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Construction of "Youth Night School" Education Model in Higher Vocational Colleges Based on Multilayer Perceptron Algorithm and Its Path to Local Economic Empowerment

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Abstract "Youth night school" is a mode of education and training that provides vocational and academic training during free time at night, and is an important way for young people in society to improve themselves. This paper discusses in detail the participating members and corresponding responsibilities in the "Youth Night School" in higher vocational colleges and universities, as well as its organizational framework model. The hypergraph neural network algorithm is used to capture complex relationships in educational data based on the existing "Youth Night School". The mapping function is constructed by multilayer perceptron (MLP) to eliminate the information bias between the domains, so as to realize the information conversion between the domains. We also design a rating prediction and construct a course recommendation system for "Youth Night School". Comprehensive above, the formation of higher vocational colleges and universities "youth night school" education model, the design of comparative experiments, application experiments to verify its effectiveness. The recommendation algorithm designed in this paper has a hit rate of up to 0.874 and a coverage rate of more than 95%, which can accurately and comprehensively recommend the courses of "Youth Night School" and improve the teaching effect.

Index Terms youth night school, multilayer perceptron, hypergraph neural network, course recommendation system

I. Introduction

At present, as people's living standards continue to rise, the aspirations of young people for their own development are also growing. Especially in the context of the current rapid development of the times, new knowledge, new technologies are emerging, new challenges follow, and new opportunities are hidden, the youth groups need to continue to absorb knowledge and improve skills to cope with the development of social changes [1]-[3]. The youth night school education model in higher vocational colleges and universities provides young people with opportunities for continuous learning, helping them to continuously update their knowledge reserves and continuously broaden their horizons [4]. It can not only satisfy young people's thirst for knowledge and skills, but also provide a colorful learning experience, so that young people can feel the beauty and colorfulness of life while learning [5], [6]. In addition, youth night school is also an important platform for young people to pursue their dreams, where young people can freely choose the courses they are interested in, learn the skills or knowledge they have longed for, and realize self-improvement [7], [8]. This is in line with the requirements of contemporary society for individual lifelong learning, and also helps to improve the comprehensive quality and competitiveness of youth [9].

Meanwhile, in the face of the explosion of youth night school, it puts forward new requirements for the government to provide higher quality public cultural services. The government should make every effort to create a new pattern of two-way running of youth and night school, to strengthen the ideological and political leadership of youth as the starting point, to focus on the center and serve the overall situation as the main line of work, to build a practical platform for two-way running with young people, and strive to use the results of the service of the night school for young people to empower the construction of local economic development [10]-[12]. By mobilizing the night school students to give full play to their respective advantages, change "input" to "output", actively participate in grass-roots governance, rural revitalization, cultural and tourism development and other central work of the municipal party committee, to create a new situation of economic development for the benefit of all parties [13]-[15].

This paper firstly describes the main members and responsibilities of the existing "Youth Night School", as well as the organizational framework based on the growth community. Then, it describes the application process of hypergraph neural network algorithm in the course recommendation system of Youth Night School. A multilayer perceptron (MLP) algorithm is introduced to enhance the feature learning of the recommender system, and the fusion of the feature space in the source and target domains is reconstructed. At the same time, the MLP-based rating prediction is designed to complete the recommendation by outputting the predicted ratings. As a result, with the support of MLP algorithm, a more personalized education model of “Youth Night School” in higher vocational colleges and universities is formed. Finally, the performance of the designed recommendation algorithm is evaluated in the form of comparing similar algorithms, and the practical application effect of the “Youth Night School” education model in higher vocational colleges is evaluated.

II. Organizational structure of the “Night School for Youth” training

II. A. Participating members

The “Youth Night School” model involves mainly young teachers (under 40 years of age), subject leaders, expert teachers, administrators and logistics staff. All pre-training tasks are carried out in small groups, and all young teachers are required to participate in each offline training activity, with expert teachers commenting on the activity, administrative teachers analyzing the activity, and logistical staff providing venue and equipment support for the training to be carried out.

II. B. Community of Growth

The “Youth Night School” divides the growth community into two parts: the teacher-apprentice growth community and the study group growth community. Every school year, the number of new teachers and other teachers are counted, and according to the subjects taught by young teachers, their growth needs, and personal characteristics, they are matched with a senior teacher to provide follow-up guidance and final comments, forming a community of growth for teachers and apprentices. The specific program for each “Youth Night School” activity integrates all participants into a large class, with reference to the classroom management model, and establishes a community of growth for the learning group according to a group of five people. The members of the community are all learners, participating in practice, observation, seminars and reflection, and establishing cooperation between different grades, disciplines and fields.

The organizational framework of the “Youth Night School” is shown in Figure 1.

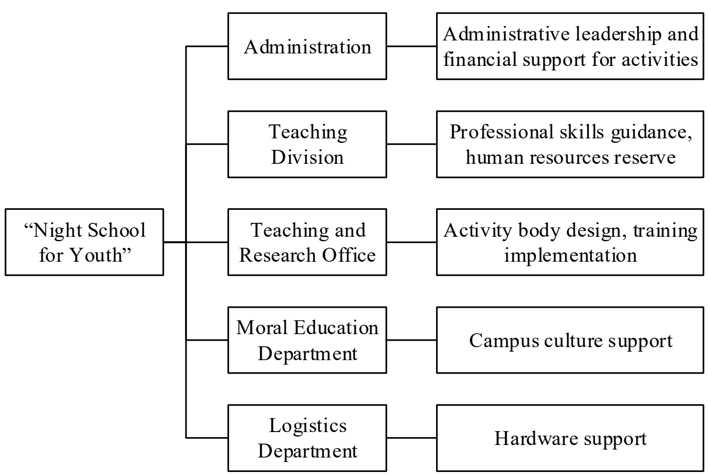

Figure 1: Organization framework of "Youth Night School"

III. Construction of the educational model of the “Youth Night School”

In this paper, the course recommendation system of “Youth Night School” is divided into three modules: dataset processing, cross-domain adaptive feature mapping and rating prediction. In this chapter, with the support of hypergraph neural network algorithm and multilayer perceptual machine (MLP) algorithm, we construct a course recommendation system applicable to “Youth Night School”, and form an educational model of “Youth Night School” based on neural network and MLP algorithm.

III. A. Hypergraph Neural Networks

When designing a course recommendation system for the Youth Night School using the hypergraph neural network algorithm (HGNN), it is necessary to consider both educational content and learner data. Educational content and learner data have extremely complex relationships with each other due to the wide range of directions and contents involved, and HGNN provides a new perspective to understand and represent the complex relationships in the data, and the graph neural network and hypergraph neural network are shown in Figure 2.

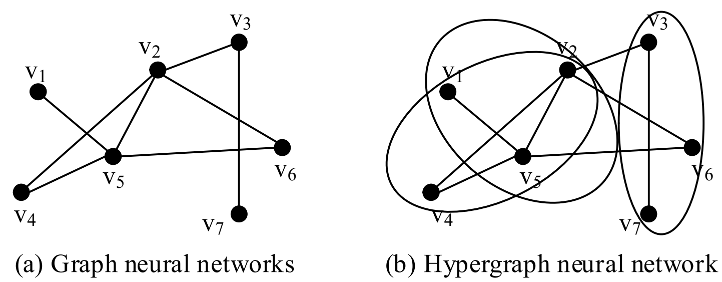

Figure 2: Graph neural network and hypergraph neural network

Unlike traditional graphs that restrict edges to connect only two nodes, edges in HGNN can connect multiple nodes, resulting in a richer data structure. In a hypergraph G, a vertex set V and a set of hyperedges E consisting of a subset of vertices are defined. For example, node V_1 is connected to two hyperedges in graph G_2, indicating that it is characterized by degree 2. By considering courses, students and teachers as nodes and modeling the diverse relationships among them as hyperedges, a comprehensive hypergraph structure can be constructed. In HGNN, a new matrix is obtained by computing the product H of the hypergraph's association matrix H and its transpose HH^T, which is able to reflect the strength of connections between nodes. However, the direct use of HH^T may lead to the problem of gradient explosion, so it needs to be avoided by a normalization operation as in Eq. (1):

$$\overline{A} = D_v^{-\frac{1}{2}} HWD_e^{-1} H^T D_v^{-\frac{1}{2}} \tag{1}$$

In Eq. (1), $\overline{A}$ denotes the adjacency matrix of the hypergraph. H is the association matrix of the hypergraph. D is the degree matrix, a diagonal matrix containing the degrees of the nodes or hyper edges. H^T is the transpose of the association matrix H whose rows denote hyperedges and columns denote vertices. W is the weight matrix of the hyperedge, which is used to store the weight information of the node or hyperedge. After calculating $\overline{A}$, it is substituted into the GCN linear formula as in equation (2):

$$g \times x = \sum_{k=0}^{K} \theta_k T_k \left(\overline{A}\right) x \tag{2}$$

In equation (2), $x \in \mathbb{R}^N$, denotes the scalar of each node. $\theta \in \mathbb{R}^K$, denotes the vector of the Chebyshev relation tree. Let $K = 1$, which leads to equation (3):

$$g \times x = \left(\theta_0 - \theta_1 D_v^{-\frac{1}{2}} HWD_e^{-\frac{1}{2}} H^T D_v^{-\frac{1}{2}} \right) x \tag{3}$$

In Eq. (3), both θ_0 and θ_1 are parameters used by the convolution kernel for training. To solve the overfitting problem, a separate variable θ is introduced as in equation (4):

$$\begin{cases} \theta_1 = -\dfrac{1}{2}\theta \\ \theta_0 = \dfrac{1}{2}\theta D_v^{-\frac{1}{2}} HWDH^T D_v^{-\frac{1}{2}} \end{cases} \tag{4}$$

After that the convolution operation of HRNN can be obtained as in equation (5):

$$g \times x = \theta D_v^{-\frac{1}{2}} HWDH^T D_v^{-\frac{1}{2}} x \tag{5}$$

The single-layer HRNN needs to take into account the form of the matrix, therefore, $X \in \mathbb{R}^{N \times C_1}$ is taken as the input, which leads to the operation as in equation (6):

$$Y = D_v^{-\frac{1}{2}} H W D_e^{-1} H^T D_v^{-\frac{1}{2}} x\Theta \tag{6}$$

In Eq. (6), C_1 refers to the dimension of the feature vector obtained after the hypergraph convolution process, and N denotes the total number of nodes representing the vocational education network, which include entities such as students, teachers, and courses. $\Theta \in \mathbb{R}^{C_1 \times C_2}$ denotes the parameter matrix that can be tuned, and after the hypergraph convolution operation, the size of the generated feature matrix Y is $\mathbb{R}^{N \times C_2}$, and C_2 refers to the dimensionality of the feature vectors obtained after the hypergraph convolution processing, reflecting the fact that rich attributes and relationships of each node in the hypergraph structure.

III. B. MLP-based feature mapping

The EMCDR framework utilizes multiple perceptrons (MLP) to construct a nonlinear mapping function between the source domain and the target course domain, which is more flexible in constructing domain-specific features in different domains. At the same time, in the feature mapping, only the students and courses of the Youth Night School, which are densely populated with data information, are considered to train the mapping function, which eliminates the noise that may be caused by the sparsity of the data, and makes the mapping framework based on the MLP robust and generalizable. The structure of the EMCDR framework is shown in Fig. 3.

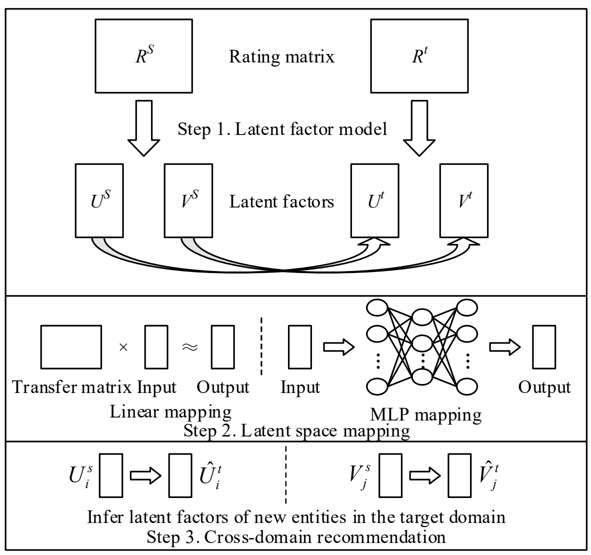

Figure 3: EMCDR framework schematic

Overall, the EMCDR modeling framework can be divided into three parts, the implicit factor modeling part aims at generating latent factors for students and courses in the two domains of the Youth Night School, the latent space mapping part aims at training the mapping function, which is able to establish the connection between the latent spaces of the source and target domains, and the cross-domain mapping part is used to measure the scores on the target domains. The recommendation part is used to measure the ratings on the target domain.

In order to obtain the implicit factors of the students and courses of the "Chinese New Year's Eve" in the source domain and the target domain, one method is to use matrix factorization to decompose the scoring matrix into two low-dimensional matrices, which represent the potential representations of the students and courses of the "Chinese New Year's Eve School", with equation (7):

$$\min_{U,V}\left(\sum_i\sum_j \left\| W_{ij} \odot \left(R_{ij} - U_i^T V_j\right)\right\|_F^2 + \lambda_U \sum_i \left\|U_i\right\|_F^2 + \lambda_V \sum_j \left\|V_j\right\|_F^2\right) \tag{7}$$

The above loss function does not distinguish between source and target domains, and potential representations of the students and courses of the Youth Night School can be obtained in each of the two domains.

Unlike the matrix decomposition method which obtains the latent representations of the students and courses of the Youth Night School by minimizing the objective function, Bayesian Personalized Recommendation Ranking (BPR) can introduce the rating ranking information and let the model learn the size relationship between different ratings when constructing the latent representations of the students and courses of the Youth Night School. BPR starts by generating a training set $\mathrm{D} = \left\{\left(u_i, v_j, v_k\right) \mid r_{ij} > r_{ik}\right\}$, which consists of any of the ratings in the ratings matrix. Set consists of any user and its pair of ratings in the ratings matrix. At this point the a priori information for $\left\{U_i, V_j, V_k\right\}$ can be constructed with equation (8):

$$p\left(r_{ij} > r_{ik}\right) = \sigma\left(U_i^T V_j - U_i^T V_k\right) \tag{8}$$

Where $\sigma(\cdot)$ represents the sigmoid function, using the above a priori information, the loss function is constructed and optimized to obtain the potential representations of $\left\{U_i, V_j, V_k\right\}$ with equation (9):

$$\min_{U,V}\left(\sum_{(u_i,v_j,v_k)\in \mathrm{D}} -\ln \sigma(U_i^T V_j - U_i^T V_k) + \lambda_U \sum_i \left\|U_i\right\|_F^2 + \lambda_V \sum_j \left\|V_j\right\|_F^2\right) \tag{9}$$

The parameters in MF and BPR can be obtained by stochastic gradient descent method, and the generated potential representations can be regarded as a set of coordinates in the potential space, thus realizing the connectivity mapping between the source and target domains.

In the potential space mapping part, two mapping methods, linear transformation and MLP-based nonlinear transformation, can be used. The linear mapping assumes that the mapping function can be expressed as a transformation matrix M, so that the potential representation of the user in the source domain is approximated to estimate the potential representation of the user in the target domain after passing through the transformation matrix, i.e., $U_i^t \approx M \times U_i^s$, and the transformation matrix M can be acquired by the following optimization problem, with Eq. (10):

$$\min_M \sum_{u_i \in \mu} L\left(M \times U_i^s, U_i^t\right) + \Omega\left(M\right) \tag{10}$$

where $L(\cdot)$ represents the loss function, and $\Omega(M)$ represents the regular term of the transformation matrix. Linear transformations may not accurately represent the mapping relationship between two domains, affecting the recommendation accuracy on the target domain. Using MLP to construct the mapping function can introduce nonlinearity, and MLP is more accurate and flexible in fitting the functional relationship, and the relevant parameters can be optimized iteratively by back propagation algorithm. Similarly, the nonlinear transformation function based on MLP can be acquired by the following optimization problem with equation (11):

$$\min_\theta \sum_{u_i \in \mu} L\left(f_{mlp}\left(U_i^s, \theta\right), U_i^t\right) \tag{11}$$

where $f_{mlp}(\cdot, \theta)$ represents the MLP-based mapping function, and θ represents the parameter set of the MLP structure, which usually contains the weight and bias parameters in each layer.

The CIT algorithm utilizes the kernel method to construct the mapping function to achieve information consistency between the source and target domains, which improves the recommendation performance in matrix decomposition-based cross-domain recommendation scenarios, and can extend this idea to neural network-based cross-domain recommendation scenarios, which utilize the flexibility of the MLP that can simulate any continuous function, and constructs the mapping function based on the MLP to achieve the information transfer between different domains.

III. C. Scoring projections

After feature mapping, we can obtain the implicit vectors of students and courses of the Youth Night School, and then based on the implicit vectors, we can predict the ratings on the target course domains, and finally, we can measure the advantages and disadvantages of the cross-domain recommendation model by the error between the actual ratings and the predicted ratings. In general, there are two methods for calculating the predicted ratings, one is to get the predicted ratings directly by inner product operation, and the other is to utilize the multiple perceptual machine model, which treats the rating prediction as a regression problem, and takes the implicit vectors of students and courses of the Youth Night School as the inputs of the model, and the final output is the predicted ratings. A comparison of the structure of the two methods is shown in Figure 4.

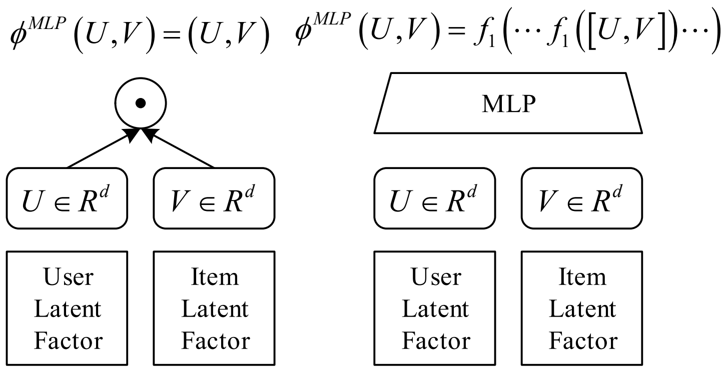

Figure 4: Inner product prediction score and MLP based prediction score

The predicted scores are obtained by inner product operation as in equation (12):

$$\hat{r}=\phi^{dot}(U,V):=\langle U,V\rangle=U^{T}V=\sum_{l=1}^{d}U_{l}V_{l} \tag{12}$$

The inner product operation can be regarded as a matrix decomposition, which can be regarded as a linear combination of the elements of the hidden vectors of the students and courses of the Youth Night School. The MLP-based rating prediction starts by combining the hidden vectors of the students and courses of the Youth Night School and inputting them into a multilayer perceptron model, where each layer of the MLP can be represented as Eq. (13):

$$f_{w,b}(U,V)=\sigma\left(W\cdot(U,V)+b\right) \tag{13}$$

Each layer of neural network can be regarded as a linear model of the merged hidden vectors, and after the introduction of nonlinearity through the activation function, the final output of the MLP is represented by the predicted scores as in equation (14):

$$\hat{r}=\phi^{MLP}(U,V)=f_{w_L,b_L}\left(\cdots f_{w_1,b_1}\left([U\oplus V]\right)\cdots\right) \tag{14}$$

The two approaches of score prediction based on inner product operation and MLP-based are essentially a comparison of matrix decomposition and MLP model, which stems from the nonlinearity and flexibility of MLP model, and the MLP-based score prediction is more accurate and flexible compared to inner product operation. In addition, MLP-based score prediction is an unsupervised algorithm, which is widely used in cross-domain recommender systems based on neural network models, and the whole framework can be regarded as an end-to-end model, which can be reduced by an overall loss function, and all the parameters can be trained by a back-propagation algorithm, which reduces the training difficulty.

IV. Testing and evaluation of the “Youth Night School” educational model

This chapter examines the reliability of the “Youth Night School” education model by comparing the performance of the proposed recommendation algorithm with that of similar recommendation algorithms in the operation process. Application experiments are set up to test the feasibility of the “Youth Night School” education model.

IV. A. Performance of the algorithm

Three classic algorithms of the same kind: MF, PMF, NCF, and the algorithm proposed in this paper are selected to carry out the course recommendation of “Youth Night School”, and the comparison experiments of hitting rate and normalized loss cumulative gain, coverage, and average absolute error are carried out in turn.

IV. A. 1) Hits and Normalized Discounted Cumulative Gain

Figure 5 shows the variation of hit rate HR with k value and Figure 6 shows the variation of normalized discount cumulative gain NDCG with k value. The hit rate HR and normalized discount cumulative gain NDCG of the four recommendation algorithms both increase with the k value, the growth rate gradually decreases, and finally stabilizes, reaching the maximum value when the k value is taken as 10. The recommendation effect of NCF, PMF, MF, and this paper's algorithms is improved in turn for different values of k. PMF performs slightly better than NCF, and MF is significantly better than NCF. This paper's algorithm also shows significant improvement compared to the better-performing NCF, and obtains the highest HR of 0.874 as well as the highest NDCG of 0.628 for a value of k taken as 10.

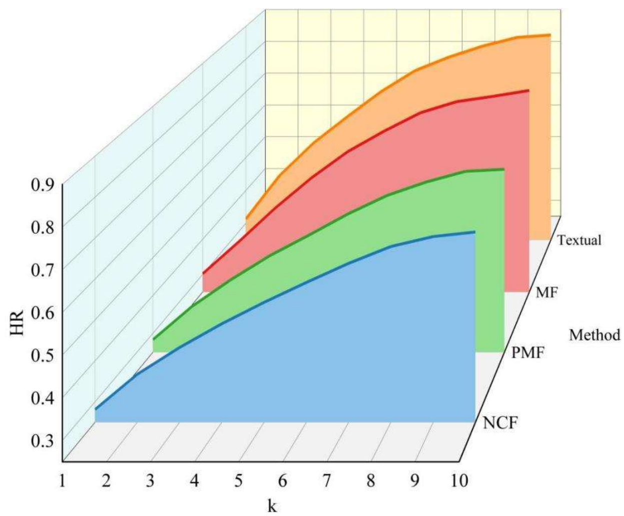

Figure 5: Hit ratio HR changes with k value

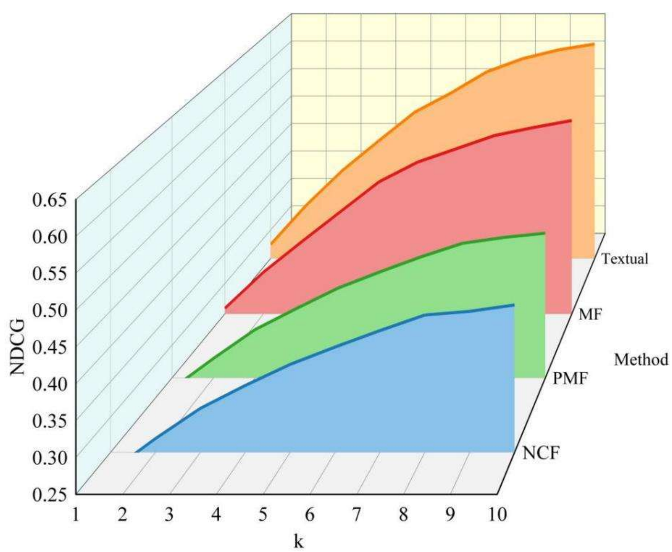

Figure 6: The change of normalized cumulative gain NDCG with k value

IV. A. 2) Coverage

In order to verify the overall validity of the model in this paper, it needs to be tested. The proposed method, the MF method, the PMF method and the NCF method are tested by using the coverage rate as a test index, and the coverage rate is calculated as equation (15):

$$Coverage = \frac{|R(U)|}{|I|} \tag{15}$$

In the formula, R(U) stands for the recommended list of night school teaching resources and I stands for the number of night school teaching resources.

The coverage test results of the four methods are shown in Table 1.

Table 1: Coverage testing for different methods

Number of iterations/times	Coverage (%)			
	Textual	MF	PMF	NCF
1	97	84	72	84
2	98	78	81	94
3	97	86	74	86
4	98	86	74	93
5	99	80	79	75
6	100	84	78	94
7	99	80	79	73
8	97	86	81	96
9	99	83	70	72
10	100	83	77	82

Analyzing the data in Table 1, it can be seen that the coverage rates are all above 96% when using this paper's method to recommend evening school teaching resources for users, and the coverage rates fluctuate around 80% when using the MF method to recommend evening school teaching resources for users. When PMF method is used to recommend night school teaching resources for users, the coverage rate is around 75%. The coverage rate fluctuates around 70%-95% when the NCF method is used to recommend evening school teaching resources for users. Comparing the coverage rates of the proposed method, the MF method, the PMF method and the NCF method, it can be seen that the proposed method has the highest coverage rate of automatic recommendation of evening school teaching resources.

IV. A. 3) Mean absolute error

In order to analyze the application effect of this paper's method, the NCF method, which has a large fluctuation in coverage, is excluded, and the MF method, PMF method and this paper's method are developed for the recommendation of online teaching resources in "Youth Night School". The results of calculating the average absolute errors of the three methods under different types of resource recommendation sets are shown in Table 2.

Table 2: Mean absolute error experimental results

Resource type	Resource number	Number of resources (PCS)	Mean absolute error		
			Textual	MF	PMF
Category A electronic books	AD1	45	0.238	7.636	7.632
Category B electronic books70	AD2	24	0.364	7.609	6.673
Category C electronic books	AD3	19	0.19	7.929	6.165
Class A electronic journal	AQ1	24	0.283	8.599	8.969
Class B electronic journal	AQ2	70	0.14	7.368	7.53
Class C electronic journal	AQ3	52	0.265	7.28	8.818
Type I database	SK1	37	0.387	7.709	8.062
Type Ⅱ database	SK2	59	0.239	8.299	6.659
Type Ⅲ database	SK3	75	0.175	7.018	6.355
Virtual Library 1	XT1	29	0.201	7.137	7.326
Virtual Library 2	XT2	23	0.369	7.546	7.062
Electronic encyclopedia	DB1	97	0.326	7.759	7.34
Education Website a	JW1	49	0.361	8.101	7.525
Education Website b	JW2	25	0.125	7.946	6.213
Electronic forum	DL1	37	0.22	8.333	7.875

As can be seen from Table 2, the average absolute errors of this paper's method under different types of resources are low only between [0,1], which are much lower than the average absolute errors of MF method and PMF method under different types of resources. The experimental results show that the method of this paper has a good recommendation effect, reliability, and certain application value, so the practical application effect assessment is carried out in the following.

IV. B. Application effect and evaluation

The methodology of this paper was applied to class CG (control group, using the general education model) and class AG (application group, using the education model designed in this paper), which were attached to the "Youth Night School" of B higher vocational college, with 25 students in each class. The learning effects of the selected 50 students in Course E and Course F were compared and analyzed through questionnaires and comparisons of test scores. The difficulty coefficients of the exams ranged from 0 to 1, with larger values indicating higher difficulty, and the differences in the scores were analyzed using the Wilcoxon rank-sum test (with P<0.05 being considered as the difference being statistically significant). The difficulty coefficients and p-values of the control group and the application group on course E, course F, and the total grade are shown in Figure 7. The difference between the mean value of the grades obtained by the control group and the mean value of the grades obtained by the application group on course E is statistically significant (P=0.035<0.05).

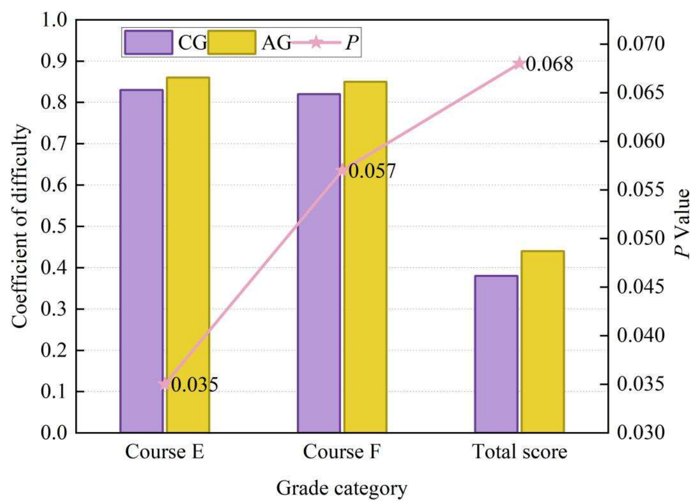

Figure 7: The difficulty coefficient of CG and AG performance and P

The statistics and distribution of the mean values of the grades of the control group and the application group on Course E are shown in Figure 8, and the mean value of the experimental grades of the application group (55.71) is higher than that of the control group (54.24), and the difference is statistically significant (P=0.035<0.05). In the distribution, the application group achievement (50-65) was more compact compared to the control group achievement (35-70).

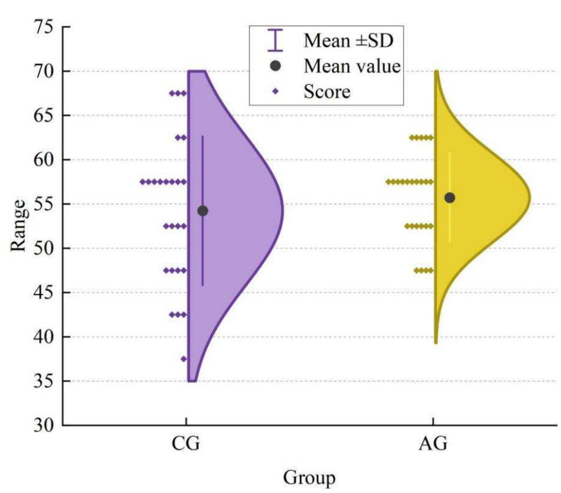

Figure 8: Course E score statistics and comparison

The statistics and distribution of the mean values of the grades of the control group and the application group on Course F are shown in Figure 9, although the mean value of the experimental grades of the application group (23.88) was higher than that of the control group (25.32), the difference was not statistically significant. In the distribution, the application group's grades (23-28) were more compact compared to the control group's grades (18-27).

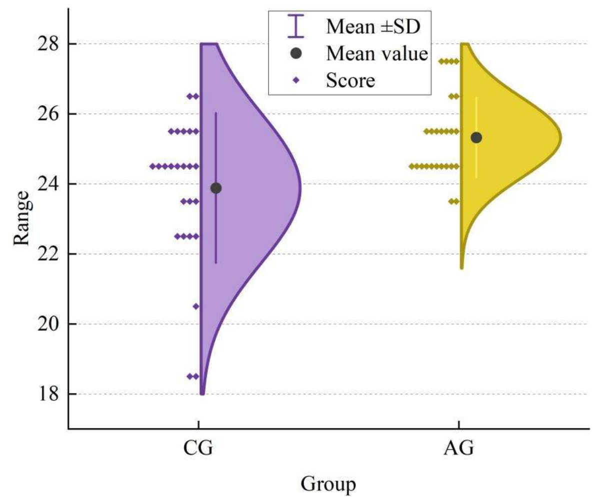

Figure 9: Course F score statistics and comparison

The statistical results of the total course grades of the application group and the control group are shown in Figure 10.From the comparison of the total grades, the mean value of the total grades of the application group (78.84) is higher than that of the control group (74.69), and the excellence rate of the total grades of the application group is higher than that of the control group, but the difference is not statistically significant (P>0.05). In terms of distribution, the total scores of the application group (65-95) were more compact compared to the total scores of the control group (50-100).

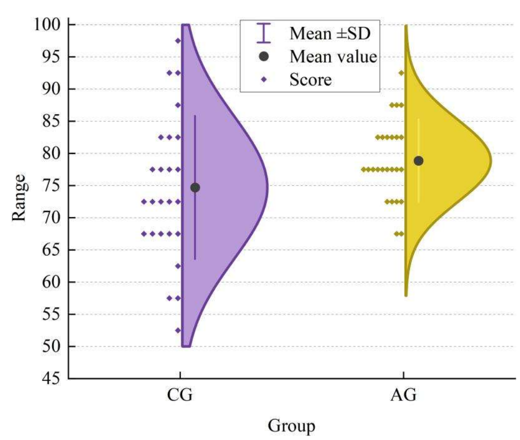

Figure 10: Statistics and comparison of total course scores

The above results reflect that adopting the educational model designed in this paper can enhance the overall learning effect of students to a certain extent. At the same time, the distribution of grades in courses E and F and the total grade distribution of the application group are more compact than that of the control group, reflecting that the overall performance of the students is more stable and the difference in the distribution is reduced after using the educational model designed in this paper.

V. Conclusion

In this paper, we design an educational model of "Youth Night School" with the core of course recommendation system, and its recommendation system utilizes multiple perceptual machines to fit the mapping function to realize accurate course recommendation based on the characteristics and needs of “Youth Night School” students, and the recommendation algorithm shows excellent results in both operation and application. The recommendation algorithm shows excellent results in both operation and application. In operation, the hit rate of the recommended course resources can reach up to 0.874, the normalized loss gain can reach up to 0.628, and the average absolute error is only between [0,1]. In terms of application, all the scores of the application group using the educational model designed in this paper are higher than those of the control group (ordinary teaching model), and the mean value of the course E scores shows a significant difference ($P=0.035<0.05$).

The “Youth Night School” education model based on the multilayer perceptron algorithm can not only personalize the recommended course resources and improve the students' learning performance, but also strengthen the vocational skills of social youths by providing rich and diverse vocational education resources and empowering the local economy.

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