A Novel Method for Constructing Online Learning Paths Based on Cognitive Level Assessment of College Students

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Abstract—The cognitive level of students is a very important factor that should be considered when constructing learning paths, however, it's not that all students could have sufficient technical skills to participate in learning programs offered by the learning paths, so in real cases, the learning paths can hardly meet the actual learning requirements of each student. To solve this matter, this paper aims to explore a new method for constructing online learning paths based on the cognitive level assessment of college students. At first, this paper introduced a deep learning model into the assessment of college students' cognitive level, that is, the collected data of the feedback assessment information of student learning was adopted to assess the cognitive level of students, then the paper introduced in detail the structure and principle of the proposed model. After that, this paper proposed a weighted learning method that integrates the learning paths of students with different cognitive levels to ensure the interpretability of the generated learning paths. For a specific student cognitive level on learning paths, the proposed method assigns different weights for learning paths based on history student cognitive level on each node of the learning paths, thereby planning better and easier learning paths for students to achieve their learning goals. At last, experimental results verified the validity of the constructed model and the proposed method.

Keywords—college students, cognitive level, online learning, learning path construction

1 Introduction

Online learning paths are the reasonable learning schemes and plans of students formulated by selecting and sorting online learning resources for the purpose of realizing learning goals [1–6]. Online learning is an ongoing process, and planning paths for it can help students keep track of new courses, resources and technology trends so as to increase their knowledge and skills, and finally achieve the learning goals by more effectively utilizing resources on the Internet [7–14]. The cognitive level of students is a very important factor that should be considered when constructing learning paths

[15–22], because different students may vary in knowledge background, learning speed, learning style, and learning ability, so designing learning paths that conform to their cognitive level can help them study in a more efficient way.

Online education contributes a lot in providing a chance of education to students who are unable to attend school, and it has become an important supplement to traditional education. However, without the direct supervision and instruction of teachers, online education is always subject to potential interference and misunderstandings. Learning Style Classification (LSC) is proposed to analyze the learning behavior patterns of online learning users, based on which personalized learning paths could be formed to help them learn and maintain their interests. He et al. [23] gave a formal definition of the unsupervised LSC problem, summarized the domain knowledge into problem-solving heuristics, and designed a rule-based approach to provide tentative solution in a principled manner. Scholar Peng [24] took the curriculum center system in Eastern Liaoning University as an example to analyze the curriculum relationship of preset learning path module, the establishment of database table, the learning path preset and modification, and other technologies in online education system; the author also described in detail the preset frameworks of serial, parallel and blended learning paths, and tested the system functions, thereby attempting to propose suggestions for improvement. The constructed online education system has the functions of presetting and modifying learning paths and is able to monitor the learning state of learners to facilitate teaching management. Casagranda et al. [25] described the learning process as it is normally implemented through learning management systems and, in some cases, by using SCORM packages, compared with the implementation obtainable by using a virtual community system and a specific set of tools that the authors grouped under the name "learning path". Eom [26] adopted a path analysis model to examine the relationship among e-learning systems, self-efficacy, and perceived learning outcomes of students in the context of university online courses. Independent variables evolved in the study include e-learning system quality, information quality, computer self-efficacy, system-use, self-regulated learning behavior, and user satisfaction, they are all potential determinants of online learning outcomes. Current research findings are meaningful for distance education workers, students and administrators. University administrators must invest constantly to upgrade the e-learning systems so that they could exhibit shorter respond time, better system accessibility, reliability, and flexibility, and ease of learning. Tao and Tian [27] briefly introduced the basic concepts of personalized e-learning and learning path and emphatically revealed the relationship of personalized e-learning and learning performance with experiments.

Although the construction of online learning paths points out a convenient way for students to learn, however, the existing construction methods are of good or bad quality, and they can hardly ensure that all recommended items could meet the high-quality teaching standards, and it's not that all students have sufficient technical skills to participate in the learning programs offered by the learning paths, so in real cases, the learning paths often fail to meet the actual learning requirements of each student. To solve this matter, this explored a new method for constructing online learning paths based on the cognitive level assessment of college students. In the second chapter, this paper introduced a deep learning model into the assessment of college students' cognitive level, used the collected data of feedback assessment information of student learning to assess students' cognitive level, and introduced in detail the structure and principle of the proposed model. In the third chapter, this paper proposed a weighted learning method that integrates the learning paths of students with different cognitive levels to ensure the interpretability of the generated learning paths. For a specific student cognitive level on learning paths, the proposed method assigns different weights for learning paths based on the history student cognitive level on each node of the learning paths, thereby planning better and easier learning paths for students to achieve their learning goals. At last, experimental results verified the validity of the constructed model and the proposed method.

2 Algorithm design for assessing college students' cognitive level

To construct reasonable online learning paths based on the cognitive level assessment of college students, it is necessary to consider students' knowledge background, learning speed and learning style, so that new knowledge could be accumulated based on the existing knowledge, students could adjust their learning speed according to their own ability and requirements, and multiple learning resources and activities could be provided to adapt to different learning styles. In the mean time, online learning resources with moderate difficulty need to be prepared for students to trigger their learning interest and enthusiasm; learning tasks of different difficulty levels, extra learning resources and personalized feedback could be provided, and the timely feedback and assessment could help students know about the progress they make or the shortcomings they have, in this way, they could adjust their learning strategies to better fit their own cognitive level. It is a very important thing to consider the cognitive level of students when constructing the learning paths, since an effective learning path should satisfy students with different cognitive levels so that they can maximize their learning efficiency and develop in an environment that suits them.

There are several existing methods for assessing students' cognitive level, such as diagnostic test, formal assessment, informal assessment, self-assessment, and peer assessment, etc. These methods generally give assessment through regular tests, exams, reports, classroom discussions, or team works to observe students' behavior and participation. However, the tests are of low efficiency and quite subjective, so in order to construct scientific and reasonable online learning paths, this paper introduced the deep learning model into the assessment of college students' cognitive level, that is, using the collected data of the feedback assessment information of student learning to assess their cognitive level (Figure 1).

Specifically, the feedback assessment information of student learning includes the following aspects:

(1) Academic performance: by analyzing students' homework, tests, exams and project scores, their mastery degree of the knowledge of a specific field could be figured out.

(2) Classroom participation: students' participation degree in class can reflect their attention to the content of the course, it can be measured by attendance, class questioning, and participation in discussion, etc.
(3) Learning progress: the speed and quality of students completing the course content can reflect their learning ability, this can be assessed by observing their learning progress of the course and the mastery degree of new knowledge.
(4) Metacognitive ability: it refers to students' ability to understand and control their own learning process, it can be assessed by observing aspects such as the setting of learning goals, learning strategy selection, time management, and self-assessment.
(5) Problem solving ability: the methods and strategies adopted by students when facing problems can reflect their problem solving ability, it can be assessed by observing their performance in finishing a task or solving a problem.
(6) Communication and team work ability: The performance of students in teamwork can reflect their communication and cooperation ability. This can be assessed by observing students' role-playing in team projects, information exchange and collaborative accomplishment of tasks.
(7) Autonomous learning ability: students' autonomous learning performance outside the class can reflect their autonomous learning ability, it can be assessed by observing their performance in independent extracurricular reading, interest group participation, and online learning.

The above indicators can comprehensively assess the cognitive level of students from different angles, help understand their merits and shortcomings, thereby constructing targeted learning paths for their online learning.

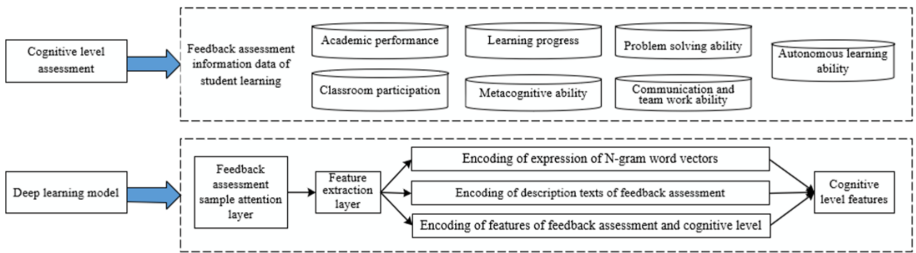

Fig. 1. Flow of cognitive level assessment of college students

This paper adopted a new-type deep learning model to mine the rich information hidden in the data of the feedback assessment information of students. The results output by the model are not limited to emotional judgment of students' feedback for online learning, but to extract more features of feedback assessment given by students to form more objective assessment results of students' cognitive level. Because one kind of feedback assessment information data of student learning may contain multiple assessment indicator tags, this paper formalized this problem as a "multi-tag classification task". Specifically, a student cognitive level attention layer was set to attain the generated feedback given by students for online learning, and these feedback contains the significant preferences of students. Then, a feedback assessment sample attention layer was set to introduce the descriptions of the feedback assessment information data of student learning. At last, the features of students' feedback assessment for online learning were mined objectively and comprehensively and were used to predict the corresponding tags, that is, the indicators for assessing students' cognitive level were tagged according to the data of feedback assessment information of student learning.

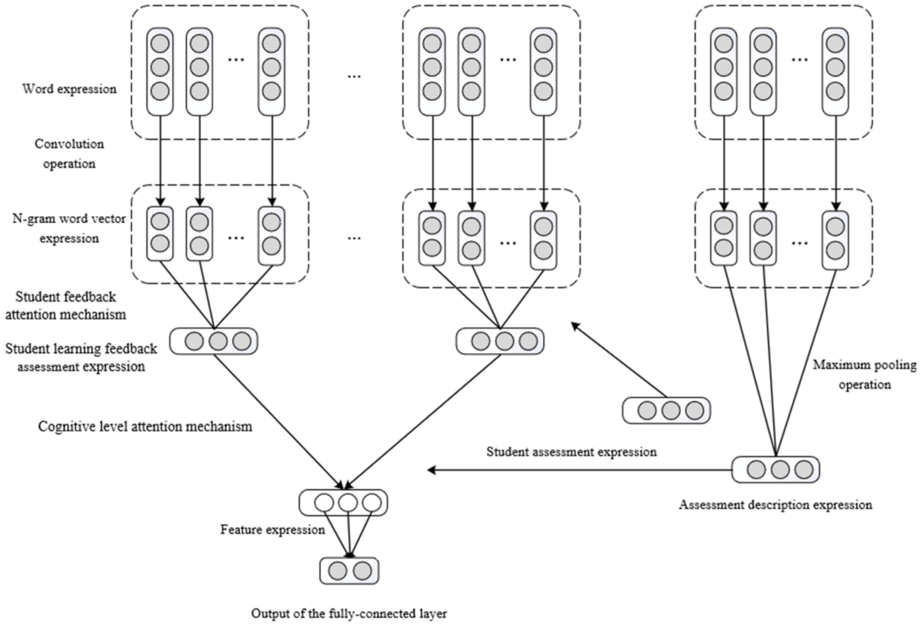

Fig. 2. Structure of cognitive level assessment model of college students

The model has two feature extraction layers, which are respectively used for encoding *N*-gram word vector expression in student learning feedback assessment and encoding the description texts of student learning feedback assessment, it also contains two attention layers, which are used to encode the features of feedback assessment and cognitive level of students. The expression of students' cognitive level features outputs the model prediction results through the fully-connected layer (Figure 2).

To ensure that a same word has different vector expressions in different contexts, the input of the constructed model was determined as the N-gram word vector expression, which could be attained through the learning of the *TextCNN* convolution layer. Assuming: $q_l \in S(2f_l+1)o$ represents the weight matrix of the *k*-th convolution core, $y_l \in R$ represents the bias of the *k*-th convolution kernel, $(2f_l+1)o$ represents the size of the *k*-th convolution kernel, o represents the dimension of word vector, $\hat{a}^i_{jl}$ represents the eigenvalue attained by the *l*-th convolution kernel, $\hat{a}^i_j \in R^{cg}$ represents the eigenvector attained by all convolution kernels by splicing the eigenvalue of the *j*-th word in the text, c_g represents the dimension of eigenvector, which is equal to the number of different convolution kernels, then the following formula calculates the convolution result of a specific convolution kernel:

$$\hat{a}^i_{jl} = g(q_l \cdot a^i_{j-f_l;j+f_l} + y_l) \tag{1}$$

Similarly, for a same word, there are differences in its meaning or emotional degree in different feedback assessments of student learning, so the model needs to design module at the word level to assign different weights to different words. The proposed model doesn't perform pooling operations on the N-gram eigenvector expression of all feedback assessment words of student learning, but adopts a student attention mechanism to screen out words that are important for the feedback assessment of student learning.

Assuming: x^i_j represents the attention weight of $\hat{a}^i_j$, it describes the importance of the j-th word in the meaning expression of feedback assessment; c_v represents the dimensionality of student eigenvector; $v_i \in R^{cv}$ represents a continuous real value vector that describes the eigenvector of the i-th student, then it can be considered that the weighted sum of the N-gram eigenvector of all words in the feedback assessment is the eigenvector expression of feedback assessment, and its form is:

$$s^i = \sum_{j=1}^{m^i} \beta^i_j \cdot \hat{a}^i_j \tag{2}$$

Assuming: $p(.)$ represents the scoring function for calculating the importance of a word to the current feedback assessment of student learning, then the attention weight β^i_j can be attained from the following formula:

$$\beta^i_j = \frac{\exp(p(\hat{a}^i_j, v^i))}{\sum_{k=1}^{m^i} \exp(p(\hat{a}^i_l, v^i))} \tag{3}$$

Assuming: u^T_v represents the transposed vector of weight vector u_v, y_v represents the bias vector, then the scoring function $p(.)$ can by defined as follows:

$$p(\hat{a}^i_j, v^i) = u^T_v \tanh(Q_q \hat{a}^i_j + Q_q v^i + y_v) \tag{4}$$

Because $\hat{a}^i_j$ and v^i are in different feature spaces, their meanings and the vector dimensions may differ greatly, so it's necessary to map $\hat{a}^i_j$ and v^i in the same feature space based on the transformed weight matrices Q_q and Q_v before calculation.

After going through the student attention layer, the different learning feedback assessments of different students could be encoded into an eigenvector with student preferences and taken as an input of the student cognitive level attention layer.

In the environment of online learning platforms, the false and meaningless feedback assessment of student learning does not make sense to the cognitive level prediction of the model, and it can even lower the generalization performance of the model. Thus, a feedback assessment information data attention mechanism has been proposed for the model to represent the importance of the different student learning feedback assessments on the cognitive level assessment of students, and to better integrate the eigenvectors of student learning feedback assessments of the student attention layer.

Different student learning feedback assessments could contribute different implicit information to the feature expression of students' cognitive level. In the constructed model, the adopted student cognitive level attention mechanism introduces the feedback assessment information data of student learning into the eigenvector generation link and assign different weights to different student learning feedback assessments, the meaning of these weights is the importance of the information contributed by different student learning feedback assessments to the cognitive level feature expression of a student and the information of the correlation between different student learning feedback assessments and the cognitive level of the student. At last, the cognitive level of each student was encoded into a specific eigenvector according to the weight. Assuming: γ^i represents the weight of learning feedback assessment s^i of the i-th student, then its calculation formula is:

$$p(s^i, w) = u_w^T \tanh(Q_s v_i + Q_w w + y_w) \tag{5}$$

$$\gamma^i = \frac{\exp(p(s^i, w))}{\sum_{l=1}^{n} \exp(p(s^l, w))} \tag{6}$$

$$\hat{w} = \sum_{i=1}^{n} \gamma^i \cdot s^i \tag{7}$$

After student learning feedback assessments and student information were input into the student attention layer, the feature expression of each piece of student feedback assessment was attained. At the same time, the descriptive information of student learning feedback assessments was input into *TexCNN* to get the feature expression of student learning feedback assessments. Then, multiple pieces of feature expression of student learning feedback assessments were input into the student cognitive level attention layer, and finally the eigenvector $\hat{w}$ of student cognitive level was attained, using which we could classify and assess the multiple tags of student cognitive level, that is, by taking $\hat{w}$ as the input of the fully connected layer of the constructed model, the distribution of the tags of student cognitive level t could be predicted. Assuming: Q_d represents the weight matrix of the fully connected output layer, y_d represents the bias vector of the fully connected layer, then there is:

$$t = Q_d \hat{w} + y_d \tag{8}$$

The bipartite cross-entropy loss was taken as the loss function of the constructed model. Assuming: O represents the training set, D represents the number of tag types, $b_d(c)$ represents whether training data c is related to tag d or not, $\varepsilon(a) = 1/1 + p^{-a}$ represents the *Sigmoid* activation function, the expression is:

$$K = -\sum_{c \in O} \sum_{d=1}^{d} [b_d(c) \log(\varepsilon(t_d(c))) + (1 - b_d(c)) \log(1 - \varepsilon(t_d(c)))] \tag{9}$$

3 Design of the learning path generation algorithm

Online learning paths can help students make effective use of online learning resources to achieve their learning goals. For a complete online learning path, the first thing is to figure out a student's learning goals, such as mastering a new skill, improving a vocational skill, or earning a certification. The second thing is to look for reliable online platforms such as Coursera, Udeme, edX, Khan, and Academy, and pick suitable courses or resources based on the student's learning interests and goals. Then, according to course difficulty, time, and the student's personal progress, a learning plan that fits the student should be formulated to determine the required learning time in each week and the time limit for finishing the course, learning sessions such as Q&A, discussion, note-taking, and key point summary could be set to stimulate students to learn and enhance their understanding and memory. By repeatedly recommending course videos, exercises or setting online discussions, the learning path can make sure that students regularly review what they learnt and consolidate their knowledge and skills. Also, the learning path can urge students to join online communities, forums or groups to share learning experiences, discuss questions, and gain support from others. If possible, when a student has completed the exam of a course or a project, a certificate could be issued to improve his/her sense of accomplishment. Because online learning is an ongoing process, platforms need to constantly update new courses and resources to maintain and improve students' knowledge and skills.

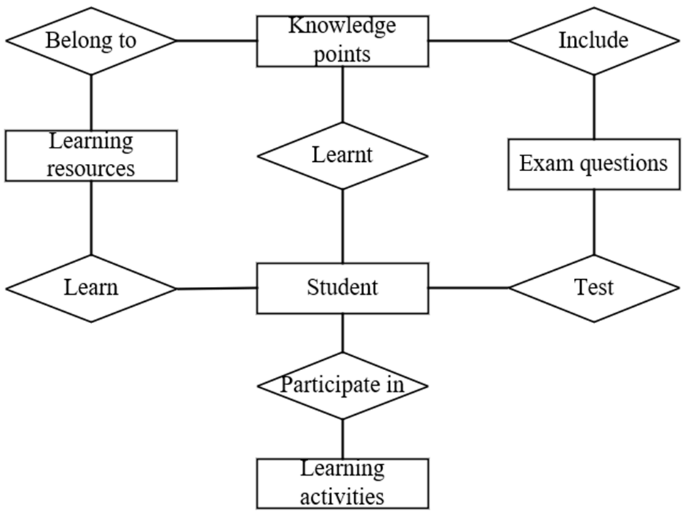

Fig. 3. Connection network recommended by learning path

Based on the cognitive level assessment results of college students in the previous section, this chapter proposed a weighted learning method that integrates the learning paths of students with different cognitive levels to ensure the interpretability of the generated learning paths. Aiming at the cognitive level of students on a specific learning path, different weights were assigned to learning paths according to the history student cognitive level on each node of the learning paths, thereby planning better and easier learning paths for students to realize their learning goals.

At first, the student, courses, learning resources, questions, exercise questions, and discussion topics were defined as the student node and the learning activity node to create a connection network, using *Node2Vec*, a sequence of nodes in a connection network could be generated and used to perform expression learning of the nodes. Figure 3 shows the connection network recommended by learning path.

Two kinds of constrained and unconstrained meta paths that start from students and end with students were designed, then by inputting the generated sequences with depth and breadth as search priorities into the *SkipGram* model, the four vector expressions corresponding to each student node could be attained. By splicing the four vectors, the vector expression of each student could be attained:

$$v = cat(v_{mc}, v_{bc}, v_{my}, v_{by}) \tag{10}$$

Based on the attained vector expression of each student, the similarity between any aspect of the learning cognitive level assessment indicators of students can be calculated further. Assuming: v_x represents the vector expression of student x, and v_y represents the vector expression of student y, then the similarity score can be calculated as follows:

$$sim(x, y) = \cos\left\langle v_x, v_y \right\rangle = \frac{v_x \cdot v_y}{\left\| v_x \right\| \times \left\| v_y \right\|} \tag{11}$$

In the online learning system, the learning records of all students can be recorded in the form of (v, d, w, h), which represents that a student v has carried out learning activity d within time period w and got a score of h. After all learning records are saved, the behavior sequence DR in the form of RT=(d_{str}, d_{nt}, v, h) can be generated, which represents that after learning activity d, student v carried out learning activity d_{nt} and got a corresponding score h, the online learning activities of all students can be defined and stored in this way.

Assuming: a student v's entire learning records are (v_1, d_1, w_1, 0.71), (v_1, d_2, w_2, 0.77), (v_1, d_3, w_2, 0.85), (v_1, d_4, w_3, 0.89), that is, the student has participated in two learning activities in time period w_2, then the student's sequential learning activity sequence can be represented by (d_0, d_1, v_1, 0.71), (d_1, d_2, v_1, 0.77), (d_1, d_3, v_1, 0.85), (d_2, d_4, v_1, 0.89), (d_3, d_4, v_1, 0.89).

When recommending a learning path for a student, it is necessary to consider the similarity between the student and other students in terms of cognitive level and the student's cognitive level on a specific learning path. The student's cognitive level can be attained through the previous section, and the similarity of students can be measured by the similarity score.

Assuming: v_x and v_y are quite different in terms of learning cognition features, v_y may not be able to achieve the same good learning effect as v_x if he/she follows the learning path of v_x. Besides, v_x and v_y have similar learning cognition features, even v_x gets unsatisfactory learning effect on a learning path, it does not mean that v_y won't get a good learning effect on that learning path. Based on above considerations, it is necessary to quantify the learning effect of each candidate learning path, and the quantification process needs to fully consider student similarity and student cognitive level. Assuming: v_i represents the current student; d_a represents the current learning activity; $d_b \in D$ represents the recommended learning activities, wherein $D = \{d_{nt}, RT \in D\hat{R}d_{str} = \hat{d}_a d_{nt} \in MR\}$; MR represents the set of learning activities not yet carried out by the target student, $R = \{RT : RT \in D\hat{R}d_{str} = \hat{d}_a d_{nt} = d_b\}$, then the recommendation score of a course can be calculated as follows:

$$score(d_a, d_b, v_i) = \sum_{seq \in R} sim(v_i, v) \cdot h \tag{12}$$

From candidate learning activities, the learning activity with the highest score is selected and taken as the first node in the learning path, then starting from this node, other candidate learning activities are chosen, and this process is repeated until the length of the learning path reaches the maximum or there is no candidate learning activity to choose, and the finally generated learning activity sequence is the recommended learning path.

4 Experimental results and analysis

The feedback assessment information data of student learning came from a few sources, including academic performance, classroom participation, learning progress, metacognitive ability, problem solving ability, communication and team work ability, and autonomous learning ability, which were numbered 1 to 7 respectively. Because the existing data sample set did not contain all the texts from the sources, so this paper combined with the text corpus containing a large amount of feedback assessment information data of student learning to construct the test data sample set. Basic information is summarized in Table 1.

Table 1. Interaction distribution of feedback assessment information data of student learning

Serial Number of the Source	Number of Training Sets	Number of Test Sets	Total Number
1	1196	308	1504
2	1946	462	2408
3	1468	358	1826
4	921	218	1139
5	1076	286	1362
6	723	188	911
7	1145	254	1399
Total	8475	2074	10549

Table 2. Experimental results of cognitive level assessment

Method	Indicator	Source of Feedback Assessment Information Data							Micro	Macro
		1	**2**	**3**	**4**	**5**	**6**	**7**		
Student attention mechanism is introduced	Accuracy	78.680	75.598	89.145	87.453	85.751	86.921	84.511	88.132	88.021
	Recall rate	81.210	80.053	87.217	88.264	83.127	89.691	86.241	88.132	87.684
	F1	80.219	77.423	83.845	86.135	84.597	88.201	82.465	88.132	81.056
	Precision	85.967								
Student cognitive level attention mechanism is introduced	Accuracy	80.125	77.264	87.668	84.214	82.745	87.413	86.395	88.215	83.127
	Recall rate	83.354	83.571	80.908	86.28	85.515	82.113	81.526	88.215	86.748
	F1	82.051	80.551	82.169	85.371	80.996	83.054	88.659	88.215	86.495
	Precision	87.169								
Student learning assessment description information is introduced	Accuracy	78.852	80.216	82.452	86.954	82.361	89.693	86.241	87.268	87.752
	Recall rate	87.295	79.568	80.415	86.517	80.541	83.515	88.634	87.268	87.584
	F1	82.103	79.590	80.602	86.214	85.214	86.548	81.245	87.268	87.295
	Precision	88.106								

Table 2 summarizes the experimental results of cognitive level assessment. According to the table, it's known that introducing student attention mechanism, student cognitive level attention mechanism, and student learning assessment description information has a positive effect on improving the accuracy of the cognitive level assessment results. The average accuracy, average recall rate, and average F1 value increased by 2.53%, 2.46%, and 2.39%, respectively. Figure 4 gives the results of the ablation experiment of the model, which further verified the validity of the adopted model. In the figure, Model 1 is a conventional *TectCNN* model which hadn't introduced the student attention mechanism, student cognitive level attention mechanism, or student learning assessment description information; Model 2 is an *TectCNN* which had only introduced the student attention mechanism; Model 3 is an *TectCNN* which had introduced the student attention mechanism and the student cognitive level attention mechanism.

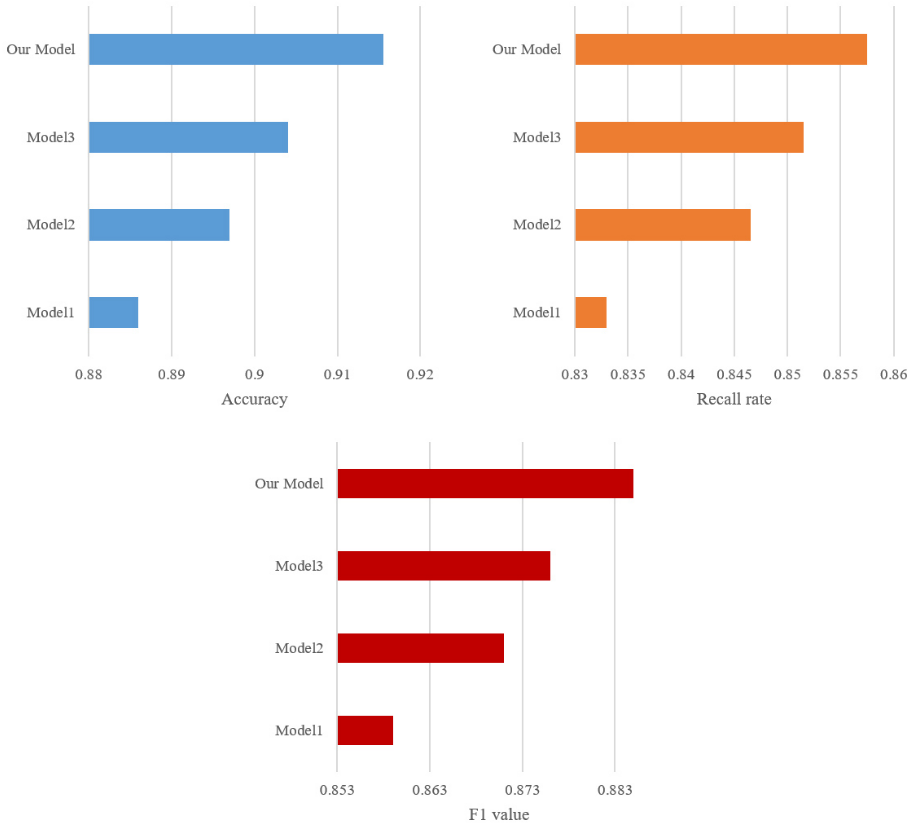

Fig. 4. Results of model ablation experiment

In order to more comprehensively and objectively extract the feedback assessment features of student learning, in this paper, the assessment evolved multiple indicator sources, so the influence of the quantity of feedback assessment information on the assessment results of the model was analyzed. The experimental results are shown in Figure 5. The vertical coordinate is accuracy, recall rate, and F1 value, respectively, and the horizontal coordinate is the quantity of feedback assessment information.

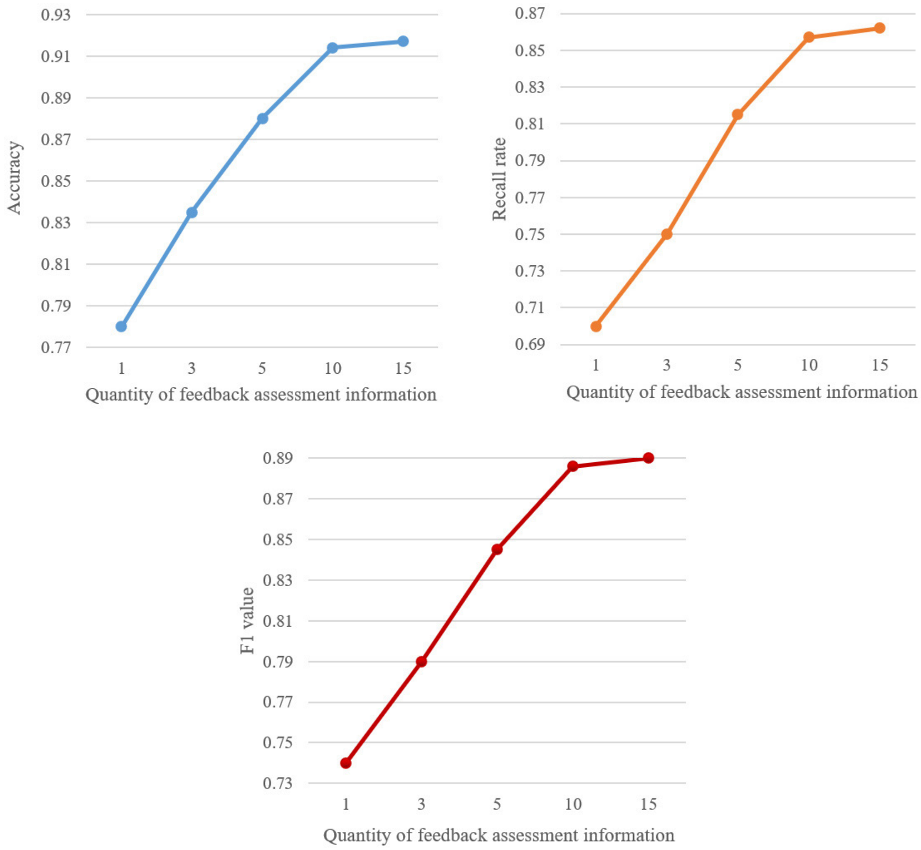

Fig. 5. Experimental results of the influence of feedback assessment information quantity on assessment results

According to Figure 5, the performance of the model rises as the quantity of feedback assessment information grows, which is in line with the performance expectations of the model. When the information quantity is small or there is only one piece of information, the information contained is not comprehensive and objective enough. But when the information quantity grows to a certain number, the model performance shows no significant improvement, and this is because the model can fully extract effective information at this time can make judgement on student's cognitive level, so increasing the quantity of assessments at this time is meaningless.

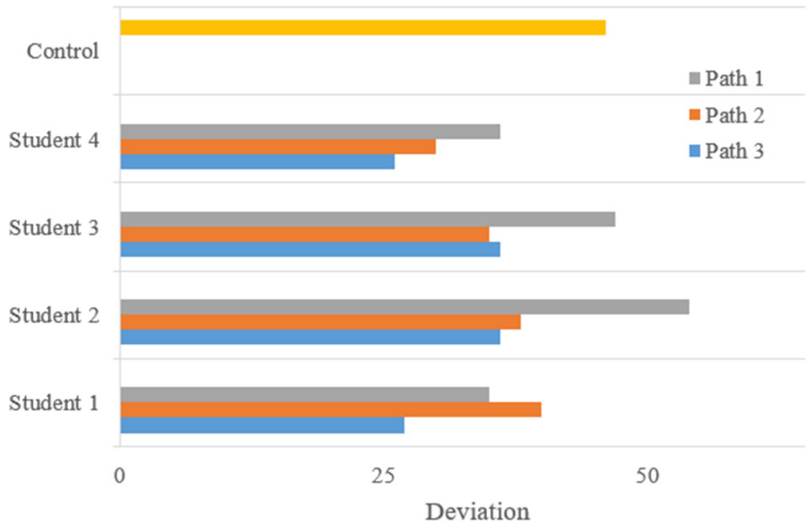

Fig. 6. Calculation of path deviation

This paper calculated the deviation of generated learning paths, and measured students' satisfaction with the learning paths. Figure 6 shows the calculation results, namely the absolute value of the difference between the node sequence of the real path and the node sequence of the generated path. According to the figure, compared with Path 2 (generated based on the KgRank algorithm) and Path 3 (generated based on the PageRank algorithm), Path 1 (generated based on the method proposed in this paper and with the student's cognitive level taken into consideration) is closer to the actual learning requirements of students, which has verified the practicability of the proposed method.

5 Conclusion

This paper studied the construction of online learning paths based on the cognitive level assessment of college students. At first, this paper introduced a deep learning model into the assessment of college students' cognitive level, that is, the collected data of feedback assessment information of student learning was adopted to assess students' cognitive level, then the paper introduced in detail the structure and principle of the proposed model. After that, this paper proposed a weighted learning method that integrates the learning paths of students with different cognitive levels to ensure the interpretability of the generated learning paths. For a specific student cognitive level on learning paths, the proposed method assigns different weights for learning paths based on the history student cognitive level on each node of the learning paths, thereby planning better and easier learning paths for students to achieve their learning goals. To carry out experiments, this paper combined with the text corpus containing a large amount of feedback assessment information data of student learning to construct the test data sample set, summarized the basic information, gave the results of cognitive level experiment and model ablation experiment, and verified that introducing student attention mechanism, student cognitive level attention mechanism, and student learning assessment description information has a positive effect on improving the accuracy of the cognitive level assessment results. Moreover, the influence of the quantity of feedback assessment information on the assessment results of the model was analyzed. In the last part, this paper calculated the deviation of generated learning paths, and found that the learning path generated based on the proposed method can better fit students' learning requirements than the learning paths generated based on the KgRank algorithm and the PageRank algorithm, and these results had verified the practicability of the proposed method.

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