International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0362
Article

Research on the Accuracy Path of College Students' Civic and Political Education Work Based on Deep Learning in the New Media Era

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Abstract: In the face of massive ideological and political education resources and textual information, how to quickly and accurately obtain ideological and political content that meets the teaching needs is an urgent problem to be solved. In this regard, this paper constructs an information extraction dataset in the field of curriculum Civics and politics, and proposes a new NCFCA algorithm based on the neural collaborative filtering algorithm of channel attention. Simulation test and coverage test of the system designed by NCFCA are carried out in the constructed information dataset of Civics and Politics, and comparative experiments are conducted with different recommendation systems. And the NCFCA method oriented to learning resources recommendation is applied to the actual Civics teaching. The results show that the average MAE value of the five groups of experiments of the system under the NCFCA algorithm is 0.606, and the F1 value is 0.306. The coverage rate of the automatic recommendation method for college students' Civic and political teaching resources based on the NCFCA model when recommending Civic and political education and teaching resources for the users is 98.4, which is superior to the performance of the system under the other three algorithms, indicating that the NCFCA system has the highest coverage rate of the resources and the best recommendation effect. . Nearly 90% of the students think that the NCFCA method is very accurate for recommending learning ideological and political resources, and in test scores 3 and 4, the average scores of the students in the experimental group and the control group are 86.54, 86.18 and 77.40, 77.47, respectively, which is a large difference between the two, indicating that the NCFCA method can effectively improve the learning effect of the students. This study fully demonstrates that the NCFCA method proposed in the article plays an important role in promoting the precision of college students' civic education and has strong feasibility and effectiveness.

Keywords: civic education; channel attention; neural cooperative algorithm; NCFCA

1. Introduction

The new era clearly puts forward the requirements for the improvement of ideological and political work, that is, in ideological and political work, it should be closely combined with traditional and information technology, so that it becomes a coordinated organic whole, and closely integrates all kinds of media, such as party newspapers and magazines, new media and so on [1]. At present, the mobile Internet is constantly developing, and the influence of microblogging, weibo, weibo, jitterbug and so on in the new media platform is becoming more and more in-depth and strengthened, which profoundly influences students' learning, life and other aspects, and helps the implementation of ideological and political education work in colleges and universities [2-3]. However, the cyberspace is relatively free, the content of communication is uneven, coupled with the network supervision has a certain degree of difficulty, the bad information out of the wanton, and some students lack of good discernment and self-control, easy to be affected by the network of diversified information [4]. Based on this, new media and ideological and political education should be closely integrated together to innovate the mode of ideological and political education. On the other hand, the rapid development of digital intelligence technology represented by big data, the Internet and artificial intelligence in the new era has brought brand new opportunities and changes to ideological and political education [5]. Grasping the valuable opportunity of digital intelligence technology empowering accurate ideological and political education in colleges and universities is the proper meaning of the transformation of ideological and political education to modernization and digitalization, and it is the answer of the times for the high-quality development of ideological and political education.

Ai, H analyzes the problems of ideological education in the context of new media and puts forward corresponding improvement suggestions to promote the innovation and reform of ideological education [6]. Gong, M et al. analyzed the impact of new media technology on students' thinking as well as ideological education, which provides some references for ideological educators to carry out ideological education work in the context of new media [7]. Zhang, X. elaborated that new media technology is both a risk and a challenge for Civic Education, and argued that teachers need to gain insight into the ideological dynamics of students in the context of new media and discover the paths of integrating new media technology into Civic Education [8]. Yu, Y. D et al. examined the path and logical mechanism of big data technology-enabled Civics precision education and concluded that big data technology effectively improves the quality of Civics education and teaching and helps to cultivate excellent talents [9]. Li, M. and Ye, D et al. combined precision teaching thinking with technological tools such as data mining and intelligent algorithms to analyze the current situation of students' thoughts, mentality, learning and life in order to personalize Civic Education [10]. Zhang, Z et al. explored the precise teaching mode of big data technology plus Civics teaching, which ensures the full picture of teaching and differentiation as well as personalization of Civics teaching, pointing out that big data technology is an effective teaching aid to improve the effectiveness of Civics teaching [11].

The data annotation tool Brat was used to annotate and construct a dataset of information extraction in the field of Curriculum Civics. The dataset covers a wide range of course civics entity types and relationship types, providing a basis for model training and evaluation. To better improve the relevance of embedded dimensions between users and programs, as well as to accurately model user preferences for programs in implicit feedback, a new channel attention-based neural collaborative filtering algorithm, NCFCA, is proposed. The model assigns personalized weights to different interaction items through the feed-forward attention mechanism to influence the user's preference for the item when the user interacts with the item, so as to accurately and efficiently obtain the feature information of the user and the item; secondly, the model utilizes the convolutional neural network to improve the correlation between the user and the item, and at the same time, adds the channel attention mechanism to the convolutional neural network to mine the rich semantic information. The generalized matrix decomposition method is used to alleviate the data sparsity problem due to user-item interactions and to integrate the prediction modules together.

2. Curriculum Civics Information Extraction Data Set Construction

2.1. Labeling of information about the course's philosophy

2.1.1. Data annotation tool Brat

Brat is an open source manual text annotation tool from the NLPLab project. In the Linux operating system based on the Web page to achieve visual interaction with the annotator. Through the user-defined configuration file can be achieved on the document entities and the relationship between entities at the same time labeling, to meet the information extraction algorithms in the named entity recognition and relationship extraction tasks.Brat text annotation tool because of its flexible and efficient features, favored by researchers of natural language processing tasks.

2.1.2. Determination of labeling specifications

When teaching staff want to retrieve examples of the application of curriculum Civics for reference, they often access the content through key information such as the name of the curriculum area they need, the elements of curriculum Civics used, the method of realizing curriculum Civics, and the Civics effect they want to achieve.

This chapter designs 7 entities according to the needs: "subject school", "professional college", "curriculum", "knowledge points", "ideological and political methods", "ideological and political elements", and "ideological and political goals", and 4 relationships of "including", "using ideological and political elements", "applying ideological and political methods", and "achieving ideological and political goals".

By the special nature of utterance expressions and constructions in the Civics case of the handbook course, the following constraints are formulated in order to make the annotated entity expressions not ambiguous: first, the annotated samples need to contain both application domain class entities and Civics method class entities, or both application domain class entities and Civics element class entities, or else they will be eliminated as invalid samples; second, when annotating a single entity, we should add as much as possible contextual Second, when labeling a single entity, contextual qualifiers should be added as much as possible to ensure that the semantics of the entity is clearer; Third, nesting of entities is not allowed.

2.1.3. Course Civics dataset labeling

First of all, according to the pre-determined annotation rules and entity and relationship categories, modify the annotation.conf file under the Brat tool folder, and at the same time, modify the visual.conf and kb_shortcuts.conflia files for entity and relationship aliases and shortcuts to improve the efficiency of the annotation.

Brat tool can realize entity and relationship annotation at the same time. Brat in the labeling of a data can be generated after the annotation file .ann, entity information contains entity number, entity type, entity start and end position and entity text. Relationship information contains the relationship number, relationship type, head entity number and tail entity number.

After the corpus is annotated, it is converted into JSON format to facilitate the processing of data during model training. Among them, "text" indicates the original delivery. "entities" represents a collection of entities, and in a single entity, "type" represents the entity type, "text" represents the original text of the entity, "start" represents the number of the entity start position, and "end" represents the number of the end position of the entity. "relations" denotes a set of relationship triples, and in a single relationship triplet "type" denotes the relationship type, "arg1" denotes the head entity, and "arg2" denotes the tail entity.

2.2. Analysis of the Curriculum Civics Data Set

In this labeling work, the labeling team was composed of 2 people from the subject group, and in order to exclude the data errors caused by subjective human factors, the labeling rules were determined and all the sample data were labeled at the same time. The labeling results were evaluated according to Cohen's Kappa labeling consistency formula (1) after the labeling was completed.

$$k = \frac{P_o - P_e}{1 - P_e} \tag{1}$$

where P_o is the rate of agreement reached by the labeling personnel, calculated as in equation (2). P_e is the random probability of the labeled personnel reaching agreement, calculated as in equation (3).

$$P_o = \frac{a+b}{n} \tag{2}$$

$$P_e = \frac{(a+b)\times(a+c)+(c+d)\times(b+d)}{n^2} \tag{3}$$

Among them, a is the number of samples with completely consistent annotation results by the annotators; b is the number of samples labeled true by annotator 1 and false by annotator 2; c is the number of samples labeled true by annotator 2 and false by annotator 1; and d is the number of samples with inconsistent annotation results by the annotators.

The final calculation of labeling consistency of $k = 0.72 > 0.6$ indicates that the labeling has high consistency and the labeling is valid. In order to minimize the error of the dataset, only the 1648 data with consistent annotation results of 2 annotators are retained to form the final dataset of course civics information extraction. It contains 10684 entities as well as 8953 relationships.

3. Channel attention based neural collaborative filtering recommendation algorithm

3.1. Model description

3.1.1. Initial model representation

For user u and item i and features (e.g., ID, item type, etc.), the features are first coded one-hot. Use v_u^U and v_i^I as their feature vectors to get their embedding vector representations p_u and q_i:

$$p_u = P^T v_u^U \tag{4}$$

$$q_i = Q^T v_i^I \tag{5}$$

where $v_u^U \in R^{M\times 1}$, $v_i^I \in R^{N\times 1}$. $P \in R^{M\times K}$ and $Q \in R^{N\times K}$ are the embedding matrix of user features and the embedding matrix of item features, respectively. $p_u \in R^{K\times 1}$ and $q_i \in R^{K\times 1}$ denote the user vector and item vector, respectively.

3.1.2. Representation of the matching function incorporating the attention mechanism

Calculate the effect of different characteristic attributes of the item on the user u purchase behavior, i.e., the importance of the characteristic attributes of the item to the user. Use the attention function $f \in R^{K\times 1}$:

$$f\left(p_u, q_i\right) = \mathrm{ReLU}\left(W\left(p_u \odot q_i\right) + b_0\right) \tag{6}$$

where $W \in R^{K\times K}$ represents the weight matrix from the input layer to the hidden layer, b_0 is the bias vector, and ReLU represents the activation function. The larger the value in the attention network, the more interested a feature attribute of user u and item i is. The SoftMax function is utilized to convert the obtained attention weights into a probability distribution with attention coefficients:

$$\alpha(u,i) = \frac{\exp\left(f\left(p_u, q_i\right)\right)}{\sum_{i\in R_u} \exp\left(f\left(p_u, q_i\right)\right)} \tag{7}$$

where R_u is the set of interaction history of user u and item i, and $\alpha(u,i) \in R^{\kappa\times 1}$ denotes the attention weights of user u and item i. In the final multilayer perceptual network based matching function learning part is defined as:

$$x_0 = \begin{bmatrix} \alpha(u,i) \\ \left(p_u, q_i\right) \end{bmatrix} \tag{8}$$

$$x_1 = \mathrm{Re}LU\left(W_1^T x_0 + b_1\right) \tag{9}$$

$$x_2 = \mathrm{Re}LU\left(W_2^T x_1 + b_2\right) \tag{10}$$

$$\cdots\cdots$$

$$x_n = \mathrm{Re}LU\left(W_n^T x_{n-1} + b_n\right) \tag{11}$$

Where, $x_0 \in R^{2K\times 1}$ represents the input vector of the multilayer perceptual network, $\{x_1, x_2, \ldots, x_n\}$ represents the corresponding input-output vector in the hidden layer, $\{W_1, W_2, \ldots, W_n\}$ and $\{b_1, b_2, \ldots, b_n\}$ represent the weight matrix and bias vector of each layer. x_n is the final prediction vector. The feed forward attention layer is utilized to learn the different importance of different feature dimensions of the item.

3.1.3. Convolutional Attention Networks

To enhance the correlation between users and items, CNNs are used to learn higher-order correlations between their embedding dimensions and to reduce the parameters between the embedding and hidden layers in the network. A channel attention mechanism is added to the convolutional neural network to enhance the semantic information of users and items in the network.The ECA-Net attention network is able to perform dimensionality reduction of feature dimensions in the convolutional neural network as well as to enhance the information interaction between channels.

First the model computes the outer product of user embeddings and item embeddings and uses the resulting outer product as a representation of their interaction:

$$FM = p_u \otimes q_i = p_u q_i^T \tag{12}$$

where $FM = R^{K \times \kappa}$, each element can be denoted as $fm_{k_1,k_2} = p_{u,k_1} q_{i,k_2}$. A two-dimensional matrix is obtained by the outer product operation, which is then pulled into a vector of dimension K^2 by the Flatten operation.

CNNs are commonly employed in CNN-based collaborative filtering research to extract higher-order interactions between users and items. This chapter innovatively extends it by adding an E-CNN component to CNN.The E-CNN module consists of two parts. First, the user-item interaction representation is input into a convolutional neural network, which is trained by convolving it with 6 hidden layers, where each layer is set with 64 channels, a convolution kernel of 2×2, and a step size of 2, so that the shape of the result obtained in each layer is half of that of the previous layer. Secondly, when the training reaches the last layer, the convolutional block shape is $1 \times 1 \times 64$, at which point the ECA-Net attention network is added between the convolutional blocks. The feature maps of $1 \times 1 \times \mathrm{C}$ are generated after a global average pooling operation between each convolutional block, and then a convolution operation is performed using a one-dimensional convolutional kernel to learn the channel attention with a Sigmoid function, which defines the channel dimensionality to be 64 dimensions, and the interaction of the user and item information between the channels w:

$$y = \frac{1}{WH} \sum_{u=1,i=1}^{w,H} \chi_{ui} \tag{13}$$

$$w = Sigmoid(CiD(y)) \tag{14}$$

where C1D denotes one-dimensional convolution and y denotes global average channel pooling. In a convolutional neural network, the input to the last convolutional layer is defined as a three-dimensional tensor and combined with the ECA-Net attention network, and the overall hidden state fm in each FM is:

$$h = \left(fm_{2a+a}, fm_{2i+b} \right) \tag{15}$$

$$H^{I-2} = h^{I-2} \cdot t_{1-a,1-b,C}^{I-1} \tag{16}$$

$$H^{I-1} = h^{I-1} \cdot t_{1-a,1-b,c}^{I} \tag{17}$$

$$fm_{u,j,e}^{I-1} = \sigma\left(o_{l-1} + \sum_{a=0}^{1} \sum_{b=0}^{1} H^{I-2} \right) \tag{18}$$

$$fm'_{u,j,e} = \sigma\left(o_l + w \cdot \sum_{a=0}^{1} \sum_{b=0}^{1} H^{I-1} \right) \tag{19}$$

$$fm_{u,j,e} = \sigma\left(fm_{u,j,e}^{I-1} + fm'_{u,j,e} \right) \tag{20}$$

where o_l denotes the bias vector of layer l, a and b denote the interaction matrix parameters of the local regions captured in each layer, respectively, $t_{1-a,1-b,c}^{t}$ denotes the convolutional filter, and σ denotes the ReLU activation function. Its output in the last layer is a $1 \times 1 \times 64$ -dimensional tensor. In the prediction layer, the final prediction score $\hat{y}_{ui}^{E-CNN} \in R^{K \times 1}$ is defined in this chapter as follows:

$$\hat{y}_{ui}^{E-CNN} = G(FM) \cdot W_G^T \tag{21}$$

where $G(FM)$ denotes the output vector of the model in multiple intermediate layers and W_G^T denotes the reweighting of user and item weights in the output vector. During model training, all inter-dimensional interactions are captured with a total of $\left(5\times32\times64+2\times2\times64+2\times2\times64\times32\times5\right)51456$ parameters. Higher-order features are extracted in the network starting from the first layer of the feature map, where each cell extracts locally connected interactions in the region of the previous layer 2×2, and the second layer extracts information from the first layer 4×4, and so on, so that in the last layer of the network the globally connected interactions are extracted from the initial feature map, which improves the user-item correlation and mines rich semantic information at the same time.

3.2. Matrix decomposition

Matrix decomposition is better able to handle sparse user-item co-occurrence matrices than collaborative filtering models, with stronger generalization capabilities and better scalability and flexibility. The principle of matrix decomposition algorithm is shown in Fig. 1.

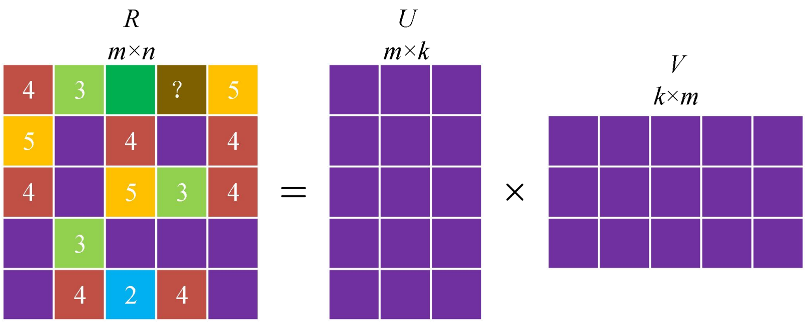

Figure 1. Principle of matrix decomposition algorithm

Matrix decomposition combines the idea of “collective intelligence” of collaborative filtering and the “deep relationship” covered by the hidden semantic model, and at the same time, it is a goal-oriented supervised learning, which to some extent overcomes the obvious head effect of collaborative filtering algorithms and the weakness of the generalization ability. The shortcomings of collaborative filtering algorithms.

Assuming that the scoring matrix $R\in\mathbb{R}^{m\times n}$ constructed by m user scoring n items, r_{ui} represents the scoring of user u for item i, according to the principle of matrix decomposition, the original large matrix $R\in\mathbb{R}^{m\times n}$ is applied singular value decomposition (SVD) to obtain two small matrices $U\in\mathbb{R}^{m\times k}$ and $V^T\in\mathbb{R}^{k\times n}$, where k denotes the length of the hidden factor vector. The specific formula is shown in equation (22):

$$R_{m\times n}\approx U_{m\times k}\Sigma_{k\times k}V_{1\times n}^T \tag{22}$$

Matrix decomposition assumes that a user's rating of an item is controlled by a series of hidden variables, which are common to both the user and the item, and can be interpreted as user preferences from the user's point of view, and attributes of the item from the item's point of view. When measuring the rating of a given user u for an item i, the user only needs to add up the products of the corresponding hidden variables in order to make a prediction of the ratings. The application of this hidden semantic model to the field of recommendation algorithms is matrix decomposition, which models the implicit structure of users and items, and mines the deeper associations between users and items.The Funk SVD algorithm only considers existing rating records, bypassing the problem of data sparsity, and decomposes the matrix into two, with the specific formulas shown in Eq. (23) and Eq. (24):

$$R_{m\times n}=P_{m\times k}\times Q_{k\times n} \tag{23}$$

$$\hat{r}_{wi}=q_i^T p_u \tag{24}$$

The idea of linear regression is adopted to learn the final user and item feature matrices by setting the objective function, and the corresponding hidden variables are multiplied and accumulated to obtain the final predicted scores. The objective function is shown in equation (25):

$$G = \min_{q^*, p^*} \sum_{(u,i)\in K} \left(r_{ui} - q_i^T p_u \right)^2 + \lambda \left(\|p_u\|^2 + \|q_i\|^2 \right) \tag{25}$$

where κ denotes the set of user items that have generated interactions and λ denotes the L2 regularization coefficient. With the objective function, the parameters can be optimized by gradient descent method to obtain the best results. However, the actual scoring is not completely affected by the user's preference for the item only, the user's scoring preference, the item's own characteristics, and the platform difference are all factors that will directly affect the user's scoring of the item.BiasSVD, as an improved algorithm of FunkSVD, adds a bias term on the basis of Funk SVD to solve the above problem. The predicted rating formula after adding the bias part is shown in equation (26):

$$\hat{r}_{ui} = \mu + b_w + b_i + q_i^T p_u \tag{26}$$

where μ denotes the global bias, which is the global average of all scoring records in the training set; b_u denotes the user bias, which measures the scoring preference of a particular user; and b_i denotes the item bias, which measures the characteristics of a particular item itself. The objective function is replaced with equation (27):

$$\begin{aligned} G = \min_{p^*, q^*, b^*} & \sum_{(u,i)\in K} \left(r_u - \mu - b_u - b_i - q_i^T p_u \right)^2 \\ & + \lambda \left(\|p_u\|^2 + \|q_i\|^2 + b_u^2 + b_i^2 \right) \end{aligned} \tag{27}$$

SVD++ sets the implicit vector by the collection of items and user attribute features that have been rated by a specific user, and then superimposes the implicit vector to depict the user's interest and preference respectively, enriches the user feature matrix, effectively uses the user attribute features, and alleviates the problem of data sparsity, so the prediction scoring formula of SVD++ can be obtained by adding the implicit feedback vector of the evaluated item set and the implicit feedback vector of the user attribute in the original user vector part of the BiasSVD prediction scoring formula (28):

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T \left(p_u + |N_u|^{-0.5} \sum_{j\in N(u)} x_j + \sum_{a\in A(u)} y_a \right) \tag{28}$$

The target equation is also replaced with equation (29):

$$\begin{aligned} G = \min & \sum_{F_{ic}, R_{rase}} \left(r_{ui} - \hat{r}_{ui} \right)^2 \\ & + \lambda \left(\|p_u\|^2 + \|q_i\|^2 + b_u^2 + b_i^2 + \sum_{jeN(u)} \|x_j\|^2 + \sum_{a\in,(u)} \|y_a\|^2 \right) \end{aligned} \tag{29}$$

Where $N(u)$ is the set of items of user u 's generated behavior, $A(u)$ is the set of user u 's feature attributes, $|N_u|^{-05}$ is a normalization factor, x_j is the hidden vector learned through the set of items of user's generated behavior, and the summed hidden vector reflects the degree of user's preference for these hidden factors: y_a is the hidden vector learned through the user's attribute features.

Matrix decomposition greatly reduces the space complexity of offline computation compared to neighborhood-based methods. LFM is generally not applied in online recommendation situations because it is too slow in generating recommendation lists when facing millions of products, and the introduction of the hidden vectors makes it difficult to have such strong interpretability as Item CF algorithm.

3.3. Forecasting module

The outputs of the last convolutional module of the user and item branches are the user hidden vector matrix and the item hidden vector matrix, which are denoted as $l^u \in \mathbb{R}^{D\times D}$ and $l^i \in \mathbb{R}^{D\times D}$. They interact according to matrix multiplication, are tiled and fed into the final fully-connected layer, and finally go through the Softmax layer to output the user's expectation of the rating of the specified item. This process can be simply represented by equation (30):

$$\hat{y}_{u,i} = Soft\max\left(FC\left(flatten\left(l^u \times l^{i^T}\right)\right)\right) \tag{30}$$

Where flatten is used to "flatten" the input, i.e., to one-dimensionalize a multidimensional input. Assuming that the rating option is $r_{u,i} \in \{r_1, r_2, \ldots, r_n\}$, the model's prediction is $\hat{y}_{u,i} = [y_1, y_2, \ldots, y_n]$ and satisfies $\sum_{i=1}^{n} y_i = 1$, the highest r_i corresponding to probability y_i is the model's prediction of the user's rating for the specified item. At the same time, we can multiply the scoring options and the model prediction results according to equation (30) to obtain the user's predicted score for the specified item, and then recommend the high scoring item to the specified user.

$$\hat{r}_{u,i} = r_{u,i} \otimes \hat{y}_{u,i} = \sum_{i=1}^{n} y_i r_i \tag{31}$$

The loss function of ACNN is shown in Equation (32), where θ and λ represent the ACNN parameters and L2 regularization coefficients, respectively:

$$L\left(r_{u,i}, y_{u,i} \mid \theta\right) = -\sum_{j=1}^{n} y_{u,i}^{j} \ln\left(r_{u,i}^{j}\right) + \lambda \|\theta\|_2 \tag{32}$$

4. Application of NCFCA to the Practice of Civic and Political Education for University Students

4.1. System Simulation Experimental Test

4.1.1. Experimental setup

Under the same experimental conditions, the designed system is compared with three existing systems including neural network recommender system, multi-factor recommender system, and collaborative filtering algorithm for personalized recommender system of Civic and Political theory resources. Verify that the recommendation quality of the designed system is higher.

The dataset used in the experiment is the course Civics dataset constructed in the second chapter, which has a high data sparsity.

The experimental dataset is cut by the five-fold cross-validation method to obtain the test set and the training set in the experiment, both of which are five in number, with about eight thousand pieces of data in the training set and about two thousand pieces of data in the test set.

4.1.2. Experimental results

In the state of the same experimental environment and experimental conditions, the four experimental systems are tested by different test sets and training sets for the average absolute error and F1 value.

The experimental data of the average absolute error of the four experimental systems are specifically shown in Fig. 2.

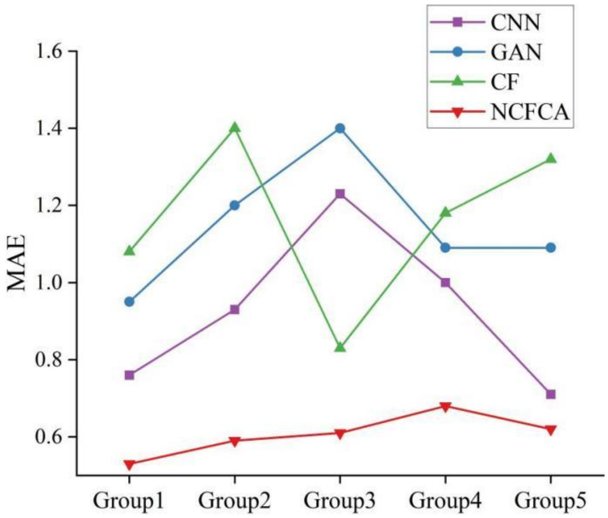

Figure 2. Average absolute error experimental data of four experimental systems

From Fig. 2, it can be seen that the MAE value of the NCFCA system proposed in this paper is significantly lower than that of the personalized recommendation system of the Civic Theory resources of Convolutional Neural Network (CNN), Generative Adversarial Network (GAN), and Collaborative Filtering Algorithm (CF), and the mean absolute error of its five sets of experiments averages 0.606, which indicates that the error of the NCFCA system is lower and more accurate.

The F1 value experimental data of the four experimental systems are specifically shown in Figure 3.

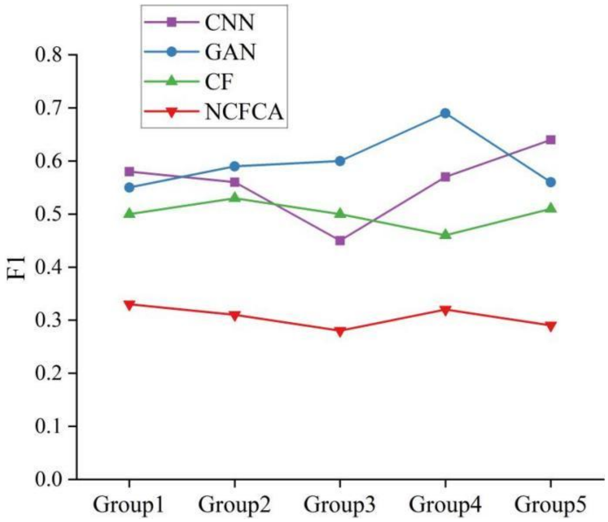

Figure 3. F1 value experimental data of four experimental systems

According to the data analysis in Figure 3, compared with the convolutional neural network (CNN), generative adversarial network (GAN) and collaborative filtering algorithm (CF) of the personalized recommendation system for ideological and political resources, the F1 values of the five groups of experiments proposed in this paper are 0.337, 0.318, 0.285, 0.326 and 0.291, respectively, which are lower than those of the other three algorithms, indicating that the recommendation effect of the NCFCA system is better.

4.2. Coverage testing

In order to verify the overall effectiveness of the NCFCA model-based automatic recommendation method for college students' Civics teaching resources, it is necessary to test the automatic recommendation method for college students' Civics teaching resources based on the NCFCA model.

The proposed method and the automatic recommendation methods of college students' Civic and political teaching resources based on NCFCA model, CNN, GAN and CF model are tested by taking the coverage rate as a test index. The results of the coverage test under the four methods are shown in Figure 4.

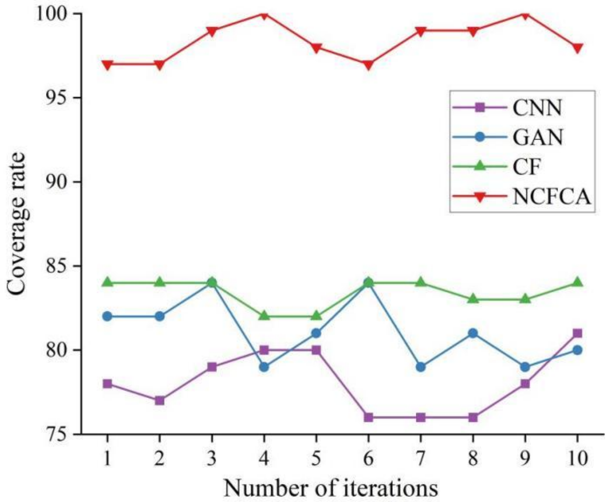

Figure 4. Coverage test results for different methods

Analyzing the data in Figure 4, it can be seen that the coverage rate of the NCFCA model-based automatic recommendation method for college students' Civics teaching resources is above 97%; the coverage rate of the CF model-based automatic recommendation method for college students' Civics teaching resources fluctuates between 82% and 85%; the coverage rate of the GAN model-based method fluctuates around 80%; the coverage rate of the CNN model-based method fluctuates below 80%; and the coverage rate of the GAN model-based method is below 80%. The coverage rate fluctuates between 82% and 85% when the method based on Generative Adversarial Network (GAN) model is used; the coverage rate fluctuates around 80% when the method based on Convolutional Neural Network (CNN) model is used; the coverage rate is below 80% when the method based on CNN model is used. Comparing the coverage rates of the automatic recommendation methods for college students' Civics teaching resources based on four algorithmic models, it can be seen that the automatic recommendation of Civics education teaching resources based on the NCFCA model proposed in this paper has the highest coverage rate. This is because NCFCA improves the coverage rate of resources by generating a retrieval model and discriminating a retrieval model to recommend Civic and Political Education teaching resources for users.

4.3. Effectiveness analysis

This experimental study applies the NCFCA method oriented to learning resources recommendation to actual Civics teaching as a way to evaluate the effectiveness of the method in real-time classroom teaching. Relevant data were collected by the system to get the learning resources recommendation accuracy and students' learning performance analysis table.

4.3.1. Resource recommendation accuracy

The study combines channel attention neural network with collaborative filtering to explore the personalized recommendation method of learning resources. Whether the learners are provided with the learning resources they need and whether the learning resources are loved by the learners, which reflects the effectiveness and feasibility of the method in actual teaching in one way or another, can be measured from the dimension of the accuracy rate of learning resources recommendation. From the relevant data provided by the system, after sorting and analyzing, we get the survey of the accuracy rate of learning resources recommendation results as shown in Table 1.

Table 1. Resource recommendation result accuracy

	Number of people	**Very accurate (85%-100%)**	**Accuracy (60%-84%)**	**Inaccuracy (0-59%)**
1	60	90.00%	6.67%	3.33%
2	59	93.22%	6.78%	1.69%
3	60	86.67%	10.00%	3.33%
4	60	86.67%	10.00%	3.33%
5	60	91.67%	8.33%	0.00%
6	60	90.00%	8.33%	1.67%

7	58	89.66%	8.62%	1.72%
8	60	86.67%	8.33%	5.00%
9	60	88.33%	8.33%	3.33%
10	59	89.83%	6.78%	3.39%

The "number of people" in this table indicates the number of valid evaluation results, and the results are "very accurate", "accurate", and "inaccurate" through collation and analysis. According to the data in the table, the following conclusions can be obtained: the average proportion of learning resource recommendation accuracy between 85% and 100% is 89.27%, the average rate of accuracy between 60% and 84% accounts for 8.22%, and the average proportion of accuracy in the range of 0-59% accounts for 2.68%. From the perspective of the accuracy of learning resources, 89.27% of the students believed that the NCFCA method was very accurate in recommending and learning ideological and political resources, which provided data support for subsequent ideological and political teaching activities.

4.3.2. Analysis of student learning achievement

In order to assess the effectiveness of the NCFCA method oriented to learning resource recommendation, students were arranged to take a test after each lecture and the test scores of the experimental and control groups were compared and analyzed. The NCFCA oriented to learning resource recommendation was applied to 60 students in the experimental group, and 60 students in the control group were taught in the traditional mode. Before the experiment was conducted, the two groups of students were allowed to take one pre-test, and the two groups of students were allowed to take four post-tests during the course of the experiment, and the data on the test scores were statistically and analytically analyzed using SPSS 22.0.

The Sig. value of the pre-test scores of the experimental and control groups was greater than 0.05, indicating that there was no correlation between the two groups. It indicates that the actual level of students in these two groups before the experiment was conducted was comparable.

Students were tested at the end of each class, and the system collected data on students' post-test scores organized by the teacher as shown in Table 2.

Table 2. Post-test performance data analysis

	Group	Mean value	N	Standard error mean	Sig.
Test 1	Experimental group	85.67	60	0.998	0.706
	Control group	85.89	60	1.014	
Test 2	Experimental group	85.78	60	1.083	0.397
	Control group	83.62	60	1.091	
Test 3	Experimental group	86.54	60	1.106	0.001
	Control group	77.40	60	1.528	
Test 4	Experimental group	86.18	60	1.049	0.000
	Control group	77.47	60	1.439	

Analyzing the data in the table, it can be seen that there were three times when the average scores of the students in the experimental group were higher than those of the students in the control group.

In post-test score 1, the average scores of the students in the experimental group and the control group did not have much difference, mainly because the teaching time was short, the students had a process of adapting to the new way of learning, and at this time, the students had already finished the first test, so the scores of this group did not reflect the teaching effect of this method. In the post-test score 2, the average scores of students in the experimental group and the control group were 85.78 and 83.62 respectively, and the average scores of students in the experimental group were slightly higher than those of students in the control group, but the difference was not obvious. In-depth investigation found that there are two main reasons leading to this phenomenon: first, the two groups of students are in fact at a comparable level, and the content of the first test is some relatively basic knowledge points, so the teaching effect is not obvious; second, the experimental group is adapting to this new way of teaching, and the mastery of their cognitive deficiencies as well as the subsequent pushing of the appropriate learning resources for them need time to digest. However, as the class unfolded, students gradually recognized their cognitive deficits and the system provided them with appropriate learning resources to remedy them, and students' academic performance improved significantly. In posttest scores 3 and 4, the average scores of students in the experimental group and the control group are 86.54, 86.18 and 77.40, 77.47, respectively, and the average scores of students in the experimental group are significantly higher than those of students in the control group. Students in the experimental group can get personalized diagnostic reports in the classroom, and the system also pushes appropriate learning resources for them according to their cognitive level, so that students can grasp their cognitive blind spots at any time and solve problems in the classroom in a timely manner, thus laying a foundation for subsequent learning. On the contrary, students in the control group had a better grasp of their overall level after each test, but their mastery of the knowledge points was still very vague, and these problems would gradually become serious in the subsequent learning, resulting in no significant improvement in academic performance. The analysis of the test data shows that the NCFCA method, which is recommended for learning resources, can help students improve their academic performance.

5. Conclusion

In this study, we propose a new channel attention-based neural collaborative filtering algorithm, NCFCA, and apply it to the work of precise college students' ideological education. The results of the study are as follows.

(1) The average MAE value of the five groups of experiments of the system under the NCFCA algorithm is 0.606, and the F1 value is 0.306, which are better than the performance of the system under the other three algorithms, indicating that the NCFCA system has a better recommendation effect.

(2) The automatic recommendation method for college students' Civics teaching resources based on the NCFCA model has a coverage rate of 98.4 when recommending Civics education teaching resources for users, which is better than the other three models.

(3) 89.27% of the students think that the NCFCA method is very accurate for recommending learning ideological and political resources. The students' learning performance analysis table shows that the NCFCA method can effectively improve students' learning outcomes.

The NCFCA method proposed in this paper can effectively solve the problem that the system is unable to select the learning resources of ideology and politics according to the knowledge state of the learners, accurately recommend the content of the ideological and political education work of college students, and is conducive to the improvement of the efficiency of college students' independent learning.

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