Computer Science and Information Systems 20(2):857–878 https://doi.org/10.2298/CSIS220706024Y

Personalization Exercise Recommendation Framework based on Knowledge Concept Graph

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Abstract. With the explosive increase of online learning resources, how to provide students with personalized learning resources and achieve the goal of precise teaching has become a research hotspot in the field of computer-assisted teaching. In personalized learning resource recommendation, exercise recommendation is the most commonly used and most representative research direction, which has attracted the attention of a large number of scholars. Aiming at this, a personalized exercise recommendation framework is proposed in this paper. First, it automatically constructs the relationship matrix between questions and concepts based on students' answering records (abbreviated as Q-matrix). Then based on the Q-matrix and answer records, deep knowledge tracing is used to automatically build the course knowledge graph. Then, based on each student's answer records, Q-matrix and the course knowledge graph, a recommendation algorithm is designed to obtain the knowledge structure diagram of every student. Combined the knowledge structure diagram and constructivist learning theory, get candidate recommended exercises from the exercise bank. Finally, based on their diversity, difficulty, novelty and other characteristics, exercises are filtered and obtain the exercises recommended to students. In the experimental part, the proposed framework is compared with other algorithms on the real data set. The experimental results of the proposed algorithm are close to the current mainstream algorithms without the Q-matrix and curriculum knowledge graph, and the experimental results of some indicators are better than Algorithms exist.

Keywords: Personalization Exercise Recommendation, Course Knowledge graph, Deep Knowledge Tracing, knowledge concept.

1. Introduction

With the continuous launch of Massive Online Open Course (MOOC), in the face of massive online learning resources, how to choose suitable learning resources is an urgent problem to be solved in the current intelligent education system [1]. The intelligent education system uses computer-aided technology to help students obtain personalized and suitable learning resources from the massive online teaching resources, thereby improving the teaching effect. It can dynamically adjust the learning resources recommended to each student according to the student's learning trajectory (learning style, knowledge mastery, etc.). In the intelligent education system, the course knowledge graph plays an important role in the recommendation of learning resources, learning path recommendation, etc., and the knowledge graph of the curriculum is also a hot spot in this field [2].

The course knowledge graph (Some scholars call it a knowledge graph, and some scholars call it a concept map, which is called a knowledge graph in the subsequent chapters of this article.) represents the dependencies between the knowledge concepts of a course. Combined with constructivist learning theory, students should learn a course according to the relationship between knowledge concepts in the knowledge graph. This is because the learning sequence of knowledge concepts affects students' learning effect [3]. If the course knowledge graph is accurately obtained, it can intuitively show the student's mastery of the knowledge concepts in one course, which can promote students to carry out meaningful learning, and can also draw students' own knowledge according to each student's mastery of knowledge concepts. In addition, it also can be used to recommend the personalized learning resources.

In the existing personalized learning resource recommendation algorithms, knowledge graphs are mostly marked by experts, on the one hand, the workload is large, on the other hand, there will be a certain deviation. In response to this, many experts and scholars have carried out corresponding research on the course knowledge graph, and proposed corresponding construction methods of the course knowledge graph [4-5]. The references [6-10] mainly use association rule mining algorithm and traditional statistical theory to build the course knowledge graph, and the references [11-13] use the machine learning method to build the course knowledge graph. Whether it is an association rule based on statistical theory or a method based on deep learning, it is assumed that the exercise-knowledge concept relationship matrix (*Q-matrix*) already exists. In practical applications, the acquisition of *Q-matrix* also requires expert annotation, and there are also problems of heavy workload and labeling deviation.

In view of the above problems, a personalized exercise recommendation framework based on course knowledge graph is proposed in this paper. First, based on the students' answer records, the exercise-knowledge concept relationship matrix is automatically obtained by using deep knowledge tracing and improved K-means clustering algorithm. Using students' answer records and *Q-matrix*, design a knowledge graph construction algorithm, and automatically obtain the course knowledge graph. Then, based on students' answer records and *Q-matrix*, a knowledge graph construction algorithm is designed, and automatically obtain the course knowledge graph. Then combine the *Q-matrix*, the knowledge graph and the students' answer records to draw the knowledge structure map of each student (that is, the mastery degree map of each knowledge concept). Then, based on the constructivist learning theory, the exercise recommendation model is constructed according to the course knowledge graph, the student knowledge structure map, and the *Q-matrix*. Then, the recommended exercises are selected according to the characteristics of the difficulty, novelty, and diversity of the exercises.

This study provides a framework for personalized learning resource recommendation based on course knowledge graph, and discusses how to automatically construct the exercise-knowledge concept relationship matrix and the relationship map between knowledge concepts (course knowledge graph). On this basis, construct the knowledge structure diagram of each student, and design a recommendation model to recommend personalized learning resources for each student (this article mainly focuses on exercises). The main contributions include the following three-fold: (1) An idea of automatically constructing the course knowledge graph is proposed. The relationship matrix between exercises and knowledge concepts is automatically constructed, and then the course knowledge graph is automatically constructed. (2) This paper proposes a personalized exercise recommendation framework based on the curriculum knowledge graph, and presents a new idea of recommending personalized learning resources based on the knowledge graph, combining the acquired curriculum knowledge graph, student answer records and *Q-matrix*. Then, the knowledge structure diagram of each student is obtained according to the answer record of each student. Then, combine the two diagrams and the *Q-matrix*, build a recommendation model, and recommend personalized exercises for every student. (3) In this paper, the calculation method of the importance of knowledge concepts is given for each student, and then selects exercises related to the most important knowledge concepts for students from many exercises to recommend.

The remaining chapters of this paper is organized as follows: The second subsection mainly analyzes the research progress of the existing personalized recommendation algorithm, and analyzes the work that still needs to be improved and the improved method. The third subsection mainly introduces the recommendation framework proposed in this paper, and introduces the problems solved in each stage and the methods to solve them in detail. The fourth subsection mainly introduces the personalized exercise recommendation model based on knowledge graph and the available recommendation methods. The fifth subsection presents several common algorithms and experimental results on common data sets, and compares and analyzes the proposed framework and the corresponding experimental results. The sixth subsection discusses and analyzes the conclusions and the main work of the next stage.

2. Related Works

This section reviews the research on personalized exercise recommendation algorithms, knowledge graph construction, and knowledge tracing. The basic ideas and implementation processes of various methods will be introduced, then analyzes the advantages and disadvantages of various methods, and proposes corresponding solutions.

2.1. Knowledge Tracing

Knowledge tracing is based on the modeling of students' behavior sequences to predict students' mastery of knowledge concept. Commonly used knowledge tracing models include Bayesian Knowledge Tracing (BKT) [15] and Deep Knowledge Tracing (DKT) [16]. In most knowledge tracing and improvement methods, the sequence of answering questions is used to train the model, however, the sequential relationship between knowledge concepts is ignored.

According to the knowledge transfer theory in the field of education [17], when a learner learns a knowledge concept, it not only changes the proficiency of the existing knowledge concept, but also changes the mastery of the associated knowledge concept. Therefore, the curriculum knowledge graph that shows the dependencies between knowledge concepts has attracted the attention of many experts and scholars [18-21]. Many scholars build the corresponding model for the knowledge graph and study the problem of knowledge tracing. Inspired by the success of graph neural network (GNN), Nakagawa et al. [18] applied GNN to knowledge tracing task for the first time, and proposed a Graph-based Knowledge Tracing (GKT). This method converts the knowledge structure into a graph, thereby indirectly reconstructing the knowledge tracing task into a time series node-level classification problem in the GNN model. Graph convolutional neural networks (GCNS) are proposed for semi-supervised graph classification, updating self-node representations based on information about itself and its neighbors.

Therefore, if multiple graph convolution layers are used, the updated node representation contains the attributes of neighbor nodes and the information of high-order neighbors. Yang et al. [19] proposed a knowledge graph tracing (GIKT) along this line of thought. To make full use of the textual information contained in the exercises and the hierarchical relationship between the exercise and knowledge concepts. Tong et al. [20] proposed a hierarchical graph knowledge tracing model framework (HGKT). The method defines a problem schema to calculate the similarity between exercises. Then, a hierarchical graph neural network is proposed based on the problem mechanism. It adopts two attention mechanisms to emphasize the important historical states of students. The hierarchical graph and sequences are full used to improve the performance of knowledge tracing. Zhu et al. [21] builds a knowledge graph based on knowledge units, target knowledge units, knowledge unit dependencies, etc. Then, multiple learning paths can be obtained, and then judges the learning progress of learners according to their learning logs, and learning paths are recommended to them. Shi et al. [22] constructed a learning goal-oriented knowledge graph across learning domains, including six semantic relations, and then combined the learner's learning goals and the characteristics of learning resources to represent the recommended learning path.

Most of the existing methods assume that the knowledge graph of the course already exists, and then build a knowledge tracing model based on the knowledge graph, answer records, and *Q-matrix* and other information. However, how to automatically and accurately obtain the knowledge graph and *Q-matrix* corresponding to the course is the key to this type of method.

2.2. Course Knowledge Graph

The curriculum knowledge graph reflects the relationship graph between the curriculum knowledge concepts, and represents the dependency between the knowledge concepts in the curriculum. According to the knowledge transfer theory [17] and the constructivism theory [32], the curriculum knowledge graph is very important in the intelligent education system. Yu et al. [4] use association rule mining algorithm to analyze the relationship between curriculum knowledge concepts, and automatically builds a knowledge graph between curriculum knowledge concepts. The key to this method lies in the setting of association rules and how to set the thresholds of each indicator, so that the pruned knowledge graph can more accurately represent the relationship between course knowledge concepts. In this article, in order to obtain the knowledge graph, the thresholds of various indicators are directly specified.

In practical applications, according to the granularity of knowledge concept division, there may be hundreds of knowledge concepts, and the key to construct the knowledge graph is each threshold. The author later improved this method [5-6]. In this method, the exercise-knowledge concept relationship matrix (*Q-matrix*) needs to be manually labeled, which not only requires a large workload, but also makes the labeling subjective and has labeling bias. In response to this problem, the literatures [7-9] use the combination of association rules and machine learning methods to construct the knowledge graph of the course. Shao et al. [7] combine text recognition and association rule mining to automatically obtain exercises related to each knowledge concept and automatically construct a *Q-matrix*. It can avoid the bias caused by manual labeling of the *Q-matrix*. This method uses the association rule mining algorithm in the literature [6] to build a knowledge graph, but it also has the problem that it is difficult to determine multiple thresholds. Huang et al. [8] uses soft rules and adversarial learning ideas to automatically build a knowledge graph, which can reduce the impact of thresholds on algorithm performance and improve the quality of the composition. Literatures [11-13] combine the ideas of deep learning and data mining to automatically build a knowledge graph to avoid the impact of setting thresholds on the algorithm. Lin et al. [11] mainly conduct research on knowledge tracing. Assuming that there is only one question related to a knowledge concept, this method can obtain the relationship map between knowledge concepts.

However, in practical applications, one knowledge concept corresponds to multiple exercises, and one exercise corresponds to multiple knowledge concepts. In response to this, Zhang et al. [12] uses a hierarchical attention mechanism and a relational graph neural network to build a knowledge graph (Relational Graph neural network with Hierarchical Attention). Hiromi et al. [13] presents six methods for constructing curriculum knowledge graph. Among them, three methods based on multi-head attention mechanism, based on Variational autoencoder (VAE) and based on probability transition matrix have better performance, and can automatically obtain the knowledge graph of the corresponding course in a given answer record and *Q-matrix*. Obviously, this method still needs Manually annotated *Q-matrix*.

2.3. Exercise Recommendation Algorithm

Building an exercise recommendation model [22-23] is crucial in an intelligent education system. Traditional methods based on product recommendation mainly include content-based recommendation algorithm [22-23] and collaborative filtering recommendation algorithm [24-25]. In recent years, graph neural networks have attracted the attention of many experts and scholars. Using graph neural networks to solve recommendation problems is a hot spot in current recommendation system research [26-28]. In order to reflect the dependencies between knowledge concepts, Lin et al [26] proposed a knowledge graph smart extraction and explicit diagnosis (CM-SEED) learning system. Use knowledge graph to describe students' mastery of knowledge. In order to more accurately describe the mastery of knowledge concept and the dependencies between knowledge concepts, Lv et al. [27] proposed an intelligent exercise problem recommendation method based on weighted knowledge graph. This method quantifies students' learning ability with students' test data, and then uses the dependence between students' learning ability and knowledge concepts to improve the effect of personalized exercise recommendation. The knowledge graph proposed in papers [26-27] is actually the cognitive structure graph of each student, not the knowledge graph of the course.

In order to make full use of the dependencies between the nodes of the knowledge graph, literatures [28-30] modeled on the course knowledge graph to realize personalized learning resource recommendation. Huang et al. [28] combines knowledge graph and collaborative filtering, and the use of collaborative filtering based on knowledge graph can not only effectively avoid the problems of data sparseness and cold start of traditional collaborative filtering recommendation methods, but also avoid the inconsistency of K value in traditional collaborative filtering recommendation algorithms. Wang et al. [29] use Graph Convolutional Networks for modeling based on knowledge graph to mine the associations between nodes on the knowledge graph, automatically discover structural information and semantic information. Then, the neighbor information of each node is used to describe the node, that is, the interrelated path between nodes can be obtained. Finally, Knowledge Graph Convolutional Networks is used to implement the recommendation of personalized learning resources. The current GNN-based models are mostly coarse-grained in relational modeling. They do not identify user-item relationships at the fine-grained graph level, and do not use relational dependencies to preserve the semantics of remote connections.

Knowledge Graph-based Intent Network (KGIN) [30] strengthens the independence of different user-item relationships, thereby enhancing the ability and interpretability of the model. A new information aggregation mechanism is used to recursively integrate relational sequences (relationship paths) of remote connections. Zhao et al. [31] use Recurrent Neural Networks (RNNs) to predict the coverage of knowledge concepts based on students' answer records, and uses Deep Knowledge Tracing (DKT) to predict students' mastery of knowledge concepts. Then, according to the two prediction results, a set of exercises recommended to students is obtained, and then a certain strategy is used to filter the set of exercises to obtain the exercises that are finally recommended to students. This method ignores the transfer of dependencies between knowledge concepts, and also does not consider the influence of the difficulty of the exercises.

3. Personalized Exercise Recommendation Framework Based on Knowledge Graph

Based on the above analysis, this section will introduce the proposed framework of personalized exercise recommendation in detail. The framework starts from the students' answering records, uses a certain method to automatically construct the *Q-matrix* (such as using DKT), and then automatically constructs the course knowledge graph course based on the *Q-matrix*. Then, combining each student's answer record, *Q-matrix* and course knowledge graph, each student's knowledge structure map can be got, and finally build a recommendation model based on the knowledge structure map and get the personalized exercise.

3.1. Recommended Framework

The personalized exercise recommendation framework based on the curriculum knowledge graph proposed in this paper is shown in Fig. 1. It is mainly divided into three stages: (1) construct a curriculum knowledge graph based on students' learning behavior data; (2) Obtain students' mastery of personal knowledge, construct the knowledge structure graph of students; (3) build a personalized exercise recommendation model, and get personalized exercise recommendation for each student. The following is a detailed introduction to the personalized exercise recommendation framework proposed in this paper from above three stages.

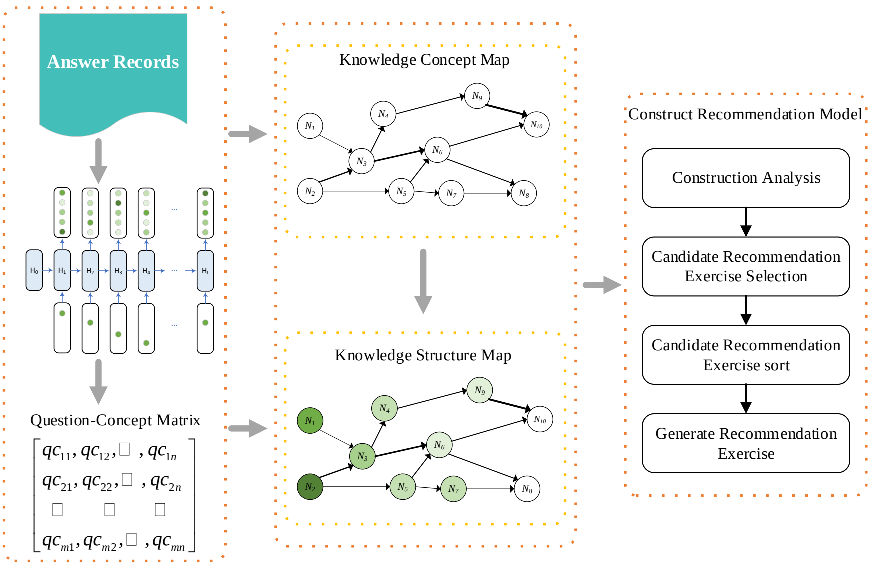


Fig. 1. Personalized Exercise Recommendation Framework

3.2. Automatically Obtain the *Q-matrix*

The curriculum knowledge graph can accurately reflect the dependencies between curriculum knowledge concepts. According to the knowledge transfer theory [17] and the constructivism theory [32], when the learner's learning and mastery of the current concept will be affected by the related knowledge concept, it will also affect the mastery of the related knowledge concept. In other words, the learning sequence of knowledge concepts has an impact on the learning effect. So, what order is a reasonable order? This is the problem to be solved by the curriculum knowledge graph. The literatures [19, 33] believe that the knowledge graph is a hierarchical tree structure. For example, each textbook is divided into several chapters, each chapter includes several sections, and so on, so there is a hierarchical tree structure between the course knowledge concepts. Some other scholars also believe that the curriculum knowledge graph is a network structure [28-30], and there is a sequential dependency between knowledge concepts. It is a directed acyclic network structure graph, that is, there are predecessor knowledge concepts and successor knowledge concepts. Learning process should be based on the order of knowledge concepts, which is more in line with the knowledge transfer theory and constructivism theory in pedagogy, so that students can obtain good learning effects.

The question now is how to obtain an accurate course knowledge graph. The course knowledge graph in the literatures [19, 28, 30, 33] is obtained by expert annotation. Due to the personal subjectivity of expert annotation, there will be deviations in the annotated knowledge graph. In response to this problem, the literatures [4-8] use association rule mining, deep learning, natural language analysis and other methods to automatically build a curriculum knowledge graph. But these methods are all constructing the course knowledge graph given the *Q-matrix*, and the construction of the *Q-matrix* is also obtained by the expert annotation. According to the different granularity of knowledge concepts, generally each course includes hundreds of knowledge concepts, and each course includes thousands of exercises (especially for middle school courses), and each exercise involves one or more knowledge concepts. Therefore, constructing the *Q-matrix* requires a lot of work, and there are biases.

Based on the above analysis, this paper presents a method to automatically construct the *Q-matrix*, The deep knowledge tracing model constructed in [15] can obtain the sequential dependencies between exercises, and the exercises are related to knowledge concepts. Assuming that each exercise is only related to one knowledge concept, the exercise related to a knowledge concept can be classified into one category through cluster analysis, thus obtaining the *Q-matrix*.

Assuming that m students have n exercises, the answer records of m students can be expressed as a matrix:

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

Where $a_{ij} = 1$ denotes that the *i*-th student answers the *j*-th exercise correctly, and $a_{ij} = 0$ denotes that the *i*-th student answers the *j*-th exercise incorrectly.

According to the students' answer records, the dependence of *i*-th exercise on *j*-th exercise can be expressed as the formula (1):

$$A_{i,j} = \frac{y(j \mid i)}{\sum_k y(j \mid k)} \tag{1}$$

Where $y(j \mid i)$ denotes the probability that *j*-th exercise is correct when *i*-th exercise is answered correctly.

Assuming that students have mastered the knowledge concepts, then the students can correctly do the exercises related to the knowledge concepts, otherwise they cannot correctly do the exercises related to the knowledge concepts. Therefore, after doing *i*-th exercise correctly and then doing *j*-th exercise correctly, then *i*-th exercise and *j*-th exercise either belong to the same knowledge concept, or the knowledge concept corresponding to *i*-th exercise is the precursor of the knowledge concept corresponding to *j*-th exercise. In the same way, after answering *i*-th exercise incorrectly, answering *j*-

th exercise incorrectly is the same. Based on this, when *K*-means clustering is performed, the distance calculation method can be expressed as the formula (2):

$$dis(vecA, vecB) = \sum_{i=1}^{n} (vecA_i \text{ e } vecB_i) \tag{2}$$

Assuming that there are *k* knowledge concepts in total, after *k*-means clustering, the question-concept matrix can be obtained as follows:

$$Q = \begin{bmatrix} qc_{11}, qc_{12}, \cdots, qc_{1n} \\ qc_{21}, qc_{22}, \cdots, qc_{2n} \\ \vdots \quad \ddots \quad \vdots \\ qc_{k1}, qc_{k2}, \cdots, qc_{kn} \end{bmatrix}$$

Where $qc_{ij} = 1$ denotes that the *j*-th exercise is related to the *i*-th knowledge concept, and $qc_{ij} = 0$ denotes that the *j*-th exercise is not related to the *i*-th knowledge concept.

3.3. Building a Knowledge Graph

After the *Q-matrix* is generated, the course knowledge graph can be constructed based on the *Q-matrix* and the students' answer records. Literatures [4-6] use the association rule mining algorithm to automatically build the knowledge graph. This method first defines the association rules, and then calculates the confidence of the rules according to the formula (3).

$$conf(Q_i \to Q_j) = \frac{\sup(Q_i, Q_j)}{\sup(Q_i)} \tag{3}$$

Then specify the minimum confidence (the value in this article is 0.75), the difference degree threshold the difference degree is 0.35, and several other thresholds. By setting a good threshold, the graph is trimmed to obtain the final knowledge graph. In this method, the setting of the threshold is very important to the constructed knowledge graph. The setting of the threshold in this paper is specified based on experience and cannot be applied to a dynamically changing environment. In response to this, the literatures [7-9] use machine learning methods to build knowledge graphs. Nakagawa et al. [18] provides two methods to calculate the relationship between two nodes, one is a statistical-based method. This method builds the relationship between neighbor nodes based on the adjacency matrix *A*, and $f_{neighbor}$ adopts formula (4) to calculate:

$$f_{neighbor}(h_i^t, h_j^t) = A_{i,j} f_{out}([h_i^t, h_j^t]) + A_{j,i} f_{in}([h_j^t, h_i^t]) \tag{4}$$

where f_{out} and f_{in} are multilayer perceptron（MLPs）, the key is the construction method of $A_{i,j}$. For examples:

(1) $$A_{i,j} = \begin{cases} \dfrac{n_{i,j}}{\sum_k n_{i,k}} & i \neq j \text{（Transition probability matrix）} \\ 0 & i = j \end{cases} \tag{5}$$

(2) $$A_{i,j} = \frac{y(j \mid i)}{\sum_k y(j \mid k)} \text{ (deep knowledge tracing）} \tag{6}$$

$y(j \mid i)$ denotes the probability that the *j*-th exercise is correct when the *i*-th exercise is answered correctly (using the RNN network).

(1) Multi-head attention (MHA): The multi-head attention mechanism is used to calculate the weight of the edge between two nodes. $f_{neighbor}$ can calculate with the formula (7).

$$f_{neighbor}(h_i^t, h_j^t) = \frac{1}{K}\sum_{k \in K} a_{ij}^k f_k(h_i^t, h_j^t) \tag{7}$$

a_{ij}^k is the *k*-th head's attention weight from v_i to v_j, and f_k is a neural network for the *k*-th head.

(2) Variational autoencoder (VAE). According to the type of edge represented by the node feature, it is calculated by the following formula (8):

$$f_{neighbor}(h_i^t, h_j^t) = \sum_{k \in K} z_{ij}^k f_k(h_i^t, h_j^t) \tag{8}$$

Where, z_{ij}^k is a latent variable sampled from the Gumbel–Softmax distribution. f_k is a neural network for the k-th edge type.

In the experimental stage, three methods of association rule, DKT and MHA are used to verify the validity of the proposed exercise recommendation framework.

3.4. Student's Personal Knowledge Structure Diagram

Analyzing the degree of knowledge mastery of students is a crucial step in the intelligent education system. Only by accurately identifying the degree of knowledge mastery of each student can we accurately recommend personalized exercises. Methods such as Bayesian Knowledge Tracing [13] and Deep Knowledge Tracing [14, 15] are commonly used to predict students' mastery of knowledge concept. Since knowledge graphs can reflect the dependencies between knowledge concepts, literatures [18-20] use graph neural networks to analyze students' mastery of knowledge concept based on knowledge graphs. The interpretability of these existing methods is poor, and it is not easy to understand the students' mastery of each knowledge concept. Therefore, this paper analyzes each student's mastery of the curriculum knowledge concepts based on the curriculum knowledge graph, and first defines several description knowledge concepts.

Definition 1. The mastery of knowledge concepts *MC*, the correct rate of students who have done exercises related to knowledge concepts is used to indicate the mastery of knowledge concepts for each student, using formula (9) to calculate:

$$\mathrm{MC_i} = \frac{\sum_{QC_{a_{j,i}}=1, \mathrm{a_j}=1} QC_{a_{j,i}}}{\sum_{QC_{a_{j,i}}=1} QC_{a_{j,i}}} \tag{9}$$

Where, $Q_{a_{j,i}} = 1$ denotes the exercise a_j is related to i-th knowledge concept. $Q_{a_{j,i}} = 1, \mathrm{a_j} = 1$ denotes that the exercise a_j is related to the *i*-th knowledge concepts are answered correctly.

Combining knowledge transfer theory [17] and constructivism theory [32], the order in which students learn knowledge concepts has an impact on the students' mastery of knowledge concepts, and what has a direct impact on the current knowledge concept is the predecessor knowledge concept. That is, the mastery of the precursor knowledge concept will affect the students' learning effect of the current knowledge concept.

Definition 2. Knowledge concept support degree *SP*, the number of the predecessor knowledge concepts that have been mastered divided by the number of all predecessor knowledge concepts, assuming that the precursor knowledge concept set of the *i*-th knowledge concept is expressed as *SC*, the support degree of the current knowledge concept can be expressed for formula (10):

$$SP(N_i) = \frac{\sum_{N_j \in SC} MC_j}{|SC|} \qquad (9)$$

Where, $SP(N_i) = 1$ denotes that the predecessor knowledge concept of this knowledge concept has been fully mastered and should be recommended first.

When recommending exercises to students, it actually selects a knowledge concept from the course knowledge graph, and then recommends exercises related to the knowledge concept. That is to say, knowledge concepts with higher importance should be selected for recommendation. How to evaluate the importance of knowledge concepts? Combined with the characteristics of the directed graph, the importance of each node (knowledge concept) is related to the in-degree, out-degree and the weight of the corresponding node and edge. For individual students, the higher the mastery of knowledge concepts, the lower the importance of knowledge concepts; the greater the out-degree of a knowledge concept, the greater the importance of the knowledge concept as the precursor of multiple knowledge concepts; if the greater the in-degree of a knowledge concept, it means that the more restricted knowledge concepts, the recommendation should be postponed, that is to say, the lower the mastery of the knowledge concept. Based on the above analysis, the definition of the importance of the knowledge concept is given as follow.

Definition 3. The importance degree of knowledge concept *CP*. The importance of the knowledge concept is inversely proportional to the mastery of the knowledge concept, and inversely proportional to the difference between the node in-degree and the node's support degree, which can be calculated by formula (11).

$$CP(N_i) = \begin{cases} (1-MC_i)\dfrac{out\_degree(N_i)}{in\_degree(N_i)(1-SP(N_i))}, & in\_degree(N_i) \neq 0 \\ (1-MC_i) * out\_degree(N_i), & in\_degree(N_i) = 0 \end{cases} \qquad (11)$$

Where $out\_degree(N_i)$ and $in\_degree(N_i)$ denote the out-degree and in-degree of node N_i. The importance of knowledge concepts is actually the priority of recommended knowledge concepts, and is the main basis for selecting recommended knowledge concepts.

The importance of knowledge concepts is for students, and each knowledge concept is of different importance to different students. In the algorithm of this paper, the knowledge concepts to be recommended and the corresponding exercises are selected according to the importance of the knowledge concepts. It is mainly considered from the following three aspects: (1) the importance of the knowledge concepts that students have mastered is less than that of the knowledge concepts that they have not mastered, because the knowledge concepts that are not mastered will affect the learning of subsequent knowledge concepts; (2) the importance of knowledge concept that has a large out-degree is greater than that of a knowledge concept with a small out-degree, because a large out-degree indicates that its mastery will affect the learning of multiple knowledge concepts, so the importance is large; (3) In-degree and support degree also have an impact on the importance of a knowledge concept. The greater the in-degree, the more affected factors. The greater the support degree *SP* of a knowledge concept, the better the mastery of the precursor knowledge concept of the knowledge concept.

3.5. Recommendation algorithm based on knowledge graph

After obtaining the course knowledge graph, build a recommendation model based on the knowledge graph. Designing recommendation models based on graph neural networks is a hot topic in current recommendation system research [26-28]. Due to the poor interpretability of deep learning, it is difficult to display the recommendation results intuitively. In this regard, this paper based on the course knowledge graph and each student Based on the Knowledge Structure Map (KSM), combined with the answer records and *Q-matrix*, a simple personalized exercise recommendation algorithm is designed. The algorithm flow is shown in Fig. 2.

The detailed process of the algorithm is described as follows:

Algorithm 1. Exercise recommendation algorithm based on knowledge graph

```
Input: Course Knowledge Graph CKG, Student Answer Record A, Question-Concept Relationship Matrix Q
Output: Recommended exercises
For i=1:K
Calculate the MCi
If MCi<threshold
    Calculate CP(Ni)
Else
    Continue
Sort CP(Ni) in descending order
Choose the recommended exercise based on A matrix and Q-matrix
```

First, according to the knowledge graph and the students' personal answer records, the students' mastery degree MC_i of each knowledge concept is obtained. If the knowledge concept has been mastered, it will not be processed. Otherwise, the importance degree $CP(N_i)$ corresponding to the knowledge concept is calculated. Then sort $CP(N_i)$ in descending order, select the first knowledge concept N_j, and then according to the *Q-matrix*, adopt a certain strategy to select the exercises related to the knowledge concept N_j and recommend them to the students. Here are two kinds of choose strategy.

(1) Random selection, randomly select one or several exercises from the exercises related to the knowledge concept N_j and recommend them to students;

(2) According to the degree of mastery of the knowledge concept, the recommended exercises are selected according to the accuracy of all students' answers to the exercises related to the knowledge concept and the students' individual mastery of the knowledge

concept. Assuming that there are K exercises related to the knowledge concept N_i, first calculate the answering accuracy rate P_k of the relevant exercises, and then calculate the mastery of the knowledge concept CP_i, and select the exercises with the smallest difference between $(1\text{-}P_k)$ and CP_i to be recommended. If the knowledge concept is poorly mastered, the exercises with low difficulty are recommended, and if the knowledge concept is well mastered, the more difficult exercises are recommended.

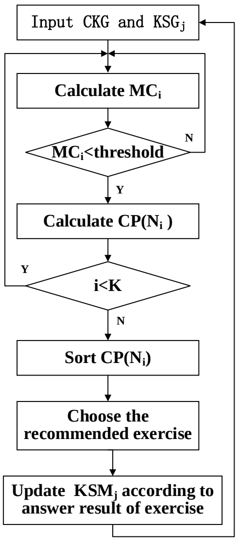


Fig. 2. The algorithm flow char

4. Experiments and Analysis

This subsection mainly verifies the effectiveness of the proposed method through experiments, and shows the comparison of various experimental data and experimental results under different data sets. The following will introduce the experimental process in detail and analyze the experimental results in detail.

4.1. Experimental data sets

The method proposed in this paper constructs the *Q-matrix* based on the assumption that an exercise is only related to one knowledge concept. In order to fully verify the framework, in this section, all the exercises in the dataset are regarded as related to only one knowledge concept. The data sets used in the experiments are described in detail below.

- *synthetic* dataset. The dataset [33] is machine simulation data, and the response performance of each student is generated using the problem difficulty, student ability and probability of random guessing based on IRT. Contains 4,000 students and 50 exercises, each with 5 knowledge points, for a total of 200,000 practice records.

- *ASSISTments 2009* data set. This dataset [33] is collected from the ASSISTments online education platform in the 2009-2010 school year, and contains 325,673 practice records of 4,151 students on 110 knowledge points after deduplication. The duplicate records of the source dataset are removed before the experiment. At the same time, the dataset has the problem of data sparsity, and its density is only 0.06.
- *ASSISTment 2015* data set. This dataset contains 708,631 practice records of 19,840 students on 100 knowledge points. Due to the large learner base, the dataset contains a small number of student records on average. This dataset is the sparsest among the available datasets, with a density of only 0.05.
- *Intellilence 2018* dataset. This dataset provided by Oneoftops Ltd., a company that provides teaching and learning services to teachers and students in the Advanced Center, includes 256,612 learning records from 1,452 students across 159 knowledge points.

Table 1. Experimental dataset

Dataset	KCs	Students	Records
Synthetic	25	4000	200000
ASSISTments 2009	110	4151	325673
ASSISTments 2015	74	19840	525535

Table 1 gives the overall description of the data set used in the experiment. The algorithm in this paper assumes that each exercise is only related to one knowledge concept. In the Synthetic data set, each subset has only 50 exercises. In order to increase the number, 5 datasets are merged, that is, 250 exercises, including 25 knowledge concepts. In the ASSISTments data set, the order of answering questions for each student is different, and the order of answering questions has an impact on the learning effect of each student, but in order to use the clustering algorithm to obtain the *Q-matrix*, the exercises done by each student are Sorting, in the answer record, the correct value of the exercises that each student has not done is 0.

4.2. Base Line

The prediction accuracy (ACC) and the area under the ROC curve (AUC) are two evaluation indicators that are often used to evaluate the classification performance. In this experiment, these two evaluation indicators are used to evaluate the effectiveness of the proposed framework. This paper compares the experimental results of the traditional classical algorithms BKT and DKT. In addition, the algorithm framework proposed in this paper is based on the knowledge graph, and the DKVMN and GKT algorithms are the classical methods in the graph neural network. Therefore, this paper mainly compares these four algorithms. KCG_MHA and KCG_VAE are the frameworks proposed in this article. The MAHA algorithm and VAE algorithm are used to build the knowledge graph. KCG_TPM and KCG_DKT use the Transportation Probability Matrix and Deep Knowledge Tracing to build the knowledge graph. The experimental results of the algorithm proposed in this paper are all without a given *Q*-matrix and knowledge graph.

BKT [15]: BKT is the traditional method based on probability. It predicts the switches between every two knowledge concepts according to the HMM rules and knowledge master degree.

DKT [16]: DKT is the first using an RNN to deal with the problem of knowledge tracing. It predicts students' next attempts on knowledge concept based on the students' knowledge mastery degree.

GKT [18]: This method adopts the knowledge graph to predict the students' knowledge mastery degree. Knowledge graphs can reflect the relationships among knowledge concepts. Therefore, this method predicts recommendation according to the GNN model.

HGKT [20]: HGKT is the improved method of GKT, and it introduces the hierarchical idea and multi-layer attention mechanism into the model to make prediction.

KCG_MHA: This adopts the above-mentioned the recommendation framework. But the adjacency matrix is constructed based on the muti-head attention mechanism. Then knowledge graph is constructed based adjacency matrix.

KCG_VAE: This adopts the above-mentioned the recommendation framework. But the adjacency matrix is constructed based on the Variational autoencoder. Then knowledge graph is constructed based adjacency matrix.

KCG_TPM: This adopts the above-mentioned the recommendation framework. But the *Q-matrix* is constructed based on the transportation probability matrix.

KCG_DKT: This adopts the above-mentioned the recommendation framework. But knowledge graph is constructed based on the deep knowledge tracing.

4.3. Experimental Results and Analysis

In our experiment, 60% of the data is used for training, and the remaining 40% of the data is used for testing. Due to the contingency in the division of the data set, the experiment in this paper uses ten random divisions of the data set. The data are the average of ten experiments results, and Figures 3, 4 and 5 are the average of ten experiments on three datasets.

Fig.3 shows the results of Accuracy and AUC on Synthetic dataset. Fig.4 shows the results of Accuracy and AUC on ASSISTments 2009 dataset. Fig.5 shows the results of Accuracy and AUC on ASSISTments 2015 dataset. The three figures intuitively show the experimental performance of 8 methods (including the four methods proposed in this paper, KCG_MHA, KCG_VAE, KCG_TPM and KCG_DKT) on three datasets. From the three figures, you can see the performance of the method proposed in this paper. The performance is better than the BKT method, and the performance is slightly worse than that of the HGKT method. This is because the method in this paper only uses the answer records in the data set, while the other four methods (BKT, DKT, GKT and HGKT) apply the answer records at the same time, and *Q*-matrix, and the acquisition of *Q*-matrix requires expert annotation.

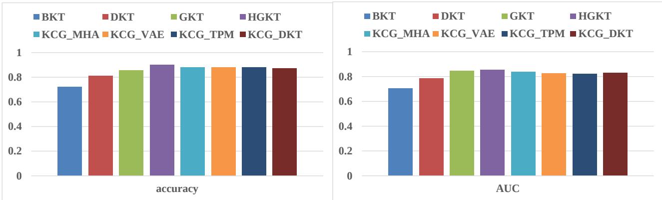


Fig.3. Experimental comparisons of Synthetic dataset

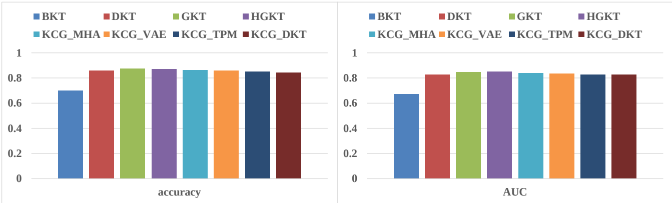


Fig.4. Experimental comparisons of ASSISTments 2009 dataset

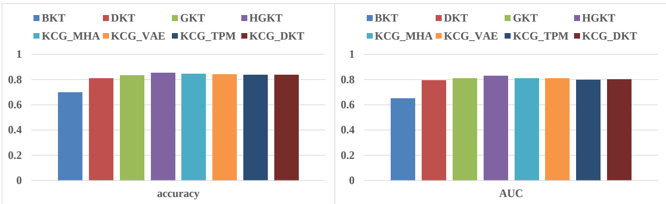


Fig.5. Experimental comparisons of ASSISTments 2015 dataset

Table 2. Experimental results of Accuracy and AUC

Model	*Synthetic*		*ASSISTments 2009*		*ASSISTments 2015*	
	ACC	AUC	ACC	AUC	ACC	AUC
BKT	0.7201	0.7036	0.7014	0.6714	0.6977	0.6511
DKT	0.8125	0.7876	0.8577	0.8263	0.8101	0.7953
GKT	0.8575	0.8443	0.8741	0.8461	0.8341	0.8102
HGKT	0.8991	0.8564	0.8715	0.8497	0.8515	0.8295
KCG_MHA	0.8812	0.8385	0.8633	0.8381	0.8433	0.8091
KCG_VAE	0.8796	0.8276	0.8574	0.8344	0.8407	0.8078
KCG_TPM	0.8788	0.8243	0.8501	0.8278	0.8376	0.7993
KCG_DKT	0.8703	0.8294	0.8449	0.8266	0.8395	0.8021

The four methods given in this paper build the course knowledge graph. The KCG_TPM method is used for the course knowledge graph on the Synthetic dataset and the ASSISTments 2015 dataset as shown in Fig. 6 and Fig. 8. After obtaining the course knowledge graph, according to the formula (11) can obtain the knowledge structure diagram of each student in the corresponding course, and you can clearly see the students' mastery of each knowledge concept. Fig. 7 shows the knowledge structure diagram of random two students' mastery of each knowledge concept on the Synthetic dataset. Fig. 9 shows the knowledge structure diagram of the random two students' mastery of each knowledge concept on the ASSISTments 2015 data set. The color depth in the figure represents the mastery of the knowledge concept, and the darker the color, the mastery of the knowledge concept. The better, the lighter the color, the worse the mastery.

From Fig. 3, we can see the dependencies between the various knowledge concepts in the course. Based on the course knowledge map, a certain path selection algorithm can be used to recommend learning paths and recommended exercises for students. Similarly, using the dependencies between courses can recommend courses for students. This paper mainly provides personalized exercise recommendation for students based on the curriculum knowledge map. Based on the knowledge graph shown in Fig. 3, Algorithm 1 is used to recommend exercises. The recommended effect is shown in Table 1. As can be seen from Table 1, on the Synthetic dataset, the performance of the four methods for building knowledge graphs provided in this paper is relatively close. The algorithm is better than the BKT, DKT and GKT methods, but the performance is 2.88%-1.79% different from the HGKT algorithm. On the one hand, in the HGKT algorithm, the *Q-matrix* is already given and accurate, which makes the constructed course knowledge graph more accurate. On the other hand, using a hierarchical graph neural network to implement recommendation on the knowledge graph requires more computing resources, but if given appropriate parameters, it will have better experimental performance.

Figures 7 and 9 are the knowledge structure diagrams of any two students on the two datasets respectively. Through the students' personal knowledge structure diagram, we can clearly see the mastery of each knowledge concept of each student. For example, Fig. 7(a) and Fig. 7(b) represent the mastery degree of knowledge concept of student a and student b respectively. Comparing student a and student b, it can be seen that student b has a better mastery of course knowledge concepts than student a (The color of multiple nodes in Figure b is darker than that of the nodes in Figure a, that is, the mastery of the corresponding knowledge concepts is better). Specifically, comparing the two figures, it can be seen that student b's mastery of knowledge concept 8 and knowledge concept 12 is better than student a, and student b's mastery of knowledge concepts 25 and 14 is slightly better than student a.

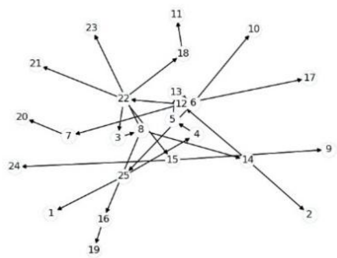
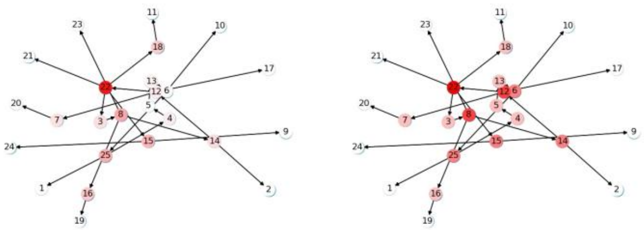


Fig. 6. The knowledge graph of Synthetic dataset



a b

Fig.7. The knowledge structure diagrams of any two students on Synthetic dataset

As can be seen from Fig. 6, there is a loop on the knowledge graph, that is to say, there is an interdependent relationship between knowledge concepts. For example, there is a ring between knowledge concepts 4, 5, and 25, that is to say, in order to master knowledge concept 4 well, you need to master knowledge concept 25; to master knowledge concept 25 well, you need to master knowledge concept 5, and mastering knowledge concept 5 requires mastering knowledge concept 4. In practical applications, the course knowledge graph should be a directed acyclic graph, so this situation should not exist. In order to eliminate the loops in the knowledge graph, we try to use the spanning tree protocol method in the computer network to prune each loop in the knowledge graph. Using the pruned knowledge graph for exercise recommendation, the recommendation performance is relatively poor. This is because this paper assumes that each exercise is only related to one knowledge concept, but in practice, one exercise is related to multiple knowledge concepts. The method proposed in this paper is used to construct *Q-matrix* and curriculum knowledge graphs, a loop will appear.

The curriculum knowledge graph of the ASSISTments 2015 dataset is shown in Fig. 8. The total number of knowledge concepts are 74, which is relatively large. Therefore, the use of circles can better display the dependencies between knowledge concepts. From the figure, we can also see that there is partial loop phenomenon. Fig. 9 shows the knowledge structure diagram of two random students, in which the shade of color indicates the degree of mastery of the knowledge concept.

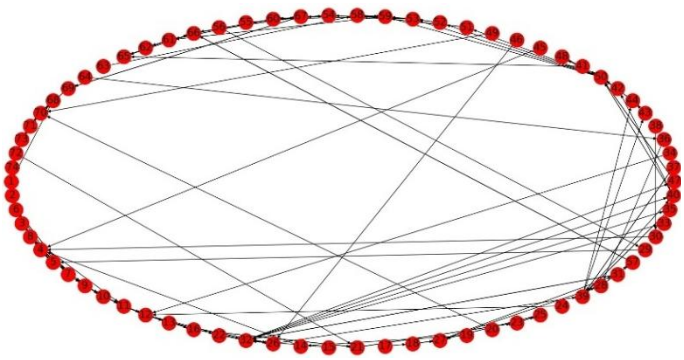


Fig.8. The knowledge graph of ASSISTments 2015 dataset

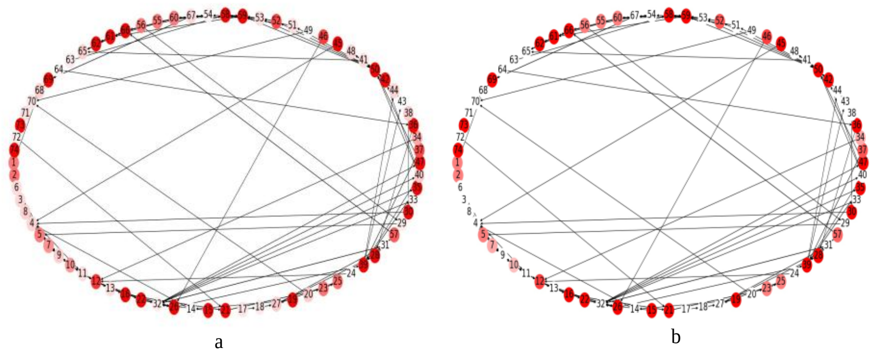


Fig.9. The knowledge structure diagrams of any two students on ASSISTments 2015 dataset

5. Conclusion

This paper attempts to build a personalized exercise recommendation framework based on knowledge graphs, which does not require manual adoption. This method starts from constructing a question-concept matrix(Q-matrix), then builds a curriculum knowledge graph based on the *Q-matrix* and student answer records, and then builds student's personal knowledge structure graph based on the course knowledge graph, *Q-matrix* and students answering records, and then uses each student's knowledge structure graph to recommend personalized exercises for students. The recommendation framework makes the recommendation process intuitive, and you can intuitively see the mastery of each knowledge concept and the recommended exercises for each student. In addition, the framework is also suitable for recommending personalized learning paths for students. The experimental results show that this method has better performance than BKT, and has better intuitiveness than DKT and GKT. However, the framework proposed in this paper also has certain limitations. (1) The method in this paper assumes that each exercise is only related to one knowledge concept, but in practical applications, each exercise is related to multiple knowledge concepts, then how to implement the framework Many-to-many relationship between exercises and knowledge concepts. The process of constructing the *Q-matrix* is actually the process of classifying each exercise (category is the concept of knowledge). Aiming at this problem, the method of semi-supervised classification is proposed to assign exercises to multiple classes, and determine which class should belong to according to the probability of belonging to each class. (2) When recommending exercises, the recommended exercises are determined according to the importance of each knowledge concept to the students. This method is relatively intuitive, but its performance is not good. For this, a graph neural network is proposed to implement personalized exercise recommendation. How to solve the problem? The above two questions will be the main work in the next stage.

Acknowledgment. This work is supported by Key Research and Development Program of Shaanxi of China (Program No.2022GY-073); Shaanxi Provincial Education Department scientific research program Foundation of China (No.21JK0616); Science and Technology Plan Project of Shangluo City of China (No. 2021-J-0002); Science and Technology Innovation Team Building Project of Shangluo University of China (No.18SCX002).

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Received: July 06, 2022; Accepted: December 06, 2022.