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A Computational Framework-Based Deep Knowledge Tracking and Knowledge Mapping in Predicting Knowledge Acquisition in College Students' Civic and Political Education

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Abstract This paper defines the knowledge tracking task based on a computational framework, and portrays the evolution law of students' Civics knowledge mastery state by introducing the knowledge point relationship graph and forgetting factor analysis. Aiming at the antecedent-successor relationship of Civics education knowledge points, a knowledge graph embedding method based on RotatE model is proposed, incorporating a type-aware mechanism to enhance semantic smoothness. The fine-grained matrix embedding technique is introduced to explore the implicit correlation features between exercises and knowledge points, which further improves the prediction effect of the Civic and Political Education knowledge tracking model. The application effect of the constructed model is examined through multi-group experiments. The results show that the predictive performance of this paper's model for question-answering situation reaches 87.3% and 86.9% in the two indicators of ACC and AUC. Embedded composite features of this paper's model predicts the answering situation AUC index is 0.85. This paper's model can well classify the cognitive hierarchy of students' knowledge mastery and accurately analyze the average knowledge mastery of the students in the three sections of high school and low school, so as to improve the accuracy rate of the recommendation of knowledge mapping resources.

Index Terms knowledge tracking, knowledge mapping, RotatE model, fine-grained matrix, civic education

I. Introduction

As the core driving force for the development of artificial intelligence, knowledge mapping is driving "Internet + education" into the new era of "artificial intelligence + education", providing a new empowering force for education teaching in the era of education informatization 2.0 [1], [2]. Knowledge mapping, as an emerging technological tool, provides new possibilities for the practice of ideological education. As a tool that graphically displays the structure and relationship of knowledge, it can help students better understand and master the knowledge system [3], [4]. At present, some colleges and universities have begun to try to apply knowledge mapping to the practice of Civic and Political education. For example, through the establishment of knowledge mapping of Civic and Political courses, the relationship between knowledge points is accurately demonstrated, and teachers can better sort out and optimize the teaching content according to the antecedent-successor relationship between knowledge points, and at the same time, diagnose the learning status of learners [5]-[7]. By constructing a knowledge map of students' civic and political literacy, accurate assessment and personalized guidance of students' civic and political literacy can also be achieved [8], [9]. However, collaborative parenting practice based on knowledge mapping is still in the exploratory stage, and further research and practice are needed to improve and optimize it.

Some scholars have examined in depth the application of knowledge mapping in higher education.Ilkou, E. et al. described the applicability of educational knowledge mapping as a pedagogical tool for both teachers and students, which provides semantically structured frameworks capable of integrating multifaceted pedagogical knowledge and adequately meets the diverse needs of the modern teaching and learning process [10]. Cui, J. and Yu, S. compared two knowledge visualization tools, knowledge mapping and concept mapping, for promoting deep thinking learning among students and found that knowledge mapping has better results in enhancing the breadth and depth of students' subject knowledge [11]. Abu-Salih, B. et al. outlined the key applications of knowledge mapping in the field of teaching and learning, stating that this structured representation of knowledge helps to enrich learning content, improve curriculum design, etc., and makes a reference to a viable path to facilitate the modernization of education [12]. Wang, Q. et al. addressed the problem of complex and intertwined knowledge structure in interdisciplinary education in colleges and universities, and proposed the construction of a knowledge map connecting cross-curricular knowledge points, which can help students clarify the knowledge vein from the complex network of relationships and promote the further development of interdisciplinary higher education [13]. Cao, Z. Y. et al. used student self-efficacy as an indicator to quantitatively analyze the difficulty and importance of teaching knowledge points, estimated student self-efficacy using Item Response Theory, and from there created a knowledge map to visualize the hierarchical relationships and correlations between knowledge points, thus providing data support for instructional design [14]. Li, N. et al. proposed a method to automatically construct a multimodal educational knowledge graph, which is able to extract educational relationships from valid information based on multimodal educational entities such as speech and text, and link them to the graph in order to form a knowledge network, which has never been able to provide a higher-quality service for educational teaching and learning [15]. Overall, the research on knowledge mapping teaching focuses on the display and dissemination of knowledge structure, subject visualization and curriculum teaching applications, and has achieved good results. However, there is a relative gap in the research on knowledge map-enabled civic education, which can provide an effective reference for innovating the teaching mode of course civic education and enhancing the effectiveness of course civic education by carrying out targeted research.

Improving the tracking level of knowledge points and the effect of resource recommendation in college students' Civic and Political Education is the key to promote the scientific and intelligent development of Civic and Political Education in colleges and universities. This paper analyzes college students' performance in answering questions related to Civic and Political Education, and explores the relationship between knowledge points and exercises. It also introduces the forgetting factor to enhance the computational ability of the mastery state of students' Civic and Political knowledge. The knowledge graph embedding model of RotatE model is introduced and improved by combining the type-aware mechanism to enhance the performance of knowledge point relationship mining. Combine the embedded knowledge tracking model based on fine-grained matrix to improve the prediction of students' knowledge mastery. Compare the prediction effect of this paper's model with that of the same type of prediction model, as well as the effect of knowledge state analysis, etc., to comprehensively verify the application value of this paper's model.

II. Knowledge tracking and knowledge mapping technology implementation based on computing frameworks

This chapter focuses on the core needs of knowledge mastery prediction in college students' civic education, and proposes a comprehensive research framework that integrates deep knowledge tracking and knowledge mapping techniques. Define the problems related to knowledge tracking prediction. The knowledge graph of Civic and Political Education is constructed, and the specific technical approach of knowledge tracking is analyzed.

II. A. Definition of the problem

II. A. 1) Knowledge Tracking (KT) Tasks

The core of the KT task is to track students' knowledge status in real time and accurately, based on their historical learning data of Civic and Political Education, and then to predict their future performance in answering questions. The realization of this task helps to get a more comprehensive picture of students' learning progress in Civic and Political Education, and provides strong support for educational assessment. The answer sequence of each student in KT consists of a series of questions and answers, assuming that Q denotes the set of questions and K denotes the set of knowledge points. Define the student's answer sequence as, where denotes the tth question that the student interacts with. Denotes the corresponding question answered by the student, where 1 denotes a correct answer and 0 denotes an incorrect answer. Given the above question-answer sequence of a student, it is realized to track the student's knowledge status in real time and predict the student's performance in answering the questions in the future t+1 moments.

Figure 1 shows the student's learning history process. The example of students' learning history process in Fig. 1 can more intuitively and clearly illustrate the task of KT, how to accurately track each individual's knowledge level through knowledge tracking based on their Civic Education history answer results, and then recommend topics for each individual to meet their own learning situation, teachers to develop an exclusive Civic Education learning plan for each student, and carry out intelligent learning diagnosis.

II. A. 2) Knowledge point relationship maps

There is a relationship between the topics and knowledge points of Civic Education during the students' answers. Figure 2 shows the relationship between the topics and knowledge points. The relationship between the topics and knowledge points in the students' answer records is represented. The topic q_2 in the figure contains knowledge points k_1 and k_3, so k_1 and k_3 are related through topic q_2.

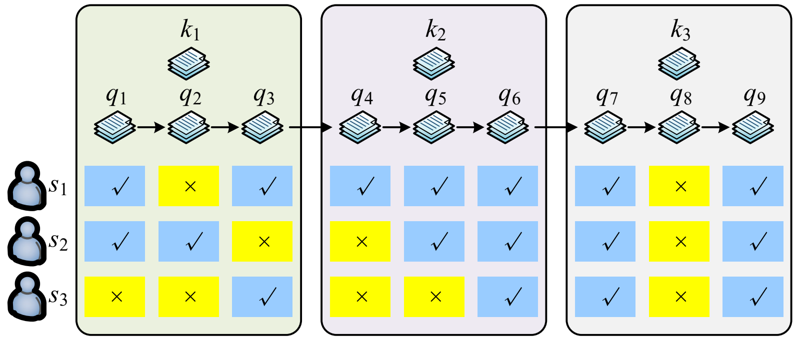


Figure 1: Students learn the historical process

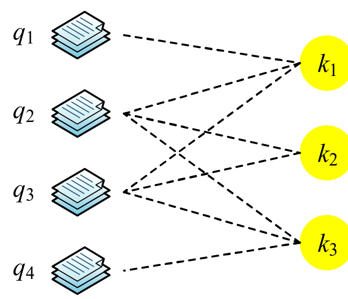


Figure 2: Topic knowledge relationship

Therefore, in the knowledge point relationship graph, the nodes are all the knowledge points, and each edge relationship is the knowledge point with the topic's first-order neighboring knowledge points generated, that is, all the knowledge points contained in a topic have relationship information. For example, q_2 in the figure contains k_1, k_2, k_3, 3 nodes have edge relations in the knowledge point relationship graph.

In order to precisely analyze the relationship that exists between the knowledge points of Civic Education, the set of knowledge points is defined as $T = \{t_i\}_{i=1}^{|T|}$, $t_i \in \{k_n\}$, $n \in |K|$. Therefore, the knowledge point relationship graph is defined as $HG = \{t_i, t_n, b_{ij}\}$, where nodes denote knowledge points, $b_{ij} \in \{0,1\}$, with 1 denoting that there is a relationship between the two, and 0 denoting that there is no relationship between the two.

II. A. 3) Forgetting factors

The pedagogical theory Ebbinghaus' forgetting curve shows that students' knowledge forgetting is affected by the number of repetitions and time intervals, which include sequential time intervals and time intervals of repetition of the same knowledge points. In addition, students' mastery of knowledge points also has an impact on their forgetting. Therefore, the following four factors affecting the forgetting of knowledge in Civic Education are considered.

Time interval of last learning (SLI), SLI indicates the time interval between the current learning time and the time generated by the last learning. The time interval of the nearest knowledge point (KLI), KLI indicates the nearest time between the current answer topic and the related topic containing the same knowledge point distance. The number of times the knowledge point has been repeated (NRS), NRS indicates the number of times the knowledge point has been studied throughout the learning process. Knowledge point original mastery level (KML), KML indicates how well a student has mastered a knowledge point itself.

II. B.Knowledge Mapping Construction of Civic Education

In the field of Civic and Political Education, the antecedent-successor relationship between knowledge points is very obvious. Knowledge map reflects the rich semantic and topological information between entities, and knowledge map has significant results in the representation of exercises related to Civic and Political Education as well as the prediction of answers, and the construction of knowledge map is the basis of the embedded representation of knowledge points. Figure 3 shows the process of knowledge map construction. The knowledge map in the field of Civic and Political Education exercises belongs to the domain knowledge map, which needs to be constructed and corrected by experts in the field through joint discussions. At the same time, the domain knowledge map needs to be combined with specific business needs, so its construction method needs to be analyzed according to the specific situation, and the knowledge map constructed by different researchers is not the same. Summarizing the experience of the predecessors, for the special characteristics of the Civic and Political Education Exercise field, we adopt the top-down knowledge graph construction method, which is divided into three main steps, namely, knowledge point acquisition, knowledge graph design and knowledge storage and visualization, to construct a knowledge graph that conforms to the Civic and Political Education Exercise field.

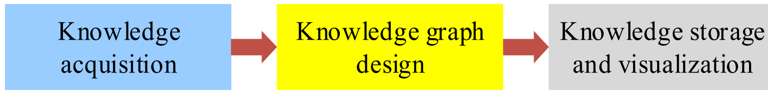


Figure 3: Knowledge graph construction process

II. B. 1) RotatE and type perception

The inference of relationship patterns in the Civic Education Knowledge Graph is the focus of the Knowledge Graph embedding model, and there are three very important and widely used relationship patterns in the Knowledge Graph, which are: symmetry, inversion, and combinatorial relationships. The definitions of the three relationships are as follows:

Symmetric relations, such as classmate relations, A is a classmate of B, then B is also a classmate of A. Formally, if there exist two entities x, y, and the relationship that exists is r and is symmetric, then one gets $r(x,y) \Rightarrow r(y,x)$.

Inverse relationship, if husband and wife relationship, A is the husband of B, B is the wife of A; or, antecedent-successor relationship between knowledge points, C is the antecedent knowledge point of D, D is the successor knowledge point of C. Formalized, $r_1(x,y) \Rightarrow r_2(y,x)$, where $r_1 = r_2^{-1}$.

Combinatorial relationships (transitive), such as the teacher-teacher relationship, where the teacher's teacher is the master; and the successor of a subsequent point of knowledge, which is a deeper and more difficult point of knowledge. Formally, if there is $r_1(x,y)$ and $r_2(y,z)$, then there is $r_3(x,z)$.

In addition to the above three cases, the one-to-many situation between entities is also very common, i.e., a teacher will have more than one student; relatively, a student may also have more than one teacher. The same phenomenon exists in the knowledge graph in the field of Civic Education, where a single knowledge point may also have multiple predecessor and successor knowledge points. Classical knowledge graph embedding methods have been successful to a certain extent, but it is difficult to involve all of them when facing these three possible relationships and one-to-many situations. In order to take into account the three relationship patterns and one-to-many practical situations involved in the knowledge map of Civic Education, and also to make the knowledge map embedding representation vector richer, the RotatE model is introduced as the main framework of knowledge map embedding.

The source of the idea is Euler's formula, i.e., $e^{i\theta} = \cos\theta + i\sin\theta$, which maps both entities and relations into a complex vector space, defining each relation as a rotation from the head entity to the tail entity. Formally, there exists a triad (h,r,t) in the knowledge graph that is expected to satisfy the following conditions:

$$t = h \circ r \tag{1}$$

In Equation (1) $h,t \in C^k$, $\circ$ denotes the Hadamard product (i.e., the corresponding multiplication of elements), and C^k denotes the complex space. h_j, t_j denotes the j th element of the embedding vector of head and tail entities, r_j denotes the j th element of the relational embedding vector with $|r_j|=1$, and $||$ denotes the complex modulus. For the embedding target it can also be refined to be expressed as $t_j = h_j * r_j$, which corresponds to a counterclockwise rotation by an angle in the complex space, which only affects the phase of the entity embedding vector and does not affect the modulus of the embedding vector. The distance score function is shown in equation (2).

$$d_r(h,t) = \|h \circ r - t\| = \sum_{j=1}^{k} \|h_j * r_j - t_j\| \tag{2}$$

To elaborate the whole process of calculating the distance score function in more detail, the entities and relations can be represented in the complex space as $h_j = m_{h,j} e^{i\theta_{h,j}}$, $r_j = e^{i\theta_{r,j}}$, $t_j = m_{t,j} e^{i\theta_{t,j}}$, where $m_{h,j}$, $m_{t,j}$, $\theta_{h,j}$, $\theta_{t,j}$

denote the modulus and phase of the j th element of the embedding vectors of the head entity and the tail entity, respectively, and k denotes the dimensionality of the embedding vectors, e is a natural constant, and i denotes the imaginary unit, and the detailed computation of the distance scoring function is as follows:

$$h_j * r_j - t_j = m_{h,j} e^{i\theta_{h,j}} e^{i\theta_{r,j}} - m_{t,j} e^{i\theta_{t,j}} \tag{3}$$

$$m_{h,j} e^{i\theta_{h,j}} e^{i\theta_{r,j}} - m_{t,j} e^{i\theta_{t,j}} = m_{h,j} e^{i(\theta_{h,j}+\theta_{r,j})} - m_{t,j} e^{i\theta_{t,j}} \tag{4}$$

Equation (3) and Equation (4) clearly show the computation process of the embedding vector of the head entity to get the embedding vector of the tail entity by rotating the embedding vector by one angle counterclockwise, and one of the main ideas of RotatE is to map both the entity and the relation vector space into the complex number space. At the same time, Euler's formula is applied to represent the complex numbers in the form of exponents, which greatly facilitates the computation process, and the Hadamard product of the head entity embedding vector and the relation embedding vector is converted to the summation of the phases. Compared with other knowledge map embedding processes, this method can accomplish the embedding of three relations and one-to-many cases in the knowledge map embedding domain, so as to get more accurate embedding representation vectors of Civic Education Knowledge Map.

In practice, each entity belongs to a certain type and each knowledge point belongs to a certain knowledge topic. The entities of the same type (knowledge topic) will be similar, and the entity embedding vector representations in the same type (knowledge topic) should be similar, i.e., the two representation vectors semantically possess smoothness. Aiming at this phenomenon, in the process of embedding training of Civic and Political Education Knowledge Graph, sensing the entity type information, constraining the embedding process of Knowledge Graph, and making the embedding vectors semantically smoother while obtaining the embedding vectors of Knowledge Graph, a type-aware Knowledge Graph embedding representation model based on RotatE is proposed as RotatE-TA method. Define the knowledge topics of all knowledge points in the knowledge graph of Civic Education as $T = \{t_1, t_2, \cdots, t_m\}$, and the knowledge topic of each knowledge point e_i as $e_i^t \in T$, and each knowledge point belongs to only one knowledge topic. Define the types of two entities i, j as e_i^t, e_j^t, and the comparison of the two entity types is calculated as follows:

$$type(e_i, e_j) = \begin{cases} 1 & if \ \ e_i^t = e_j^t \\ 0 & else \end{cases} \tag{5}$$

In Equation (5), the value is 1 when the types of i, j two entities e_i^t, e_j^t are the same, otherwise the value is 0. In Civic Education Knowledge Graph, the entities with the same type are closer in the Knowledge Graph, and the two entities belonging to the same type embedding representations vectors should be similar as well. Therefore, the type information of entities is sensed during model training to make the entity embedding vectors of the same type closer, i.e., $\|m_h - m_t\|$ should be as small as possible. In the original RotatE model, the distance score function only calculates the mapping from head entity to tail entity, in RotatE-TA the entity type-aware constraints are added in calculating the score function, and finally the distance score function of RotatE-TA model is:

$$d_r(h,r) = \sum_{i=1}^{k} \left\| m_{h,i} e^{i(\theta_{h,i}+\theta_{r,i})} - m_{t,i} e^{i\theta_{t,i}} \right\| + \lambda * \|m_h - m_t\| * type(e_h, e_t) \tag{6}$$

In Eq. (6), λ is a hyperparameter indicating the size of the type-aware weights.

II. B. 2) Embedded knowledge tracking model based on fine-grained matrices

In this paper, we extract the implicit information between Civic Education practice questions and skills through the Knowledge Component (KC) matrix and extract the latent vector representation of the matrix in an embedded way, and input the embedded information as additional features into the knowledge tracking model, so that the model can more accurately predict the students' proficiency level by learning the correlation between the topic features and the skill features.

The KC matrix is a two-dimensional matrix where the rows represent students and the columns represent different knowledge components or knowledge points. Each element represents the student's mastery of the corresponding knowledge component, usually denoted by 0 or 1. For example, if a student has mastered a knowledge component, the corresponding element has a value of 1; if the student has not yet mastered the knowledge component, the corresponding element has a value of 0. Embedding is a technique for mapping high-dimensional data into a low-dimensional vector space while maintaining the specific structural or semantic relationships of the data. With this mapping, the similarity of the data can be measured in the vector space by a metric such as distance or angle. This continuous vector representation can contain richer information. Figure 4 shows the modeling framework proposed in this paper.

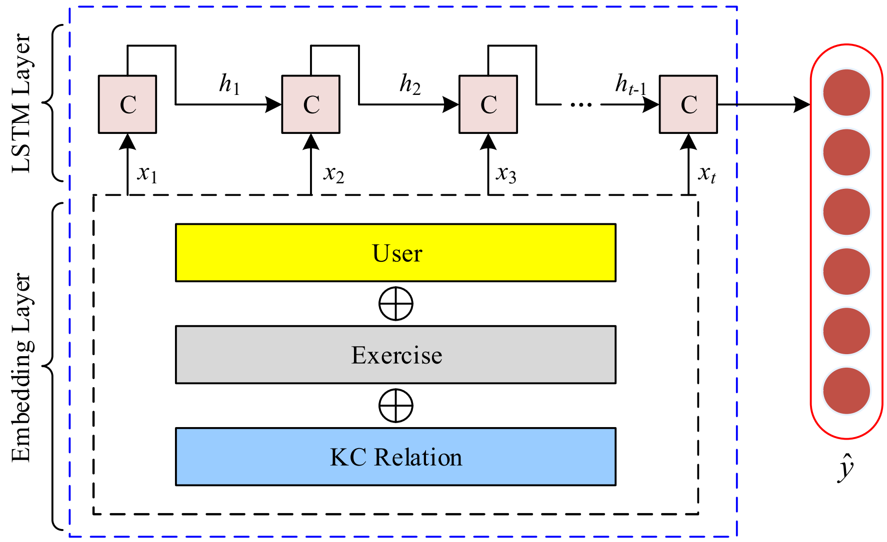


Figure 4: Embedded knowledge tracking model based on fine grained matrix

First, we explore the influence of the potential knowledge and practice associations therein on the state of students' Civic Education knowledge acquisition based on the given records of students' Civic Education related exercises $r_i = (I_H, x_1, x_2, \cdots, x_n)$, the weight of which is denoted as γ_t. Specifically, the practice-to-practice relationship table $E \in \mathbb{R}^{n \times n}$, the skill-to-skill relationship table $R \in \mathbb{R}^{v \times v}$, and the practice-to-skill relationship table $T \in \mathbb{R}^{n \times v}$ were established for storing these weights. In the exercise-practice relationship table, for time t, if both exercise i and exercise j are related to the same Civic Knowledge concept k, then exercise i and exercise j are considered to be related as well, i.e., $\gamma_t^{ij} = 1$ otherwise $\gamma_t^{ij} = 0$, $0 \le i$, $0 \le j$, and skill table and the exercise-skill table are set up in the same way. In addition, in the actual situation, there is a phenomenon that the relationship between knowledge and exercises is close and only slightly related, and the existing model lacks a richer and more detailed expression of the relationship with only two states of "related" and "unrelated". Therefore, in the model of this paper, a new weight ε_t is set according to the closeness of the relationship to quantify the relevance weight in the relationship table. For example, the relevance weight of exercise i to skill u is computed as the average of all skills included in exercise i.

$$\varepsilon_t^{iu} = \frac{1}{\sum_{u=1}^{v} \gamma_t^{iu}} \tag{7}$$

Next the three relation tables were put through an embedding algorithm to generate a relation embedding matrix $K_i \in \mathbb{R}^{128 \times M}$.

The knowledge embedding vector x_i, student embedding p_i, and relation embedding r_i taken from the knowledge embedding matrix are then merged into the learner's information sequence v_i. The three features are encoded into one feature as a new learner's information sequence, which combines the entity information and the information implied between exercises and knowledge to understand the ability of different learners to learn knowledge during the learning process and to track the student's knowledge status.

The learner's information sequence is acquired as:

$$v_i = Concat(x_i, p_i, r_i) \tag{8}$$

After the learner information sequence passes through the LSTM layer the output features will also enter a residual connectivity layer as well as a fully connected layer for more efficient gradient updating.

Finally, the model was optimized by means of a cross-entropy loss function, specifically, the following objective function between the true answer c_i and the predicted outcome $\tilde{c}_i$ at each interaction was minimized by Adam optimization.

$$L = -\sum_t \left(c_i \log \tilde{c}_i + \left(1 - c_i\right) \log\left(1 - \tilde{c}_i\right)\right) \tag{9}$$

Compared with previous models, this model considers not only the information of learners and knowledge points, but also the relationship between practice questions and knowledge points. Features are spliced to form composite features, and then target vectors are obtained through residual and fully connected layers to indicate the students' knowledge mastery. Finally, the probability of a student answering a question correctly $\tilde{P}_i$ is output.

III. Application of model knowledge tracking and knowledge graph resource recommendation

In this chapter, the model constructed in the previous section is applied in the knowledge tracking and resource recommendation of the civic education of students in actual colleges and universities to verify the model's knowledge tracking effect, resource recommendation ability, and answer prediction performance.

III. A. Validation of the validity of test questions

III. A. 1) Comprehensive analysis of the level of difficulty differentiation

Since it is necessary to excavate the relationship between the answer sequences related to Civic and Political Education and the knowledge points as well as the students' state, the difficulty distribution and differentiation situation of the selected questions were first analyzed to ensure that the questions involved in the study meet the validity requirements. One final exam paper was randomly selected from each of the constructed Civic Education Test Banks 1 and 2 for difficulty and differentiation validation. Each test paper had 20 questions, totaling 40 questions. Figure 5 shows the results of the difficulty and differentiation analysis of the test questions. As can be seen from Figure 5, the difficulty distribution of the questions is reasonable. Nearly 75% of the questions have a difficulty greater than 0.55 and less than 1. The difficulty is moderate and the differentiation is good, indicating that the quality of the test questions is good. Among the exercises with a differentiation of less than 0.25, the difficulty value is higher, with 9 questions having a difficulty distribution of 0.85 or more, indicating that these questions are all more difficult, and thus can lead to a smaller differentiation. The selected questions contain 3 levels of difficulty, high school and low school, while there is also a clear difference in the differentiation level, which is in line with the actual situation and research needs.

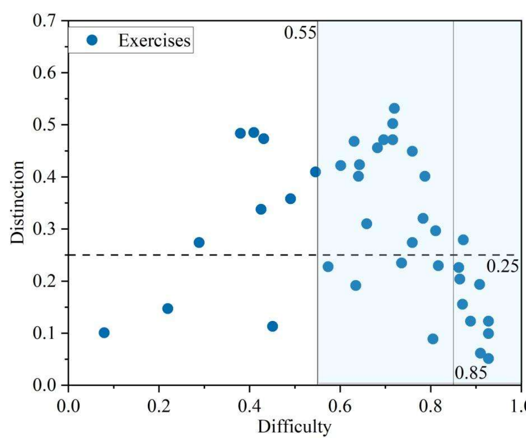


Figure 5: Distribution of difficulty and differentiation of each question

III. A. 2) Differentiation of the level of difficulty of the test bank

Further statistics on the difficulty differentiation of each topic in the constructed test bank are provided to provide data support for the subsequent research on the effect of knowledge tracking. Table 1 shows the distribution of the number of questions (in channels) in the Civic Education Exercise Question Bank for the target difficulty grading of easy, medium and hard. The overall percentages of easy, medium and difficult are 25.40%, 61.09% and 14.51%

respectively. Overall, most of the questions were of moderate difficulty, with a small percentage of easier and harder questions. The test bank used for the study had a good level of differentiation.

Table 1: Distribution of target difficulty level in the system

	Easy	Middle	Hard
Marxist principle	10	23	19
Outline of modern Chinese history	29	82	32
Ideology, morality and rule of law	35	47	17
Introduction to MAO Zedong Thought and the theoretical system of socialism with Chinese characteristics	150	378	60
Total	224	530	128

III. B. Comparison of model prediction effects

III. B. 1) Comparison of predictive effectiveness of different models

In order to verify the advantages of this paper's model in predicting the answering situation, this paper's model is compared with five same-type prediction models, namely, DKT, DKVMN, SAKT, AKT, LPKT, and LBKT, for tracking the learners' knowledge status and predicting their answering situation in the constructed test bank.

Figure 6 shows the results of the comparison experiments of the six models. It can be seen that the prediction performance of the question-answering situation of this paper's model is 87.3% and 86.9% on the indicators of ACC and AUC, respectively, which is the best prediction effect among all the compared models. In particular, compared with the 74.8% and 73.6% of the DKT model, this paper's model has a performance improvement of 12.5% and 13.3% in the two metrics. The superior prediction performance of this paper's model is mainly due to the introduction of the forgetting factor, RotatE-TA type-aware model, and KC matrix, etc., as a result of which more composite feature information such as topic features and knowledge point relationships are obtained, which provides better results in predicting students' answers.

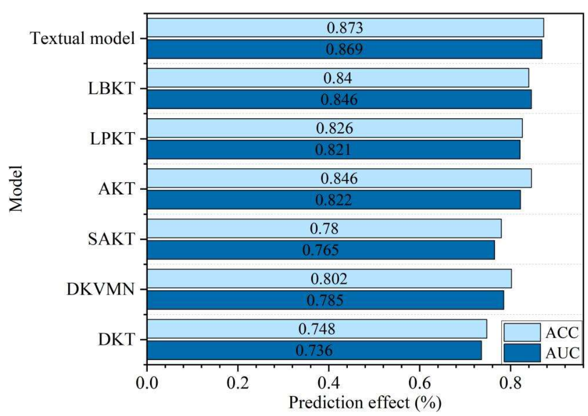


Figure 6: Comparative experimental results of 6 models

III. B. 2) Comparison of the prediction effect of different embedded feature quantities

Further verify the enhancement effect brought by composite feature relationship matrix embedding to this paper's model. The experiment compares the prediction effect of the answering situation of this paper's model in the five cases of not embedding composite features, only embedding knowledge information, only embedding students' knowledge status, only embedding knowledge-exercise relationship, and comprehensively embedding composite features, to judge the role of composite feature relationship matrix embedding. Figure 7 shows the comparison of the prediction effect (AUC) of the five cases. From Fig. 7, it can be seen that after continuously predicting the question-answering situation of 50 students, the model of this paper with embedded composite features reaches 0.85 in the AUC index of predicting the question-answering situation, close to 1, which is better than the other cases with no embedded features or with only one set of features embedded. It shows that embedding composite features helps the model to find more information, so as to comprehensively judge the students' question-answering situation, understand the students' knowledge mastery status, and carry out corresponding knowledge tracking and question-answering situation prediction.

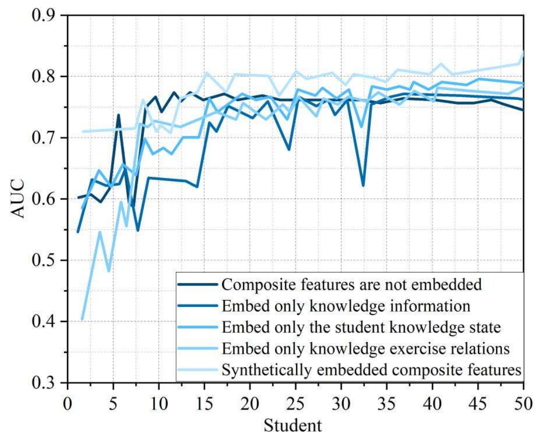
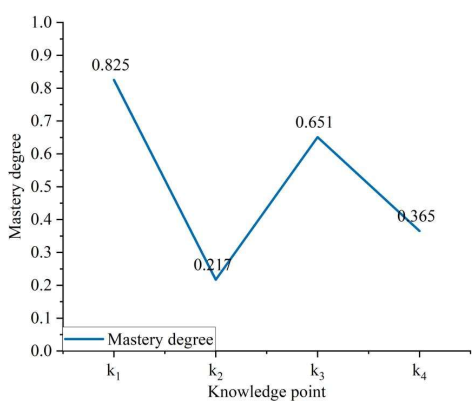


Figure 7: Comparison of predictive effects (AUC) in the five scenarios

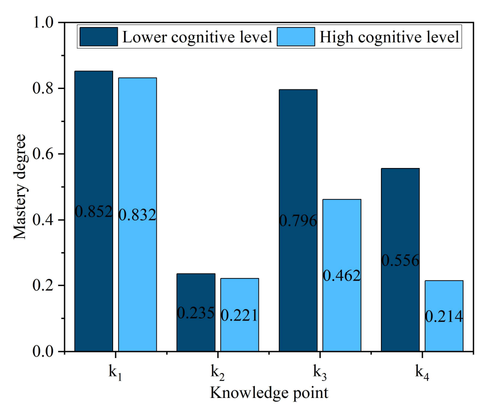
III. B. 3) Comparison of the Effectiveness of Different Models for Knowledge State Analysis

Since the model in this paper is based on students' historical learning data of Civics education to predict students' future question-answering performance, the model can more accurately analyze the students' current knowledge status situation and the change of knowledge status during the question-answering process during the process of analyzing the knowledge status of the students, and thus more accurately determine where the knowledge status of the students is located. When analyzing a student's answer to a question, the degree of mastery of four different knowledge points k1,k2,k3,k4 related to the question, most knowledge tracking models usually judge the degree of mastery of the knowledge point based on the likelihood of the student answering this knowledge point correctly. When the percentage of correct answers is greater than 50% it is judged as mastery, and when it is less than 50% it is judged as no mastery. However, only through the correct rate of correct answers can only judge the general knowledge status of the student. This model can more accurately determine which level of knowledge students have mastered. The lower level represents the degree of students' memorization and understanding of the knowledge point. The high level represents the degree of students' mastery of how to apply the knowledge point. Depending on the specific practical needs, the complete low-high cognitive hierarchy can also be used to analyze at which level the student's mastery of the knowledge point is.

Figure 8 shows a comparison of the analysis of student A's knowledge status between this paper's model and other models. Figure 8(a) shows the knowledge status analysis of other models. Figure 8(b) is the knowledge status analysis situation of this paper's model. Figure 8(a) shows that other models only simply give the degree of mastery of each knowledge point of Student A, and can be judged to be greater than 0.5 or less than 0.5, while in Figure 8(b), this model not only gives the degree of mastery of Student A's knowledge, but also intuitively determines that the degree of mastery of a certain knowledge point is at a low cognitive level or a high cognitive level, so as to facilitate the knowledge mapping of the student to recommend the corresponding learning resources for students.



(a) Analysis of the state of knowledge of other models



(b) Knowledge state analysis of the model in this paper

Figure 8: Knowledge state analysis of this model and other models

III. C. Analysis of Average Knowledge Acquisition of Learners by Segments

As can be known from the previous section, the model in this paper can determine at which cognitive level a student's mastery of a specific knowledge point is based on the composite feature information such as the student's historical answer situation, and give the corresponding resource recommendation in combination with the knowledge graph. According to the cognitive level of students' knowledge points, students are categorized into three segments: high school and low school. High students are those who have mastered most of the knowledge points at the high cognitive level; middle students are those who have mastered different knowledge points at both the low and high cognitive levels; and low students are those who have mastered most of the knowledge points at the low cognitive level.

In this section, the constructed model is applied to analyze the average probability of knowledge mastery derived from the completion of different amounts of questions by learners of each segment in the test bank 1 and 2 of the Civic Education Test Bank, and to verify the practical application effect of the model. Figure 9 shows the specific results of test bank 1. Figure 10 shows the specific results of test bank 2. In Fig. 9, with the gradual increase of the number of questions from 0-55, the predicted probability of knowledge mastery of the model for students in the high score band decreases from 0.92438 to 0.88224, the predicted probability of knowledge mastery for students in the middle segment rises from 0.83761 to 0.86606, and the predicted probability of knowledge mastery for students in the low score band rises from 0.77636 to 0.84451. in Fig. 10, with the gradual increase of the number of gradual increase in the number of questions from 0-45, the model's predicted probability of knowledge mastery decreases from 0.88596 to 0.88265 for students in the high scoring band, from 0.84405 to 0.87858 for students in the middle band, and from 0.76608 to 0.81423 for students in the low scoring band.

From these two graphs, it can be seen that the learners in the low-scoring and middle-scoring segments increased and stabilized with the increase of the amount of questions done the model predicted learner knowledge mastery; the learners in the high-scoring segments decreased and stabilized with the increase of the amount of questions done the model predicted learner knowledge mastery. Moreover, the phenomenon of mastery rate change of learners in each segment also reflects the ceiling effect, i.e., when approaching the top, it is natural to feel a layer of invisible obstacles blocking the top, so their mastery tends to be only up to a certain stage and then it is impossible to continue to go up. Such a situation is the so-called glass ceiling barrier. With the change of the question volume of each segment learners on these two data sets using this paper's model to give the learner cognitive diagnosis results of the trend change is acceptable, indicating that this paper's model can be very good according to the learner answering the questions to analyze the state of their knowledge mastery, and combined with the knowledge graph to give the corresponding resource recommendations.

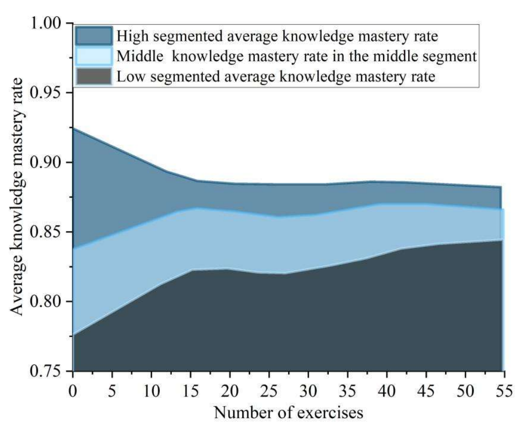


Figure 9: Specific results of test bank 1

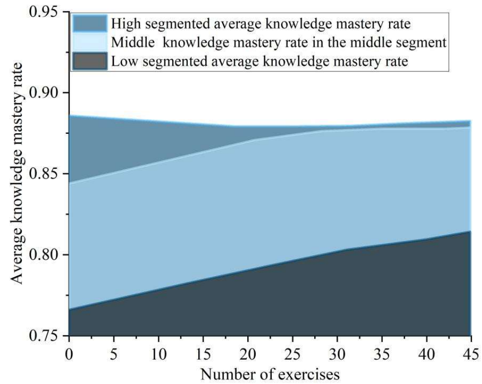


Figure 10: Specific results of test bank 2

IV. Conclusion

This paper combines the knowledge tracking task with the application of knowledge mapping to comprehensively improve the prediction accuracy and resource recommendation ability for the knowledge points and answer situations, knowledge mastery level, etc. of college students' Civic and Political Education. In comparison with the prediction performance of five similar models, the prediction performance of this paper's model for question-answer situation reaches 87.3% and 86.9% in terms of ACC and AUC, which has a better prediction level. Comparing the predictive performance of this paper's model with different feature embedding, it is found that the AUC value of this paper's model embedded with composite features is 0.85, which is closer to 1. This paper's model can give the degree of mastery of different knowledge points and the cognitive level to which they belong, and effectively predict the average knowledge mastery of the students in each segment. In the future, the application of real-time updating of the knowledge graph can be further studied to improve the timeliness of the prediction of the mastery of students' civic politics knowledge points, and to promote the innovative development of civic politics education in colleges and universities.

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