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Recommendation of Teaching Resources for Ideological Education Based on Machine Learning and Knowledge Graphs

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Abstract. *In the existing ideological education teaching resources recommendation system algorithms and models continue to progress, but the recommendation strategy still stays in the two aspects of student preference analysis or content relevance calculation, ignoring the control of teaching objectives and the role of practical value guidance by lecturers in the recommendation of teaching resources, which leads to unsatisfactory recommendation outcome. To this end, a method of recommending teaching resources for ideological education based on machine learning and Knowledge Graph (KG) is suggested. The KG of teaching resources are first constructed, and the established KG are perturbed with data using data enhancement strategies to suppress extraneous noise. Then, the Graph Convolutional Network (GCN) is then utilized to generate feature embeddings on the paths of different teaching resources and knowledge points to compute the correlation between teaching resources and knowledge points. Finally, GCN is adopted to obtain the estimation of the rating vectors of teaching resources from different subjects, and the attention mechanism is introduced to aggregate the rating vectors of different subjects to obtain the predicted scores, and the scores are used to rank the teaching resources and form a list of TOP N teaching resources to be recommended to students. The experimental results imply that when the number of students is 20, the average accuracy and hit rate of the designed method have an improvement of 4.9%–16.8% compared to the comparison method, which can achieve a better recommendation effect.*

Keywords: machine learning; knowledge graph; graph convolutional network; data enhancement; attention mechanism

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1. **Introduction.** Through the scientific and reasonable application of ideological education teaching resources recommendation method, it can collect and analyze teaching-related data, enhance the teaching effect of the ideological education course to a certain extent, and enrich the learning experience of students. In the vast amount of ideological education teaching resources data, by quickly and effectively extracting the demand data, students' political literacy can be improved, so that they can accurately choose the

learning content suitable for them [1, 2]. To better meet students' needs and improve the efficiency and effectiveness of teaching resources, the application of recommendation methods in ideological education teaching resources has gradually become a hot research topic [3]. However, the research and practice of existing recommendation methods still face many challenges, and the problems of how to accurately capture students' interests, ensure the authenticity and reliability of recommended resources, and improve the accuracy of recommendation methods have been troubling the researchers [4]. Thus, at this stage, with the method of recommending teaching resources for ideology and politics as the object of research, searching and digging deeper to find out the teaching resources that match students' learning preferences, and providing students with ideological education teaching resources in line with their needs has become a crucial issue.

1.1. **Related Work.** Carchiolo et al. [5] built a learner's learning behavior model and a learning resource model, and constructed and developed an online personalized recommendation system for learning resources, but there is a cold start problem. Wang and Fu [6] designed a similar user model based on Item Reflection Theory (IRT), improved the formation method of the set of nearest-neighbor users and the collaborative filtering recommendation algorithm, and implemented a learning resource recommendation system. Yang and Duan [7] analyzed students' assessment data to find students' learning problems and designed a hybrid push strategy to recommend ideological education learning resources that better meet students' learning needs, but the accuracy of the recommendations was low.

With the development of Knowledge Graph (KG) and machine learning, the combination of KG and machine learning techniques can not only increase the interpretability of teaching resources, but also improve the extraction ability of hidden information, so as to achieve better recommendation outcome [8]. Zhu et al. [9] proposed to integrate the resource rating history and its background knowledge together to form a KG, and use a decision tree to correlate the information with the student's information, and finally calculate the recommendation degree of the learning resources. Ma et al. [10] used k-means clustering to mine the students' knowledge grasping on the basis of the knowledge graph, and recommended the teaching resources for the students that were appropriate to their cognitive level. Guan [11] incorporates recommendation algorithms with KG and reinforcement learning to capture learners' interests, but the accuracy of the recommendation results is not high. Yan et al. [12] design a meta-path based mutual attention mechanism for Top N learning resource recommendation for generating user, item, and meta-path based contextual representations.

Graph Neural Network (GNN) can encode key topologies to improve user representations and item representations [13, 14] and have excellent ability to learn graph-structured data, hence a number of researchers have proposed various models for recommending learning resources based on GNN. Mezni et al. [15] proposed KG-based Intent Network (KGIN), which explores the intentions behind students' interactions with resources through the use of auxiliary knowledge and encodes them into the representations of students and resources. Zhang et al. [16] utilized the GNN and an attentional mechanism to predict the resources of interest to the students based on the anonymous conversations and to recommend them. However, the teacher's rating factor is ignored, resulting in inefficient recommendations. Zhang et al. [17] learnt learners' representations by embedding hyperedges in GCNs, which took into account short-term sequential relationships of courses through a modified GRU module. Ahmadian Yazdi et al. [18] devised a hierarchical attentional mechanism with residual chunks in order to generate homogeneous and heterogeneous node embeddings but the node embeddings were insufficient. Zhang et al.

[19] combined student-resource interactions and knowledge graphs into a heterogeneous graph, and then applied an aggregation mechanism on it to recommend Civics teaching resources of interest to students.

1.2. **Contribution.** However, the existing research ignores the teacher's guidance factor and fails to meet the students' quality demand for teaching resources, resulting in poor recommendation accuracy. For this reason, this article suggests a method for recommending teaching resources for ideological education based on machine learning and KG. The main work of the method can be summarized as follows.

(1) A KG containing teaching resources, knowledge points and their attributes is constructed, and a comparative learning approach is used to perturb the data of the established knowledge graph to maximize the mutual information between the views, thus enhancing the generalization ability of the model.

(2) GCN is adopted to generate feature embeddings on the paths of different teaching resources and knowledge points; these feature embeddings are then synthesized through semantic aggregation to form an overall feature embedding representation; finally, the feature embeddings of teaching resources and knowledge points are mapped to the same space using the TransR model and the correlation between them is calculated.

(3) Using GCN to obtain the estimation of the rating vectors of teaching resources from different subjects, aggregating the rating vectors of different subjects through the attention mechanism, obtaining the predicted scores, using the scores to rank the teaching resources, and forming a list of the optimal teaching resources to be recommended to the students.

(4) Experiments were conducted on publicly available ideological education teaching datasets, and the results show that the proposed method has an average accuracy rate of more than 90%, which improves the accuracy of teaching resource recommendations and has certain application value.

2. Theoretical Analysis.

2.1. **Knowledge Graph.** KG is a tool for presenting information, which is represented as a triad: entities, relationships and attributes [20]. In the education sector, KG is used to assist learners in learning subject knowledge, to aid teachers in teaching, to help users clarify their knowledge, and to promote the efficient use of knowledge and the improvement of teaching quality. Its construction process includes collecting data, extracting knowledge, integrating knowledge, and processing knowledge, as shown in Figure 1.

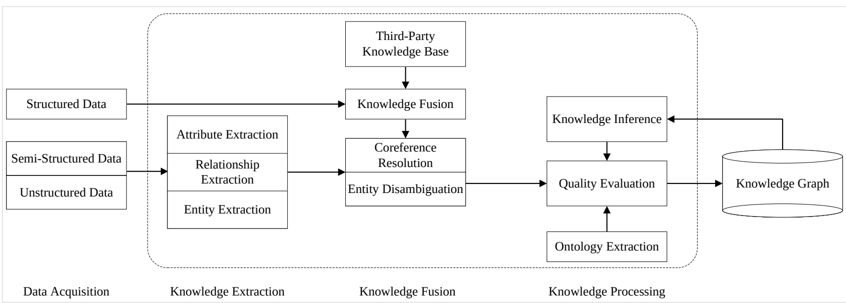

Figure 1. The building framework of a KG.

Traditional KGs have issues such as high computational complexity and data sparsity, in order to alleviate these problems Knowledge Graph Embedding (KGE) has attracted wide attention [21]. KGE is the process of creating propositional feature vector representations of the components of a KG (entities and relations), which can solve a variety of complex, real-life graphical issues in a simpler way. For these issues, traditional graph representations are inadequate. Therefore, KGE is now widely used to address the issues of knowledge graph completion, entity recognition, and relationship classification.

2.2. **Graph Convolutional Network.** GNN is the graph-structured machine learning technique, which is, as a branch of GNN, extends the utilization of convolutional functions from conventional data kinds to diagram-constructed data, extracting characteristics from diagram data in essence [22]. A GCN can have multiple graph convolutional levels, where the process of aggregating information from surrounding nodes is performed independently for each node and simultaneously for all nodes. For each node w of the diagram, its original embedding is the feature $g^{(0)} = x$. In level l ($l = 1, 2, \ldots, L$), node w averages the information from its neighbors in the former level and blends it with the embedding message from the former level to gain the characteristic embedding of w in level l as shown in Equation (1).

$$g_v^{(l)} = \delta\left(V^{(l)} \cdot \frac{1}{N(w)} \sum_{u \in N(w)} g_u^{(l-1)} \ + \ A^{(l)} \cdot g_v^{(l-1)}\right) \tag{1}$$

where δ stands for the nonlinear activation function, V and A stand for the parameter matrix, w is the degree of node, and $N(w)$ denotes the number of w's adjacent nodes.

Through the L-th level of adjacent collection, w is obtained at the last level as follows:

$$z = h^{(L)}. \tag{2}$$

The vectorized representation of Equation (2) is shown in Equation (3), where G is the characteristic matrix of whole nodes.

$$\mathbf{G}^{(l+1)} = \delta(\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{B}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{G}^{(l)}\mathbf{V}^{(l)}) \tag{3}$$

where $\tilde{\mathbf{B}} = \mathbf{B} + \mathbf{I}$, and $\tilde{\mathbf{D}}$) is the degree matrix of $\mathbf{B}$.

3. **Construction and Data Enhancement of a Knowledge Graph of Ideological Education Teaching Resources.** To construct the KG of learning resources for ideological education, this article models the knowledge points of the civics course and related learning resources as a graph, and establishes the mapping relationship of different entity structures in the resource library, as shown in Figure 2.

Taking the teaching resource entity knowledge point as a spatial structure and denoting it as (h, r, t), the transformation process of entity information in space can be expressed as follows:

$$f(h, t) = -\|h + r - t\| \tag{4}$$

where f denotes the translation function of entity information in space; h denotes head entity; r denotes entity translation; and t denotes tail entity. In the transformation process, the larger the value of $f(h, t)$ is, the higher the match between the corresponding knowledge point and the fact is. To achieve the physical expression of KG and establish the semantic relationship between different knowledge points, the KG shown in Equation (5) is designed using the transformed entity information.

$$R = f(h, t)\, h^t M t \tag{5}$$

where R denotes the teaching resource KG; M denotes the entity dimension corresponding to the knowledge point.

For the goal of suppressing the issues of long-tail phenomenon and noisy data in the ideological education teaching resources KG, the data enhancement strategy in comparative learning [23] is used to perturb the original teaching resources KG to mine the

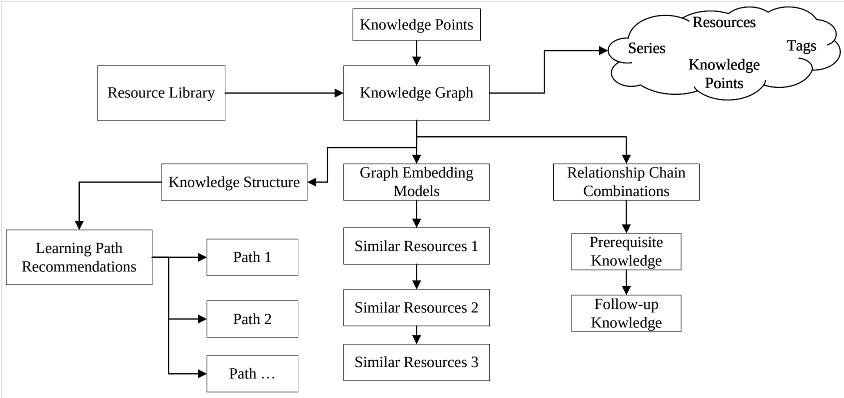

Figure 2. The KG of teaching resources for ideological education.

self-supervised signals and maximally enhance the mutual information between the views [24], so as to effectively enhance the feature representation of the optimized nodes and the generalization ability of the model.

The original view R_k of R is first subjected to two independent data enhancement operations F_1 and F_2 to generate two related sub-views $F_1(R_k)$ and $F_2(R_k)$, as shown below:

$$Z_1^{(l)} = H(Z_1^{(l-1)}, F_1(R_k)), \quad Z_2^{(l)} = H(Z_2^{(l-1)}, F_2(R_k)) \tag{6}$$

where $Z_1^{(l-1)}$ and $Z_2^{(l-1)}$ denote the feature representations of the nodes in the previous level at the time of information dissemination, H denotes the knowledge aggregation operation on the input views and layer $l-1$ inputs, and $Z_1^{(l)}$, $Z_2^{(l)}$ are the feature representations of the nodes in the l-th layer in the subviews, respectively.

The nodes in R_k are then discarded with probability p as shown in Equation (7).

$$F_1(R_k) = (M_1 \cdot (h, r, t)), \quad F_2(R_k) = (M_2 \cdot (h, r, t)) \tag{7}$$

where $(h, r, t) \in R_k$ is the entity in the KG and its associated knowledge triad, $\cdot$ denotes the product operation, $F_1(R_k)$ and $F_2(R_k)$ denote the two homologous augmented subgraphs used for comparison. Any node on the graph and the edges connected to it will be removed with probability p, which is described by two mask vectors $M_1, M_2 \in \{0, 1\}$ generated based on the Bernoulli distribution [25], i.e., $M_1, M_2 = 0$ when the current tail node t and relation r are removed in the subview. Capturing the local structural information around the target node prevents overfitting of the model's dependencies, accurately matches ideological and educational teaching resources with students' preferences, and reduces the impact of noisy interactions on the representation learning, conferring greater stability to node representations in combating noise interference.

4. Recommendation of Teaching Resources for Ideological Education Based on Machine Learning and Knowledge Graph.

4.1. Embedded Representation Learning for Knowledge Graphs. Based on KG of the constructed teaching resources, this article suggests a teaching resources recommendation method for ideological education based on machine learning and KG, and the entire framework is implied in Figure 3. Firstly, GCN is used to generate feature embeddings on the paths of different teaching resources and knowledge points, and calculate the correlation between the two, and then obtain the estimation of the rating vectors of the teaching resources from different subjects, and then obtain the predicted scores by aggregating the rating vectors of different subjects through the mechanism of attention, and then finally use the scores to rank the teaching resources, and then form a list of the most optimal teaching resources to be recommended to the students.

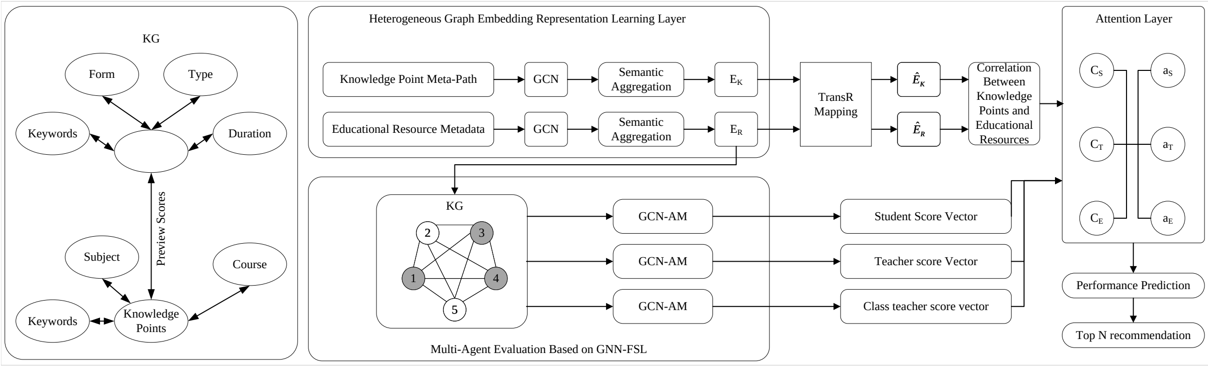

Figure 3. General framework of the designed recommendation methodology.

In the enhanced knowledge graph R, W is used to denote the set of nodes, E denotes the set of edges, S denotes the node of civic teaching resource, K is the node of knowledge points, C_S is the set of attributes of teaching resource, C_K is the set of attributes of knowledge points, and $E \in \{S \leftrightarrow K, S \leftrightarrow C_R, K \leftrightarrow C_K\}$, where $S \leftrightarrow K$ denotes the set of teaching resource used by the knowledge points, $S \leftrightarrow C_R$ denotes the set of attributes possessed by teaching resources, and $K \leftrightarrow C_K$ denotes the set of attributes possessed by knowledge points.

GCN is used to mine the obscured information between teaching resources and knowledge points in ideological education. GCN contains multi-level hidden layers, which can encode the features of neighboring nodes, and each layer is updated according to the state of neighboring nodes and itself. Let the relationship matrix be $X \in \{X_S, X_K\}$, where X_S is the teaching resource–teaching resource relationship matrix and X_K is the knowledge point–knowledge point relationship matrix, and the dimensions of the above two relationship matrices are the number of teaching resources and knowledge points respectively. To make the update of each node related to the embedding of its neighbors and the hidden state of the previous level of the node, a self-connection relationship is added, as shown below:

$$\tilde{\mathbf{X}} = \mathbf{X} + \mathbf{I} \tag{8}$$

where $\mathbf{I}$ is the unit matrix.

To prevent the numerical values of the node features from being over-amplified in the multi-layer propagation process and to maintain numerical stability, the nodes are normalized as follows:

$$\tilde{\mathbf{X}}' = \tilde{\mathbf{C}}^{-\frac{1}{2}} \tilde{\mathbf{X}} \tilde{\mathbf{C}}^{-\frac{1}{2}} \tag{9}$$

where $\mathbf{C}$ is the degree matrix of the relation matrix.

The features between neighboring nodes are fused as shown in Equation (10). After GCN processing, the embedding representation of individual paths can be obtained.

$$\mathbf{g}_h^{(l+1)} = \mathrm{ReLU}\left(\tilde{\mathbf{X}}' \, \mathbf{g}_h^{(l)} \mathbf{V}^{(l)}\right) \tag{10}$$

where $\mathbf{g}^{(l)}$ is the node feature matrix of level l, and $\mathbf{V}^{(l)}$ is the corresponding weight matrix.

In the process of aggregating multiple paths, firstly, the embedding vectors of the same paths are averaged over all the ideological education resources or knowledge nodes, as follows:

$$\boldsymbol{\mu}_B = \frac{1}{|w|} \sum_{w \in B} \tanh\left(\mathbf{V}_B \mathbf{g}_w^i + \mathbf{a}_B\right) \tag{11}$$

where node type $B \in \{S, K\}$ is a node of ideological education teaching resource or knowledge point type; $|w|$ is the number of nodes; $\mathbf{g}_i^w$ is the embedding vector obtained from the i-th path of node w; V_B and a_B are trainable parameters.

Then, the embedding vectors of different paths of the same type of nodes are fused using the attention mechanism, as shown in Equation (12).

$$\alpha_i = \frac{\exp(\mathbf{q}_B^T \boldsymbol{\mu}_i)}{\sum \exp(\mathbf{q}_B^T \boldsymbol{\mu}_i)}, \qquad \mathbf{E}_B = \sum \alpha_i \mathbf{g}_B^i \tag{12}$$

where $\mathbf{q}^T$ is the parameterized attention vector for node type B, and α_i is the weight of path i on node type B.

Finally, all the paths of B are weighted and fused to get the final node embedding vector $E_B \in \{E_S, E_K\}$, where E_S is the feature vector matrix of teaching resources after semantic aggregation, and E_K is the feature vector matrix of knowledge points.

Since E_S and E_K are two different types of feature vectors, it is not possible to calculate their similarity directly, so the TransR model [26] is used to map them to the same feature space. Let E_{Si} and E_{Kj} be the vectors of the entities of the i-th teaching resource and the j-th knowledge point in the original entity space. There exists a mapping matrix M, which maps the vectors of the original feature space to the same relationship space, then the mapped entity vectors are as shown in Equation (13).

$$\begin{cases} \hat{E}_{Si} = E_{Si} M \\ \hat{E}_{Kj} = E_{Kj} M \end{cases} \tag{13}$$

where $\hat{\mathbf{E}}_{Si}$ and $\hat{\mathbf{E}}_{Kj}$ are vector representations after mapping.

4.2. **Grading Teaching Resources Based on the GCN.** To make the recommendation results of ideological education teaching resources take into account the expectations of students, ideological and political teachers and class teachers, a fine-grained evaluation index is designed for the above different subjects. Student scoring vector is defined as s_a; teacher scoring vector is defined as s_b; class teacher scoring vector is defined as s_c. The specific scoring process is shown in Figure 4.

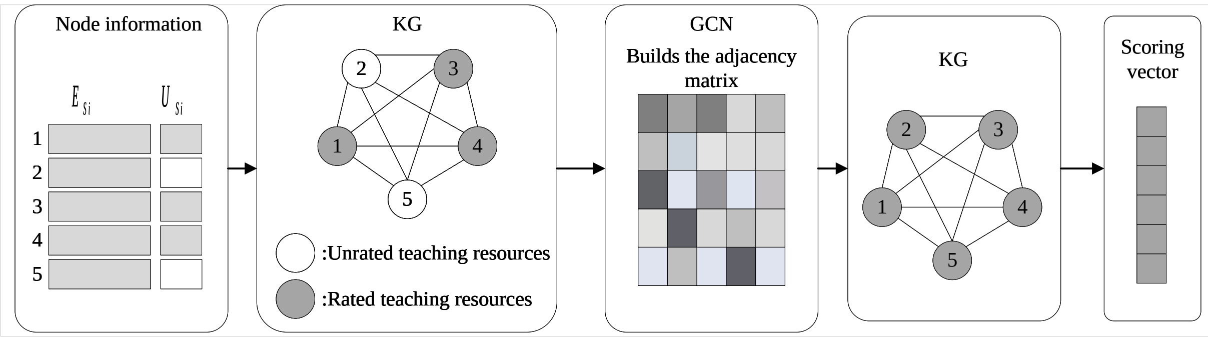

Figure 4. Multi-subject rating based on GCN.

The node information vector is:

$$\mathbf{f}_i^{(0)} = \text{Concat}(\mathbf{E}_{S_i}, \mathbf{U}_{S_i}) \tag{14}$$

where Concat indicates the connection operation and $\mathbf{U}_{S_i}$ indicates the score vector of the node.

Using GCN to learn the deep relationship between teaching resources, the updating process is:

$$\mathbf{f}^{(l+1)} = Gc\big(\mathbf{f}^{(l)}\big) \tag{15}$$

where Gc represents the graph convolution operation.

Then, by using gradient descent [27] to minimize the difference between the predicted score and the true score, the loss function is:

$$L_1 = \frac{1}{N_U}\sum_{i=1}^{N_U}(s_i - \hat{s}_i)^2 \tag{16}$$

where NU is the number of elements in the rating matrix; s_i is the element in the real rating matrix; $\hat{s}_i$ is the final predicted score.

Finally, the output is the rating matrix $\hat{s} \in \{\hat{s}_a, \hat{s}_b, \hat{s}_c\}$ of the corresponding groups.

4.3. **Recommended Resources for Teaching Ideological Education.** The attention mechanism is used to synthesize the effect of teaching resource rating and the correlation between teaching resources and knowledge points. First, cosine similarity [28] is used to obtain the teaching resource–knowledge point similarity matrix O:

$$\mathbf{O} = \mathrm{sim}_{ij} = \frac{\hat{\mathbf{E}}_{S_i} \cdot \hat{\mathbf{E}}_{K_j}}{\|\hat{\mathbf{E}}_{S_i}\|\,\|\hat{\mathbf{E}}_{K_j}\|} \tag{17}$$

where $\hat{\mathbf{E}}_{Si}$ and $\hat{\mathbf{E}}_{Kj}$ represent the mapped vectors.

The similarity matrix is fused with the three subject evaluations, as follows:

$$\begin{cases} D_a = Concat(O, \hat{s}_a) \\ D_b = Concat(O, \hat{s}_b) \\ D_c = Concat(O, \hat{s}_c) \end{cases} \tag{18}$$

Then, using the attention mechanism to get the prediction results:

$$\hat{P} = \sum D \cdot Softmax(\mathbf{V}_d D + \mathbf{b}_d) \tag{19}$$

where $D \in \{D_a, D_b, D_c\}$ V_d and b_d are trainable parameters.

At last, according to the predicted results, a set of ideological education teaching resources $C = \{C_i, i \in 1, 2, \dots, n\}$ satisfying students' requirements is formed, where n is the total number of candidate resources. For each candidate teaching resource C_i, the frequency of use G of students and the score of each teaching resource are calculated, the candidate teaching resources are ranked according to the predicted results, and a TOP-N list of the best teaching resources is formed and recommended to students.

5. **Performance Testing and Analysis.**

5.1. **Experimental Comparison and Analysis.** For the goal of analyzing the practical application effect of the teaching resource recommendation method based on machine learning and KG, a comparative test was carried out. The experimental data set participating in the test is Junyi academy, a data set of ideological education and teaching collected by an education platform, which contains 2,381 learning records and evaluation information of 394 students and 89 ideological and political learning resources. 60% of the data set is divided into training set, 30% into test set and 10% into verification set.

In this article, the dimension of the dataset vector is 100, the grouping length is 64, the Adam optimizer is used, and the initial learning rate is 0.0001. The processor of this experiment is Intel (R) Core (TM) i7-10875H, 2.3GHz, the graphics card is NVIDIA

GeForce RTX 2060, the memory is 6G, the programming language is Python3.8.2, and the framework is Tensorflow1.14.0.

On this basis, MCLP method in literature [9] and KGAN method in literature [19] were used as the control group respectively to compare with MLKG method in this paper. For specific effect evaluation, the average accuracy rate (A), hit rate (H), average reciprocal ranking (M) and cumulative gain of normalized loss (D) were selected for four evaluation indicators [29]. Table 1 shows the recommended performance of different methods with different number of students (N).

Table 1. Comparison of the results of the recommended teaching resources for ideological education (%)

N	MCLP				KGAN				MLKG			
	A	H	M	D	A	H	M	D	A	H	M	D
10	65.1	18.2	1.24	4.15	71.9	19.3	1.29	3.75	80.1	23.9	3.15	4.96
20	72.4	25.6	2.59	4.33	76.7	28.1	2.05	4.22	87.5	33.6	3.39	5.16
30	75.6	39.1	2.58	4.19	80.4	43.2	2.97	4.69	92.4	48.1	3.61	5.02
40	76.9	51.9	3.28	4.61	82.8	56.2	2.33	4.58	93.1	62.8	3.93	4.92
50	76.7	63.9	1.92	4.26	82.5	66.8	3.51	4.91	92.8	74.5	3.88	5.09

As can be seen from Table 1, the test results of the three different recommendation methods show different characteristics. Firstly, the average accuracy of A is compared. When the number of recommended students is 30, the A and H of MLKG are 92.4% and 48.1% respectively, which are 16.8% and 9% higher than MCLP and 12% and 4.9% higher than KGAN respectively. MCLP uses the fusion of resource rating and background knowledge to form a knowledge graph, and realizes the prediction and recommendation of resource rating through decision tree. However, it does not de-noise the knowledge graph, nor does it carry out in-depth feature extraction of nodes in KG. KGAN designs student-resource heterogeneity maps and applies the aggregation mechanism of GCN to implement resource recommendation, without considering teachers' grading of resources or enhancing the constituted heterogeneity maps. The accuracy of MCLP and KGAN recommendation still needs to be improved.

In addition, the fluctuation degree of M and D in MCLP is relatively large, with the minimum value of M being 1.24 and the upward fluctuation amplitude reaching 2.04. The minimum value of D is 4.15, and the upward fluctuation amplitude reaches 0.46. The fluctuation degree of M and D in KGAN significantly increases, with the maximum value of M being 3.51 and the downward fluctuation amplitude reaching 2.22. The maximum value of D is 4.91, and the downward fluctuation amplitude reaches 1.16. In contrast, in the test results of MLKG, M and D not only showed high stability, but also remained at a high level, with corresponding intervals of 3.1–3.9 and 4.9–5.2, respectively. Overall, MLKG can effectively recommend resources.

The comparison of recommended times of different methods is shown in Figure 5. The maximum recommendation time of MCLP is 21.3s, while the maximum recommendation time of MCLP and KGAN is 41s and 38s respectively. Thus, it can be proved that MLKG has a higher recommendation efficiency for teaching resources. The main reason is that MLKG can quickly locate related resources by effectively matching teaching resources with knowledge structure and correlation. Greatly increase the speed of recommendations.

5.2. **Analysis of Ablation Results.** To verify the effectiveness of major components in MLKG, ablation experiments were performed on them. Where, "-DE" means to remove the data enhancement module of KG, "-ERL" means to remove the embedded learning

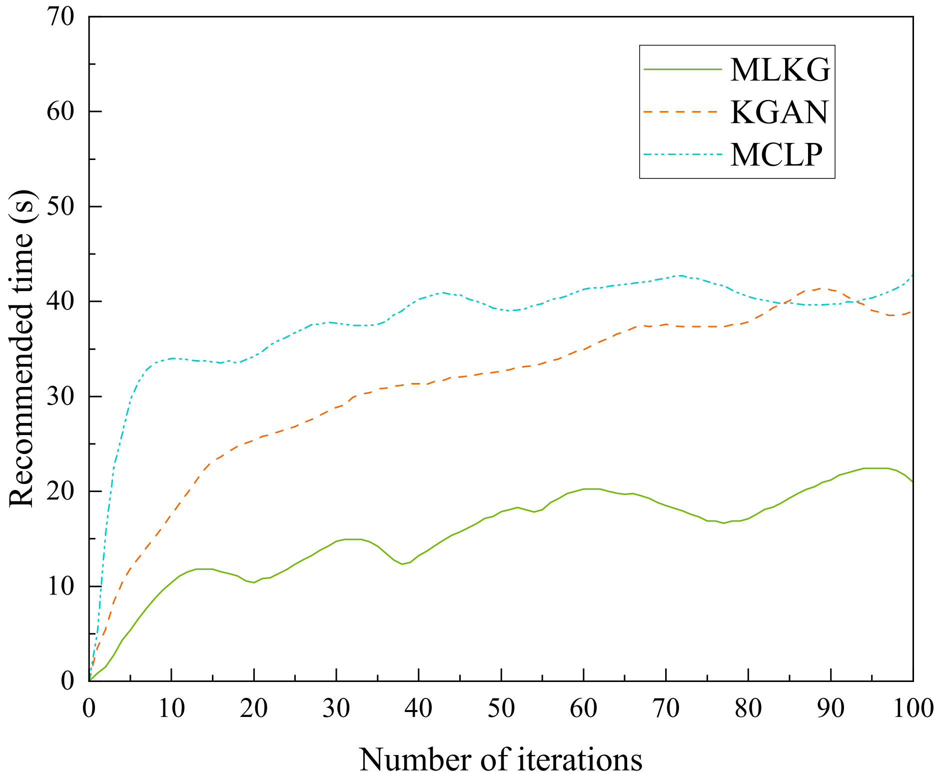

Figure 5. Comparison of recommended time of different methods.

module of KG, and "-AM" means to remove the attention mechanism of multi-agent score aggregation and replace it with simple summation. The ablation experimental results under different student numbers are shown in Figure 6.

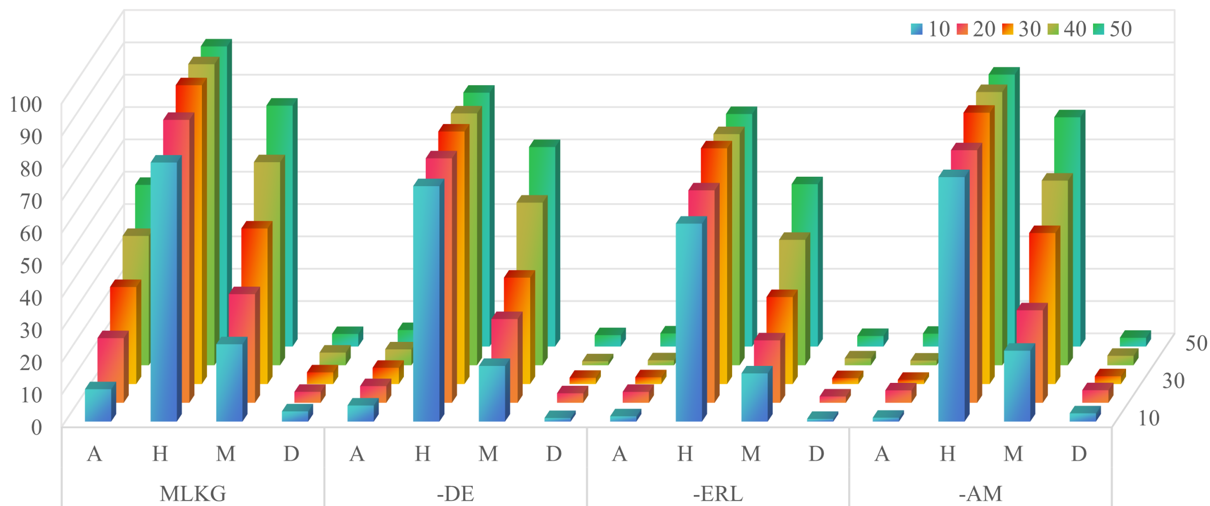

Figure 6. The ablation experimental results under different student numbers.

From Figure 6, "-ERL" has the lowest index, and M and D have the largest fluctuation range, which proves that the characteristic representation of KG is indispensable. The A, H, M, and D values of "-DE" are low. If the KG data enhancement module is missing, more noise is generated in the view, which affects the recommendation effect. "-AM" is superior to "-DE" and "-ERL" in all metrics, but the lack of an attention mechanism to combine the scores of multiple agents will hurt the performance of recommendations. From the above comparison, MLKG without any of the components, the recommendation effect is not as good as the full model, so the major components involved in MLKG are valid.

6. **Conclusion.** To improve the recommendation accuracy of current ideological education teaching resources, a method of recommending ideological education teaching resources based on machine learning and KG is proposed. The teaching resource KG is established, and the irrelevant noise of the KG is suppressed by data enhancement strategy. GCN and semantic aggregation are used to generate and synthesize these feature embeddings to form an overall feature embeddings representation, and TransR models are used to map the feature embeddings to the same space and calculate the correlation between the two. The attention mechanism is used to aggregate the scoring vectors of different subjects, obtain the predicted grades, use the grades to sort the teaching resources, and form a list of the best teaching resources to recommend to students. Simulation results indicate that the suggested method has advantages in recommendation accuracy and timeliness. In the future, this paper will add the characteristics and attributes of knowledge points and teaching resources, and explore the influence of the relationship between the upper and lower knowledge points on the recommendation performance in KG to optimize the model performance.

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