapping relationship, and actively pushes the resources matched with learners to learners. According to the basic attributes and characteristics of resources, the intelligent education system will also select suitable learners for them and actively push the resources to suitable users, so as to improve the utilization of resources of the intelligent education system and improve the service quality of educational information resources.

## 5. Conclusion

This research designs a resource matching model of intelligent education system based on machine learning, and has achieved good application results. The K-means clustering algorithm applied in the model can effectively improve the defects of unstable initial center point, easy to fall into local optimization and difficult to select the best cluster number. The final resource matching result of intelligent education system is obtained through the similarity between users and resources. The model can accurately match the required resources for users according to their needs, and has high practicability.

In the following research, the model in this paper will be further optimized from the perspective of improving the timeliness of matching and shortening the time consuming of the matching process.

## Acknowledgements

This paper is supported by Pedagogy of National Social Science Foundation of China (BJA180097).

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