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Research on Personalized Exercise Recommendation Based on Graph Representation Learning

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Abstract:
Traditional exercise recommendation systems often ignore the cognitive differences of learners and the dependencies between exercises, resulting in a mismatch between the recommended exercises and the learners' learning level and needs, which affects the recommendation effect. To solve this problem, a graph recognition system A personalized exercise recommendation algorithm for knowledge diagnosis is proposed in this paper. Firstly, build and use the learners' answer records to dig out the relationship between the knowledge concepts, and build a domain knowledge concept map. Then, based on graph cognitive diagnosis, the learner's mastery level of each knowledge concept (Abbreviated as KC) is calculated and learners' knowledge structure diagram is obtained. Then, graph representation learning is used to recommend personalized exercises for learners based on diagnosis results. Finally, the effectiveness of the personalized exercise recommendation model and heterogeneous graph representation learning proposed in this paper are verified through simulation experiments on public datasets. Compared with traditional methods, this method has achieved significant improvements in recommendation accuracy and learning effect.

Keywords: heterogeneous graph neural, cognitive diagnosis, personalized learning, knowledge concept map networks

INTRODUCTION

Nowadays, there are massive online learning resources available, online learning has become an important part of education. How to recommend personalized learning resources for learners (education subjects) has become a hot and difficult research topic in the field of intelligent guidance. Research on individualized differences between learners is the basis for personalized, precise, and intelligent guidance [1]. At present, it mainly focuses on cognitive diagnosis [2,3] and learning style detection [4], knowledge tracking [5,6] and other modeling methods based on learner learning behavior data to evaluate the differences between learners, and then implement learning path planning based on the evaluation results [7,8], personalized learning resource recommendation [9-12] and other intelligent assisted teaching. Cognitive psychologist believes that "the only important factor affecting learning is what the learner already knows", and to evaluate the learner's "what is known" and "what is unknown", it is necessary to map the learner to the corresponding in the knowledge space. It can be seen that the evaluation of learners' learning effects and the diagnosis of knowledge mastery status should not only consider the main factors (knowledge base, cognitive structure, learning style, etc.) but also the knowledge space [13] factors, such as the planning of learning paths or the learning resources recommendation that learners have not mastered, modeling with the corresponding knowledge space will be more accurate [1,12].

For above problem, this paper proposes a personalized exercise recommendation model based on graph cognitive diagnosis (abbreviated as PER-GCD). This model is based on learners' online interaction records to conduct cognitive diagnosis and obtain personalized features of learners. Then, it uses knowledge concept maps to obtain high-order relationships between learners and exercises, and recommends exercises for learners. Based on knowledge concept map, knowledge concepts mastery of each learner is deeply analyzed. And knowledge structure map is obtained. Finally, the graph representation learning method is used to recommend personalized exercises for learners, based on the diagnosis results, thereby improving the learning effect and recommendation accuracy. The effectiveness of this method is verified on a large-scale data set to verify. Personalized exercise recommendation model proposed in this paper have achieved significant improvements in recommendation accuracy and learning outcomes.

In summary, it is to propose a personalized exercise recommendation algorithm that comprehensively utilizes graph cognitive diagnosis and graph representation learning is the main contribution of this paper. By fully considering the cognitive characteristics of learners and the dependencies between exercises, more accurate and targeted exercise recommendations. In the field of education, this research result is expected to make positive contributions to promoting learners' personalized learning and improving the quality of education. The following chapters will introduce the design and implementation of the algorithm in detail, and show the experimental results and analysis to further verify its superiority and feasibility.

RELATED WORKS

In the field of education, learning rescues recommendation have always been a research direction that has attracted much attention. In order to help learners better grasp knowledge, many scholars and researchers are committed to designing and improving exercise recommendation algorithms to provide personalized and efficient exercise recommendation services. In the existing related work, we can divide it into the following aspects:

(a) Recommender system based on learner model. This type of method usually collects learner data from multiple dimensions by establishing a learner model, including learning behavior data (such as answer records, learning progress), learning history data (such as learning path), learning situation data (such as learning environment, learning objectives, etc.), etc. Exercises are recommended by evaluating learners' mastery of different knowledge points. Recommendation algorithms can be divided into recommendation algorithms based on collaborative filtering, recommendation algorithms based on content filtering and algorithms based on hybrid recommendation. However, these models often ignore the dependencies between exercises, which may lead to a mismatch between recommended exercises and learners' actual needs.

(b) Exercise recommendation based on KG. As a structured knowledge representation method, KG (knowledge graph) has rich semantic information, can capture the relationship between knowledge concepts, and provides new ideas and methods for exercise recommendation. In this field of research, many exercise recommendation algorithms based on knowledge graphs have emerged. The following are some typical algorithms: (1) Exercise recommendation algorithms based on graph matching, which combine exercises and knowledge concepts in KG. It is represented as a graph structure. And a graph matching algorithm is used to find the matching relationship between exercises and learner. By calculating the similarity between exercises and knowledge graphs, these algorithms can recommend exercises for learners that match their learning objectives and knowledge level. (2) Exercise recommendation algorithm based on knowledge concept association. This type of algorithm analyzes the association relationship between knowledge concepts in the knowledge map, and combines the associated knowledge concepts into exercise groups to provide learners with more comprehensive and comprehensive exercises. recommend. Such a recommendation method can help learners better understand the connection between knowledge concepts, promote the comprehensive application of knowledge and improve the learning effect. (3) An exercise recommendation model based on graph representation learning maps the knowledge concepts to a low-dimensional vector space. In low-dimensional space, knowledge concepts are effectively represented. The learning needs and knowledge level of learners are also passed. Vector representations are in the same space. By calculating the similarity between learners and exercises in the vector space, these algorithms can recommend personalized and accurate exercises for learners. However, traditional knowledge graph methods often do not fully consider the cognitive differences of learners, so the recommendation results may still not be personalized enough.

(c)Exercise recommendation based on machine learning. The learner's answer record is the main data source for the exercise recommendation algorithm based on machine learning. By analyzing the learner's answering behavior, the algorithm can extract the learner's learning characteristics and preferences. In addition, other relevant features, such as the learner's knowledge level, hobbies, learning style, etc., can also be combined to construct a comprehensive learner model. On this basis, machine learning algorithms can train predictive models to recommend the most suitable exercises for learners based on the individual characteristics of learners and the attributes of exercises. There are various types of exercise recommendation methods based on machine learning, including but not limited to collaborative filtering, content-based recommendation, matrix factorization, etc. However, these methods usually only focus on recommendation accuracy while ignoring the learner's cognitive state, so there are certain limitations in personalized recommendation.

PER-GCD MODEL

It is needed to construct the knowledge concept map for PER-GCD model. Based on the learning interaction records, exercise database, and Q-matrix, we can get the knowledge concept map. And then obtain the learner's knowledge structure graph through the results of cognitive diagnosis. Then obtain the relationship matrix among the knowledge concepts. Then obtain the relationship matrix between learners obtains. Then obtain the list of recommended exercises. Finally, filter the exercises to obtain the final recommended exercises. The model is shown in Figure 1.

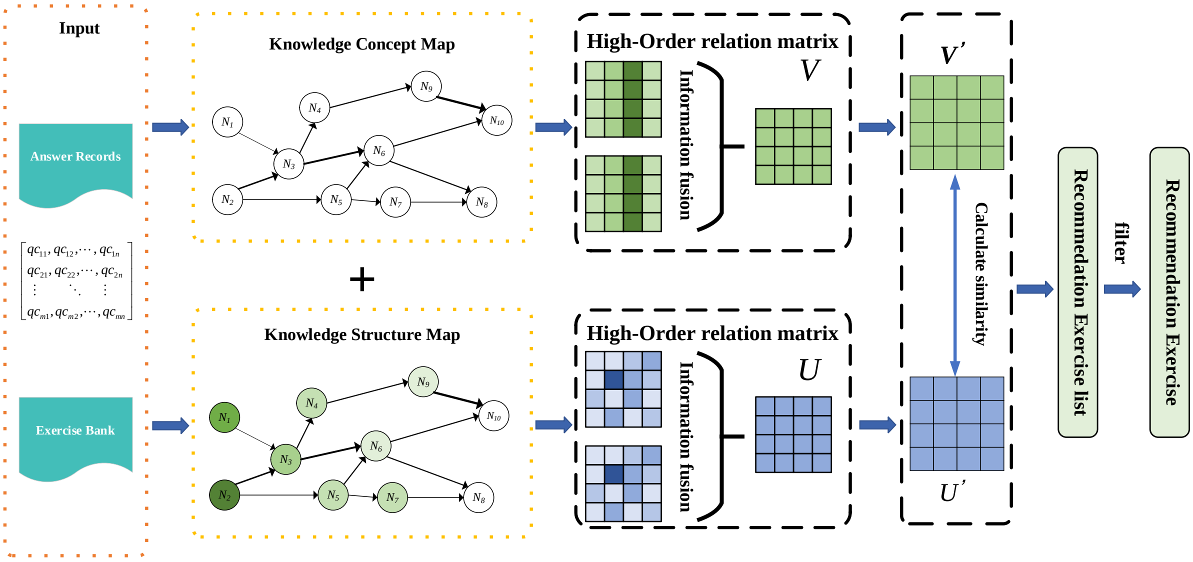

Figure 1. Recommendation model

Construct a Knowledge Concept Map

The dependency relationship can be calculated by a variety of methods, such as association rules, multi-head attention mechanism, deep learning, etc. This paper uses the traditional probability statistics method, which is more intuitive to show the dependency relationship between knowledge concepts. The detailed calculation method is as follows:

Algorithm 1: Constructing a Knowledge Concept Map

Input: Q matrix, learner answer records

Output: knowledge concept map (adjacency matrix)

Step 1: Obtain knowledge concepts in the domain according to the Q matrix;

Step 2: Calculate the dependencies between any two knowledge concepts;

Step 3: Determine the threshold and optimize the knowledge concept map

Step 4: Obtain the adjacency matrix according to the probability.

Assuming that there are n knowledge concepts and m exercises, the relationship between knowledge concepts and exercises can be expressed as Q-matrix, and expressed as formula (1).

$$Q=\begin{bmatrix} qc_{11}, qc_{12}, \cdots, qc_{1n} \\ qc_{21}, qc_{22}, \cdots, qc_{2n} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ qc_{m1}, qc_{m2}, \cdots, qc_{mn} \end{bmatrix} \tag{1}$$

Definition 1. Dependency relationship Rpq, if learners answer exercise i (Related to knowledge concept p) correctly and then answer exercise j (Related to knowledge concept q), then the knowledge concept q is dependent on knowledge concept p, expressed as Rpq, Calculate with formula (2).

$$R_{pq} = \frac{y(e_j \mid e_i)}{\sum_{e_j \in p, e_k \in q} y(e_j \mid e_k)} \tag{2}$$

Here $y(e_j \mid e_i)$ represents the probability of correctly answering exercise e_j after correctly answering exercise e_i . $e_j \in p, e_k \in q$ indicates that exercise e_i is related to concept p and exercise e_k is related to the concept q.

The formula (3) is used to trim the knowledge map to prevent two concepts from becoming interdependent.

$$\begin{cases} R_{qp} = 0, \ R_{pq} \geq R_{qp} \\ R_{pq} = 0, \ R_{qp} \geq R_{pq} \end{cases} \tag{3}$$

Recommendation Algorithm

Algorithm 2: Personalized Exercise Recommendation Based on Graph Representation Learning (PER-GCD)

Input: learner answer record, Q matrix, exercise bank and learner number

Output: list of recommended exercises

Step 1: Use Algorithm 1 to construct a knowledge concept map;

Step 2: Diagnose learners' mastery of each knowledge concept based on the knowledge concept map;

Step 3: Recommend personalized exercises for learners

3.1 Construct the vector representation of learners and exercises;

3.2 Use cosine similarity to calculate the similarity between learners and exercises;

3.3 Use the K-nearest neighbor algorithm to obtain recommended personalized exercises.

Step 4: Obtain a list of recommended exercise IDs.

Exercise recommendation based on domain knowledge concept map and learner knowledge structure map requires embedding learner and knowledge concepts, that is, using vector representation. Commonly used methods include DeepWalk, Node2vec, Metapath2vec, LINE, etc. In order to verify the effectiveness of the PER-GCD model and graph representation learning, the mature Node2vec method is used to realize the vector representation of learners and exercises.

In this paper, the knowledge concept mastery of each learner is represented by the accuracy of answering exercises related to the knowledge concept. If learner i-th answers n exercises related to knowledge concept j, the knowledge concept mastery can be calculated using formula (4).

$$M(k_{ij}) = \frac{\sum_{p=1, e_{ip}=1, e_p \in k_j}^{n} 1}{\sum_{p=1, e_p \in k_j}^{\mathrm{n}} 1} \tag{4}$$

Where, $M(k_{ij})$ represents the mastery level of the j-th knowledge concept by the i-th learner. $e_{ip} = 1$ represents the i-th learner correctly answering the exercise p. $e_p \in k_j$ represents the knowledge concepts related to exercise p.

Calculate the similarity between learners and exercises by formula (5),

$$S_{uv} = \frac{u \cdot v}{\| u \| \| v \|} = \frac{\sum_{i=1}^{m} u_i \times v_i}{\sqrt{\sum_{i=1}^{m} (u_i)^2} \times \sqrt{\sum_{i=1}^{m} (v_i)^2}} \tag{5}$$

EXPERIMENT

For the proposed PER-GCD model, this section mainly verifies the effectiveness of the model through simulation experiments. The detailed experimental dataset, evaluation indicators, experimental results, and analysis are shown as follows.

Experimental Dataset

Synthetic Dataset [14]. The author artificially generates a multi-task learning dataset with temporal relationships, and dares to compare the performance of different models in temporal multi-task learning. Since the learner's answering process is a time series, the time series will affect the learner's learning effect, so this paper uses this method to obtain experimental data. In addition, PER-GCD assumes that 1:n relationship between knowledge concepts and systems. So this restriction is also made in the generated dataset. The data set generated by the algorithm designed by the author includes 4,000 learners, 50 exercises and 5 knowledge concepts, with a total of 200,000 answer records. To increase the number of corresponding exercises and concepts for each learner, the data set generated in this paper includes 1,000 learners, 100 exercises, 30 knowledge concepts, and a total of 200,000 answer records. And according to the generated data set, the corresponding Q matrix is given.

Evaluation Indicators

How to evaluate the performance of exercise recommendation models is an important issue in the field of recommendation. The performance evaluation methods of traditional classification algorithms are relatively mature. Therefore, this article transforms the performance evaluation of recommendation models into the evaluation of traditional classification problems. First, given the following definition 2:

Definition 2: The recommendation result is correct. If all the leading KCs of the current KC have been mastered (The accuracy of exercises related to precursor concepts is greater than the threshold.), and the current KC has not been mastered (The accuracy of exercises related to precursor concepts is little than the threshold.), then the recommendation result is considered correct, otherwise the recommendation result is considered wrong.

Based on Definition 2, the evaluation of exercise recommendation problems can be transformed into the evaluation of classification questions, which requires labeling the training dataset with categories. In addition, this article assumes that the exercises correctly recommended to learners can be answered correctly, while the exercises recommended incorrectly cannot be answered correctly. Continuous recommendations are needed to ensure that the accuracy of exercises related to knowledge concepts exceeds the threshold.

The training dataset for classification problems is crucial, which means that experimental results have a certain degree of randomness. Therefore, the mean and standard deviation of the ten experiments of randomly selects 10 experiments from the dataset and calculates is used to verify the performance in this paper. G-mean, AUC, Recall, F-mean, and Precision five evaluation metrics are used to assess the performance of the algorithm.

Results and Analysis

This section validates the effectiveness of the algorithm by comparing it with several graph based on knowledge tracing algorithms, including GKT [5], HGKT [15], and DGMN [16].

In the experiment, half of the data (100000 records) were randomly selected as the training set. Firstly, a knowledge concept map was constructed, and then the learning effectiveness of learners was diagnosed based on the knowledge concept map to obtain their mastery of each knowledge concept. Then, the remaining data (100000 records) was used for testing, and exercises were recommended to learners based on the test results. Finally, the effectiveness of the recommendations was predicted using the above method. The experimental results of 10 random experiments are shown in Table 1.

Table 1. Experimental results

Algorithm	Evaluation Indicators (Mean ± Standard Deviation)					
	Accuracy	*AUC*	*F_mean*	*G_mean*	*Precision*	*Recall*
GKT	0.8573±0.0031	0.8748±0.0030	0.8161±0.0026	0.8464±0.0033	0.8271±0.0028	0.7995±0.0028
HGKT	0.8676±0.0025	0.8518±0.0031	0.8257±0.0029	0.8383±0.0032	0.8348±0.0034	0.7792±0.0031
DGMN	0.8659±0.0039	0.8608±0.0041	0.8211±0.0035	0.8345±0.0037	0.8314±0.0039	0.7761±0.0036
PER-GCD	0.8841±0.0024	0.8784±0.0026	0.8438±0.0029	0.8491±0.0027	0.8695±0.0031	0.8017±0.0029

The experiment in this section mainly verifies the effect of recommended exercises, so it mainly focuses on Whether the recommended exercises correspond to the knowledge concepts that the learner has mastered, there is no need to repeat the exercises for the knowledge concepts that have already been mastered. This is also an important basis for recommending learning resources. Accuracy rate indicates the common accuracy rate of positive and negative types. The larger the value, the more the recommended exercises meet the needs of learners. Precision rate, recall rate, F1-mean, AUC and Gmean have the same meaning as classification evaluation.

According to Definition 2, accuracy indicates that the recommended content can meet the needs of learners. But for the exercise recommendation, the focus is on whether the recommended exercises meet the needs of learners. For exercises that learners have already mastered the corresponding knowledge concepts, there is no need to continue recommending them to avoid learners repeating exercises and improve learners' learning efficiency. This section mainly compares the performance under six indicators. Accuracy refers to the common accuracy of both positive and negative categories, and the larger the accuracy value, the more suitable the recommended results are for the needs of learners. Precision refers to the ratio of the number of correct exercises recommended by a recommendation system to the total number of recommended exercises, reflecting the accuracy of the recommendation results. The higher the Precision value, the greater the proportion of exercises that meet the needs of learners in the recommended results. Recall Recall rate refers to the proportion of exercises that are correctly recommended as needed among all exercises that are needed. The larger the recall value, the more the recommendation results meet the needs of learners. F1 needs to consider both precision and recall to achieve a balance, with larger values being better.

From Table 1, the accuracy rates of various algorithms are more than 85%. Compared with the DGMN method, the GKT and HGKT methods have lower standard deviations, indicating that GKT and HGKT have better stability than the DGMN algorithm. Accuracy, precision and recall of the PER-GCD algorithm are the best among the four algorithms. It indicates that PER-GCD has a better recommendation effect. In addition, the standard deviation of the PER-GCD method is also the smallest among the four algorithms. It indicates that the model has good stability.

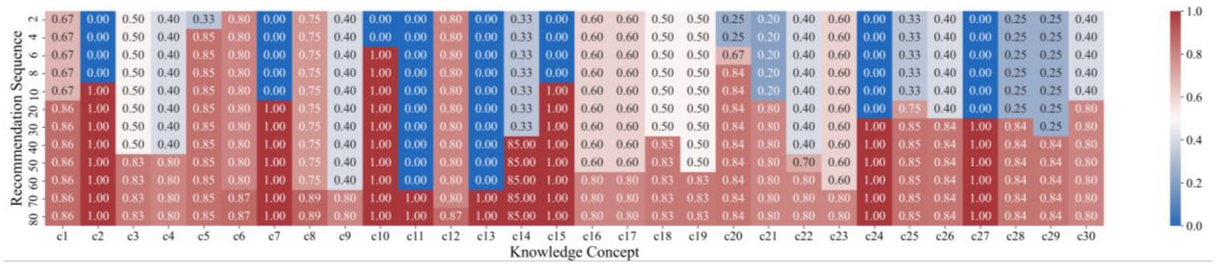

Figure 2. Heat map of state changes in knowledge concept mastery

To see the impact of the recommended exercises more intuitively on the learners' learning effect, the following shows the effect of the recommendation in the form of a heat map. If the knowledge concepts corresponding to the exercises are recommended for learners, learners can master them through learning learners can answer the exercises recommended for learners correctly, and then it is necessary to update learners' mastery of each KC. The change of a random learner's mastery of KCs is shown in figure 2 after multiple rounds of recommendation. In order to see the change of the state of knowledge mastering more clearly, the results after 10 exercises are recommended by 1-5 behavioral learners (equivalent to the K value of the K nearest neighbor in the algorithm is

5, which is equivalent to the results after two recommendations), from the first It starts with 6 lines, and each line represents the result after recommending 50 exercises (that is, making 10 recommendations) for learners.

In Figure 2, the horizontal axis represents the number of knowledge concepts, and the total axis represents the number of recommended times. The values in the cells represent the level of mastery of each knowledge concept. In this experiment, the threshold is set to 0.8, which means that if the knowledge concept mastery is greater than 0.8, it is considered that the KC has been mastered. From Figure 2, we can see that after 70 recommendations, learners have mastered more than 0.8 of each knowledge concept. If you continue to recommend exercises for learners (the change in the bottom row in Figure 2), you will continue to recommend no predecessors. For the exercises related to knowledge concepts or precursor knowledge concepts that are not well mastered, you can see that exercises are recommended for knowledge concepts C6 and C12. From Figure 2, it can be seen intuitively that PER-GCD can recommend exercises for learner who have not mastered the concepts of knowledge, which is helpful for learners to check for gaps, carry out precise learning, and improve learning efficiency.

CONCLUSION

This study is based on knowledge concept maps for cognitive diagnosis, and recommends exercises based on the results of cognitive diagnosis, proposing new ideas for exercise recommendation methods. From the experimental results, it can be seen that the model can effectively recommend exercises corresponding to unfamiliar concepts to learners. However, this method relies more on the dependency relationships between knowledge concepts and assumes that it is one to many relationships between KCs and exercises. But in practical applications, one exercise may be related to multiple knowledge concepts. Additionally, learners may forget the concepts they have already learned over time. In addition, the recommended algorithm in this article does not consider factors such as the type, difficulty, and distinguishability of exercises. In the next stage, a hierarchical heterogeneous graph will be constructed to address these issues and a learning resource recommendation model will be designed.

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