International Journal for Housing Science and Its Applications
Publish August 3, 2025. Volume 46, Issue 3 Pages 1076-1088

https://doi.org/10.70517/ijhsa46383

Research on Personalized Learning Strategies of College English Based on Reinforcement Learning Algorithm in the Era of Internet+Intercultural Education

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Abstract Personalized learning is a strategy that recommends the best learning strategies (including learning resources, test questions, etc.) based on the individual learner's situation, so that the learner can obtain the optimal development. This paper takes the automatic prediction and recommendation of test question difficulty as the research object, and proposes a convolutional neural network model based on semantic attention mechanism for college English test questions. The model is based on the practice characterization method of semantic comprehension to extract semantic features and quantify the semantic dependence degree of English reading test questions, so as to assess the quality of reading test questions. At the same time, the automatic prediction model of test question difficulty is constructed by taking into account the content, difficulty and objectives of multiple test question types in English learning. The model is based on convolutional neural network and deep attention network algorithms to realize automatic prediction of English test difficulty. And through reinforcement learning settings, personalized rewards are set to guide the recommendation, and the test question recommendation model is constructed by combining the difficulty prediction of test questions. The model always shows optimal results in predicting the difficulty of test questions on different datasets, and the average absolute error is lower than 0.33 and the root mean square error is lower than 0.38, which demonstrates the high reliability of personalized recommendation of test questions.

Index Terms personalized learning, test question difficulty prediction, test question recommendation model, convolutional neural network, university English language

I. Introduction

Intercultural learning ability covers four aspects: language ability, critical thinking ability, intercultural ability and humanistic literacy, which are important qualities that high-quality talents should have [1]. With the proposal and implementation of China's new “Belt and Road” initiative, international exchanges will be more frequent and in-depth, which means that the direction of internationalized talents training is further clarified. Enhance cross-cultural awareness, effective humanistic exchange and communication to cultivate high-quality composite and applied foreign language talents has become a further requirement for foreign language education [2]. At the same time, “Internet + education” is the exploration of the deep integration of information technology and education in the Internet era, which brings unprecedented challenges and opportunities for teaching methods, teaching methods, learning styles, teachers' roles, etc., and becomes an inevitable trend for the reform and development of teaching in colleges and universities [3]-[5]. On the one hand, with the support of modern information technology such as the Internet and intelligent devices, the construction of diversified hybrid teaching mode and diversified interactive learning environment, so that the students from passive acceptance of knowledge to active exploration of knowledge, and then realize the students' personalized learning, independent learning as well as in-depth learning [6]-[8]. On the other hand, in the face of the Internet-supported information technology and the phenomenon of the coexistence of online classrooms and school classrooms, the use of intelligent algorithms to promote the implementation of personalized learning strategies, and to achieve a significant improvement in the quality of teaching English majors [9]-[11].

Intercultural English teaching cultivates students to be “application-oriented” that is, market demand-oriented, and English intercultural education perspective of students' communicative and communicative ability and intercultural thinking ability is difficult to achieve only by relying on the traditional collective teaching, the need to use the Internet to expand the learning of English intercultural competence to English teaching. Sorokovykh, G. V. et al. described the specific application of digital technologies in the context of informatization of English education, the emergence of digital educational spaces provides individualized learning paths for differentiated students and effectively improves the effectiveness of English language learning [12]. Dou, A. In order to promote the integration of professional English skills and intercultural communicative competence, it is proposed that innovative teaching methods and applications based on digital technology can be used to implement personalized teaching strategies and continuous professional development in diverse cultural contexts [13]. Sun, G established an English intelligent teaching system based on deep learning technology, which is able to propose a more personalized English teaching plan by analyzing students' cultural background and learning needs, and plays an important role in improving students' intercultural communication skills [14]. Sun, L. examined the impact of a virtual collaborative program on the intercultural competence of English majors and found that collaborative activities and artificial intelligence tools greatly facilitated students' intercultural understanding and personal development, providing inspiration for developing intercultural English education practices [15]. Chen, H. and Mei, K. The use of mobile technology for English intercultural education provides a learning experience based on interactivity and personalization, which both improves the effectiveness of students' intercultural learning and provides unprecedented opportunities for innovative applications of educational technology [16]. In addition, intelligent algorithm is also a hotspot in the current research of education informatization, which is a product of the deep integration of new technology and education, and the use of enhanced learning algorithms to create a personalized intelligent classroom can improve the quality of the whole process of English teaching before, during and after class, and maximize the benefits of the English intercultural classroom.

For the method of personalized learning strategy of college English, this paper conforms to the characteristics of the Internet + intercultural education era. Taking test question difficulty feature extraction, test question difficulty prediction and test question recommendation as the research ideas, the research on personalized learning strategy of college English is carried out. Considering that English test questions belong to language practice questions, based on its semantic richness, the study of feature extraction and characterization of reading test questions is carried out. A prediction model incorporating semantic representations is proposed, namely, a convolutional neural network model based on semantic attention mechanism. On the basis of this model, we further explore the automatic difficulty prediction model that can be adapted to multiple types of test questions. In order to improve the accuracy of the automatic prediction model of test question difficulty, reinforcement learning as well as personalized rewards are set to construct a test question recommendation model based on reinforcement learning algorithm. The reliability of the model is examined at multiple levels by comparing it with similar model algorithms.

II. Convolutional neural network model based on semantic attention mechanism

The solution in this work is an automated data-driven solution, which is a two-phase framework containing a training phase and a testing phase. First, in the training phase, combining the historical quiz data and the corresponding practice test question texts, this paper first proposes a semantic understanding-based practice test question characterization method (TACNN) to synthesize and understand multiple content parts of the text in each question Q_i, so as to represent its semantic information and predict its difficulty $\tilde{P}_i$. Then, in order to address the incomparability due to the computational error that exists to the observed difficulty of the representation, this paper proposes a quiz-dependent training strategy based on biased order learning. Again, in the testing phase, the TACNN model can directly input the text of the test questions to be practiced and directly predict their difficulty attributes without organizing the corresponding quiz examination. The whole program process has a wider application value.

Next, we introduce the technical details of the TACNN framework, which is shown in Figure 1 and consists of four main modules:

Input Layer: Input the text of each part of the question, and initialize the corresponding representation according to the word.

The utterance comprehension layer: using a unified CNN model to slice the topic text in utterances and perform semantic comprehension at the utterance level.

Semantic association layer: using the attention mechanism, quantify the semantic dependency of each question on different utterances in the exercise, and obtain question-specific semantic representation results.

Prediction Layer: splicing the semantic representations about each part of the question to predict the difficulty.

II. A.Input layer

The input to TACNN is the textual content of various parts about a question Q_i, including: the background document TD_i, the question TQ_i and the option TO_i. The document TD_i consists of a set of sequences of statements, i.e., $TD_i = \{s_1, s_2, \cdots, s_M\}$, where s_j denotes the j th statement and M is the number of statements in the document. The question TQ_i and each option TO_i are modeled as a separate utterance. Further, each utterance consists of a set of word sequences: $s=\{w_1,w_2,\cdots,w_N\}$, where each word is represented using a pre-trained word embedding vector of dimension d_0, i.e., $w_i \in \mathbb{R}^{d_0}$, and N is the number of words in each sentence. After the initialization operation, each document can be represented as a tensor, i.e., $TD_i \in \mathbb{R}^{M\times N\times d_0}$, and each question statement and each option statement can be represented as a matrix, i.e., $s \in \mathbb{R}^{N\times d_0}$.

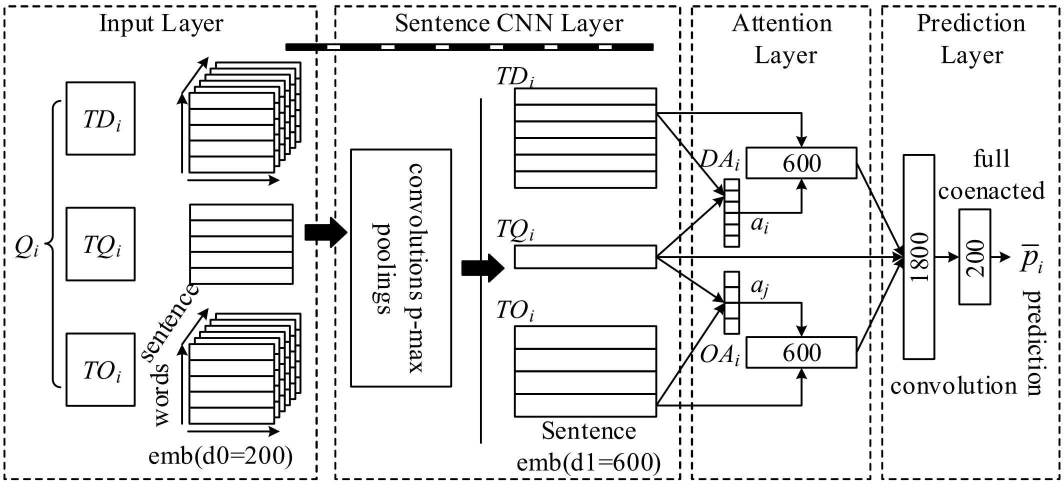


Figure 1: TACNN framework

II. B.Statement comprehension layer

The goal of the utterance understanding layer is to aggregate word-level semantics and learn a semantically comprehensible representation of each utterance. In this paper, we propose a unified CNN utterance understanding framework that has the following three advantages: first, by using the convolution-pooling operation, CNNs can learn the most important semantic information of each utterance from the perspective of local phrases to global utterances. Second, using a unified CNN model to understand the semantics at the utterance level can project the text from different parts of the exercise into a comparable semantic space, which is important for practicing semantic understanding. Finally, compared with other deep model structures, the weight sharing mechanism of CNN can effectively reduce model complexity and improve learning efficiency.

The CNN model of the utterance comprehension layer is shown in Fig. 2. it is an improved traditional CNN model, which alternately uses multi-layer convolution and maximum pooling operations to gradually converge each utterance into a semantic embedding vector. Next, this paper describes the details of the convolution and pooling operations in the first layer, and the rest of the multilayer operations are similar to the first layer technique.

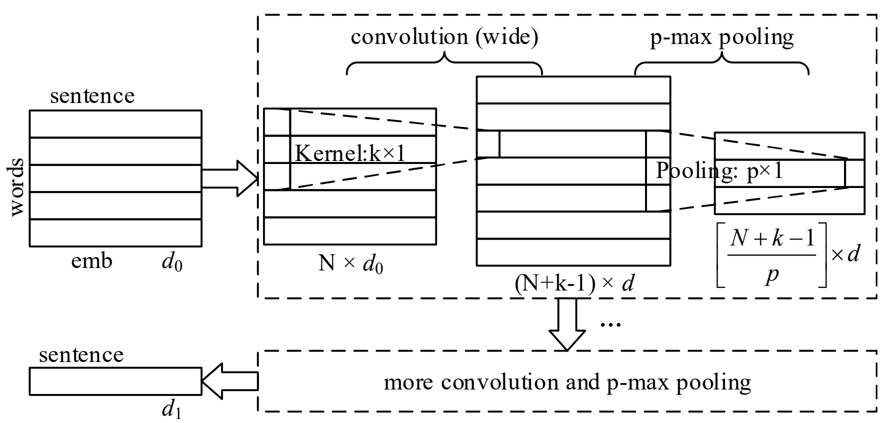


Figure 2: Statement understanding layer

As can be seen from Fig. 2, the input to the utterance comprehension layer is every utterance matrix, i.e., $s \in \mathbb{R}^{N \times d_0}$. In this paper, we use a wide convolution operation (convolution kernel size of $k \times 1$) to perform local semantic understanding at the utterance level every k words. Specifically, the input utterance: $s = \{w_1, w_2, \cdots, w_N\}$, and after the first layer of convolutional operation, a sequence of hidden layers can be obtained: $h^c = \{h_1^c, \cdots, h_{N+k-1}^c\}$, where each of the hidden layer elements, h_i^c, is in Equation (1):

$$h_i^c = \sigma\left(G \cdot [w_{i-k+1} \oplus \cdots \oplus w_i] + b\right) \tag{1}$$

where $G \in \mathbb{R}^{d \times kd_0}$, $b \in \mathbb{R}^d$ is the parameter of the convolution operation and d is the dimension of the output vector. $\sigma(x)$ is the nonlinear activation function: $ReLU(x) = \max(0, x)$. $\oplus$ is the splicing operation, i.e., k word vectors are spliced into one vector.

In the above convolution operation, the model can learn local semantic information in terms of every k words directly in the utterance. Next, the model uses the p-dimensional maximum pooling operation to aggregate locally important information in the convolutional hidden layer sequence h^c to obtain a global-level hidden layer sequence: $h^{cp} = \left\{h_1^{cp}, \cdots, h_{\lfloor (N+k-1)/p \rfloor}^{cp}\right\}$, where each hidden layer element h_i^{cp} is Eq. (2):

$$h_i^{cp} = \left[\max \begin{bmatrix} h_{i-p+1,1}^c \\ \cdots \\ h_{i,1}^c \end{bmatrix}, \cdots, \max \begin{bmatrix} h_{i-p+1,d}^c \\ \cdots \\ h_{i,d}^c \end{bmatrix} \right] \tag{2}$$

The model alternately uses multi-layer similarity convolution-pooling operations to gradually learn the global semantic information at the utterance level, and finally obtains an utterance embedding vector: $s \in \mathbb{R}^{d_1}$, where d_1 denotes the dimensions of the utterance embedding vector.

After the utterance comprehension layer, each document is transformed into a document semantic matrix $TD_i \in \mathbb{R}^{M \times d_1}$ consisting of M utterance embedding vectors. Each question TQ_i and each option TO_i is transformed into a statement embedding vector $s \in \mathbb{R}^{d_1}$.

II. C.Semantic Dependency Layer

After the utterance comprehension layer obtains each utterance embedding vector at the text level, the semantic dependency layer learns the semantic representation of the text from the reading question level. The phenomenon of dependency at the semantic level requires learning different semantic representations depending on different questions. Therefore, the model needs to be able to automate the quantification of the degree of dependency of the practice text for different questions, which is referred to in this paper as question-level attention representation.

The question-integrated representations will aggregate the semantic information of the weighted utterances from the document level and the option level, respectively. For each question Q_i, the document-level attention vector DA_i is shown in equation (3):

$$DA_i = \sum_{j=1}^{M} \alpha_j s_j^{TD_i}, \alpha_j = \cos\left(s_j^{TD_i}, s^{TQ_i}\right) \tag{3}$$

where $s_j^{TD_i}$ denotes the j th statement of the document TD_i-heavy. The s^{TQ_i} denotes the vector of statement representations of the problem. The cosine similarity α_j denotes the weight score, which quantifies the dependency of each utterance s_j in document TD_i on question Q_i. Similar to the document-level attention vector DA_i, the option-level attention vector OA_i for each question Q_i can also be computed by Equation (3).

The weight score α_j enhances the interpretability of the TACNN model, i.e., the higher the weight, the higher the dependency of question Q_i on that corresponding statement.

II. D.Forecasting layer

The prediction layer combines the already obtained question utterance vector Q_i, document attention vector DA_i, and option attention vector OA_i to predict the difficulty attribute $\tilde{P}_i$ of the question. Specifically, the prediction layer first merges the inputs from the above three parts, and then uses the fully connected network to learn the comprehensive semantic representation o_i of each question, and then predicts the corresponding difficulty $\tilde{P}_i$, and the whole process is described in Equation (4):

$$
\begin{aligned}
o_i &= \operatorname{Re}LU\left(W_1 \cdot \left[DA_i \oplus OA_i \oplus s^{TQ_i}\right] + b_1\right) \\
\tilde{P}_i &= Sigmoid\left(W_2 \cdot o_i + b_2\right)
\end{aligned}
\tag{4}
$$

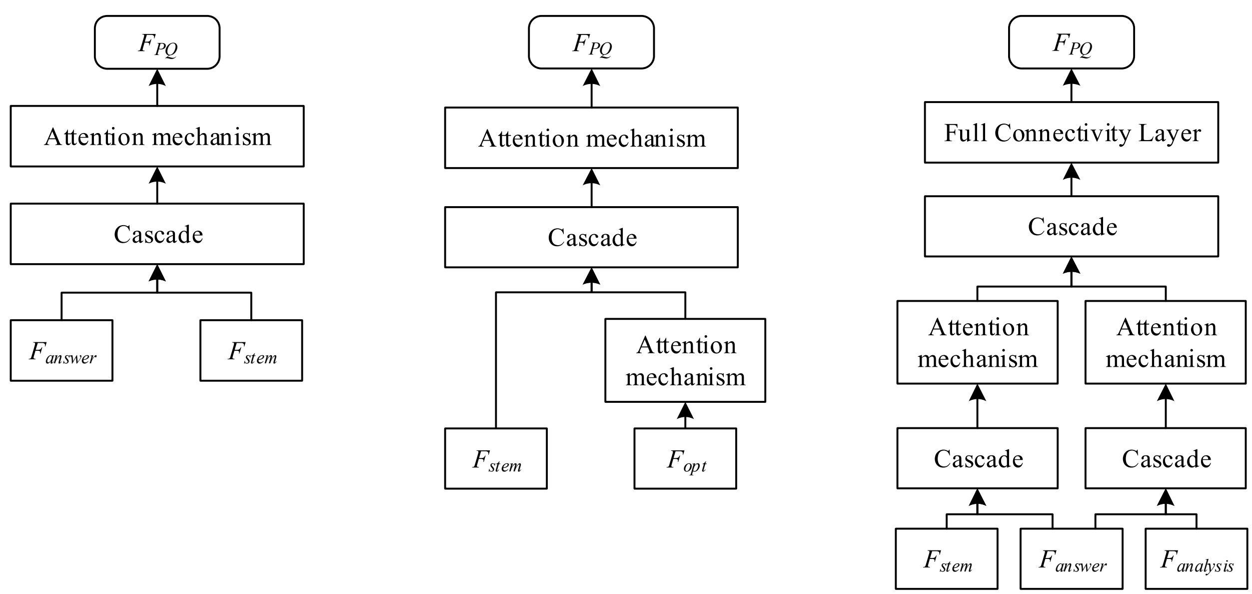
where W_1, b_1, W_2, and b_2 denote network model parameters. In particular, the difficulty attribute $\tilde{P}_i$ here can be generalized to any of the exercise attributes defined in pedagogy, such as differentiation, similarity, etc., if the historical data record contains other attribute labels.

III. Automatic Prediction Model of Test Question Difficulty

Considering the test text, test structure, depth of knowledge and cognitive goals and other factors affecting the difficulty of test questions, we construct an automatic prediction model for the difficulty of test questions adapted to a variety of question types.

III. A. Methods of textual characterization of test questions

Firstly, we formally define fill-in-the-blank, multiple-choice and short-answer questions, obtain the text vectors, extract and fuse the features in the text representation vectors, and realize the textual representations of test questions of multiple question types.



(a) Fill in the blanks feature fusion network structure

(b) Multiple choice feature fusion network structure

(c) Short-answer feature fusion network architecture

Figure 3: Topic feature fusion network structure

III. A. 1) Textual Representation of Test Questions and Textual Feature Alienation Vector

Fill-in-the-blank, multiple-choice, and short-answer questions are taken as objects of study. Summarize T_{stem} (stem), T_{answer} (answer), $T_{analysis}$ (answer resolution) and T_{opt} (options), which are inputted into the model to obtain the textual representation vectors X_{stem}, $X_{analysis}$, X_{answer} and X_{opt}.

BiLSTM and TextCNN models are used for feature extraction.BiLSTM gets the hidden vector output as in equation (5) by inputting text representation vector:

$$h_t = \sigma\left(W_x x_t + W_h h_{t-1} + b_t\right) \tag{5}$$

σ is the sigmoid function, W_x, W_h are the weight matrices, b_t is the bias, $x_t \in X$ is the t th word vector of X, h_t is the current hidden layer output vector, and the cascade of X from the forward and backward inputs is processed to obtain the feature vector $F=\left[\vec{h};\bar{h}\right]$. TextCNN obtains local features c_i from the text representation matrix of $n\times k$ as in equation (6):

$$c_i = f(W\cdot x_{i:i+h-1}+b) \tag{6}$$

$x_{i:i+h-1}$ is the window of size $h\times k$ from row i to row $i+h-1$ in the matrix, W is the weight matrix, b is the bias, and f is the nonlinear function, which is spliced after maximum pooling to obtain the feature vector representation. Input X_{stem}, $X_{analysis}$, X_{answer}, and X_{opt} into the above neural network model, and output the feature vectors F_{stem}, F_{answer}, $F_{analysis}$, and F_{opt}, which are used as inputs to the model in the feature fusion stage.

III. A. 2) Integration of features adapted to different question structures

On the basis of feature vectors, this paper designs hybrid neural networks adapted to the structural characteristics of different question types to realize differentiated feature fusion, and the feature fusion network structure of fill-in-the-blank, multiple-choice, and short-answer questions is shown in Fig. 3(a)-(c).

III. B. Automatic extraction of information for in-depth recognition of knowledge points of test questions

III. B. 1) Supervised multi-knowledge classification

The test question knowledge point extraction task is transformed into a multi-knowledge point classification task, and the output is the probability value that the test question belongs to each knowledge point. Take a fill-in-the-blank question as an example, input its feature vector F_{FQ} into the multilayer perceptual machine MLP, and get the probability that the fill-in-the-blank question belongs to each knowledge point as in equation (7):

$$P\left(\overline{F}_{FQ},K\right)=\frac{1}{\sum_{i=1}^{N}e^{f_i}}\left[e^{f_i}\right] \tag{7}$$

III. B. 2) Weakly supervised band noise based training

Based on the weakly supervised learning approach, prepare the labeled knowledge point trial samples $\{(q_1,K_1),(q_2,K_2),\cdots,(q_n,K_n)\}$ and the unlabeled knowledge point trial samples $\left\{\tilde{q}_1,\tilde{q}_2,\cdots,\tilde{q}_m\right\}$. Use the expert model to pseudo-label the unlabeled samples, and train another novice model N-Model with a mixture of real and pseudo-labeled samples, and use the cross entropy as the loss function to calculate as in Eq. (8):

$$\frac{1}{n}\sum_{i=1}^{n}l\left(K_i,f_{N-Model}^{noised}(q_i)\right)+\frac{1}{m}\sum_{j=1}^{m}l\left(\tilde{K}_j,f_{N-Model}^{noised}(\tilde{q}_j)\right) \tag{8}$$

At this point the trained model becomes the new expert model and the previous steps are repeated until the training iterations converge.

III. C. Cognitive target categorization and methods of difficulty prediction

This paper proposes an automatic test difficulty prediction method based on Bloom's Cognitive Objective Classification, which integrates the textual features of test questions, topological distance of knowledge points and cognitive objectives.

III. C. 1) Methods of categorizing cognitive objectives of test questions

Input the cognitive target behavioral verbs and test question context features into the deep attention network to realize the automatic classification of test question cognitive targets. Clean the text content data of the test questions to get the embedded feature vector representation F_{verb} of all the behavioral verbs in the test questions.

Deep attention network is used to mine the network blocks, combined with residual network to realize feature reinforcement, and guide the network to learn the implicit combination pattern independently. The feature cascade of the test question text feature vector representation F_{stem} and the behavioral verb feature vector representation F_{verb} yields $F_{cognition}$, which is input into the network block composed of the nonlinear transformation layer and the self-attention layer. After a multi-layer network block, the probabilities under the six cognition goals to which the trial belongs are output through the Softmax layer, where the one with the highest probability is used as the cognition goal c_i for the trial q_i.

III. C. 2) Methods for automatic prediction of test-trial difficulty

Based on the classification of cognitive objectives of test questions, under the same cognitive objective, we integrate the textual features, knowledge depth and cognitive objectives of test questions to realize the automatic prediction of the difficulty of test questions under cognitive objectives.

Define all knowledge points undirected graph $G=(K,E)$, K is the set of knowledge points, E is the correlation edge between knowledge points. Based on the obtained knowledge depth information K_q represents all the knowledge points examined in a test question q, $K_q \subseteq K$, the shortest topological distance between any two knowledge points k_i and k_j in G is $DFS(k_i,k_j)$, and the topological distance between knowledge points of the test question q is equation (9):

$$d_q=\frac{2\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}DFS(k_i,k_j)}{N(N-1)} \tag{9}$$

After cascading the knowledge point topological distance embedding representation $embedding(d_q)$, the test question cognitive target $embedding(c_q)$, and the test question text feature vector F_{FQ}, it is inputted into the fully-connected layer FC and activated with the function, which is normalized to obtain the prediction value of the difficulty of the test question p_q.

IV. Reinforcement Learning Algorithm Based Test Question Recommendation Modeling

IV. A. Enhanced learning settings

From a multi-objective reinforcement learning perspective, the process of personalized test question recommendation can be formalized as a multi-objective Markov decision process, where the model state is the student's mastery of the knowledge concepts and the action is to recommend a test question for the student. The environment is to recommend test questions and interact with the intelligences in a sequential manner, ultimately maximizing the discounted cumulative rewards. Formally, the (S,A,R,γ) tuple in reinforcement learning can be described as follows:

(1) State S: S is the state space that describes the student's state. The student's current state s_t is defined as the degree of mastery θ_t^u of each knowledge concept by student u at the current moment t.

(2) Action A: A is the action space that contains all the test questions in the system. Each action a_t is to recommend a test question e_t for the student based on the student's current mastery of the knowledge concept θ_t^u.

(3) Reward R: $R(S,A)$ is a reward function. Once the intelligent body chooses the action a_t based on the current state s_t, the student will answer the selected test question, after which he/she will receive the corresponding feedback. To be precise, after the model recommends the test question e_t based on the student u's mastery of the knowledge concept θ_t^u, the student u answers the test question e_t and gets the answer result x_{u,e_t}. Subsequently, the reward value $r(s_t,a_t)$ is calculated based on the answer result x_{u,e_t}. The reward design covers multiple objectives, including knowledge graph-based rewards and rewards based on the difficulty of personalized test questions.

(4) Parameter γ: γ is a discount factor for future rewards. When $\gamma=0$, the intelligent body only considers the rewards of the current moment, while when $\gamma=1$, all future rewards are fully considered except the rewards of the current moment action.

IV. B. Personalized Reward Setting

This section addresses a key aspect that plays an important role in contributing to the learning of optimal recommendation strategies, namely reward design. Traditional test question recommendation systems, such as collaborative filtering-based approaches, usually focus on recommending only to students who have not mastered the test questions, a single goal that does not fully satisfy students' learning needs. Two key factors are incorporated into reward estimation in this section, namely, knowledge graph-based rewards and personalized difficulty. The former takes into account the dependencies between knowledge concepts, both backward and forward. It promotes efficient student learning through review as well as pre-review stages. The latter tailored the difficulty of test questions to each student by calculating the individualized difficulty of each test question. This solved the problem of test questions being too difficult or too easy leading to loss of interest in learning. In addition, it ensured that students with different levels of mastery of knowledge concepts were able to accurately perceive the difficulty of the test questions.

IV. B. 1) Knowledge graph-based rewards

The recommended test questions must consider knowledge concept prerequisite relationships that indicate the order in which knowledge concepts should be mastered before moving on to subsequent knowledge concepts. According to the theory of knowledge concept prerequisite relationships, it is known that students can move on to subsequent knowledge concepts only after they have mastered earlier knowledge concepts. Since there are forward and backward relationships between knowledge concepts, students' learning should be oriented to this process. For example, the concept of multiplication relies on an understanding of addition, so addition becomes the forward knowledge concept of multiplication. Therefore, students should master the concept of addition before moving on to multiplication, following a sequential learning process.

(1) Review Factors

Incorporating a review factor is critical to help students relearn knowledge concepts they have not yet mastered. When a student incorrectly answers a test question at the moment $t-1$, it is an indication that he has not yet become proficient in the corresponding knowledge concept, or even the forward knowledge concept associated with it. In this case, it is important to recommend test questions on the same knowledge concept or on a forward knowledge concept related to it, designed to promote mastery of that particular knowledge concept. Failure to follow these guidelines will result in a penalty, which can be formalized as equation (10):

$$r_1 = \begin{cases} 1 & (e_{t+1}(k) \in K^{-1}) \ and \ (x_{u,e_t} = 0) \\ -1 & (e_{t+1}(k) \in K^{+1}) \ and \ (x_{u,e_t} = 0) \end{cases} \tag{10}$$

where $x_{u,e_t} = 0$ denotes that student u incorrectly answered test question e_t. K^{-1} denotes the knowledge concepts contained in the test question e_t and the forward knowledge concepts of these knowledge concepts. K^{+1} denotes the backward knowledge concepts corresponding to the test question e_t.

(2) Pre-test factors

In contrast, the prep factor emphasizes the importance of introducing new knowledge concepts to enhance student understanding. Under this factor, if a student answers a test question correctly at time $t-1$, he is considered to have mastered the corresponding knowledge concept. In this case, if a student explores a new knowledge concept, a reward will be provided as it promotes further learning. However, excessive repetition of the same test question is considered unnecessary and leads to a penalty, which is formally represented as equation (11):

$$r_2 = \begin{cases} 1 & (e_{t+1}(k) \in K^{+1}) \ and \ (x_{u,e_t} = 1) \\ -1 & (e_{t+1}(k) \in K^{-1}) \ and \ (x_{u,e_t} = 1) \end{cases} \tag{11}$$

where $x_{u,e_t} = 1$ indicates that student u answered the test question e_t correctly.

IV. B. 2) Personalized Difficulty

Test questions that are too difficult or too easy may not contribute significantly to increased mastery of knowledge concepts. Typically, questions that are consistent with the learning process lead to faster changes in conceptual mastery than similar questions. The concept of “deliberate practice” emphasizes that optimal performance can be achieved through repetition in increasing order of difficulty. By aligning recommended questions with the student's current learning pace, it avoids recommending questions that may be inappropriate or too advanced. Keep the student engaged and interested in the learning process by avoiding questions that are too challenging or too easy.

Considering the differences in knowledge and conceptual mastery among students, their perception of the difficulty of test questions may vary. Relying only on the error rates of all students to determine the difficulty of test questions may lead to biased results. To address this issue, this paper proposes a new method for calculating the difficulty of test questions that takes into account individual student differences. The first step is to identify students who have a similar level of mastery of knowledge concepts as the target students, as in equation (12):

$$sim\left(\theta^{u_i}, \theta^{u_j}\right) = -\frac{\left\|\theta^{u_i} - \theta^{u_j}\right\|^2}{2\sigma^2} \tag{12}$$

where θ^{u_i} denotes the mastery level of student u_i on each knowledge concept.

Based on their similarity in $top-M$ values, a set of similar students $M(u_i)$ is created for a given student u_i. The individualized difficulty of the test questions is then determined by calculating the error rate $diff(e_j)$ of the similar students on the test questions e_j, with equation (13):

$$diff(e_j)=\frac{\left\|\left\{(u_z,e_j,x_{z,e_j})\mid u_z\in M(u_i),x_{z,e_j}=0\right\}\right\|}{\left\|\left\{(u_z,e_j,x_{z,e_j})\mid u_z\in M(u_i)\right\}\right\|} \tag{13}$$

This perspective provides the difficulty of the test questions that have been done for students at a given level. As a guideline, test questions recommended for students should be reasonably consistent in terms of difficulty. Significant fluctuations in the difficulty of test questions will result in penalties, while appropriate levels of difficulty will be rewarded, formalized as in equation (14):

$$r_3=\begin{cases}-1 & \left|diff(e_i)\right|>d\\ 1 & \left|diff(e_i)\right|\le d\end{cases} \tag{14}$$

where d is the average difficulty of the test questions completed by the target students.

Therefore, the final reward is made by combining the three equilibrium coefficients as in equation (15):

$$r=\alpha_1\times r_1+\alpha_2\times r_2+\alpha_3\times r_3 \tag{15}$$

where α_1, α_2, and α_3 are three balancing coefficients, each of which takes on values ranging from 0 to 1 and whose sum is equal to 1. These coefficients allow for higher weights to be assigned to the reward values that are perceived to be more important in a specific task.

V. Testing and Evaluation of Models

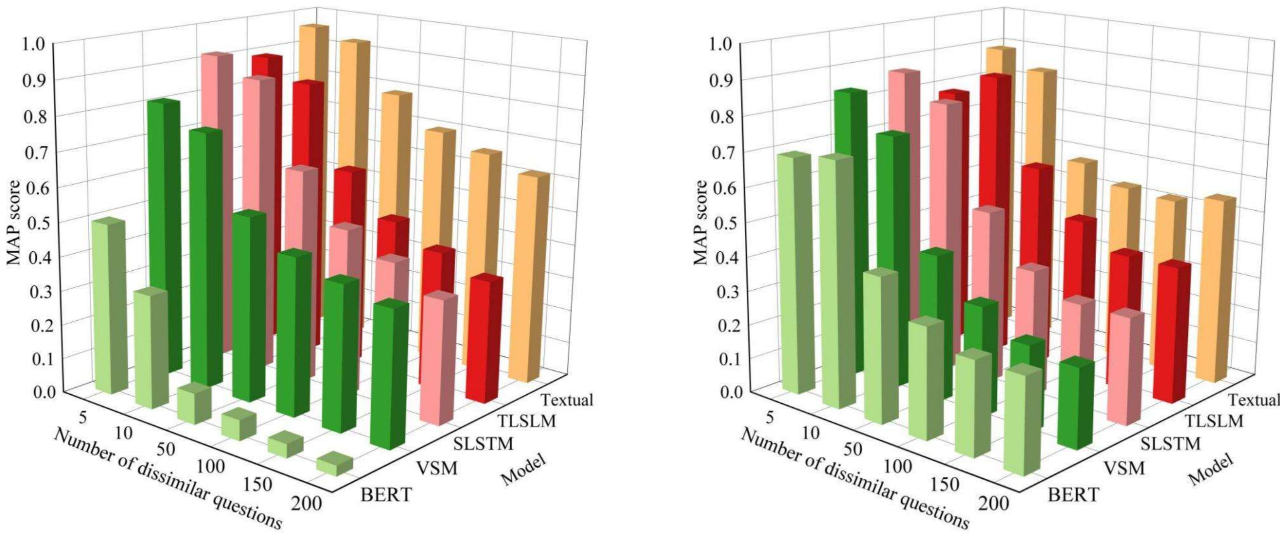
In order to verify the operational performance and application value of test question recommendation models based on reinforcement learning algorithms, this chapter selects four classic test question recommendation models, namely, VSM, BERT, SLSTM, and TLSLM, as comparative models, and launches the experimental analysis and evaluation of the five models in searching for similar test questions, visualizing test question features, and recommending test questions.

V. A. Finding similar test tasks

The MAP scores of the five models in the task of finding similar test questions were calculated and compared. When a model is designed to obtain higher quality textual representations of test questions (similar test question textual representations are closer together and dissimilar test question textual representations are farther apart), the model is more likely to give better results in the task of finding similar test questions.

Fig. 4 shows the MAP scores obtained by different models for similarity ranking on a randomly generated task dataset with a fixed number of similar test questions of 5 and a number of dissimilar test questions of 5, 10, 50, 100, and 200 dissimilar test questions, where the input of Fig. 4(a) is the question text and the input of Fig. 4(b) is the answer text. In this paper, when experiments are conducted with question text, the candidate set of each test question is all the candidate set composed of the question text of the test question, while when experiments are conducted with answer text, the candidate set of each test question is all the candidate set composed of the answer text of the test question. In Fig. 4, it can be seen that the score of the BERT model on the test question task is the lowest among the five models, with a maximum of only 0.71, while the model in this paper is the one that obtains the highest score, with not only the highest score of 0.96 but also the lowest score of 0.52.

From Figure 4, it can be found that the training effect of inputting the answer text of the test questions is generally not as good as inputting the question text of the test questions, and this phenomenon can also be found in the subsequent experiments, in order to simplify the experiments, in the next section, we only input the question text of the test questions and the answer text of the test questions to the proposed model in this paper and to the reference model of the TLSTM which has a more stable performance, respectively.



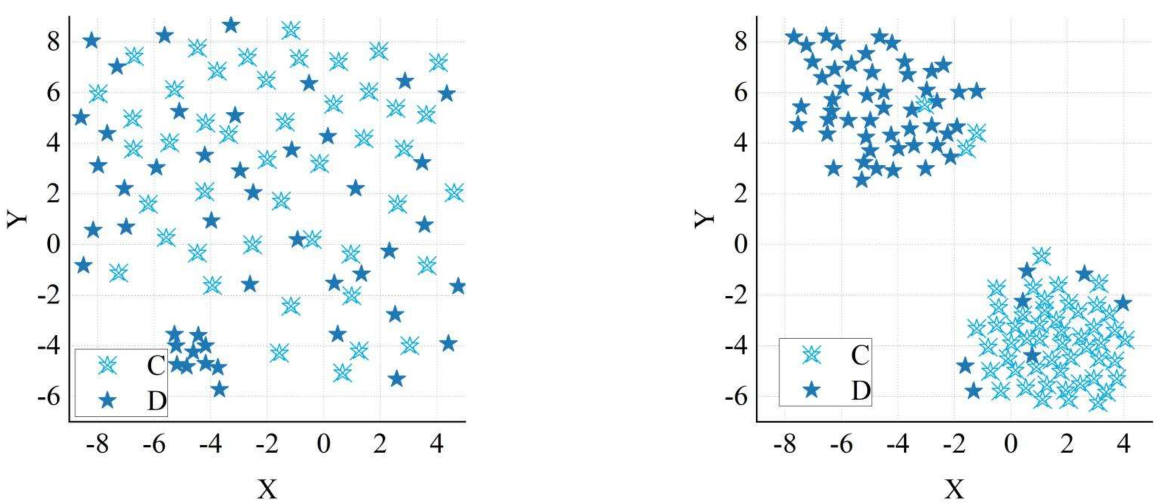
(a) Input: question text

(b) Input: answer text

Figure 4: Model Effect Comparison in Finding Similar Exercises Task

V. B. Visualization of test question features

The performance of a model in a test-question task is closely related to its ability to characterize the test-question text. Visualizing the test question representations can assist in the experimental analysis. Therefore, in order to further analyze the effect of the obtained test question representations, two types of test questions under the labels of “reading comprehension” (C) and “completing the blanks” (D) were selected, and these test questions were vectorially characterized and downscaled for visualization using five models. Figure 5(a) shows the test question features obtained by the TLSTM model, and Figure 5(b) shows the test question features obtained by the TLSTM model.



(a) TLSTM Model

(b) Textual Model

Figure 5: The characteristics of the exercises obtained by different models

Observation of Figure 5 reveals that the test question representations obtained by the TLSTM model do not have obvious demarcation lines after dimensionality reduction, indicating that it does not have good enough text characterization ability. On the other hand, the test question representations obtained by this paper's model have relatively obvious demarcation lines, and the centroids of the test question representations under the two types of labels are farther away from each other, indicating that this paper's model is able to better characterize the text of the test questions.

V. C. Predicting the difficulty of test questions and recommendations

V. C. 1) Accuracy

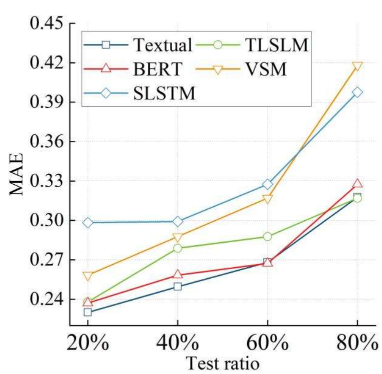
The test prediction problem is treated as a classification problem, and ACC (accuracy) is used as the evaluation index, and the test ratio is set to 20% for the experiment, i.e., the training set accounts for 80%, and the test set accounts for 20%, and the experimental results of this paper's model and the other four models are shown in Table 1. It can be seen that the ACC values of this paper's model on the three datasets are: 84%, 73%, and 81%, which are more than those of the other models, and higher than that of the optimal comparison model (TLSLM) by 9%-13%. Among them, the comparison with the BERT model can highlight the advantages of the student-test weighting strategy, and neither the traditional VSM model nor the SLSTM model is based on a personalized weighting strategy. The model in this paper comprehensively considers the student ability and the difficulty of the test questions, and enriches the loss function as a priori knowledge to achieve a better prediction effect.

Table 1: ACC experiment results of different models

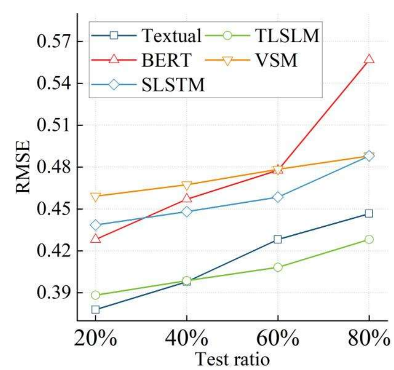
Data set	FreSub	English1	English2
BERT	0.35	0.41	0.37
VSM	0.54	0.57	0.52
SLSTM	0.65	0.61	0.67
TLSLM	0.75	0.66	0.68
Textual	0.84	0.73	0.81

V. C. 2) Mean absolute error and root mean square error

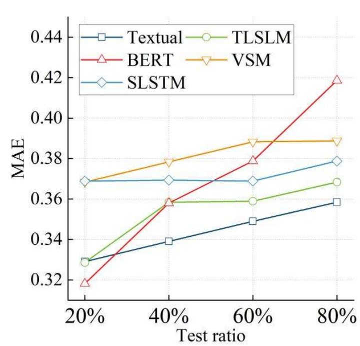
In this group experiment, the test prediction problem is used as a regression problem, and the mean absolute error (MAE) and root mean square error (RMSE) are used as the evaluation indexes, and the test ratios are designed to be 20%, 40%, 60%, and 80% in multiple experiments.The results of MAE and RMSE for the five models in English1 dataset are shown in Fig. 6(a)-(b), and the results of MAE and RMSE for the English2 dataset are shown in Fig. 6(c)-(d). The MAE and RMSE results of the five models under the English1 dataset are shown in Fig. 6(a)-(b), and under the English2 dataset are shown in Fig. 6(c)-(d).



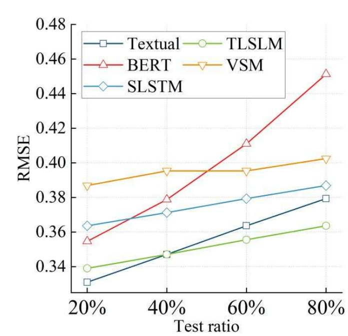
(a) MAE for the Enligsh1 data set



(b) RMSE for the Enligsh1 data set



(c) MAE for the Enligsh2 data set



(d) RMSE for the Enligsh2 data set

Figure 6: MAE/RMSE experiment results of different models on different data

Taking the dataset as a distinction can be obtained: in the Enligsh1 dataset, the model of this paper presents the optimal effect, with the MAE lower than 0.33 and the RMSE lower than 0.45. In addition, taking the test ratio as a distinction can be obtained: in the case of the test ratio of 20%, the model of this paper outperforms the other models in all cases. However, as the test ratio rises to 40%, the RMSE of the TLSLM model outperforms the model of this paper by 0.02, but the other models still fail to outperform the model of this paper. In the Enligsh2 dataset, this model is still optimal, with MAE below 0.36 and RMSE below 0.38. Using the test ratio as a differentiator, it can be obtained that, at a test ratio of 20%, this model outperforms all the other models. However, as the test ratio rises to 40%, the RMSE of the TLSLM model is better than that of this paper's model by 0.02, but the other models still fail to exceed this paper's model.

V. C. 3) Recommended effects and fitting performance

A comparison of the accuracy of the five models for test question recommendation in the English1 dataset is shown in Fig. 7. It can be seen from Fig. 7 that the first four models have different degrees of overfitting, while the new model constructed in this paper can well prevent the occurrence of overfitting, so the model in this paper has a certain enhancement effect.

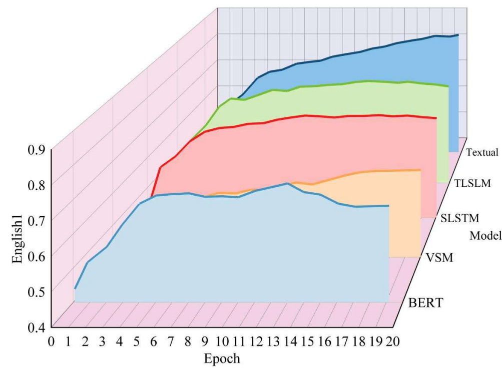


Figure 7: Accuracy comparison of models in the English1 data set

In addition, it is necessary to verify how much N in TopN is the most appropriate. In the experiment, the number of recommended questions is set to 5, 10, 15, 20, 25 and 30, and the most appropriate recommendation list is found through the accuracy index. The accuracy of the datasets with different numbers of recommended questions is shown in Figure 8, which shows that choosing N=15, i.e., the first 15 questions, is the most accurate, which is due to the fact that the number of questions in English1 is small and the distribution of each question is more concentrated, so the English1 dataset is the most effective. The other two datasets (English2 and DouDouYun) have a larger number of questions, so the students' records of doing questions under each question are more scattered, which is not conducive to the calculation of the accuracy rate.

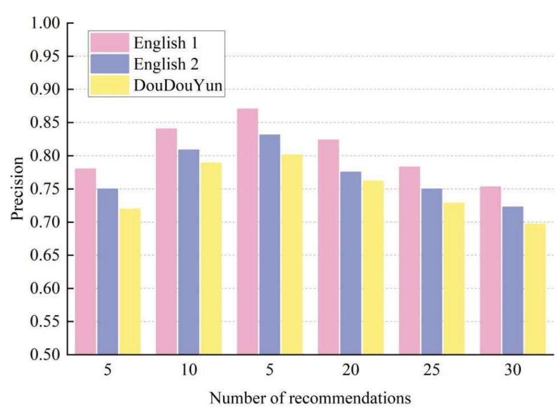


Figure 8: Data set precision with different number of recommendations

VI. Conclusion

This paper takes test question recommendation as the core part of personalized learning of college English, and under the guidance of the research idea of realizing personalized recommendation of test questions by predicting the difficulty of test questions, we have successively constructed a convolutional neural network model based on the semantic attention mechanism as well as an automatic prediction model of the difficulty of test questions, so as to realize comprehensive prediction of the difficulty of test questions of different contents and different types of college English. The personalized rewards of the model algorithm are also set to guide the model to accurately recommend test questions and even learning resources, and the test question recommendation model based on reinforcement learning algorithm is established.

The proposed test question recommendation model shows superior performance in finding similar test questions, visualizing test question features, and recommending test questions, which is far superior to similar algorithms. Under a variety of experimental settings, it obtains a MAP score as high as 0.96 for the task of finding similar test questions, has good textual characterization of test questions, has an accuracy of up to 83% in predicting the difficulty of English test questions, has an average absolute error of up to 0.36, a maximum root mean square error of up to 0.45, and has the ability to prevent overfitting. With the support of reinforcement learning algorithm, the test question recommendation model constructed in this paper shows high practical application value while responding to the development trend of Internet+education, which is of reference value in the research of personalization strategy of college English.

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