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PAPER

Optimizing Personalized Learning Paths in Mobile Education Platforms Based on Data Mining

Yifei Zhang (✉)

School of Economics and Management, Henan Polytechnic, Zhengzhou, China

zhangyf6014@163.com

ABSTRACT

With the rapid development of information technology, mobile education platforms have become an integral part of the education sector, demonstrating significant potential in optimizing personalized learning paths. Traditional educational models struggle to provide individualized support tailored to each student's characteristics and learning progress. However, the integration of big data and artificial intelligence (AI) offers new approaches for constructing personalized learning paths. Data mining techniques analyze students' learning behaviors and academic performance in depth to recommend suitable learning resources and pathways. Nevertheless, existing research methods face several challenges in practical applications, such as the insufficient utilization of multimodal student data and the inability to dynamically adjust learning paths, limiting the effectiveness and scalability of personalized learning optimization. Most current studies rely on single-source data, lacking a comprehensive analysis of students' multidimensional learning information. Additionally, traditional collaborative filtering methods suffer from data sparsity and cold-start issues. To address these limitations, this study proposes a collaborative filtering model based on graph convolutional networks, combined with a dynamic optimization mechanism. By leveraging multimodal learning data to construct a comprehensive knowledge graph, this approach enhances the precision of personalized recommendations and dynamically adjusts learning paths according to students' real-time learning status. The proposed method holds significant academic value and practical applicability in advancing personalized education.

KEYWORDS

mobile education platform, personalized learning path, data mining, multimodal data, graph convolutional networks, dynamic optimization

1 INTRODUCTION

With the continuous development of information technology, mobile Internet has become an indispensable part of people's daily life and learning [1, 2]. Particularly in the field of education, the rapid rise of mobile education platforms has provided

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learners with more flexible and convenient learning methods [3, 4]. Traditional educational models often lack personalized services [5–8] and find it difficult to provide targeted support based on learners' actual needs and learning progress. With the application of big data and AI technologies, the construction of personalized learning paths has become an important trend in the development of mobile education platforms [9–11]. By accurately analyzing students' learning behaviors and interests, mobile education platforms can provide each learner with a customized learning path, thereby improving learning efficiency and effectiveness.

In the research on personalized learning path optimization, data mining technology, as a core approach [12, 13], has significant application value. By mining multidimensional information such as students' learning behaviors, learning content, and academic performance, researchers can deeply analyze students' learning needs and interest preferences [14–16], thereby recommending the most suitable learning resources and paths. In addition, in recent years, with the rise of deep learning and graph computing, more and more scholars have begun to explore how to combine graph neural networks with collaborative filtering and other technologies to further improve the accuracy and efficiency of personalized recommendations. How to construct an efficient and accurate learning path optimization model has become one of the hotspots in the field of educational technology research.

However, although some methods and models for personalized learning path optimization already exist, there are still many shortcomings in practical applications. The study [17] relies too much on a single learning data source and fails to fully mine students' multimodal information, such as learning behaviors, emotional states, and social interactions, resulting in unsatisfactory personalized recommendation effects. The study [18] focuses on static data analysis and cannot dynamically adjust learning paths to accommodate students' continuously changing learning needs and progress. In addition, traditional collaborative filtering methods often face data sparsity and cold-start problems, limiting their widespread application in personalized learning. Therefore, how to use graph neural network technology to process multimodal data and combine it with dynamic optimization mechanisms to improve the personalization and real-time adaptation of learning paths is an urgent issue that needs to be addressed in current research.

This study focuses on two main aspects. First, we will construct a knowledge graph for mobile education platforms based on multimodal data, integrating multidimensional information such as students' learning behaviors, learning content, and emotional states to form a comprehensive learning knowledge graph, providing data support for the optimization of personalized learning paths. Second, this study proposes a collaborative filtering model based on graph convolutional neural networks, combined with a dynamic optimization strategy, to adjust learning paths according to students' real-time learning situations, achieving precision and adaptability in personalized recommendations. This study not only enhances the learning efficiency of mobile education platforms but also provides new ideas and methods for the dynamic optimization of personalized learning paths, with high academic value and application prospects.

2 MODEL CONSTRUCTION

Definition of Multi-Modal Knowledge Graph in Mobile Learning Scenarios: In a mobile learning platform, the construction of a graph structure is the foundation for achieving personalized recommendations. This graph needs to integrate three types of nodes: students, content, and environment, forming a multi-modal heterogeneous network. The student nodes not only include the students' basic attributes

but also quantify their knowledge mastery using the IRT model, dynamically reflecting changes in cognitive levels. The content nodes cover resources such as courses, knowledge points, and quizzes, with attributes including textual descriptions, difficulty coefficients, and dependency relationships between knowledge points. The environment nodes capture spatiotemporal and device-related information specific to mobile scenarios, such as learning time periods, device types, and geographic locations. The design of edge relationships must take both explicit and implicit interactions into account: the edge weights between students and content are dynamically adjusted based on behavioral data such as learning duration, quiz accuracy rate, and replay frequency; the edges between content nodes are established under dual constraints of knowledge topology and semantic similarity; and the social edges between students are constructed through discussion forum interaction frequency and collaborative learning records, forming a potential learning community network. Additionally, the connection between student and environment nodes introduces a spatiotemporal adaptive mechanism. For example, when a student is detected using a mobile phone during a commuting period, the system automatically lowers the cognitive load of recommended content and prioritizes short video-based resources, thereby achieving context-aware personalized adaptation. Specifically, let $I = \{i_1, i_2, i_3, ..., i_l\}$ be the set of students, and $O = \{o_1, o_2, o_3, ..., o_v\}$ be the set of personalized points of interest. The student-interest interaction matrix W represents the interaction relationships between l students and v points of interest. The check-in matrix E is a binary matrix that records student check-in records. If student i_u has a check-in activity at POI point O_k, then $E_{iu,ou} = 1$; otherwise, $E_{iu,ou} = 0$. The graph $H = (N, \varkappa, R)$ is a bipartite graph, where $N = I \times O$, and $\varkappa$ represents the interactions between students and points of interest.

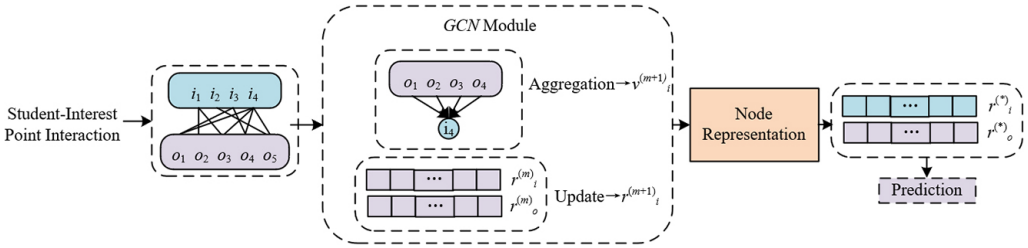


Fig. 1. Overall framework of the collaborative filtering recommendation model for personalized learning points of interest

Figure 1 presents the overall framework of the collaborative filtering recommendation model for personalized learning points of interest. When constructing the personalized learning interest point recommendation model, it is necessary to first establish the bipartite graph $H = (N, \varkappa, R)$. Each student and interest point is a node in this graph and is represented by learnable embedding vectors. The edges between students and interest points represent their interaction relationships, such as a student having previously visited a particular interest point. At this stage, the initial embedding vectors of student nodes and interest point nodes are r_i and r_o, respectively, which together form the embedding matrix R. Through the propagation mechanism of a graph convolutional network, the embeddings of students and interest points will be continuously updated and optimized in the following steps, ultimately enabling the recommendation of personalized learning interest points for students. Let the model parameters be denoted as ϕ, and the model expression is:

$$d\left(E^{-} \mid H, E^{+}, \varphi\right): N_i \times N_o \to E^{+} \tag{1}$$

In each layer of graph convolution, node embeddings are updated based on information from their adjacent nodes. This update rule is typically achieved through a linear transformation and a nonlinear activation function, aiming to aggregate information from neighboring nodes to capture the potential structural relationships in the graph. Specifically, the embedding vectors of nodes are updated by performing a weighted sum with their adjacent nodes' embeddings, followed by a nonlinear transformation using an activation function. Let the nonlinear activation function be represented by $\delta(.)$, the weight matrix be represented by $Q^{(m)}$, the degrees of students and interest points be represented by f_i and f_o, and the set of nodes directly connected to student i be represented by V_i. The update rules in matrix and vertex form are usually expressed as follows:

$$R^{(m)} = \delta(\hat{X}G^{(m-1)}Q^{(m)}) \tag{2}$$

$$r_i^{(m)} = \delta\left(\sum_{o \in V_i} \frac{1}{\sqrt{f_i + 1}\sqrt{f_o + 1}} r_o^{(m-1)} Q^{(m)}\right) \tag{3}$$

Let the adjacency matrix, diagonal degree matrix, and identity matrix of the corresponding network graph be denoted by X, F, and U, respectively. Define $\tilde{X} = X + U$, $\tilde{F} = X + U$, then:

$$\hat{X} = \tilde{F}^{-\frac{1}{2}} \cdot \tilde{X} \cdot \tilde{F}^{-\frac{1}{2}} \tag{4}$$

The initial embedding vectors $r_i^{(0)}$ and $r_o^{(0)}$ of students and interest points, after iterative computation in the graph convolutional layer, will aggregate information from their neighboring nodes. This process captures the latent relationships between students and interest points, enhancing recommendation accuracy. The function of the graph convolutional network is to iteratively update each node's embedding vector through neighbor aggregation operations, so that it better represents the semantic information of the node, thereby more accurately reflecting students' interests and needs in subsequent recommendations. This update process continues until the embedding vectors converge. Finally, the pooling function is used to generate vertex embeddings, with the calculation formula:

$$p_i = POOL(r_i^{(0)}, \ldots, r_i^{(m)}) \tag{5}$$

Based on the updated vertex embeddings, the model can estimate the interaction relationships between students and interest points. This estimation is achieved by computing the similarity or correlation between students and interest points, usually using inner product or cosine similarity methods. Through these similarity computations, the model can recommend the most relevant interest points for each student. The graph convolutional neural network can fully exploit the complex relationships between students and interest points, enabling personalized recommendations and continuously optimizing recommendation accuracy as the training process progresses. The estimation of the interaction relationships between students and interest points is as follows:

$$\hat{e}_{UP} = p_i^T p_o \tag{6}$$

The overall process of the model is to update the vertex embedding layer using the embeddings from the previous layer. Let $R^{(m)}$ and $R^{(m-1)}$ represent the vertex

embeddings at layer m and (m–1), respectively, and let d(.) denote the function used to update the vertices; then the expression is:

$$R^{(m)} = d(R^{(m-1)}, H) \tag{7}$$

3 GRAPH SIGNAL PROCESSING PROCEDURE

In the personalized learning interest point recommendation model based on graph convolutional collaborative filtering, neighborhood aggregation is an important component of the graph convolution operation. It updates node embeddings by aggregating features from neighboring nodes, thereby capturing the relationships between students and interest points. However, traditional graph convolution operations may fail to effectively extract and express key features in certain complex graph structures. To improve this, this paper proposes using a denoising autoencoder instead of the neighborhood aggregation process in the model, aiming to extract vertex features better and reduce dimensionality, thereby achieving more precise feature aggregation and representation.

By learning graph signals through self-encoding, the denoising autoencoder can extract more refined features and reduce the interference of noise on model performance. Specifically, the denoising autoencoder first receives an input signal containing node features and graph structure information, then learns the potential relationships between node features through an autoencoder framework and effectively removes noise while preserving key features in the graph signal. This process enables the model to focus on the most representative features, thereby enhancing the recommendation capability for learning interest points.

For any signal on graph H, the difference in graph signals can be defined as follows:

$$\left\| a - \hat{X}a \right\| \tag{8}$$

The variation $c(u)$ of signal a at vertex u can be defined by the following formula:

$$c(u) = \sum_{k \in V_u} q_{uk}(a(u) - a(k)) \tag{9}$$

When using a denoising autoencoder for graph signal processing, it is necessary to define the difference in graph signals and measure variations. The feature vector of each node constitutes a graph signal, and the propagation of this signal in the graph reflects the relationships between nodes and their neighbors. The variation of the signal is the difference between the signal at a vertex and its neighbors, which is closely related to the structure of the graph. By measuring the variation of the graph signal, the smoothness and roughness of the signal in the graph can be assessed, thereby determining which signals have a greater impact on the final recommendation results. Specifically, suppose the total number of vertices is denoted by V, the weight value of the connection between vertex u and vertex k is denoted by q_{uk}, and the variation measurement of the entire graph is represented as:

$$VA = \sum_{u=1}^{V} c(u)a(u) = \sum_{k \in V_u} q_{uk}(a(u) - a(k))a(u) \tag{10}$$

Let the eigenvector of the normalized adjacency matrix be denoted as n_s, and the eigenvalue be denoted as η_s, then:

$$\left\| n_s - \hat{X} n_s \right\| = 1 - \eta_s \tag{11}$$

There is a close relationship between the variation of graph signals and the eigenvalues of the graph. Signals with larger eigenvalues often appear in relatively smooth areas of the graph, meaning that these nodes have more consistent or stable relationships with their neighbors, whereas signals with smaller eigenvalues represent areas of the graph with greater variation, where the differences between nodes and their neighbors are larger. With the help of the denoising autoencoder, the model can extract signals with smaller variations, enhance information in smooth regions of the graph, and denoise highly variable parts, thereby effectively reducing noise interference.

4 MODEL FRAMEWORK

The model constructed in this paper consists of an embedding layer, a domain aggregation layer, and a combination/prediction layer. The model framework structure is shown in Figure 2.

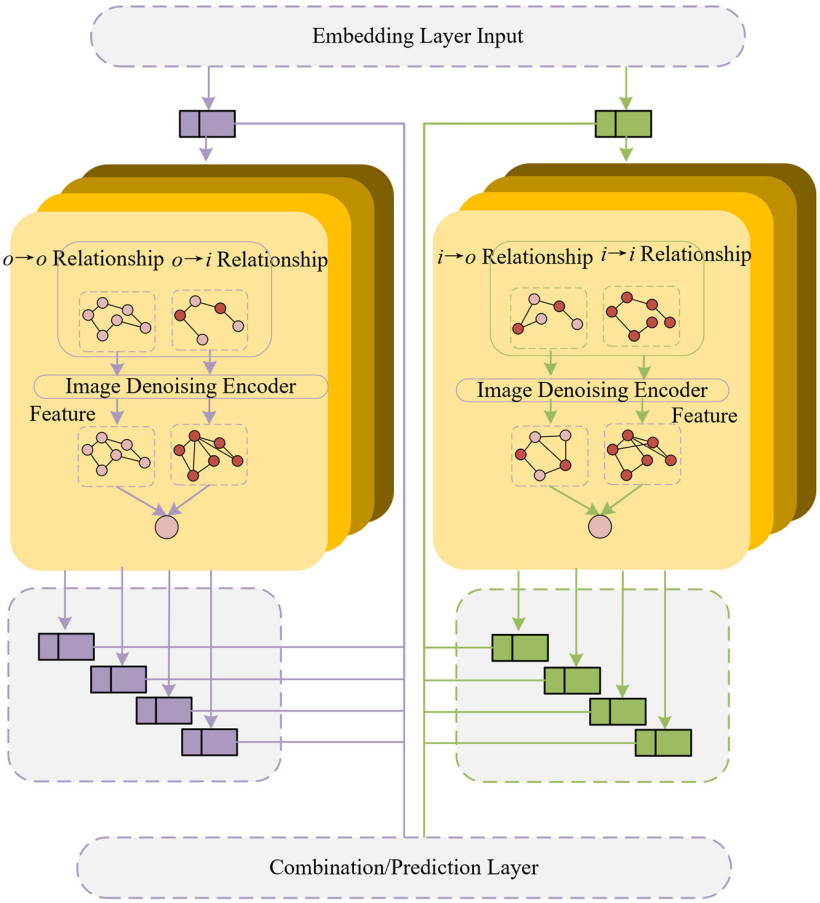


Fig. 2. Improved graph convolutional collaborative filtering-based personalized learning interest point recommendation model

The core purpose of the embedding layer is to convert the features of students and interest points into low-dimensional embedding vectors to facilitate subsequent learning and prediction. In mobile learning scenarios, the features of students and interest points may include multimodal information, such as students' learning behavior data, the knowledge content of interest points, and their interaction information with student behaviors. To obtain effective feature representations, this paper uses a single-layer perceptron and applies the *Tanh* activation function to map the features of students and interest points. Through this approach, the embedding layer reduces the high-dimensional features of students and interest points into fixed-size vectors, thus laying the foundation for subsequent domain aggregation. These low-dimensional embedding vectors can capture the potential similarities and relationships between students and interest points, serving as important input features for the recommendation system.

$$R_i = \tanh(N_i Q^i) \tag{12}$$

$$R_o = \tanh(N_o Q^o) \tag{13}$$

By concatenating the above two formulas, the initial propagation matrix is obtained:

$$R = [R_i, R_o] = \left[r_{i_1}, r_{i_2}, r_{i_3}, \ldots, r_{i_v} \| \, r_{o_1}, r_{o_2}, r_{o_3}, \ldots, r_{o_l} \right] \tag{14}$$

In the model proposed in this paper, a denoising autoencoder is used instead of the traditional neighborhood aggregator to enhance the capability of the domain aggregation layer. Suppose the embedding results of the first layer are represented by $r_i^{(0)}$ and $r_o^{(0)}$, then the m-th layer can be generally defined as:

$$r_i^{(m)} = \sum_{o \in V_i} \frac{1}{\sqrt{|V_i|}\sqrt{|V_o|}} r_o^{(m-1)} \tag{15}$$

$$r_o^{(m)} = \sum_{o \in V_o} \frac{1}{\sqrt{|V_o|}\sqrt{|V_i|}} r_i^{(m-1)} \tag{16}$$

The interaction between students and interest points can be determined by the following formula:

$$E_{UP} = \begin{cases} 1, \text{interactive} \\ 0, \text{without} \end{cases} \tag{17}$$

The embedding vector matrix of students and interest points after the m-th layer is:

$$R^{(m)} = \left(\tilde{F}^{-\frac{1}{2}} \tilde{X} \tilde{F}^{-\frac{1}{2}} \right) R^{(m-1)} \tag{18}$$

Assuming the predefined importance of the m-th layer representation is denoted as x_m, the final embedding matrix used for prediction is:

$$\begin{aligned} R^{(m)} &= \beta_0 R^{(0)} + \beta_1 R^{(1)} + \beta_2 R^{(2)} + \ldots + \beta_l R^{(m)} \\ &= \beta_0 R^{(0)} + \beta_1 \hat{X} R^{(0)} + \ldots + \beta_m \hat{X}^m R^{(0)} \end{aligned} \tag{19}$$

A hypergraph is used to represent the interactions between students and learning content. Suppose the diagonal matrices of students and interest points are denoted by F_i and F_o, respectively, then:

$$X_I = F_i^{-\frac{1}{2}} E F_o^{-1} E^S F_i^{-\frac{1}{2}} \tag{20}$$

$$X_O = F_o^{-\frac{1}{2}} E F_i^{-1} E^S F_o^{-\frac{1}{2}} \tag{21}$$

Assuming the relationship between students and interest points is represented by $\{P, \tau\}$ and $\{P, \delta\}$, the importance of different features in the student-interest point interaction is denoted by $\varepsilon(.)$, the element-wise multiplication is represented by $\otimes$, and the embedding matrices of students and interest points are represented by R_I and R_O, respectively. The embedding form generated on the hypergraph is as follows:

$$R_I = (P \otimes \varepsilon(I, \tau) P^T) R_I \tag{22}$$

$$R_O = (P \otimes \varepsilon(O, \delta) P^T) R_O \tag{23}$$

The improved graph convolution-based collaborative filtering paradigm can be expressed as:

$$R^{(m)} = \bar{X}_I R^{(m-1)} \tag{24}$$

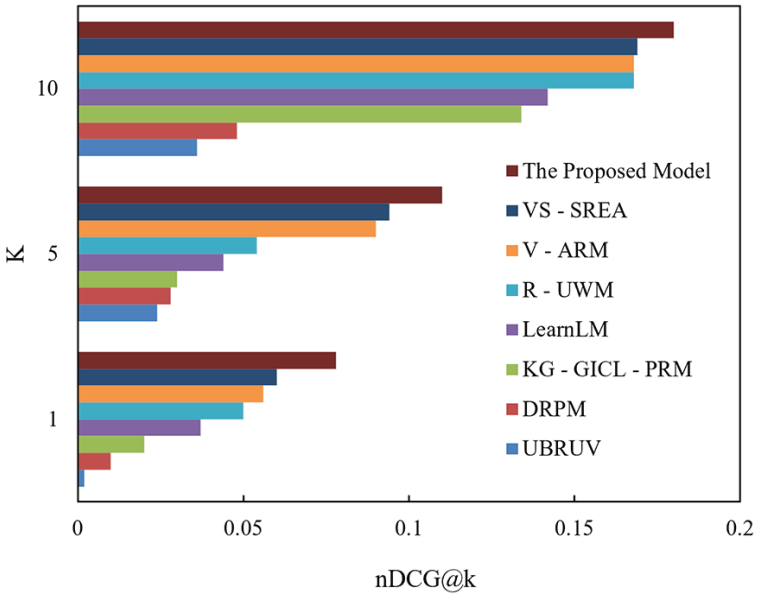
After multiple propagation layers are updated and refined, the final embedding representations of students and interest points will be combined for personalized recommendation. At this layer, multiple representations of students are concatenated to form a comprehensive embedding vector that contains hierarchical information, reflecting students' preferences in different connections and message-passing processes. Similarly, interest points are processed in the same way, concatenating representations learned at each layer to obtain the final interest point embedding. This multi-level concatenation operation effectively reduces the excessive weighting of individual layers and integrates them into a more comprehensive and accurate representation, allowing the model to fully capture students' personalized learning needs and the multi-dimensional characteristics of interest points. At the final prediction stage, the model generates personalized learning interest point recommendations by calculating the similarity between student and interest point embeddings, providing targeted and highly effective learning resource recommendations. Specifically, assuming the predefined importance of the m-th layer representation is denoted by x_m, and $\|$ represents the concatenation operation, then the final representations of student r_i and interest point r_o are:

$$r_i^* = \sum_{m=0}^{M} \beta_m r_i^{(m)} \tag{25}$$

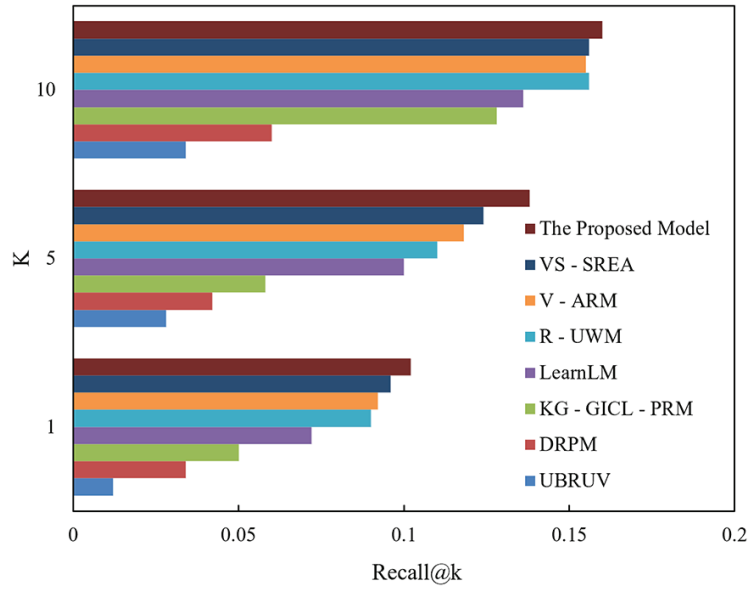
$$r_o^* = \sum_{m=0}^{M} \beta_m r_o^{(m)} \tag{26}$$

$$d_{G-C}(i, o) = r_i^{*S} r_o^*, r_i^* = r^{(0)} \| \cdots \| r^{(m)}, r_o^* = r^{(0)} \| \cdots \| r^{(m)} \tag{27}$$

5 EXPERIMENTAL RESULTS AND ANALYSIS



a) Normalized Discounted Cumulative Gain (NDCG)

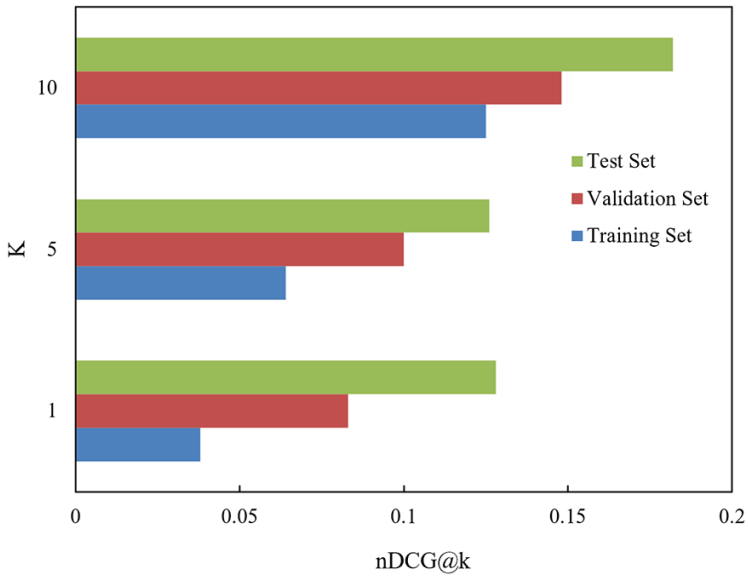


b) Recall

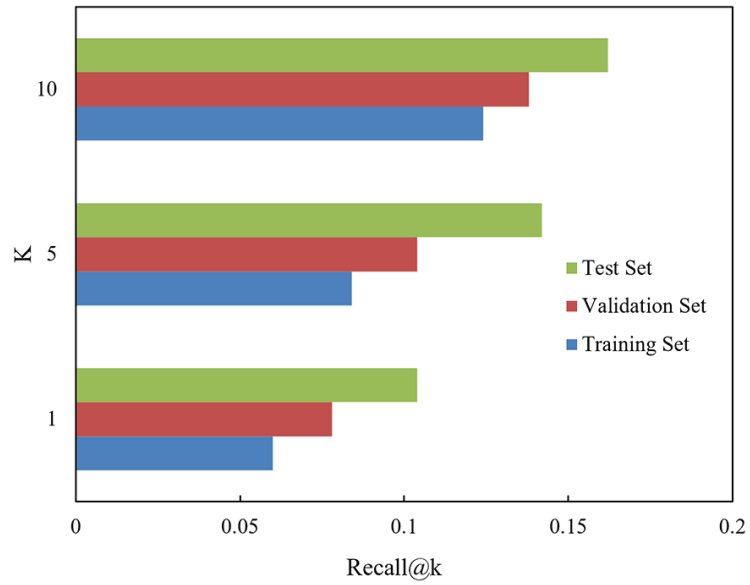
Fig. 3. Experimental results of different models on NDCG and Recall

From the experimental results provided in Figure 3, the proposed model in this paper exhibits significant advantages in both NDCG and Recall evaluation metrics. Particularly when the value of K is 10, the performance of this model is more outstanding compared to other models. The advanced models compared with the proposed model include: UBRUV (Utility-based Binary Vector Model of Resources and Users), DRPM (Deep Learning Recommendation Model based on Reader's Interest Mining), KG-GICL-PRM (Knowledge-Guided Graph Convolutional Interest Contrast Learning Personalized Recommendation Model), LearnLM, R-UWM (Rocchio-based

Utility Weight Update Model), V-ARM (Vikor-based Academic Recommendation Model for Personalization), and VS-SREA (VSrank-Social Relationship Utility Element Algorithm). In terms of NDCG, the proposed model achieves values of 0.078, 0.11, and 0.182 at K values of 1, 5, and 10, respectively, which are significantly higher than other models such as UBRUV, DRPM, and LearnLM. This indicates that the proposed model can more accurately recommend learning content related to students' learning interests. Additionally, in terms of Recall, the proposed model achieves a Recall of 0.16 when K = 10, which is superior to most comparative models, such as V-ARM and VS-SREA. This demonstrates that the proposed model performs better in capturing students' interest points and can more comprehensively cover students' learning needs.

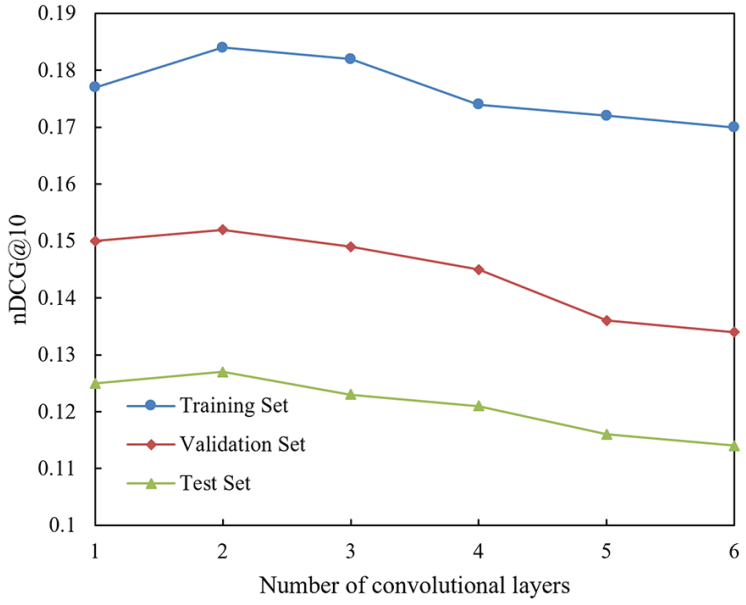


a) NDCG

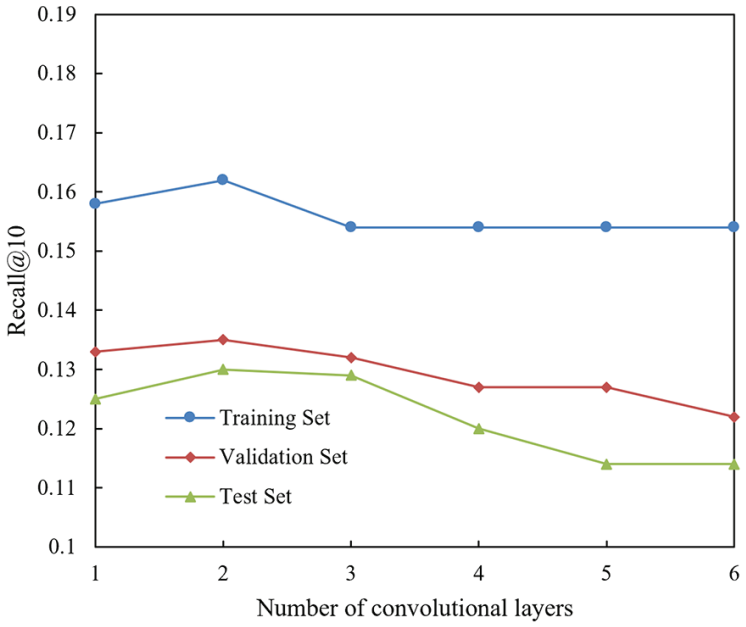


b) Recall

Fig. 4. Comparative analysis of recommendation results for different K values on three datasets



a) NDCG



b) Recall

Fig. 5. Comparative analysis of recommendation results with different convolutional layers

From the experimental results in Figure 4, the proposed graph convolutional neural network-based collaborative filtering model demonstrates good personalized recommendation effects on the training set, validation set, and test set. Specifically, NDCG shows a gradual improvement under different K values. On the test set, when K is 1, 5, and 10, the model achieves favorable results of 0.128, 0.126, and 0.182, respectively. Notably, when K = 10, the test set results significantly improve compared to other datasets, indicating that the model has strong precision in recommending students' interest points. Regarding Recall, the test set results also perform well. The Recall values for K = 1, 5, and 10 are 0.104, 0.142, and 0.162, respectively.

Particularly, the noticeable improvement at K = 10 reflects the model's advantage in capturing students' potential interest points broadly.

According to the experimental results in Figure 5, the proposed graph convolutional neural network-based collaborative filtering model exhibits a certain pattern under different convolutional layer settings. Regarding NDCG, as the number of convolutional layers increases, the results on the training set show some fluctuation, with the highest value appearing when the number of convolutional layers is 2 (0.184). However, overall, there is no significant upward trend. The best value for the validation set occurs at a convolutional layer count of 1 (0.15), while the test set shows a slight increase at a convolutional layer count of 2 (0.127). For Recall, the training set results are relatively stable, with the highest value of 0.162 appearing when the number of convolutional layers is 2. However, as the number of convolutional layers further increases, Recall does not show a significant improvement. A similar pattern is observed in the validation and test sets, where Recall is higher when the number of layers is small but declines when exceeding three layers. This suggests that too many convolutional layers may lead to overfitting or performance degradation.

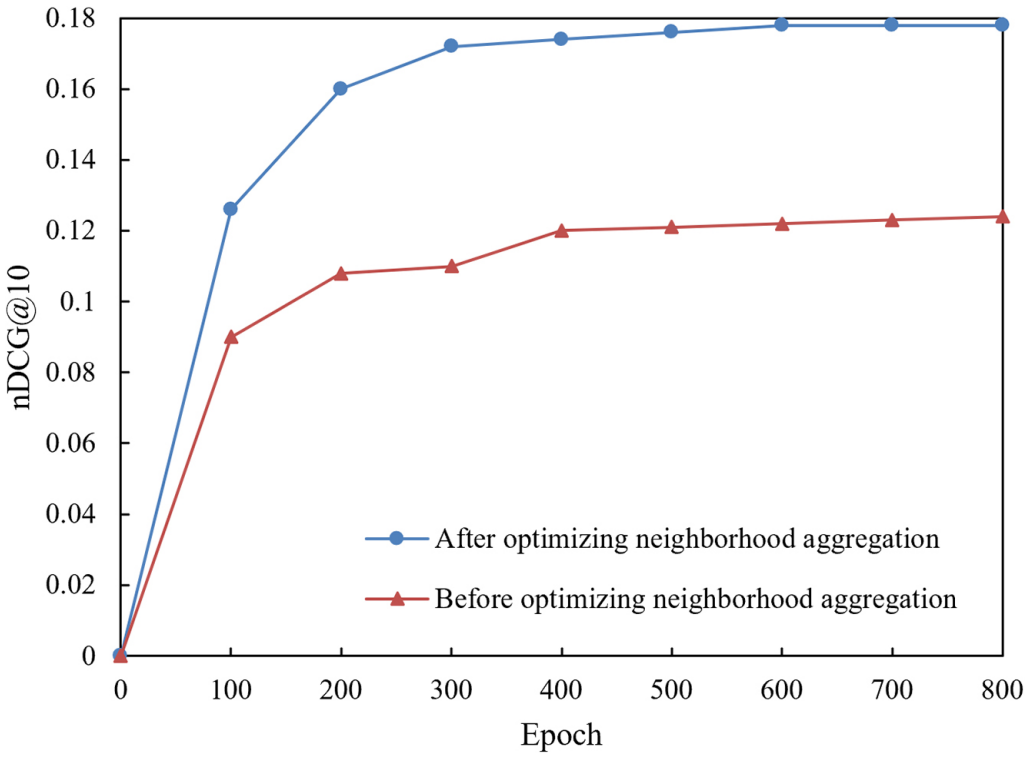


Fig. 6. Training curves before and after neighborhood aggregation optimization

According to the training curve data in Figure 6, there is a significant difference in performance before and after optimizing neighborhood aggregation. After optimizing neighborhood aggregation, the model's performance gradually improves with increasing training epochs. Specifically, in the optimized model, the NDCG value increases continuously every 100 epochs, rising from 0 to 0.178, and stabilizing at the end of training. In contrast, the pre-optimized model performs relatively poorly, with the NDCG value only increasing from 0 to 0.124 at the same number of epochs. This indicates that after optimizing neighborhood aggregation, the recommendation accuracy of the model significantly improves.

This trend reflects that by optimizing neighborhood aggregation, the model can better capture students' learning behaviors and interests, thereby providing more

accurate personalized recommendations. The comparative analysis of training results before and after optimizing neighborhood aggregation clearly demonstrates the significant advantages of the optimized model in personalized learning path recommendations. After optimization, the model can more effectively mine potential information in learning data. Through a refined neighborhood aggregation strategy, the performance of the graph convolutional neural network in processing students' learning interests and behaviors is enhanced. This optimization not only ensures better stability in the training process but also improves its adaptability in real applications, enabling better personalized and dynamically adjusted learning path recommendations for students.

6 CONCLUSION

The research results of this paper mainly focused on optimizing personalized learning paths by combining multimodal data and graph convolutional neural networks with collaborative filtering. By constructing a knowledge graph that includes multidimensional information such as students' learning behaviors, learning content, and emotional states, this paper provided strong data support for personalized learning path recommendations. Combining dynamic optimization strategies, the model can adjust learning paths in real-time to ensure accurate recommendations based on students' learning conditions and interest changes. This method not only improved the accuracy of personalized recommendations on mobile education platforms but also significantly enhanced students' learning efficiency and the user experience of the platform. Experimental results show that the model optimized with neighborhood aggregation achieves significant improvements in NDCG and Recall compared to traditional methods, verifying its effectiveness in optimizing personalized learning paths.

However, despite the progress made in this study, some limitations still exist. First, the model may face challenges in complexity and computational efficiency, especially when dealing with large-scale user data, where computational resource consumption may be high. Second, this paper mainly relies on students' historical learning behavior data and emotional states, which may overlook real-time emotional and behavioral fluctuations, leading to learning path recommendations that may not fully adapt to students' sudden needs in certain situations. Therefore, future research can further optimize the computational efficiency of the model and incorporate more dynamic factors (such as students' immediate emotional feedback and learning contexts) to refine personalized recommendations. In addition, integrating cross-platform data and adopting multi-task learning strategies will also be important directions for future research, which can further improve the accuracy and adaptability of recommendation systems to better support students' personalized learning paths.

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8 AUTHOR

Yifei Zhang graduated from Northwest A&F University in 2004 and works at the School of Economics and Management, Henan Polytechnic. He is engaged in the research on business administration. He got first prize in Henan Province higher vocational education teaching ability. He published "Foundation of Management" which has been approved as a high-quality online open course for vocational education and continuing education in Henan Province (E-mail: zhangyf6014@163.com).