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Research on Personalized Generation and Adaptation Model of Civic Education Content Based on Self-Organized Mapping Networks

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Abstract This study proposes CIFW, a framework for personalized generation and adaptation of civic education content that integrates self-organizing mapping network SOM and deep learning, aiming to address the limitations of traditional recommendation methods in data sparsity, dynamic adaptation of user interests, and matching of resources across education stages. The low-dimensional mapping and dynamic clustering of user behaviors and item features are achieved by introducing an improved Item-SOM model, combining a multilayer perceptron MLP with bilinear feature interaction technology. The CIFW model is further proposed to optimize the feature weight allocation by using the channel attention mechanism and to enhance the higher-order feature combination capability by bilinear interaction. The experiment is based on the data of 30 users' ratings of six types of Civic Education resources, and comparing the MAE value and coverage rate, it is found that the MAE value of Item-SOM-CIFW is 0.754 and the coverage rate of 68.9% significantly outperforms that of the traditional algorithms User-CF and FCM-CF. The test of the number of matches by grades reveals that the fitness value of this model at different stages of the college freshman to the senior year, e.g., G5's 1469 group improves up to 43.3% compared with the control group, which verifies the adaptability of dynamic recommendation for Civic Education.

Index Terms self-organizing mapping network, civic education, personalized generation, channel attention, bilinear interaction

I. Introduction

The contents of Civic and Political Education are rich and varied, and develop with the progress of the times. The main contents of current Civic and Political Education include education on the theory of socialism with Chinese characteristics, education on patriotism, collectivism and socialism, education on socialist core values, excellent historical and cultural traditions, and education on ideals, morality, discipline, the legal system, national defense and national unity, etc. [1], [2]. The development of the content of Civics education plays a key role in guaranteeing the effectiveness of Civics teaching, realizing the goals of Civics, enhancing the relevance of Civics courses, and stimulating students' interests [3]-[5]. Due to the short time and few hours of education and training in higher education about Civics courses, the storage of Civics elements is limited, and it is impractical for its Civics courses to carry out all the contents of education [6], [7]. At the same time, in classroom teaching, there is the problem that professional teachers do not know how to develop and use the resources of the Civic and Political courses correctly, and there is a lack of vivid cases and interactions, which leads to a formality in the construction of the Civic and Political courses [8]-[10]. Based on this, we should implement the value orientation of moral education, design personalized educational content according to different training themes, especially highlighting the content elements of political literacy, moral literacy and professional literacy, and improve the effectiveness of Civic and Political education [11]-[13].

In this study, we propose a Civic Education Content Adaptation Framework that integrates self-organizing mapping network SOM and deep learning to achieve accurate clustering and personalized recommendation of educational content through multi-level feature learning and dynamic weight adjustment. The article first starts from the basic principle of SOM network, and explains its unsupervised clustering ability and data dimensionality reduction characteristics. On this basis, it proposes a diversity propensity modeling method based on Item-SOM, which maps user interaction behaviors and item characteristics to the low-dimensional space through the joint training of multilayer perceptron (MLP) and SOM, and constructs user diversity propensity indicators. Finally, the compressed interaction and feature weighting model CIFW is proposed by combining the channel attention mechanism and the bilinear feature interaction technique. The channel attention mechanism optimizes the feature weight allocation through the three stages of Squeeze-Excitation-Reweight and introduces the bilinear feature interaction module, which realizes the nonlinear combination between features through the parameter crossover matrix. On the basis of explicit higher-order feature interaction, the weight assignment of key information is enhanced to alleviate the data sparsity problem.

II. Personalized Recommendation Generation and Adaptation Model Construction Based on Self-Organizing Mapping Networks

II. A.Principles of SOM networks

SOM network is a heterogeneous structured network that belongs to the outside of classical feedforward and feedback networks, and its basic idea is to simulate the distributed storage of information on the human brain cortex. The network uses unsupervised training to automatically cluster the training data according to its relevance, and is a classical model of competitive learning. The structure of the classical SOM network is shown in Fig. 1.

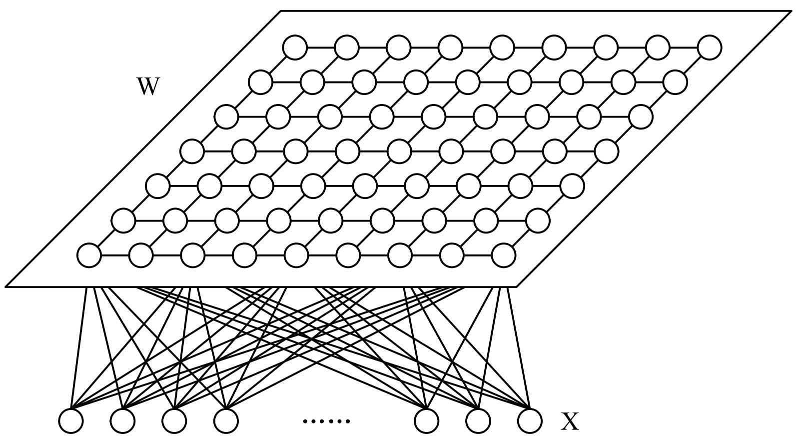

Figure 1: The structure of the classic SOM network

The network is divided into two layers: the input layer X and the competing layer W, during the training process, the network calculates the degree of activation of the input samples to each node in the competing layer, generally using the inner product

$$f = x_i \cdot w_m \tag{1}$$

Or the European distance approach.

$$d = \frac{1}{n}\left(x_i - w_m\right)^2 \tag{2}$$

Then the neuron with the largest activation or closest to the input sample, i.e., the winner of the competition, is selected according to the

$$w_m^{t+1} = w_m^t + \alpha \cdot h \cdot \left(x_i - w_m^t\right) \tag{3}$$

The rules of the network are adjusted in terms of weights, and so on iteratively until the state of the network is finally stabilized. The network is characterized by the fact that not only the neuron that wins the competition, but also all neurons in its neighborhood are weighted at the same time. The step size of the tuning compared to the winning neuron is multiplied by a coefficient less than 1. The value of this coefficient is related to the physical distance between the neuron to be tuned and the winning neuron in the competition layer. The closer the distance, the larger the coefficient, and as the distance increases, the coefficient decreases rapidly and is eventually approximated to 0. There are many coefficient-distance functions that satisfy this condition, but the most commonly used are the Gaussian function and a “Mexican Hat” function. Through this collective weighting approach, the SOM network can ensure that the winning neuron is gradually close to the input sample, but also allows its neighboring neurons to take the value of the sample close to achieve the purpose of automatic clustering.

In addition to the competitive layer of SOM as shown in Fig. 1, there are various variations, which can be categorized into hexagonal array and quadrilateral array from the shapes of the connections between the nodes. According to the shape of the whole competition layer there are generally three types: planar, column and ring.

Theoretically, SOM is not limited to designing the competing layers in the form of specific 2D arrays, so it can also be used as an effective means of data dimensionality reduction. However, this 2D planar array is most suitable for data visualization, and in this paper, it is very convenient to make observations on the structure and weight changes of the network.

II. B.Item-SOM diversity propensity-based modeling

The unsupervised clustering ability of SOM network provides theoretical support for data dimensionality reduction and visualization, however, in the personalized recommendation scenario of Civic Education content, it is difficult to effectively integrate the high-dimensional features of user behavior and item labels by solely relying on classical SOM. For this reason, this section proposes an improved Item-SOM model, which maps the discrete features to a low-dimensional space by introducing a multi-layer MLP with a dual full connectivity layer, and combines the loss function optimization to achieve dynamic clustering of recommended items and modeling of user diversity propensity.

The input of Item-SOM network structure is the feature data of recommended items (user interaction feedback and item labeling information), and in recommender systems, for the processing of discrete features, the common method is to convert the features into the form of One-Hot. Considering directly inputting One-Hot type features into SOM will lead to too many network parameters, increase the complexity of network training, and at the same time reduce the accuracy of the network.The Item-SOM recommender item network model is shown in Fig. 2.Item-SOM adopts a multi-layer MLP to perform a higher-order nonlinear combination of recommender item features, and then inputs the higher-order features of lower dimensions into SOM for item clustering analysis.

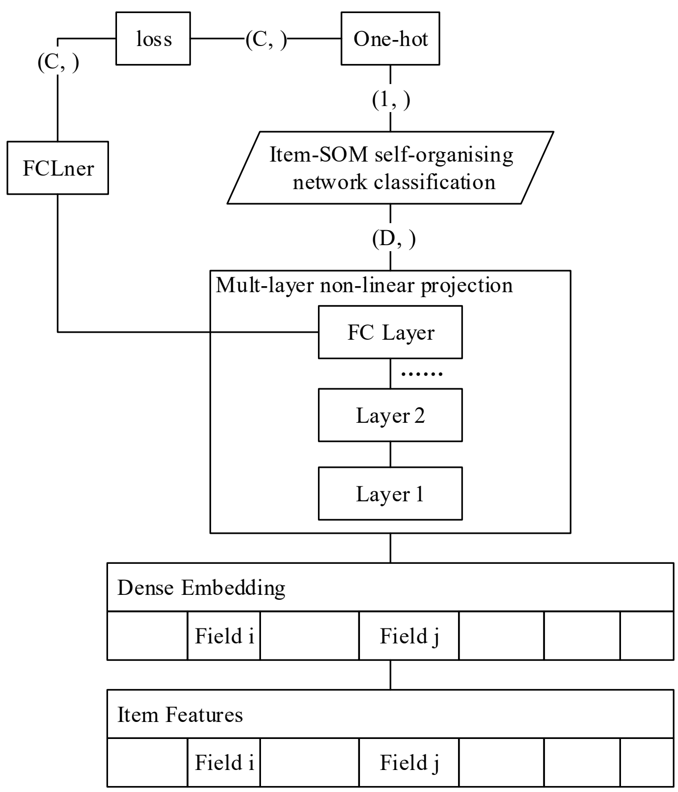

Figure 2: Item-som recommended Item network model

Besides, the Item-SOM network structure contains two fully connected layers (FC layers). In Figure 2, the first FC layer outputs a D-dimensional vector for the input of the SOM neural network; the second FC layer outputs a C-dimensional vector (C denotes the total number of categories of the items to be recommended), and the output of the vector, $\hat{y}_i$, is used as the predicted value of the recommended item category. The winning category obtained from SOM neural network is converted to One-Hot as the truth value y_i of this output vector, and the loss function is calculated according to Eq. (4), and the parameters of the two FC layers and the layer parameters of the multilayer MLP feature extraction are adjusted by reverse optimization.

$$loss = -\sum_{i}^{n} y_i \log(\hat{y}_i) \tag{4}$$

where: y_i is the i th value of the SOM output after One-Hot; $\hat{y}_i$ is the corresponding component in the vector output normalized by the second FC layer. From the loss function, it can be seen that when the classification is more accurate, the component corresponding to $\hat{y}_i$ will be closer to 1, and thus the value of loss will be smaller.

The Item-SOM structure enables similar recommendation items to be mapped to the same neurons, and a clustering model of recommendation items is obtained. Using this clustering model in the prediction stage of recommended item categories, only the feature data of recommended items need to be input into Item-SOM, and the learned weight parameters can be used to calculate the position of the output node that has the closest Euclidean distance to the input feature data, and the category represented by this output node is the categorical category to which the recommended item belongs.

All the items in the item set I are clustered by Item-SOM module, and the total number of item categories is obtained as C, and the item set I_u that user u has interacted with is clustered by Item-SOM module, and the number of item categories is obtained as C_u, and $F_d(u) = \frac{C_u}{C}$ is defined as the value of diversity propensity of user u.

II. C. CIFW modeling based on compressed interaction and feature weighting

Although Item-SOM can reflect the diversity of user interests through clustering analysis, its adaptability to complex interaction patterns with sparse features is still limited. In order to further improve the model's ability to adapt to the content of ideological education, this section proposes the CIFW model, which dynamically filters the key features through the channel attention mechanism and realizes the explicit higher-order feature combinations with the help of the bilinear feature interaction technique, and finally constructs a recommendation framework that takes both efficiency and accuracy into account.

II. C. 1) Channel Attention Mechanisms

The main idea of channel attention mechanism is to correct the original channel by establishing the relationship between the channels as a way to improve the performance of the neural network. The channel attention mechanism has three main parts of work, which are Squeeze, Excitation, and Reweight.

The channel attention mechanism starts from U, first do a global rating pooling operation on U, which is the process of Squeeze.The calculation of Squeeze is shown in equation (5).

$$Z_c = F_{sq}(u_c) = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i,j) \tag{5}$$

The data is compressed to a data size of $1 \times 1 \times C$ after the Squeeze process, and then passes through a two-stage fully connected network with the activation function chosen to be Relu and sigmoid, respectively, and the whole operation is known as the Excitation process.The Excitation process is shown in equation (6).

$$s = F_{ex}(z,W) = \sigma\left(g(z,W)\right) = \sigma\left(W_2 \delta(W_1 z)\right) \tag{6}$$

After the Excitation process, a C -dimensional vector is output and the value of the vector is the weight of the channel. The input features will be multiplied with the weights, the important features will be enhanced and the useless features will tend to 0. The process of assigning weights to the inputs is known as Reweight and the Reweight process is shown in equation (7).

$$\tilde{X} = F_{scale}(u_c, s_c) = s_c \cdot u_c \tag{7}$$

II. C. 2) Bilinear feature interaction

Figure 3 shows the schematic diagram of the computational process of bilinear feature interaction, the bilinear feature interaction introduces the parameter cross matrix to realize the interaction between features, and in the computational process, feature i firstly performs the inner product with the parameter matrix, and the computational result then performs the Hadamard product with feature j. And according to the different number of parameter cross matrix, there are three models:

(1) FieldAll Type

All cross features share one parameter matrix.

(2) Field Each Type

Each field shares one parameter matrix.

(3) Field Interaction Type

Each Filed combination enjoys one parameter matrix.

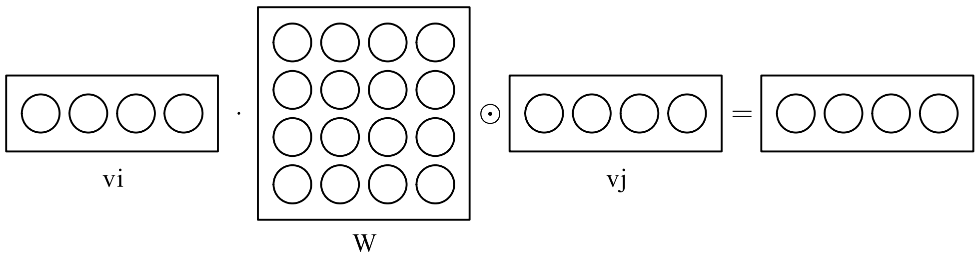

Figure 3: The interactive calculation process of bilinear features

The bilinear eigeninteraction formula is shown in equation (8):

$$p_{ij} = v_i W \circ v_j \tag{8}$$

II. C. 3) CIFW model

In this paper, based on the XDeepFM model, the original explicit higher-order interaction part is retained, and the channel attention mechanism is added on the basis of the original DNN module to enhance the weight of the valid information in the input features, so as to improve the network performance. And the weight sharing technique of bilinear feature interaction module is used to alleviate the problem of feature sparsity.The network structure of CIFW is shown in Fig. 4:

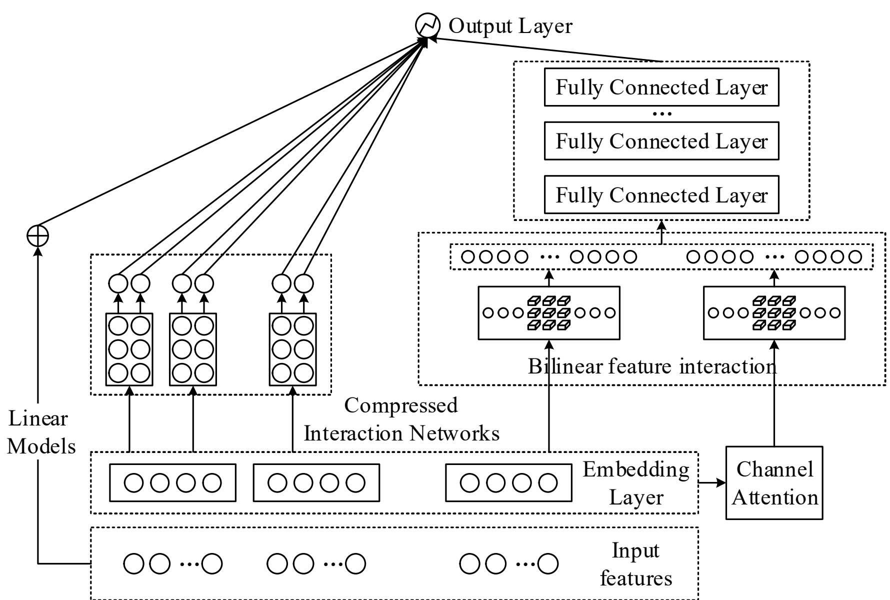

Figure 4: CIFW model

(1) Input layer

The input layer serves as the first layer of the network structure, the inputs are divided into two types, sparse input x_{sparse} and dense input x_{dense}, the sparse inputs are the discrete features, $x_{sparse} = [x_1, x_2, \cdots, x_n]$, n is the number of discrete features. The sparse inputs need to be processed by solo thermal coding before they can be input into the model, and the dense inputs are numerical features that can be directly input into the model.

(2) Embedding layer

After the features have been encoded in the input layer by unique thermal coding, they will form high-dimensional sparse data, which cannot be directly applied to the neural network. The embedding layer can map the high-dimensional sparse features to the low-dimensional dense feature space in order to better utilize the neural network for feature processing. The recommendation algorithm model presented in this paper maps all the discrete features to the embedding layer and splices all the mapped features as the output of the embedding layer. The embedding mapping is shown in equation (9):

$$e_i = v_i x_i \tag{9}$$

where e_i is the embedding vector of the i th feature and v_i is the embedding matrix of the i th feature. The output of the embedding layer is formed by splicing the embedding vectors of the input features, $E=[e_1,e_2,\cdots,e_n]$, where n is the number of features.

(3) Explicit Interaction Layer

The input of the explicit interaction layer $x_{cin}=\left[E,x_{dense}\right]$ is the output of the embedding layer spliced with the dense input, and the output of the explicit interaction layer is p^+.

(4) Feature enhancement layer

The input of the feature enhancement layer is the output of the embedding layer, after the data enters into the feature enhancement layer, it is divided into two parts according to the direction of data flow, the first part will directly input the input data to the bilinear feature interaction module and get the output cross-feature. The second part will first dynamically learn the importance of features through the channel attention mechanism to get the enhanced embedding vector, and then input the enhanced embedding vector to the bilinear feature interaction module to get the output cross-feature. These two parts of the output cross-features are concatenated together and input into the multilayer perceptron network, and the output of the multilayer perceptron network is shown in equation (10):

$$h_f = MLP\left(Concat(E_{bilinear1},E_{bilinear2})\right) \tag{10}$$

(5) Prediction layer

The prediction layer generates predicted values based on the output of the interaction layer, and the recommendation algorithm model used in this paper uses the sigmoid function as the activation function of the prediction layer. The predicted value is shown in equation (11):

$$y_{pred} = \sigma\left(W_{linear}x_{linear} + [p^+,h_f]W_o + b_o\right) \tag{11}$$

III. Experimental validation and performance analysis of SOM-based recommendation model for civic education

After constructing the Civic Education Recommendation Model (CIFW) that integrates SOM and deep learning in Chapter 2, Chapter 3 verifies its practical efficacy through experiments. Based on the comparison of user rating data and multi-dimensional metrics, this chapter systematically evaluates the recommendation performance of the model in three dimensions: accuracy, coverage and adaptability.

III. A. Preliminary validation of user rating data collection and recommendation effect

The personalized recommendation method based on self-organizing mapping network proposed in this paper is used as an experimental method to conduct simulation test experiments to verify the recommendation effect of the studied method.

There are 30 experimental test users, each with their own attribute labels, and 30 users are invited to rate the six ideological and political education resources generated by the personalized recommendation model (A1: Ideal Belief Education; A2: Patriotism and Collectivism Education; A3: Socialist Democracy and the Rule of Law Education; A4: Moral and Ethical Education; A5: Mental Health and Character Education, and A6: Cultural Inheritance and Ecological Concept Education). Comprehensive scoring was carried out and scored according to the criteria of 1-5, and an example of the scoring results is shown in Table 1.

Table 1 shows the results of 10 users' comprehensive ratings of the six types of Civic and Political Education resources. In terms of average scores, A3 Socialist Democracy and Rule of Law Education scored the highest, 4.53, followed by A1 Ideal Conviction Education, 4.39 and A2 Patriotism and Collectivism Education, 4.36; A5 Mental Health and Personality Education and A6 Cultural Heritage and Ecological Philosophy Education scored relatively low, 4.09 and 4.12, respectively. There are obvious individual differences in user ratings, for example, user 3 rated

A3 as high as 4.84, but only 3.78 for A2; user 10 rated A4 Moral and Ethical Education as high as 4.80, but only 3.89 for A2. Overall, A3 and A1 have higher user recognition, while there may be room for optimization of resources in the mental health and ecological philosophy categories.

Table 1: An example of a user's comprehensive rating of resources

User	A1	A2	A3	A4	A5	A6
1	4.54	4.25	3.98	4.05	4.32	4.88
2	4.20	4.41	4.73	4.45	4.04	3.87
3	4.68	3.78	4.84	3.78	3.82	4.14
4	4.18	4.62	4.77	4.19	4.03	3.51
5	4.84	4.51	4.41	4.33	4.15	4.46
6	4.79	4.85	4.79	4.46	4.24	3.98
7	4.02	4.27	4.20	4.72	3.83	3.69
8	4.19	4.57	4.24	4.49	3.88	4.77
9	4.18	4.49	4.78	4.73	4.16	3.28
10	4.32	3.89	4.52	4.80	4.45	4.59
Average	4.39	4.36	4.53	4.40	4.09	4.12

III. B. Multi-Algorithm Comparison Experiments and Quantitative Evaluation of Model Performance

The preliminary analysis based on user ratings reveals the preference differences of recommended content, and this section further validates the superiority of Item-SOM-CIFW in mitigating data sparsity and improving recommendation accuracy by quantitatively comparing the MAE value with the coverage rate.

III. B. 1) Experimental setup and experimental environment

In order to be able to verify the effectiveness and superiority of the Item-SOM-CIFW algorithm proposed in this paper, relevant experiments are designed in this chapter. In the experiment, the commonly used 5-fold cross-validation method is adopted, and the experiment is repeated five times, i.e., the original data is divided into five parts with equal amount of data, and each time the experiment will select different four parts as the training set and one part as the test set for testing, and construct the recommender system with the data of the training set, and then test the target users in the test data, and the final result is taken as the average value of the five tests. After that, it is compared with other algorithms in terms of MAE value and coverage rate, which represents the accuracy of the prediction of user ratings, which is evaluated from the user's point of view; and the coverage rate represents the ratio of recommended Civics resources to total resources. The comparison proves that the algorithm proposed in this paper has better performance.

One Dell laptop is used for this experiment with the following configuration: CPU: Inter(R)Core(TM)i5-6200U CPU@2.30GHz 2.40GHz, Memory (RAM): 8GB, Operating System: Windows 10 64-bit. All algorithm programming is implemented using Python language and database MySql.

III. B. 2) Contrasting models

Experimental comparisons are conducted to verify the recommendation performance of the Item-SOM-CIFW algorithm proposed in this paper. The algorithms involved in the comparison experiments include:

(1) User-CF: traditional user-based collaborative filtering algorithm.

(2) FCM-CF: a fuzzy C-mean clustering collaborative filtering algorithm without optimizing the clustering center, which does not use the flower pollination algorithm to determine the initial clustering center, and there is the problem of local optimal solution.

(3) WAUP-CF: a collaborative filtering algorithm with weight adjustment and user preference, the algorithm also constructs a user preference matrix and pays attention to user interaction behavior on cold items, and improves the similarity calculation formula. However, the algorithm does not consider the effect of time factor, and it is not interested in solving the problem of data sparsity.

(4) URCC-CF: A personalized recommendation method based on user ratings and category clustering.

Each algorithm is given the optimal weight coefficient $\lambda = 0.7$, the number of clusters $k = 5$, so that the number of nearest neighbors is incremented from 5 to 50, and the growth interval is 5.

III. B. 3) Comparison of accuracy

Firstly, the mean absolute error MAE value is used as the evaluation standard for the performance of the algorithms, the smaller the MAE value indicates that the algorithms are more accurate, and the comparison results of five different algorithms are shown in Fig. 5.

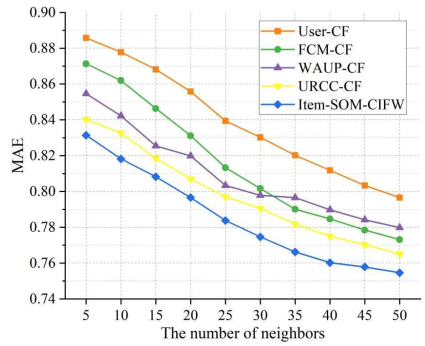

Figure 5: The MAE values of five different algorithms

As can be seen from the figure the algorithm proposed in this paper outperforms the other four algorithms in evaluating the performance MAE value after optimizing the data sparsity and clustering. As the number of nearest neighbors increases, the MAE value decreases, i.e., the higher the performance of the recommender system. While the trend of decreasing MAE value is getting slower and slower, it can be expected that when the number of nearest neighbors is large enough, the MAE value will level off. The MAE values of User-CF, FCM-CF, WAUP-CF, URCC-CF and Item-SOM-CIFW are 0.796, 0.773, 0.779, 0.765 and 0.754, respectively, when the number of nearest neighbors is 50.The traditional user-based collaborative filtering algorithms are not optimized in any way and have the worst recommendation accuracy. The recommendation method proposed in this paper has more accurate clustering results compared with the FCM-CF algorithm, and when the number of nearest neighbors is small, the difference between the recommendation accuracy of the two methods is not large, while with the increase in the number of nearest neighbors, the FCM-CF algorithm identifies some users who are not actually similar to the target user as nearest neighbors, which affects the recommendation accuracy. In contrast, the recommendation method proposed in this paper has a higher recommendation accuracy compared with the WAUP-CF algorithm by weighting the original Civic Resources data with time factor weighting and matrix filling, which alleviates the problems of user interest drift and data sparsity.

III. B. 4) Comparison of coverage

Using only the MAE value to unilaterally evaluate the strengths and weaknesses of a recommendation algorithm is not convincing, even if the algorithm can recommend to the user the content of Civic Education that he/she is interested in, and improve the user's satisfaction, it is only analyzed from the user's point of view. Therefore, in order to further prove the effectiveness and superiority of this algorithm, the following will be a comparative study of the changes in coverage. Setting the number of nearest neighbors as 30 people, the recommended Civics education content for each person is incremented from 5 to 50 with an interval of 5, comparing the coverage rate of the five algorithms, and the comparison results are shown in Figure 6.

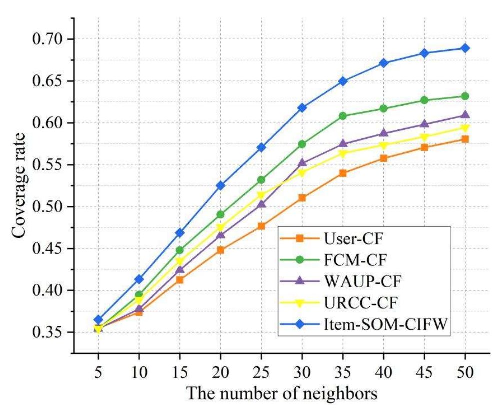

Figure 6: Coverage rates of the five algorithms

Figure 6 compares the coverage performance of the five recommendation algorithms for different numbers of recommended resources. As the number of recommended resources increases from 5 to 50, the coverage of all algorithms shows an increasing trend, but Item-SOM-CIFW always outperforms the other algorithms. For example, when the number of recommended resources is 50, Item-SOM-CIFW has a coverage of 68.9%, which is significantly higher than the traditional methods such as 58.1% for User-CF and 63.2% for FCM-CF. When the number of recommended resources is 30, Item-SOM-CIFW coverage is 61.8%, which is 7.3 percentage points higher than the 57.5% of the second best FCM-CF. The data show that Item-SOM-CIFW significantly alleviates the problem of data sparsity through the dynamic clustering and feature weighting mechanism, and is able to cover the content of the Civic Education Resource Base more comprehensively.

III. C. Comparative Analysis of Clustering Algorithm Optimization

After completing the cross-sectional comparison of multiple algorithms, Section 3.3 focuses on the optimization of clustering algorithms, and elucidates the key role of SOM network in solving the problem of initial center randomness and high-dimensional data clustering by comparing the K-means with the FCM clustering of flower pollination optimization.

In previous recommendation algorithms, many scholars use clustering to improve recommendation efficiency, and K-means clustering is one of the most widely used clustering methods.K-means clustering is convenient to operate, the principle is easy to understand, and has a faster speed and higher efficiency than other clustering methods. However, it also has some problems:

(1) The initial clustering center is obtained by random selection, and the clustering may fall into the local optimal solution. It both makes clustering more complicated and leads to some users with truly similar target users being assigned to other clusters and thus not being selected into the neighbor set.

(2) Clustering is not effective for the data used in this paper - high dimensional data. Clustering algorithms that use Euclidean distance as a similarity metric usually only find spherical or spherical-like cluster structures with a more uniform distribution of data objects. In this section, the performance of clustering using K-means clustering will be compared with fuzzy C-mean clustering optimized using the flower pollination algorithm applied to the recommendation algorithm. The optimal weight factor is selected as 0.7, the number of nearest neighbors is 30, and the number of clusters is an integer between [2,8], and the MAE value is used as an evaluation criterion for the performance of the algorithms. Comparison of MAE for applying two clustering algorithms is shown in Fig. 7.

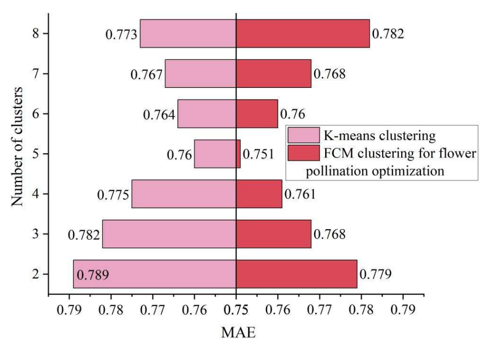

Figure 7: MAE comparison of two clustering algorithms

As can be seen from the figure, at the beginning when the number of clusters is small, the recommendation performance gap between the two methods is small, and as the number of clusters increases, the performance gap between the algorithms increases. For the recommendation algorithms using flower pollination optimization of FCM clustering and K-means clustering both the algorithm performance is optimal when the number of clusters is 5, which is 0.751 and 0.76, respectively, when the number of clusters is more than 5, it appears that the individual classes contain too few users, which affects the prediction of ratings of the users among them, and the error value of K-means clustering increases, overall, the recommendation algorithms using flower pollination optimization of recommendation algorithm using fuzzy C-mean clustering performs better than the recommendation algorithm using K-means clustering.

III. D. Matching Comparison Results of Different Recommendation Methods

In order to further verify the actual adaptation ability of the model, this section proves the effectiveness and application value of Item-SOM-CIFW in dynamic recommendation of Civic and Political education resources by grade-by-grade matching degree test, combining the needs of different education stages.

In order to verify that the method of this paper can effectively personalize the recommendation of Civic and Political Education Resources, the method of comparison test is used to complete the demonstration. The four recommendation methods mentioned above are chosen as the control group respectively, and students from freshmen to seniors in a university are taken as the test objects, and thousands of sets of Civic and Political Education Resources are chosen from the resource library as the test data to verify the recommendation effect of different methods.

III. D. 1) Data preparation

In order to ensure the accuracy of the data testing, students within the universities of a certain province were randomly selected, and 1,000 students each in the order of freshmen to seniors were taken as test subjects. Civic education resources were retrieved from the National Resource Library, and thousands of sets of data were randomly selected as recommended samples according to the courses taught at different grades, categorized by the sample groups of G1-G12.

III. D. 2) Analysis of results

Here, different recommendation methods are used to recommend the Civic Education resources so that they can be taught in different stages of university lectures. The selected resource samples are uploaded to the MATLAB test platform and connected to five groups of recommendation methods respectively. The matching test results of each group of methods are shown in Fig. 8.

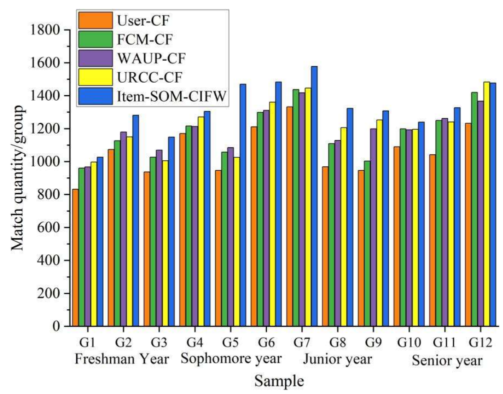

Figure 8: The matching degree test results of each group of methods

Fig. 8 compares the fitness of different recommendation methods through the grade-by-grade matching test.Item-SOM-CIFW performs the best in all grades and sample groups, e.g., the number of matches in the freshman G1 group reaches 1,027 groups, which is much higher than the 832 groups of User-CF and the 960 groups of FCM-CF; and the number of matches in the sophomore G5 group is as high as 1,469, which is 43.3% higher than that of URCC-CF's 1025 groups by 43.3%. As the grade level rises, the recommended matching degree increases, for example, the matching degree of Item-SOM-CIFW reaches 1,577 groups in the junior G7 group, and 1,477 groups in the senior G12 group, compared with the obvious fluctuation of the traditional method User-CF in the cross-grade adaptation, for example, the number of matches of User-CF in the senior G11 group is only 1,042, and the number of matches of Item-SOM-CIFW is 1,327 groups. 1327 groups. The results show that Item-SOM-CIFW can dynamically integrate user behavior and resource characteristics, adapt to the needs of Civic Education at different educational stages, and has stronger practical application value.

IV. Conclusion

In this study, by constructing a CIFW model that integrates SOM and deep learning, we successfully improve the accuracy and adaptability of the Civic Education content recommendation.

(1) The MAE value of Item-SOM-CIFW is 0.754, which is significantly lower than the 0.796 of User-CF of traditional collaborative filtering algorithm, indicating that it effectively alleviates the data sparsity problem through dynamic clustering and feature weighting.

(2) When the number of recommended resources is 50, the coverage rate of CIFW reaches 68.9%, which is 5.7% higher than the 63.2% of FCM-CF, proving that it can more comprehensively explore potential educational resources.

(3) In the grade-by-grade test, the number of matches of CIFW in the sophomore G5 group is 1,469, which is far more than the 1,025 of URCC-CF, and the matching degree increases with the grade, such as the junior G7 group reaches 1,577, which verifies the adaptability of the model to the dynamic changes of educational needs.

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