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Research on Multidimensional Algorithm Optimization of Accurate Path of Marxist Education Communication in New Media Environment

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Abstract With the explosive growth of information resources, recommender systems play a pivotal role in alleviating information overload and have been widely adopted in many services. This paper combines Bayesian personalized ranking method and graph convolutional neural network to construct an accurate recommendation model based on the dissemination of Marxist education information, and realize the multi-dimensional optimization of the recommendation path. Compared with several traditional collaborative filtering recommendation models, this paper's model achieves better results in terms of RMSE, Precision, and coverage indicators, which verifies the effectiveness of this paper's model in information dissemination recommendation. In addition, compared with other six recommendation models such as SVD, Social_MF and CUNE, this paper's model is only slightly worse than the CUNE model in RMSE indexes, and is smaller than other models in RMSE and MAE indexes, with smaller prediction error and higher recommendation accuracy. It shows that the model in this paper can effectively mine the user's interest preferences and the personalized characteristics of the items, and realize the multi-dimensional optimization of the precise path of Marxist education dissemination.

Index Terms recommender system, Bayesian personalized ranking, graph convolutional neural network, Marxist education dissemination

I. Introduction

Marxism, as a profound scientific theoretical system, is a scientific worldview and the ideological weapon of the working class to understand and transform the world, and is an outstanding cultural achievement of mankind [1]-[3]. Marxism is the core idea that guided China's revolutionary struggle for many years, and is the ideological foundation of China's establishment of a socialist country. The core connotation and purpose of Marxist theory education for college students lies in helping college students form a correct outlook on life, values and worldview [4]-[7]. As the nation-builders of the new era, college students should have a comprehensive and in-depth understanding of Marxist thought [8]. And with the rise of new media, the educational communication path of Marxist theory presents a new situation due to the characteristics of new media communication such as rapidity, interactivity and extensiveness [9], [10].

Marxist education dissemination plays an important role in the construction of China's political and ideological theories, and in the context of the era of cultural pluralism and communication, it is urgent to promote the change of the Marxist education system, focus on the construction of educational concepts that are in line with the times, and strengthen the connection between the social environment and education [11]-[14]. While the popularization and rapid development of new media, the dissemination of Marxist education has ushered in the hope that new media platforms such as social media, online education tools and so on provide diversified channels of dissemination, which is of great significance in promoting the dissemination of Marxist education [15]-[17]. And at the same time, it is also accompanied by the problem of information flooding and communication distortion. Based on this, the multi-dimensional optimization of the precise path of Marxist education dissemination has become an urgent problem to be solved at present.

In this paper, for the multi-dimensional optimization problem of precise path of Marxist education dissemination in the new media environment, a recommendation model based on the Bayesian personalized ranking method and information dissemination is proposed, and the embedding vectors of users and items mined by graphical convolutional neural network are input into the matrix decomposition based on the Bayesian personalized ranking when the training reaches a certain number of times, so as to realize the personalized features of users' interest preference and items to realize the effective mining of user interest preferences and item personalized features, so

as to achieve the goal of accurate recommendation. In order to verify the effectiveness of the proposed model, it is experimentally compared with the traditional collaborative filtering recommendation model and other recommendation models.

II. Recommendation model based on Bayesian personalized ranking and information dissemination

In order to realize the multi-dimensional optimization of the precise path of Marxist education dissemination in the new media environment, this paper combines the Bayesian personalized ranking method and graph convolutional neural network to construct the precise path model of Marxist education dissemination.

II. A.Bayesian Personalized Ranking Method

The goal of personalized ranking is to provide the user with a list of items that may be of interest, which is also known as item recommendation. Ranking recommendation algorithms can be broadly classified into three categories, the first category of ranking algorithms category is the peer-to-peer methods, these algorithms transform the ranking problem into a classification, regression or something like that and implement it using the existing classification, regression and other methods. The second category of ranking algorithms is pairwise methods, in which ranking is transformed into pairwise sequence classification or pairwise sequence regression. The third class of ranking algorithms is the list approach, which takes a more direct approach to the ranking problem. It uses the ranked list as a sample in both the learning and prediction process.

Bayesian personalized ranking algorithm [18] is the pairwise approach. In the Bayesian personalized ranking algorithm, marking any user u corresponding to an item, if the user u chooses the item i among the items i and j, then a triple $\langle u,i,j\rangle$ is obtained, which denotes that relative to the item j the user prefers the item j. prefers item i. If user u has m sets of such interaction data, a training sample of m items for user u is obtained.

Given the set of all users U and the set of all items V, the implicit feedback S of a user on an item is a subset of the Cartesian product of the sets U and V, and the task of the recommender system is to provide the user with a personalized total ranking $>_u \subset V^2$ from all items, where $>_u$ satisfies the the full order relation:

$$\begin{aligned} &\forall i,j \in V : i \neq j \Rightarrow i >_u j \vee j >_u i \\ &\forall i,j \in V : i >_u j \wedge j >_u i \Rightarrow i = j \\ &\forall i,j,k \in V : i >_u j \wedge j >_u k \Rightarrow i >_u k \end{aligned} \tag{1}$$

It is known that the full-order relation $>_u$ with optimization objective $P(\theta|>_u)$, according to the Bayesian formula has:

$$P(\theta|>_u) = \frac{P(>_u|\theta)P(\theta)}{P(>_u)} \tag{2}$$

Assuming that the ordering of a single user is independent of other users, then for any user u, $P(\theta|>_u)$ is the same for all items, so there:

$$P(\theta|>_u) \propto P(>_u|\theta)P(\theta) \tag{3}$$

To wit:

$$\prod_{u,i,j} P(\theta \mid i >_u j) \propto \prod_{P} P(i >_u j \mid \theta)P(\theta) \tag{4}$$

which is about the likelihood component:

$$P(i >_u j \mid \theta) = \sigma\left(\hat{x}_{u,i} - \hat{x}_{u,j}\right) \tag{5}$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{6}$$

where $\hat{x}_{u,i} - \hat{x}_{u,j}$ is the difference between user u's preference for item i and item j.

II. B.Graph Convolutional Networks

Graph Convolutional Neural Network (GCN) [19] is a deep learning model generalized from Convolutional Neural Network (CNN) [20]. Graph Convolutional Neural Network breaks through the requirement of Convolutional Neural Network for Euclidean structure and becomes one of the important research methods in the field of skeletal behavior recognition. In this case, the null field graph convolution is mathematically computed by feature maps with adjacency matrices, which achieves a similar design to the receptive field in convolutional neural networks.

The receptive field of an image and a topological map is shown in Fig. 1, where the left figure shows the Euclidean structure of a conventional image and the right figure shows a topological map. Where the circles represent nodes, the solid lines represent adjacencies, and the area shown by the dashed line represents the range size of the receptive field centered on the green node at a distance of 1. In the traditional image, its standard rectangular structure makes the range of the receptive field fixed to an *n*×*n* size, and its convolution kernel can also be designed to a fixed size, and the mathematical computation and formula expression are relatively easy. In topological graphs, the number of neighboring nodes around different nodes is different, so it is not possible to design a convolution kernel of the same size, and it is also not possible to use mathematical calculations directly to carry out the convolution operation, which leads to the application of convolutional neural networks on topological graphs to be more difficult, and the main problem of graph convolutional neural networks is the design of the convolution kernel.

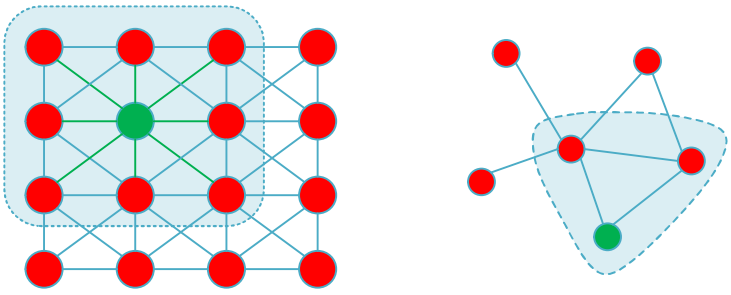


Figure 1: Receptive field of image and graph

For a topological graph with N nodes, its identity matrix consists of two matrices, its node matrix V and its adjacency matrix A, which includes the data representation of each node with dimension $\{N \times C\}$. Where C represents the data dimension of the node. And the dimension of the adjacency matrix is $\{N \times N\}$, the value of each element in the matrix represents the adjacency between two nodes corresponding to the number of rows and columns in which it is located, and often, this adjacency will be normalized to the range of $(0,1)$ to represent the weight of its relationship. In order to enrich the representativeness of topological map features, the degree matrix (D) and the Laplace matrix (L) are also often introduced. The degree matrix is a matrix of dimension $(N \times N)$ with values only on the diagonal, each value representing the number of neighboring nodes around the corresponding node; the Laplace matrix is commonly defined as $L = D - A$. Depending on the task, there are different applications of these two matrices. For example, the degree matrix is often used to normalize the adjacency matrix, calculated as $D^{-1}A$, in the computation of the null domain graph convolution commonly used in behavioral recognition, in order to prevent the differences in the eigenvalues of different nodes due to the differences in the number of neighboring nodes around them.

The graph convolution neural network takes the topological map as input data and performs graph convolution operations on all nodes and their surrounding neighboring nodes within the sensory field at each layer in order to complete the feature update for each node. A ReLU activation function is generally employed after each layer of the graph convolutional network to enhance the nonlinear capability. Similarly, the pooling operation is often limited by the fact that the design of the receptive field cannot be directly applied to the topological map, so a global pooling operation is generally performed for each channel before the final fully connected layer.The final classification layer of the GCN is responsible for converting the features of the nodes into the labeled counterpart scores for the classification task.

The order of nodes in Fig. 1 with the adjacency matrix and degree matrix is shown in Fig. 2, for this topology, the computation of each graph convolutional layer in a graph convolutional neural network can be written as a one function containing the node information with the adjacency matrix:

$$V^{l+1} = f\left(V^{l}, A\right) \tag{7}$$

In the formula V^l represents the node feature matrix of layer 1, i.e., the input data, $V \in R^{N \times C}$, C stands for the dimension, and the function f adopted by different graph convolution models varies, and the features between each node and its neighboring nodes after each layer of graph convolution are aggregated. And through the stacking of layers, the information between the more distant nodes is effectively communicated, which in turn realizes a similar operation to the convolutional neural network. For the graph convolution model used, the topological edge between each node v in the node set H is denoted as $E = \{v_i v_j \mid (i,j) \in H\}$. The convolution operation is applied to 2D feature maps and its inputs and outputs are defined as 2D matrices, and a convolution with a step size of 1 is generally used to keep the size of the feature maps constant. For a convolution kernel with a sensory field size of $k \times k$, the relationship between the input features f_{in} and the input features f_{out} can be written as:

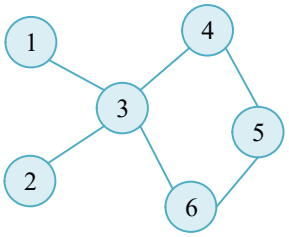
$$f_{out} = f_{in}\left(P(S,h,w)\right) \cdot w(h,w) \tag{8}$$

where the sampling function P denotes the neighborhood with distance S in the feature map with width and height h,w, which is generally computed by convolution based on the topology map modeled after the sensory field of $k \times k$ in the convolutional neural network. The W is the weight function, i.e., the convolution kernel, which is used to compute features layer by layer. The above formula is used in the computation of graph convolution, that is, it is expressed as for each node there is a feature vector, using the sampling function and weight function to convolve the features. Designing different sampling and weighting functions for different tasks is the core of graph convolution operation.

In the spatial domain graph convolution used in the field of behavior recognition, the operation of graph convolution is defined as follows:

$$f_{out} = W\left(f_{in} A\right) \tag{9}$$

In the formula, W_k denotes the trainable parameters of the convolution kernel, f_{in} and f_{out} denote the feature matrices of the inputs and outputs of this layer, and A stands for the neighboring matrices, which plays the role of the sampling function here. The features of each layer are learned by 1×1 convolution and then computed by matrix multiplication with the adjacency matrix, so that the features of neighboring nodes are aggregated.



$$\begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} \qquad \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 \end{pmatrix}$$

Matrix A　　Matrix D

Figure 2: Graph and adjacency matrix and degree matrix

II. C.Model framework design

II. C. 1)　Overall framework of the model

The basic structure of the recommendation model based on Bayesian personalized ranking and information propagation proposed in this chapter is shown in Figure 3. The model designed in this chapter can be divided into three main parts: first, the information propagation module using lightweight graph convolutional neural network, and second, the BPR-MF module that can increase the embedding spatial distance of the items in the graph when the information propagation reaches a certain degree. The third is the rating prediction module. This model first transforms the user-item interaction records into the adjacency matrix of the user-item two-part graph, and then assigns a random initial embedding vector to all the nodes in the two-part graph. Then the node embedding matrix composed of the embedding vectors of all nodes can be input into a lightweight graph convolutional neural network for information propagation and training. When the training reaches a specified number of times, the matrix of embedding vectors trained by the graph convolutional neural network is input into the matrix decomposition based on Bayesian personalized ranking, which increases the distance between items in the embedding space. Finally, the user's preference level for the items is obtained by means of inner product.

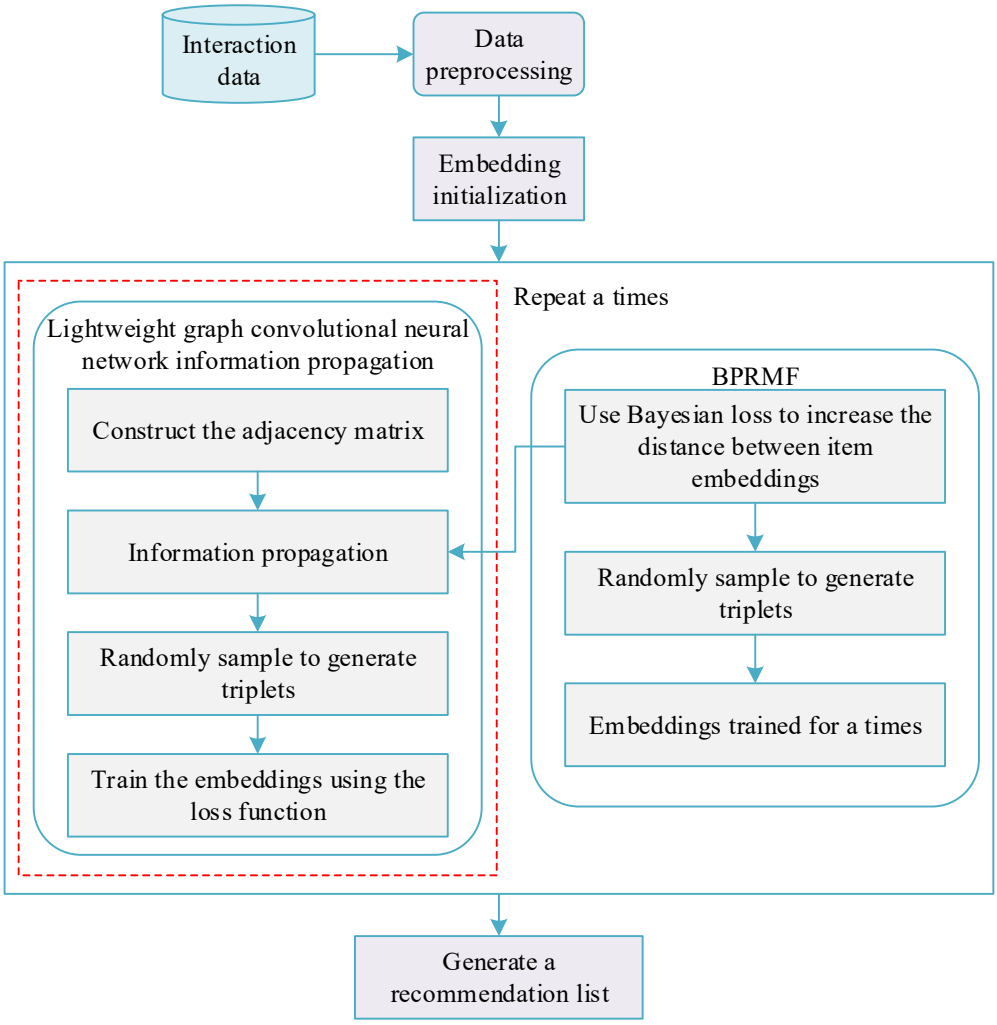


Figure 3: The structure of the recommendation model

II. C. 2) Constructing two-part diagrams

The datasets of recommender systems can all be easily converted to the adjacency matrix of the user-item bipartite graph. However, this step is essential in order to use graph convolutional neural networks to process recommendation tasks. The datasets of recommender systems usually contain two sets, the user set $U=\{u_1,u_2,\ldots,u_m\}$ consisting of m users, and the item set $I=\{i_1,i_2,\ldots,i_n\}$, using these two sets can be constructed into an interaction matrix $R\in\square^{m\times n}$. If a user u in R has interacted with an item i then $R_{ui}=1$ otherwise it is 0. Its counterpart is a bipartite graph $G=(V,E)$ which contains $|V|=m+n$ nodes and $|\mathrm{E}|$ edges. The adjacency matrix A of G is:

$$A=\begin{pmatrix}0 & R\\ R^T & 0\end{pmatrix} \tag{10}$$

II. C. 3) Information Propagation Using Graph Convolutional Neural Networks

The biggest advantage of graph convolutional neural network-based recommender systems over non-graph neural network-based recommender systems is that it can utilize the graph structure for information propagation. That is, the optimization goal of traditional collaborative filtering is to predict user-item interactions, and the training samples have only observed user-item interactions. This means that the model parameters are updated for a particular user in such a way that only items that have a direct interaction with that user will be used. Since graph convolutional neural networks can aggregate information from neighboring nodes by embedding information propagation iterations. By overlaying the propagation layers, each node gets information about its higher-order neighbors instead

of only first-order neighbors as in traditional methods. This allows better use of the collaborative filtering effect for recommendation, because according to the collaborative filtering effect, we believe that the items interacted by two users with similar preferences should also be broadly similar. After information propagation through the graph convolutional neural network, the target user can get information about the items that their similar users have interacted with.

Information propagation allows nodes in the graph to obtain information in higher-order nodes, thus obtaining better user and item embedding vectors. Let the bipartite graph node embedding matrix be $E^{(0)}$, and input this node embedding matrix into LightGCN for information propagation.The simplified node information propagation formula in LightGCN is as follows:

$$e_u^{(l+1)} = \sum_{i \in \mathrm{N}_u} \frac{e_i^{(l)}}{\sqrt{|\mathrm{N}_u|}\sqrt{|\mathrm{N}_i|}} \tag{11}$$

$$e_i^{(l+1)} = \sum_{u \in \mathrm{N}_i} \frac{e_u^{(l)}}{\sqrt{|\mathrm{N}_u|}\sqrt{|\mathrm{N}_i|}} \tag{12}$$

$e_i^{(l)}$ and $e_u^{(l)}$ are the user embedding vectors and item embedding vectors of the matrices E after l layers of information propagation, respectively, $|\mathrm{N}_u|$, $|\mathrm{N}_i|$ are the degrees of the user u and project i nodes, respectively.

After completing the propagation of information in layer l according to the parameters, the node vectors in each layer from 0 to l are weighted and summed. Then a random sampling of items that the user has not interacted with is required. One of the many uninteracted items is randomly selected as a negative interaction item to generate the (u,i,j) triples needed for training. For every positive interaction item there is a randomly sampled negative interaction item. Training can then be performed using Bayesian personalized ranking loss with the following loss function:

$$L_{BPR} = -\sum_{u=1}^{M} \sum_{i \in \mathrm{N}_u} \sum_{j \notin \mathrm{N}_u} \ln\sigma\left(\hat{y}_{ui} - \hat{y}_{uj}\right) + \lambda \left\| E^{(0)} \right\|^2 \tag{13}$$

where $\hat{y}_{ui} = e_u^T e_i$, which is the preference value of user u for positive interaction items, $\hat{y}_{uj} = e_u^T e_j$, which is the preference value of user u for negative interaction items, and e_u, e_i, e_j are the embedding vectors for u,i,j of the embedding vector. N_u is the neighbor node of user u, and the neighbor nodes of user u in the two-part graph are the items that have interacted with user u, that is, the positively interacted items of user u. The nodes in the graph that are not linked to user u are also the negatively interacting items of user u. The $\lambda \left\| E^{(0)} \right\|^2$ is the positive term. With this loss function we can then make the preference value of the item with which the user has interacted with greater than the preference value of the item with which the user has not interacted.

II. C. 4) Increasing the Distance of Items in Embedding Space

In recommender systems, implicit feedback occupies a large portion of the user-item history because of its easy accessibility. Many recommendation algorithms that utilize implicit feedback data only utilize positive user-item interactions, while negative interactions are not well utilized. In this paper, the items are divided into two sets of items for a specific user, the items that have interacted with a specific user are put into the positive interaction set, and the items that have never interacted with a specific user are put into the negative interaction set. Then we use random sampling to add a negative interaction item to the existing user-item pairs, i.e., changing from (u,i) to (u,i,j). Where u belongs to the user set U, i belongs to the positive interaction set I, and j belongs to the negative interaction set J. Let $>_u$ denote user u's preference for item, and $i >_u j$ denote user u's preference for item i among item i and item j. Formulating the above idea yields:

$$P\left(\Theta \mid >_u\right) \propto P\left(>_u \mid \Theta\right) P(\Theta) \tag{14}$$

where Θ denotes the parameters in the model that need to be learned, i.e., the embedding vector.

Assuming that user behavior as well as user preferences are independent of each other, it can be obtained:

$$P(>_u|\theta)=\prod_{u\in U}P(>_u|\theta)=\prod_{(u,i,j)\in D}P(i>_u j|\theta) \tag{15}$$

It is further proposed to replace $P(i>_u j|\Theta)$ in the above equation with a function that can be obtained:

$$P(i>_u j|\Theta)=\sigma\left(\bar{x}_{uij}(\Theta)\right) \tag{16}$$

where σ denotes the Sigmoid activation function. For convenience, $\bar{x}_{uij}$ is used below to denote $\bar{x}_{uij}(\Theta),\bar{x}_{uij}$, and $\bar{x}_{uij}$ to denote the difference in the degree of favoritism of the user u over the items i and j:

$$\bar{x}_{uij}=\bar{x}_{ui}-\bar{x}_{uj} \tag{17}$$

Then Bayesian assumptions are made on $P(\theta)$ so that it conforms to the normal distribution can be obtained:

$$P(\theta)\sim N\left(0,\lambda_\theta I\right) \tag{18}$$

where λ_θ is the eigenvalue and I is the unit matrix, and together they form the covariance matrix.

Next, a matrix decomposition model is used to train the parameter Θ, and letting R be the user-one-item matrix, $P^{m\times k}$ be the user embedding matrix, and $Q^{n\times k}$ be the item embedding matrix, we have:

$$R^{m\times n}=P^{m\times k}\cdot\left(Q^{n\times k}\right)^T \tag{19}$$

where m denotes the number of users, n denotes the number of items, and k denotes the embedding dimension.

The loss function of the model is:

$$L_{BPR}=\min\sum_{(u,i,j)\in D}\left(-\ln\sigma\left(\bar{x}_{uij}\right)+L(\theta)\right) \tag{20}$$

where $L(\Theta)$ is a regularity term to prevent overfitting of the model.

II. C. 5) Specific Algorithm Flow

The specific flow of the recommendation algorithm based on Bayesian personalized ranking and information dissemination proposed in this paper is as follows:

Input: rating matrix R with parameters a,l,λ.

Output: list of top-k recommendations.

Step1: Use the rating matrix R to construct the adjacency matrix via equation (10).

Step2: Construct (u,i,j) ternary using random sampling.

Step3: Use Eqs. (11)~(12) for l-layer information propagation.

Step4: Use Eq. (13) training to obtain node embeddings.

Step5: Repeat Step2-4 until a preset number of times a is reached.

Step6: Train the embedding vectors using Eq. (20) to increase the distance of item nodes and repeat Step5 again.

Step7: Use the inner product to find the preference of all users-items.

Step8: For each user the top-k items that have not interacted are selected to generate a recommendation list.

III. Recommendation model application experiment and result analysis

In order to verify the effectiveness of the proposed recommendation model, this paper compares the model with other recommendation models for experiments.

III. A. Experimental data set

This experiment uses the Foursquare dataset, which includes four sets of data: users, friendship, tips, and venues. After preliminary data preprocessing, the users dataset has 512850 users, because some users have not yet mentioned to add friends, the users with friend relationship will be extracted to obtain 43,786 users with friend relationship, of which there are 1157584 friend relationships. The tips dataset has 32684 items, and the venues dataset has 224825 items. According to the geographic location information of the check-in in the dataset, the distribution state of some check-in data at different time points is shown in Fig. 4 and Fig. 5.

From the figure, it can be seen that the user check-in locations present the phenomenon of aggregation, some locations are densely checked-in, and some locations are almost not checked-in, which also indicates that the densely checked-in areas are also the concentrated areas of Marxist education dissemination locations. At the same time, users' check-in locations at different times are changing based on their original preferences.

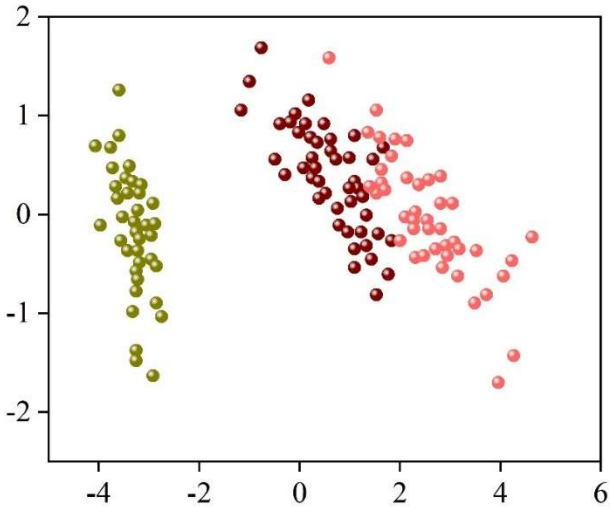


Figure 4: Example of the distribution of Foursquare's partial check-in data when *t*=1

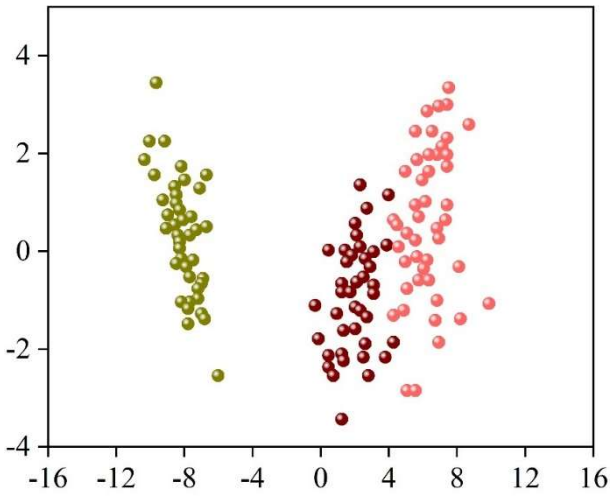


Figure 5: Example of the distribution of Foursquare's partial check-in data when *t*=2

III. B. Comparison Experiments with Traditional Recommendation Models

On the basis of the designed improved recommendation algorithm, the recommendation accuracy of this paper's recommendation algorithm based on Bayesian personalized ranking and information dissemination is compared with the traditional information recommendation algorithm with the help of Foursquare dataset. For each prediction test, the training set and test set are set to 80% and 20%, respectively, and the improved recommendation algorithm learns and adjusts the parameters on the training set, and then calculates the recommendation results on the test set.

First, the traditional user-based collaborative filtering algorithm (UserCF) and Bayesian network collaborative filtering algorithm (Bayesian-CF) are selected for comparison experiments with this paper's algorithm. The experimental results are shown in Fig. 6, which shows that the RMSE value of this paper's algorithm is much smaller than that of UserCF and Bayesian-CF, and the recommendation performance is better.

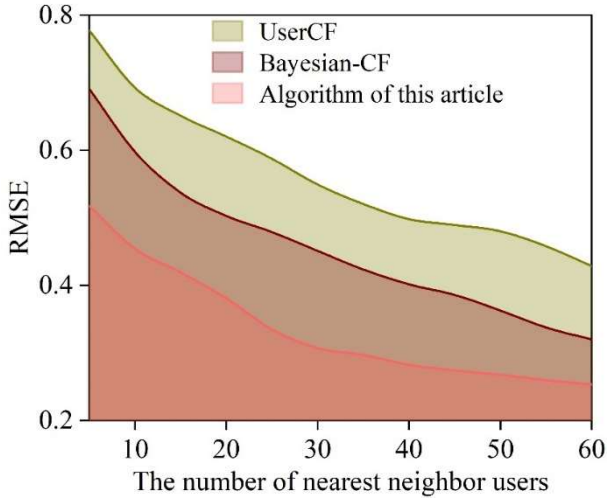


Figure 6: Experimental results of similarity among different users

For this paper's algorithm, K=20 in TOP-K is obtained to compare the accuracy of this paper's algorithm with that of the traditional user-based collaborative filtering algorithm, in which the parameter in the improved algorithm takes the uniform value of 0.20. Thus, the results of comparing the RMSE values of the different algorithms are obtained, as shown in Fig. 7. From the figure, it can be obtained that the difference between the prediction error of this paper's improved algorithm and the traditional user-based collaborative filtering algorithm is large, and the error value of the improved algorithm is smaller, which shows that the accuracy of the algorithm that incorporates multidimensional information is much higher compared to the accuracy of simply using the scoring matrix. At the same time, the accuracy of this paper's algorithm is further compared to the Bayesian network collaborative filtering algorithm, achieving more accurate results, indicating that the introduction of graph convolutional neural network in the consideration of the attribute information of the user and the project optimizes the recommendation effect and reduces the gap between the actual ratings and the predicted ratings.

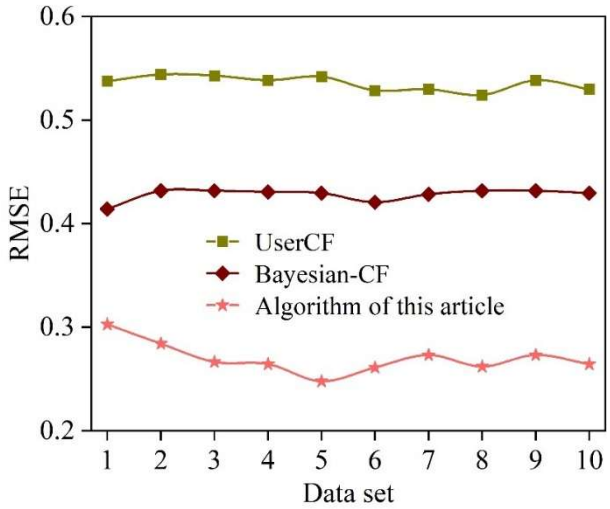


Figure 7: Comparison of RMSE values among different algorithms (1)

Secondly, the recommendation algorithm in this paper is compared with ItemCF, a traditional collaborative filtering recommendation algorithm based on item scores, and Attri-CF, a collaborative filtering recommendation algorithm based on item attributes. The experimental results for different item similarities are shown in Fig. 8. It can be seen that the root mean square error value of item similarity corresponding to this paper's algorithm is lower than that of the traditional recommendation algorithm.

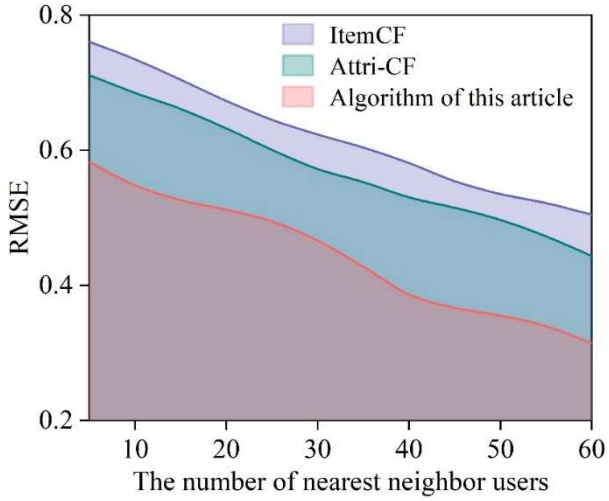


Figure 8: Experiment results between different Item similarity

In addition, for the improved recommendation algorithm of this paper and the traditional collaborative filtering recommendation algorithm to recommend the results of the comparison, take its recommended list of the first 20 recommended items, i.e., TOP-20, also in the aforementioned data experiments, take the value of each parameter uniformly 0.25, in the constructed model and algorithm based on the verification of the improved recommendation algorithm accuracy experimental results as shown in Figure 9. The accuracy of the improved recommendation algorithm in this paper is much higher than the accuracy of the traditional project-based recommendation algorithm. It can be seen that the fusion of multi-dimensional information on items will greatly reduce the gap between the score prediction value and the actual value, and at the same time, the improved recommendation algorithm has a very good recommendation effect and recommendation accuracy. In the experimental dataset, the traditional ItemCF algorithm has a more stable accuracy, but the root mean square error of the recommendation are higher than 0.54, and the information recommendation accuracy is low. The improved information recommendation algorithm in this paper obtains results with root mean square error fluctuating in the range of 0.27 to 0.32, with high accuracy.

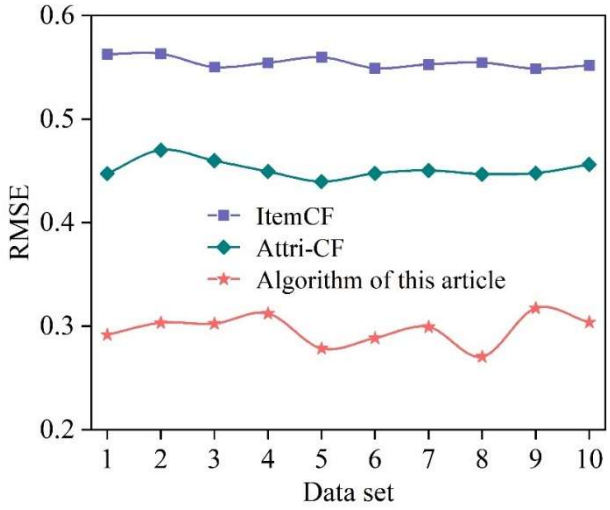


Figure 9: Comparison of RMSE values among different algorithms (2)

According to the accuracy and coverage formulas, the results of the accuracy and coverage comparison experiments of different algorithms are derived as shown in Fig. 10 and Fig. 11, respectively. The accuracy value of this paper's recommendation algorithm fluctuates around 80%, which achieves a higher accuracy rate compared with the traditional recommendation algorithm. Meanwhile, the coverage rate of the improved recommendation algorithm in this paper is also better than the traditional recommendation algorithm. In conclusion, as shown by the

results of accuracy and coverage, the improved recommendation algorithm in this paper is generally better than the traditional recommendation algorithm.

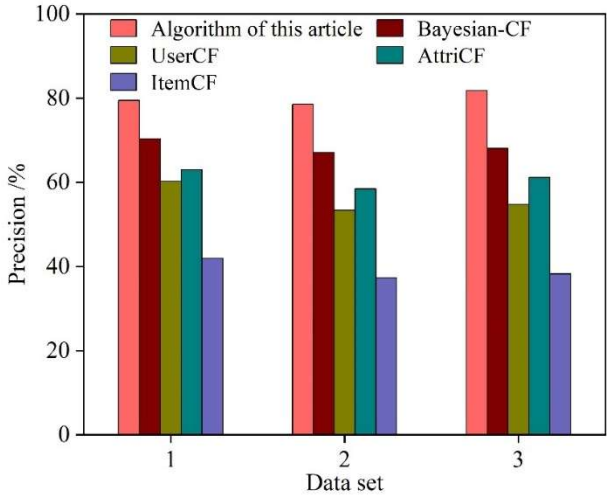


Figure 10: Results of the accuracy experiment in the Foursquare dataset

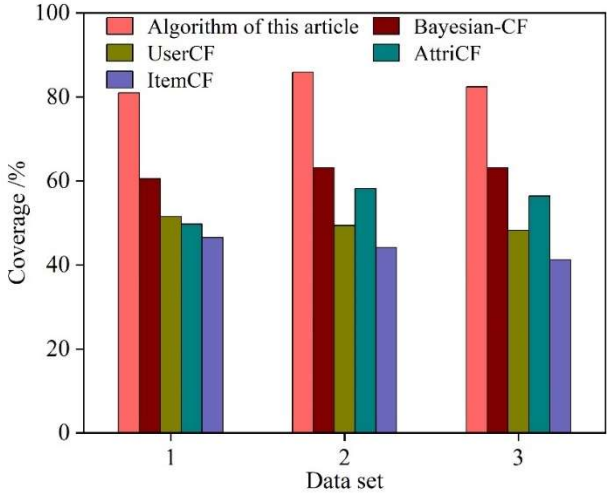


Figure 11: Results of the coverage experiment in the Foursquare dataset

III. C. Comparison experiments with other recommendation models

This section further proves the effectiveness of this paper's model by comparing the experimental analysis of this paper's recommendation model with other recommendation models, such as SVD, SVD++, Social_MF, and so on.

III. C. 1) Assessment of indicators

In order to study the accuracy of recommendation results, the prediction accuracy assessment metric is used in this section as a measure of recommender system performance. Prediction accuracy is used to assess the discrepancy between the predicted score and the true score. A smaller degree of deviation indicates a more accurate prediction. In this section, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to assess the goodness or badness of model performance. The assessment metrics are shown in equations (21) to (22), respectively:

$$RMSE = \sqrt{\frac{1}{|D_{test}|}\sum_{(u,i)=D_{test}}\left(r_{ui}-\hat{r}_{ui}\right)^2} \tag{21}$$

$$MAE = \frac{1}{|D_{test}|}\sum_{(u,i)\in D_{test}}\left|r_{ui}-\hat{r}_{ui}\right| \tag{22}$$

where D_{test} denotes the experimental dataset, r_{ui} denotes the user u's ratings of item i, and $\hat{r}_{ui}$ denotes the predicted ratings of user u on item i.

III. C. 2) Experimental comparison model

The accurate recommendation model of Marxist education dissemination path studied in this paper is an information dissemination recommendation model based on Bayesian personalized ranking method and graph convolutional neural network. In order to verify the effectiveness of this model in the field of Marxist education dissemination path recommendation, this section introduces a relevant model researched in social recommendation in recent years, which is used as a comparison model for the experiment. The experimental comparison models are as follows:

(1) Singular value decomposition model (SVD)

This model projects explicit feedback data into two feature spaces and then utilizes the correspondence between feature vectors in the feature spaces to predict user preferences. It also takes into account the personalization bias of users and items.

(2) SVD++

SVD++ is an improved recommendation model of the SVD model. It fuses explicit and implicit feedback data into a matrix decomposition to predict whether a user likes the item or not by the vector relationship between the user and the item in the low-dimensional feature space.

(3) Probability matrix factorization (PMF)

Probabilistic matrix factorization utilizes the matrix decomposition method to map the explicit rating data to the corresponding low-dimensional feature space, and predicts the user's preference for the item through the linear relationship between the vectors in the feature space.

(4) Social recommendation based on matrix factorization (Social_MF)

Social MF is a typical social recommendation algorithm based on matrix decomposition, the principle is to learn the features of explicit rating data and social information by matrix decomposition method, project them to the corresponding feature space and perform information fusion, and finally decide whether to recommend for the user according to the vector relationship between the user and the item in the feature space.

(5) Collaborative filtering based on social information and rating information (Trust SVD)

Trust SVD algorithm is a collaborative recommendation algorithm based on explicit and implicit feedback information such as social information and explicit rating information, which takes explicit rating data and implicit social data into account while performing matrix decomposition, and further improves the accuracy of recommendation by fusing explicit and implicit information into the predictive rating mechanism.

(6) Collaborative User Network-based Social Recommender System (CUNE)

CUNE is a graph-based recommendation algorithm, this algorithm establishes a user-item bipartite graph based on the user-item interaction records, and then performs pattern projection on the bipartite network, which generates the corresponding collaborative user network, and then collects a set of node sequences in the network using a randomized wandering method and performs data processing through the skip-gram model, which ultimately serves as a vector of embeddings to represent each user. The embedding vector measures the similarity between users and searches for Top-N similar users for each user, and then fuses the information of similar users into the matrix decomposition to predict the user's preference for items.

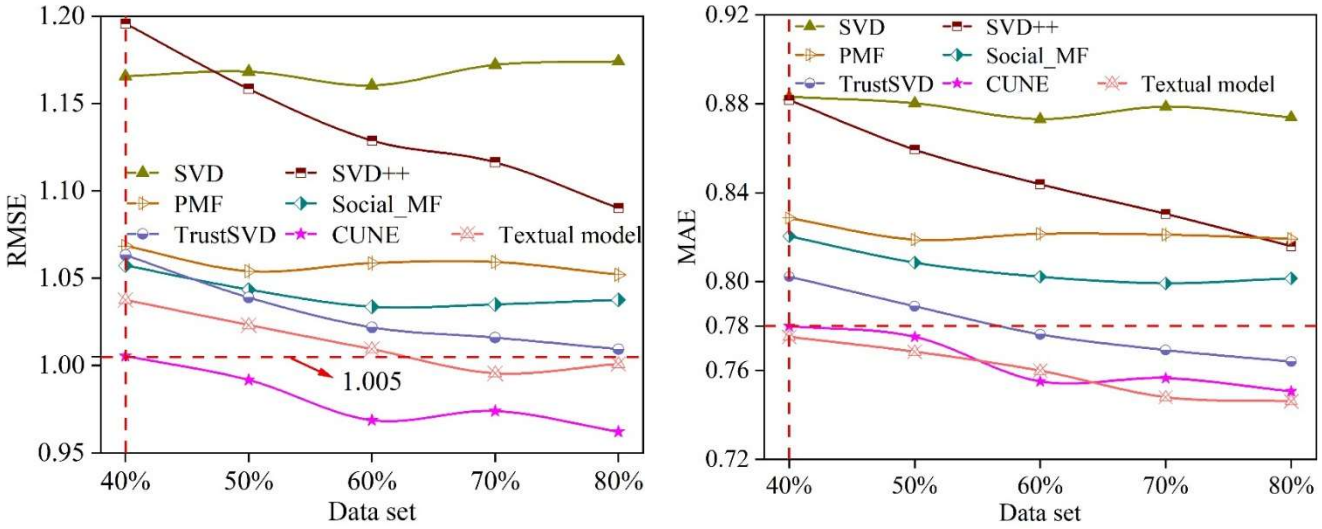
III. C. 3) Analysis of experimental results

In this section, experimental research work is carried out on the proposed model and some models as comparison in the dataset Foursquare. Before training the model, the dataset is divided into training set and test set. Among them, the training set can be categorized into 5 types: {40%, 50%, 60%, 70%, 80%}. In this section, all the models will be analyzed experimentally with different training set proportions, and the experimental results of all the models in different training sets are shown in Fig. 12. Where (a) and (b) denote the comparison results of RMSE and MAE metrics, respectively.

The experimental results show that some basic recommendation models, such as SVD, SVD++ and PMF, their experimental results under different proportions of training sets are not very satisfactory, and the evaluation metrics, RMSE and MAE, are relatively poor compared to other models. In contrast, social recommendation models, such as Social_MF, TrustSVD, and CUNE, achieved a large advantage in the evaluation metrics results. This indicates that these models have achieved some success in social recommendation. And comparing with Social_MF and TrustSVD models, the RMSE and MAE metrics of this paper's model are improved to a great extent. This demonstrates that this paper's model fuses the matrix decomposition based on Bayesian personalized ranking into the lightweight graph convolutional neural network, which can deeply mine the user's interest preferences and personalized features of items, and can effectively improve the recommendation results while mitigating oversmoothing. In addition, the RMSE index of the CUNE model is better than the model in this paper, and the MAE

index is slightly worse than the model in this paper, which side by side reflects that the performance of the CUNE model using the deep learning algorithm is better than other models. Even so, the recommendation performance of this paper's model is very similar to that of the CUNE model, indicating the potential development value of the recommendation model based on Bayesian personalized ranking and information dissemination proposed in this paper.

For Social_MF, TrustSVD and the model in this paper, the experimental results of these three recommendation models have some differences, but their changing rules are extremely similar. The experimental results are all gradually decreasing with the increase of the proportion of training set, and then tend to stabilize. Taking the model of this paper as an example, when the proportion of the training set is small, such as 40%, this model can not learn the features better during the training process, resulting in a larger error in the model's recommendation results, the RMSE and MAE reached 1.005 and 0.780, respectively. With the increasing proportion of the training set, the model's evaluation indexes began to decrease until it reached a stable experimental results. It indicates that the model in this paper can be trained more efficiently at 60%~80% of the training set, further learning the feature representation of users and items in the feature space, which makes the prediction results of this model become more accurate.



(a) RMSE (b) MAE

Figure 12: RMSE and MAE values of the model at Foursquare

IV. Conclusion

In this paper, a recommendation model based on Bayesian personalized ranking method and information dissemination is constructed to realize the multi-dimensional optimization of the precise path of Marxist education dissemination in the new media environment.

Through the Foursquare public dataset, according to the root mean square error value of the recommendation algorithm, as well as the accuracy and coverage of the recommendation results of the actual validation, it is concluded that the improved recommendation algorithm in this paper achieves better experimental results, with the root mean square error fluctuating within the range of 0.27~0.32, which is superior to the traditional collaborative filtering recommendation algorithms in terms of both accuracy and coverage.

The evaluation metrics RMSE and MAE of the base recommendation models, such as SVD, SVD++ and PMF, are relatively poorer than the other models under different proportions of training sets. Social recommendation models, such as Social_MF, TrustSVD and CUNE, achieved a greater advantage in the evaluation metrics results. And comparing with Social_MF and TrustSVD models, the RMSE and MAE metrics of this paper's model are improved to a great extent. This shows that this paper's model can effectively improve the recommendation results while alleviating oversmoothing. The recommendation performance of this paper's model is very similar to that of the CUNE model, which is better than other comparative models, indicating the potential development value of this paper's model. In addition, the RMSE and MAE of this paper's model reach 1.005 and 0.780 respectively when the proportion of the training set is 40%. and with the increasing proportion of the training set, these two evaluation indexes keep decreasing until they reach a stable experimental result, and ultimately more efficient training can be obtained at 60%~80% of the training set to get a higher recommendation accuracy.

References

[1] O'Connell, P. (2018). Law, Marxism and Method. tripleC: Communication, Capitalism & Critique. Open Access Journal for a Global Sustainable Information Society, 16(2), 647-655.

[2] Cheng, E., & Wang, Z. (2018). Enriching and developing Marxism in the twenty-first century in various aspects: Six definitions of Marxism. International Critical Thought, 8(2), 177-192.

[3] Sayers, S. (2021). What Is Marxism?. International Critical Thought, 11(3), 377-388.

[4] Rockmore, T. (2021). Marx, Chinese Marxism and poverty. Journal of global ethics, 17(1), 42-54.

[5] Dirlik, A. (2016). The Discourse of “Chinese Marxism”. In Modern Chinese Religion II: 1850-2015 (2 vols.) (pp. 302-365). Brill.

[6] Yang, Y. (2023). Exploring the influence of Marxist ideology on episodes of bi-directional affective illness among undergraduates. CNS Spectrums, 28(S2), S36-S37.

[7] Cheng, E. (2022). Ten views of Marxism originating from the revolution and development in China and the world. International Critical Thought, 12(1), 15-34.

[8] Lingling, H. E. (2014). Opportunities and Challenges: The Spread of Marxism in Contemporary China. Canadian Social Science, 10(3), 123.

[9] Dong, X. (2024). Research on the Education and Communication of Marxist Theory in the New Era. Journal of Art, Culture and Philosophical Studies, 1(1).

[10] Wang, Z. (2021). Re-thinking on the Popularization Path of Marxism in the New Media Era. International Journal of Social Science and Education Research, 4(7), 214-219

[11] Yang, W. (2025). Research on the construction of accurate path of Marxist education communication in new media environment based on deep learning modeling. J. COMBIN. MATH. COMBIN. COMPUT, 127, 39-53.

[12] Wang, C. (2025). The Difficulties and Countermeasures of the spread of Marxism in Omnimedia Era. Advances in Education, Humanities and Social Science Research, 13(1), 322-322.

[13] Chu, Y. (2021). Analysis on the path of ideological and political education and popularization of marxism in colleges and universities. Journal of Higher Education Research, 2(5).

[14] Fangbin, C. (2021). Research on the Translation and Dissemination of Marxism Before and After the Founding of the Communist Party of China. Academic Journal of Humanities & Social Sciences, 4(2), 17-19.

[15] Wang, Y. (2015). We-media and the popularization of marxism in China. In Proceedings of the International Conference On Creative Education (pp. 175-179).

[16] Fuchs, C. (2017). Marx’s Capital in the information age. Capital & Class, 41(1), 51-67.

[17] Shan, Z. (2018). The Influence of New Media on College Students' Marxism Belief Education and Its Countermeasures. Journal of Hubei Correspondence University.

[18] Cao Yuanhao. (2022). Rapid Restoration of Medical Images Relying on Bayesian Personalized Sorting Algorithm. Mobile Information Systems,2022,

[19] Yue Zhong, Jun Li, Hong Hao, Ling Li & Ruhua Wang. (2025). Structural damage identification using phase space matrix with convolutional neural networks. Structures,76,108885-108885.

[20] Yue Zhong, Jun Li, Hong Hao, Ling Li & Ruhua Wang. (2025). Structural damage identification using phase space matrix with convolutional neural networks. Structures,76,108885-108885.