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AI-assisted personalized learning path optimization strategy

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Abstract This paper proposes an artificial intelligence-driven personalized learning path optimization framework for the problems of high dropout rate and low course passing rate in online learning. A fuzzy cognitive diagnostic model (Fuzzy-CDF) is introduced to replace the traditional binary diagnosis, and through fuzzy intersection and merger operation and 4-Logistic parameter correction, the continuous cognitive level value is output, so as to realize the fine-grained quantification of the mastery degree of knowledge points. A two-dimensional learning state model of "basic knowledge + pattern knowledge" is constructed, in which the pattern knowledge dynamically portrays the cognitive structure from four attributes: overall level, feature point level, coverage set level, and coverage level. We also design a knowledge graph-based failure rate update mechanism to locate the weak points through the initial failure rate matrix, and dynamically correct the assessment results using the contribution value of the centrality of the knowledge points, so as to realize the accurate push of personalized resources. Experimental validation shows the effectiveness of Fuzzy-CDF diagnosis, in the test of 237 students, the model accurately identifies the weak points of the group, the mastery rate of curve integral A3 is 31.71%, the reintegration application A8 is only 27.42%, and the mastery rate of the strong knowledge point of the infinite number of steps A4 reaches 90.55%. Oriented to the four differentiated learning state users, the satisfaction of this method for planning paths reaches up to 4.823, which significantly exceeds the genetic algorithm GA and the ant colony algorithm ACO, with an average improvement of 14.7%, and the matching degree reaches 0.79-0.91.

Index Terms fuzzy cognitive diagnosis, personalized learning paths, Fuzzy-CDF, learning state characteristics, learning resource pushing

I. Introduction

With the development of information technology, online learning platforms are increasingly tending towards personalized, intelligent and precise services [1]. In the face of learning resources with large amount of data, strong specialization and complex knowledge structure, the problem of online users' learning lost is particularly prominent, so online users urgently need personalized learning path recommendation services to help them discover the knowledge information they need in a timely and accurate manner [2]-[4]. Personalized learning path is the route of learning activities and knowledge sequence chosen by online users according to their own learning preferences, learning styles and learning levels as well as environmental factors in the learning process [5]. Practice has proved that personalized learning path recommendation can realize the dynamic guidance and effective control of online users' learning behavior [6].

At present, there are still many problems in the field of education, such as uneven distribution of teaching resources, single teaching method, and poor learning effect of students [7]. And artificial intelligence technology, with its powerful data processing and analysis capabilities, provides new possibilities for solving these problems. On the one hand, AI technology can realize intelligent teaching design and implementation, intelligent classroom management and interaction, and personalized learning support by optimizing teaching methods [8]-[10]. On the other hand, AI technology can improve students' learning effects in inquiry-based learning through intelligent assessment and feedback, and help students' personalized development [11]-[13]. Therefore, the development of AI technology provides strong support for students' personalized independent learning.

In this paper, an innovative framework integrating cognitive diagnosis, learning state modeling and dynamic resource pushing is proposed around AI-driven personalized learning path optimization. The article introduces a fuzzy cognitive diagnosis model (Fuzzy-CDF) to quantify the cognitive level, constructs a bi-dimensional learning state feature model, and designs a knowledge graph-based updating mechanism for the failure rate. Firstly, breaking through the traditional binary diagnosis limitations, the Fuzzy-CDF model is adopted to realize the fine-grained assessment of cognitive level. The model quantifies the knowledge mastery as [0,1] continuous values through fuzzy set theory, combines fuzzy intersection/combination operations to deal with the subjective and objective differences in the question types, and introduces a 4-Logistic model to correct the interference of guessing/failure factors, so as to ultimately output a more accurate cognitive level score. Then we constructed a two-dimensional learning state feature model of “basic knowledge + pattern knowledge”. In the explicit knowledge dimension, the overall knowledge level is calculated from the collection of historical test scores. In the implicit knowledge dimension, the concept of “pattern knowledge” is innovatively proposed, and a dynamic cognitive portrait is constructed from four attributes: overall level, feature point level, coverage set level, and coverage level. The model breaks through the traditional static framework and can be updated in real time with the learning process, so as to accurately portray the evolution of cognitive structure. Finally, personalized resource pushing strategy is designed based on the output of the aforementioned model. The weak points are initially screened through the knowledge point failure rate matrix, and then the knowledge graph topology is introduced to dynamically correct the assessment results by utilizing the contribution value calculation and failure rate update mechanism.

II. Personalized Learning Path Recommendation and Learning Resource Push Design

II. A.Fuzzy-CDF cognitive diagnostic modeling

Cognitive level refers to the learner's mastery of knowledge, including what he/she has mastered and what he/she has not mastered. For learners, cognitive level reflects the process of learners from quantitative change to qualitative change, and this process can not be directly observed, so you can get a learner's cognitive level through the test questions test, so you can analyze the learner's learning status.

In cognitive psychology, the modeling process of the learner's mastery of knowledge is called cognitive diagnostic model. In personalized learning, the more typical cognitive diagnostic models are DINA model, DINO model, etc., but these models are all second-level scoring cognitive diagnostic models, i.e., only mastery and not mastered two states. In order to get the learner's cognitive level at a finer granularity, this paper adopts the fuzzy cognitive diagnostic model Fuzzy-CDF model to obtain the learner's knowledge mastery, the output of this model is a continuous value between 0-1, which can get the learner's mastery of the knowledge points more accurately, the Fuzzy-CDF model takes into account the mistakes and guessing factors to generate the observable scores of candidates on the questions.

Incorporating fuzzy set theory in the Fuzzy-CDF model and applying fuzzy numbers to quantify subjective, qualitative and uncertain information, assuming that the learner's level of knowledge competence is the learner's degree of affiliation in the fuzzy set corresponding to that knowledge competence, then in the objective questions, the mastery level of learner j on test i, η_{ji}, is the fuzzy intersection of the degree of cognition of learner j for the knowledge point, and in the subjective questions, η_{ji}, the fuzzy concatenation of learner j's cognitive degree for the knowledge point, and the specific calculation is shown in equations (1) and (2).

$$\eta_{ji} = \bigcap_{1 \le k \le K, q_{ik}=1} \mu_k(j) \tag{1}$$

$$\eta_{ji} = \bigcup_{1 \le k \le K, q_{ik}=1} \mu_k(j) \tag{2}$$

where $q_{ik} = 1$ indicates whether test question i examines knowledge point k, and K indicates the total number of knowledge points examined in test question i. Whether a learner answers a question correctly or incorrectly is affected by the learner's mastery of the knowledge points, and also affected by the guessing and error factors, which leads to the inability to accurately obtain the learner's true ability, so the 4-Logistic model can be used to estimate the error and guessing parameters, and intervene in the acquisition of the learner's ability. The specific calculation is shown in Equation (3).

$$P\left(X_{ij} = 1 \mid \theta_j; a_j, b_j, c_j, d_j\right) = c_j + (d_j - c_j)\frac{e^{1.7a_j(\theta_j - b_j)}}{1 + e^{1.7a_j(\theta_j - b_j)}} \tag{3}$$

a_j, b_j, c_j, and d_j denote the differentiation, difficulty, guessing, and missing parameters, respectively. Finally, the learners' true response scores on objective and subjective questions are obtained, which are calculated as shown in Eqs. (4) and (5).

$$P(R_{ji} = 1 \mid \eta_{ji}, s_i, g_i) = (1 - s_i)\eta_{ji} + g_i(1 - \eta_{ji}) \tag{4}$$

$$P\left(R_{ji} = 0 \mid \eta_{ji}, s_i, g_i\right) = N\left(R_{ji} \mid (1 - s_i)\eta_{ji} + g_i(1 - \eta_{ji}), \sigma^2\right) \tag{5}$$

where R_{ji} denotes learner j 's score on trial question i , and s_i and g_i denote learner j 's misses and guesses on trial question i , respectively.

II. B. Learning state characteristics

The fine-grained cognitive level data obtained based on the Fuzzy-CDF model provides a quantitative basis for comprehensively portraying the learning state. In order to further reveal the deeper features of the cognitive structure, this paper constructs a dynamic learning state model from the dual perspectives of explicit and tacit knowledge.

II. B. 1) Basic knowledge learning state

Describes the level of mastery of basic knowledge, i.e. explicit knowledge. The learning status dimension of basic knowledge includes the characteristic attribute “overall knowledge level”. The overall knowledge level of basic knowledge refers to the student's overall mastery of previously learned explicit knowledge. If S_{BKS} represents the set of test scores for the explicit knowledge that the target student has learned, then we have

$$S_{BKS} = \left\{ s_{BK_1}, s_{BK_2}, \cdots, s_{BK_n} \right\} \tag{6}$$

where s_{BK_i} is the test score of basic knowledge bk_i . Then the overall knowledge level of basic knowledge of the target students can be represented by S_{BKS} .

II. B. 2) Schema knowledge learning state

Describe the student's level of mastery of pattern knowledge, i.e., tacit knowledge. The dimension of pattern knowledge learning status includes four feature attributes: "overall knowledge level", "feature point knowledge level", "pattern knowledge coverage set knowledge level" and "pattern knowledge coverage level".

(1) Overall knowledge level: the overall knowledge level of schema knowledge refers to the overall mastery of the schema knowledge that students have learned in the past. Let S_{PKS} denote the set of test scores of all n schema knowledge that the target student has already learned, then there are

$$S_{PKS} = \left\{ s_{PK_1}, s_{PK_2}, \cdots, s_{PK_n} \right\} \tag{7}$$

where s_{PK_i} is the test score of pattern knowledge pk_i . Then the overall knowledge level of pattern knowledge of the target students can be represented by the set S_{PKS} .

(2) Characteristic point knowledge level: the characteristic point knowledge level of pattern knowledge refers to the degree of students' mastery of each characteristic point of pattern knowledge that has been learned in the past. Let S_{PKFS} denote the set of test scores of each feature point of all schema knowledge that the target students have learned, then there are

$$S_{PKFS} = \left\{ S_{FS_1}, S_{FS_2}, \cdots, S_{FS_n} \right\} \tag{8}$$

where n is the total number of all schema knowledge that has been learned by the target student, S_{FS_i} is the set of all feature point scores of the schema knowledge pk_i that has been learned by the target student, and there are

$$S_{FS_i} = \left\{ sp_{PK_i,F_1}, sp_{PK_i,F_2}, \cdots, sp_{PK_i,F_m} \right\} \tag{9}$$

where m is the total number of feature points of schema knowledge pk_i , and $sp_{PK_iF_j}$ is the test score of the j th feature point of schema knowledge pk_i that has been learned by the target student. Then the pattern knowledge feature point knowledge level can be represented by the set S_{PKFS} .

(3) Pattern knowledge coverage set knowledge level: pattern knowledge coverage set knowledge level refers to the overall mastery of the basic knowledge points in the coverage set of pattern knowledge by students. Let S_{PKCS} denote the collection of test scores of all the basic knowledge points that students have learned in the coverage set of pattern knowledge that the target students have learned, then there are

$$S_{PKCS} = \left\{ S_{CS_1}, S_{CS_2}, \cdots, S_{CS_n} \right\} \tag{10}$$

where n is the total number of all schema knowledge that has been learned by the target student, S_{CS_i} is the set of test scores for all basic knowledge points that have been learned by the student in the coverage set of schema knowledge pk_i, and there are

$$S_{CS_i} = \left\{ s_{BK_1}, s_{BK_2}, \cdots, s_{BK_m} \right\} \tag{11}$$

where m is the total number of all basic knowledge points that students have learned in the coverage set of schema knowledge pk_i, and s_{BK_j} denotes the test scores of the basic knowledge bk_j that students have learned in the coverage set of schema knowledge pk_i. Then the pattern knowledge coverage set knowledge level can be represented by the set S_{PKCS}.

(4) Pattern knowledge coverage level: pattern knowledge coverage level refers to the proportion of basic knowledge points in the coverage set of pattern knowledge that students have mastered. Let S_{CD} denote the set of coverage level of all schema knowledge of the target students, then there are

$$S_{CD} = \left\{ p_{PK_1}, p_{PK_2}, \cdots, p_{PK_n} \right\} \tag{12}$$

where n is the total number of all schema knowledge that the target student has learned, and p_{PK_i} denotes the target student's coverage level of schema knowledge pk_i. Then the coverage level of schema knowledge of the target student can be represented by S_{CD}.

The individual learning characteristic model constructed in this paper has the following characteristics compared with the traditional learning characteristic model:

(1) Based on the knowledge construction idea of constructivism, the concept of pattern knowledge is introduced into the model, which emphasizes students' mastery of pattern knowledge and focuses on portraying students' pattern knowledge learning state, which can truly reflect students' cognitive structure.

2) The model reflects the idea of dynamic development. The traditional individual learning characteristic model is usually static and will not be changed once it is constructed. With the development of learning activities, students construct new knowledge through assimilation, conformity and other ways, the schema is constantly being transformed, and the cognitive structure is constantly developing. The individual learning characteristic model proposed in this paper can be updated with the changes of students' cognitive structure, and the characterization of students' learning characteristics is more accurate.

3) Adapt to network teaching. Network teaching can collect information about students' learning activities in real time during the teaching process and use big data technology to analyze students' individual learning characteristics. The model proposed in this paper can utilize this information to efficiently construct students' learning characteristics, especially learning state characteristics. In addition, most of the traditional learning characteristic models are difficult to be directly applied in online teaching, and the model proposed in this paper is improved by analyzing the traditional model, which is more suitable for online teaching.

II. C.Personalized Learning Resources Push

In order to realize personalized learning resources push, the system recommends learning resources for corresponding knowledge points to student users according to the learning path of the course, calculates the knowledge point failure rate of the student user based on the data obtained from the constructed student model data that the student user completes the test questions for the corresponding knowledge points, and then uses the centrality of the knowledge points to update the knowledge point failure rate of the student user.

II. C. 1) Initialization of Student User Knowledge Points Failure Rate

Definition 1: The test question loss rate is the ratio of the number of points lost by a student user completing a test question with an error to the full score of the test question.

Assuming that the test trial completed by student user S_i is denoted as $T_{S_i}^{Z}$, $Z \in 1, 2 \cdots, M$, and the lost score rate of the completed test trial is denoted as $\varnothing_{S_i}^{Z}$, the vector of the lost score rate of all completed test trials by student user S_i is shown in Eq. (13):

$$\varnothing_{S_i} = \left(\varnothing_{S_i}^{1}, \varnothing_{S_i}^{2}, \cdots, \varnothing_{S_i}^{M} \right) \tag{13}$$

Definition 2: The Knowledge Point Missing Ratio is the ratio of the sum of the Missing Ratio of the Knowledge Point test exercises completed by the student user to the total number of all exercises completed.

A test question may contain one or more knowledge points, and the ratio of the sum of the failure rate of the knowledge point K_N test questions completed by the student user and the total number of all the exercises completed by the student user is denoted as $R_{S_i}^{K_N}$, and the vector of failure ratios for the N knowledge points that the student user S_i has completed in the course of the learning process is shown in Eq. (14):

$$R_{S_i} = \left(R_{S_i}^{K_1}, R_{S_i}^{K_2} \cdots R_{S_i}^{K_N} \right) \tag{14}$$

Definition 3: The occurrence rate of a knowledge point refers to the ratio of the number of times the knowledge point appears in the test exercises completed by the student user to the total number of test exercises completed.

Assuming that student user S_i has completed a total of α test questions, the occurrence rate of the knowledge point K_N in the α test exercises completed by student user S_i is recorded as $P_{S_i}^{K_N} = \frac{\sum_1^{\alpha} r_{S_i}^{Z}}{\alpha}$, then the vector of occurrences of N knowledge points learned by student user S_i is shown in Equation (15):

$$P_{S_i} = \left(P_{S_i}^{K_1}, P_{S_i}^{K_2}, \cdots P_{S_i}^{K_N} \right) \tag{15}$$

Definition 4: Knowledge point failure rate refers to the ratio of the knowledge point failure ratio to the knowledge point occurrence rate of the student user in completing the course. Its calculation formula can be expressed as $f_{S_i}^{K_N} = \frac{R_{S_i}^{K_N}}{P_{S_i}^{K_N}}$, and it can be seen from Eq. that the matrix of N knowledge points lost points ratio learned by U student users is shown in Eq. (16):

$$F = \begin{pmatrix} f_{S_1}^{K_1} & \cdots & f_{S_1}^{K_N} \\ \vdots & \ddots & \vdots \\ f_{S_U}^{K_1} & \cdots & f_{S_U}^{K_N} \end{pmatrix} \tag{16}$$

In this paper, the method of calculating the lost score rate of knowledge points is to calculate the lost score rate of knowledge points that are independent of each other, and $f_{S_i}^{K_N}$ denotes the lost score rate of student user S_i in completing the test exercises that contain the knowledge point K_N.

II. C. 2) Updating Knowledge Point Loss Rates Using Knowledge Point Centrality

Since the knowledge points of the initialization model of the knowledge point loss rate of student users established are independent of each other, in order to improve the assessment accuracy of the system to assess the mastery of knowledge points by student users, the system uses the knowledge point centrality degree to update the knowledge point loss rate. The contribution value between knowledge points is calculated according to the formula of knowledge point centrality, and the contribution value of knowledge point K_b to knowledge point K_a is represented by $W(K_a, K_b)$, and the assessment coefficients $\alpha = 1$ and $\gamma = \frac{1}{2}$ are taken to be $W(K_a, K_b)$ is calculated as follows:

$$W(K_a, K_b) = C(K_a) + \left(\frac{1}{2}\right)^m C(K_b) \tag{17}$$

where m denotes that knowledge point b is an m-order neighbor of knowledge point a, then the lost score rate of knowledge point a is updated as $\left(f_{S_i}^{K_a}\right)'$, which is calculated as follows:

$$\left(f_{S_i}^{K_a}\right)' = f_{S_i}^{K_a} + f_{S_i}^{K_p} W(K_a, K_b) \tag{18}$$

The matrix F' of the failure rate of N knowledge points learned by U student users after updating is shown in Equation (19):

$$F' = \begin{pmatrix} \left(f_{S_1}^{K_1}\right)' & \cdots & \left(f_{S_1}^{K_N}\right)' \\ \vdots & \ddots & \vdots \\ \left(f_{S_U}^{K_1}\right)' & \cdots & \left(f_{S_U}^{K_N}\right)' \end{pmatrix} \tag{19}$$

The system evaluates whether the student's learning of the corresponding knowledge points meets the course requirements or the student's customized learning objectives through the student user's failure rate of the knowledge points, and pushes the learning resources corresponding to the knowledge points with a lower mastery degree to the student user for learning, realizing personalized learning resource push and improving the efficiency of the student user's learning course.

III. Fuzzy-CDF-based learning diagnosis and personalized test question recommendation application

The cognitive diagnostic models based on Fuzzy-CDF can both diagnose learners' learning and recommend personalized learning resources to them. Based on this, this chapter applies the learning diagnosis and personalized learning resource recommendation method integrating Fuzzy-CDF to specific teaching, firstly, verifies the effect of the Fuzzy-CDF cognitive diagnosis model proposed in this study through experiments, and then combines the results of the Fuzzy-CDF cognitive diagnosis model's diagnosis of the learner's knowledge state to realize the personalized learning resource recommendation for the learner. The results of the Fuzzy-CDF cognitive diagnosis model on learners' knowledge status are then combined to realize the recommendation of personalized learning resources for learners.

III. A. Experimental setup

III. A. 1) Experimental environment

The environment for the experiments in this study is shown below: the CPU is AMD Ryzen 5 5500U with Radeon Graphics 2.10 GHz, the GPU is NVIDIA Tesla V100 with 32G, and the operating system of Windows 10 is utilized. All the models in this experiment were done using the Python 3.7 programming language; also, the Python based Py2neo graph database toolkit was utilized to call the open source graph database Neo4j to construct the knowledge graph; and the data analysis software SPSS was also used to statistically analyze the collected dataset.

III. A. 2) Data acquisition

This chapter focuses on applying the fuzzy cognition-based learning diagnosis and personalized learning resource recommendation methods to specific experiments.The data used in this experiment comes from the real data of the midterm test of the 2024 nuclear engineering majors of a university about Advanced Mathematics (second year of sophomore year), which is used as the object of the study. The dataset contains a total of 4 classes with a total of 237 students' midterm math test test data.

The test can be broken down into 10 knowledge points, A1: Differential of Multiple Functions, A2: Integration of Multiple Functions, A3: Integration of Curves and Integration of Surfaces, A4: Infinite Series, A5: Fourier Series, A6: Ordinary Differential Equations, A7: Differential of Vector-Valued Functions, A8: Applications of Reintegration, A9: Integration of Included Parametric Variables, and A10: Preliminary Field Theory.

III. B. Fuzzy-CDF Cognitive Diagnostic Model Diagnosis

In response to the diagnostic results of the Fuzzy-CDF model, a fuzzy cognitive diagnostic model, this experiment focuses on the analysis of the overall student mastery of the knowledge points.

By diagnosing the records of students' test responses in four classes, this experiment obtains the specific mastery level of overall students for the 10 knowledge points. Table 1 shows the probability of 237 students' mastery for the 10 knowledge points.

Table 1: The probability of students' mastery of 10 knowledge points

Knowledge points	Master probability/%	Number of students	
		Mastered	Not mastered
A1: Differential calculus of multivariate functions	62.41	156	81
A2: Integral calculus of multivariate functions	64.37	161	76
A3: Curve integral and surface integral	31.71	62	175
A4: Infinite series	90.55	230	7
A5: Fourier series	71.28	184	53
A6: Ordinary differential equation	56.96	139	98
A7: Vector-valued function differentiation	54.44	132	105
A8: Application of multiple integrals	27.42	27	210
A9: Integral with parameters	86.98	194	43
A10: Introduction to Field Theory	73.66	164	73

From the table, it can be seen that the overall students' probability of mastering knowledge points A1, A2, A4, A5, A6, A7, A9, and A10 is higher than 50%, which indicates that as a whole, the students have reached the level of mastery for these knowledge points; The probability of students' mastery of Knowledge Point A3 and Knowledge Point A8 was only 31.71% and 27.42%, indicating that students did not reach the mastery level of either of the two knowledge points.

The above gives the probability values of overall students' mastery of the 10 knowledge points. Next, this experiment specifically analyzed how many students reached mastery level and how many students did not reach mastery level for each knowledge point. Knowledge point A3 and knowledge point A8 are curve and surface integrals and reintegration applications, respectively. For knowledge point 3, out of the 237 students selected for the experiment, 62 students mastered this knowledge point and 175 students did not. For knowledge point 8, only 27 students mastered this knowledge point and 210 students did not. The specific students' mastery of knowledge points A3 and A8 is shown in Figure 1.

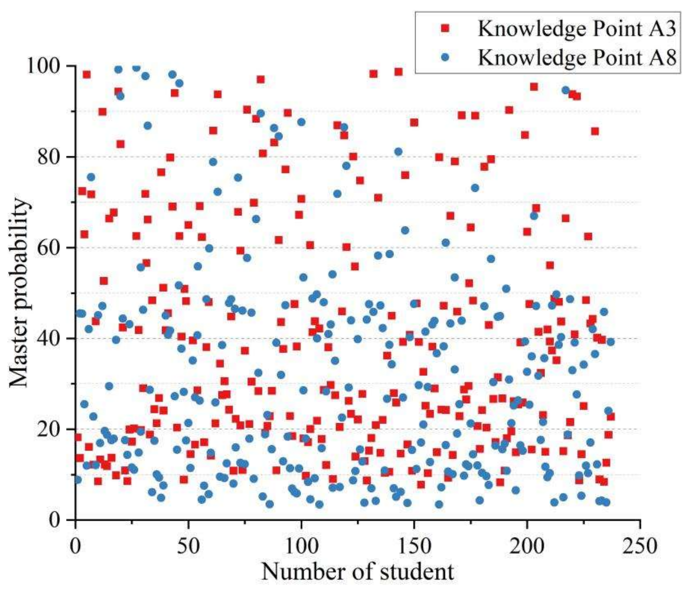

Figure 1: Students' mastery of knowledge points A3 and A8

Further observation of Table 1 shows that the knowledge point A4 Infinite series was best grasped by the students, with only 7 students not grasping it, and Figure 2 demonstrates the mastery of the students regarding the knowledge point A4.

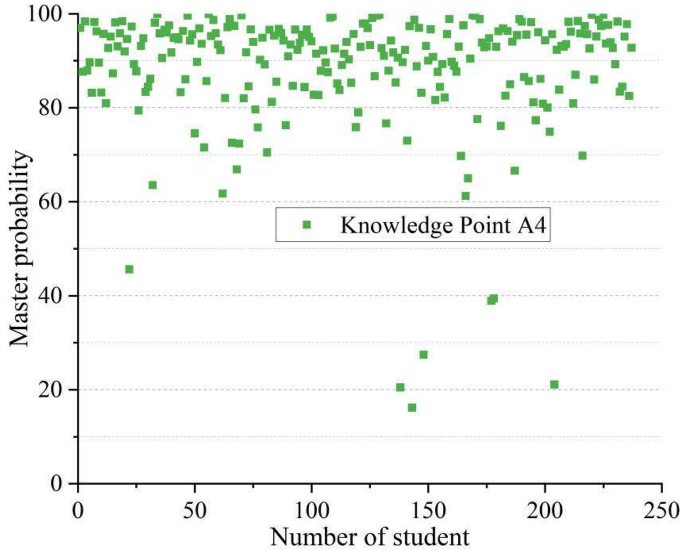

Figure 2: Students' mastery of knowledge point A4

IV. Experiments on personalized recommendation of online learning resources and learning path planning

The diagnostic results of Fuzzy-CDF reveal students' knowledge weaknesses, but locating the shortcomings alone is not sufficient for path optimization. For this reason, Chapter 4 fuses the diagnostic output and learning state features, introduces a knowledge graph-driven updating mechanism for the failure rate, and validates the feasibility and effectiveness of the online learning path planning method through comparative experiments. This subsection verifies the feasibility and effectiveness of the algorithm proposed in this paper based on user learning state features from two perspectives respectively by comparing it with two algorithms, Genetic Algorithm (GA) and Ant Colony Algorithm (ACO).

IV. A. Experimental design

IV. A. 1) Data sets

The data for this experiment comes from the web data in the online learning platform-MOOC Academy, which has courses categorized according to different fields, and each course has corresponding user ratings, level of difficulty, and a list of courses associated with the course. In this paper, we use a web data collector-Octopus Collector to capture all the course information in the fields of Computing and Data and Statistics. Among them, there are 1028 courses in the field of computing and 836 courses in the field of data and statistics, totaling 1864 course information. Second, four users with widely different learning status characteristics were simulated as experimental subjects to illustrate the objectivity of the experiment. The four users are described as follows:

User 1: (5, -2, 3, -4), with a high overall level of schema knowledge, but an uneven mastery and low coverage of feature points;

User 2: (-3, 1, -5, 7), high coverage of pattern knowledge but weak mastery of overall level and feature points (e.g., good at application but weak theoretical foundation);

User 3: (-2, 4, 6, -1), outstanding level of feature point knowledge but low level of coverage set knowledge (e.g., proficient in details but lacks the ability to correlate knowledge);

User 4: (0, -7, 2, 5), medium level of coverage set knowledge but very weak level of feature point knowledge (e.g., able to understand the framework but unable to break down the application).

IV. A. 2) Judging criteria

The e-learning path planning method proposed in this paper aims to plan an efficient learning path for users that is suitable for the characteristics of users' learning state and in line with the actual learning process, to help users effectively achieve their learning goals, to improve user satisfaction, and to solve the problem of high dropout rate and low course pass rate of e-learning. Therefore, the validation of the e-learning path planning method mainly includes two parts: the degree of conformity between the learning path and the user's learning style and the user satisfaction.

IV. B. Iterative Analysis of Learning Paths

One of the experimental subjects is randomly selected, for which a learning path is planned according to the online learning path planning method based on learning state proposed in this paper, and the results are compared with those obtained by GA and ACO methods, thus verifying the feasibility of the method. In this experiment, the initial population number is set to be 7, the number of nodes to be 12, and the maximum number of iterations to be 50.Taking user 1 as an example, Fig. 3 shows the results of the learning path iterations for user 1. Its learning state is characterized by (5, -2, 3, -4), and the learning path planning method proposed in this paper, after 50 iterations, finally plans a learning path with a user satisfaction score of 4.823.

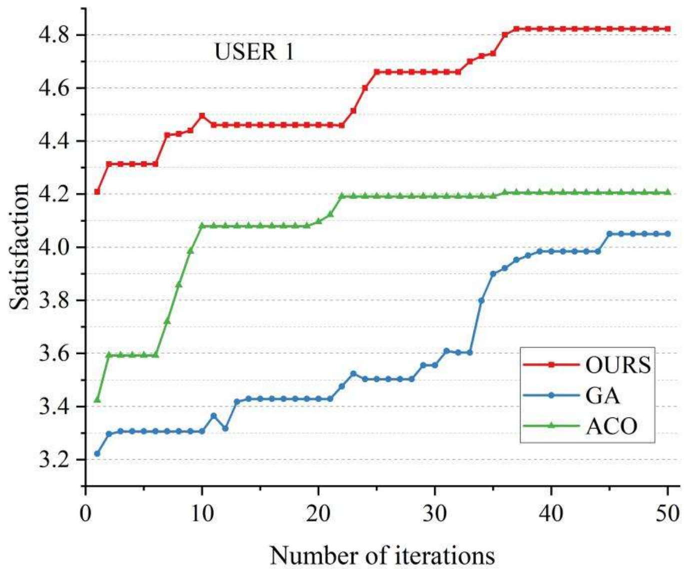

Figure 3: The iterative result of the learning path of User 1

The experimental results show that the user satisfaction under the online learning path planning method based on learning state proposed in this paper is 4.208 at the beginning, and the satisfaction of user 1 will be stabilized at 4.823 after 37 iterations, whereas the user satisfaction derived from GA and ACO based methods is only 4.152 and 4.206, which verifies the superiority of the method of this paper, and that the user 1 based on the design of this paper has a learning style matches with user 1 is 0.83, while the matching degree of GA and ACO methods is only 0.67 and 0.72.

This experiment was tested on the remaining three experimental users, and Table 2 shows the matching degree and satisfaction of the learning paths of four users with different learning status characteristics. The results of the learning path iterations for users 2, 3 and 4 are shown in Fig. 4, Fig. 5 and Fig. 6, respectively. It can be clearly seen that all the three methods continuously produce learning paths with higher user satisfaction as the number of iterations increases, and gradually stabilize after reaching a certain height. It can be seen that for users with different learning styles, all three methods are able to plan online learning paths for users. However, from the experimental results of all four users, it can be seen that through 50 iterations, the results iterated by the method proposed in this paper are better than the other two, that is, the learning path planning method proposed in this paper can obtain higher user satisfaction.

Table 2: The matching degree and satisfaction of the learning paths of four users

	User characteristics	User satisfaction at 50 iterations			Matching degree		
		OURS	GA	ACO	OURS	GA	ACO
User1	(5, -2, 3, -4)	4.823	4.152	4.206	0.83	0.67	0.72
User2	(-3, 1, -5, 7)	4.07	3.71	3.89	0.91	0.58	0.73
User3	(-2, 4, 6, -1)	4.33	4.11	4.22	0.79	0.66	0.69
User4	(0, -7, 2, 5)	4.75	3.81	4.05	0.87	0.63	0.76

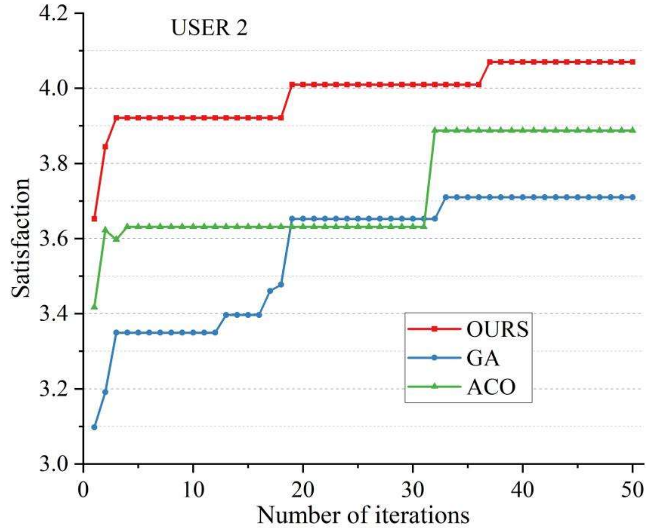

Figure 4: The iterative result of the learning path of User 2

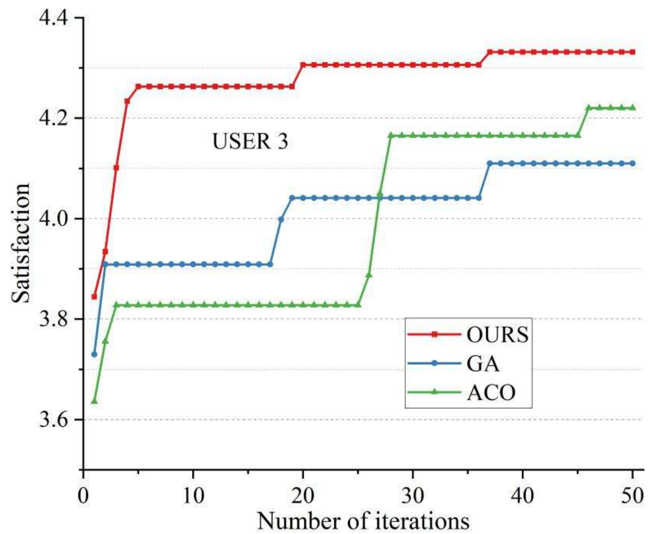

Figure 5: The iterative result of the learning path of User 3

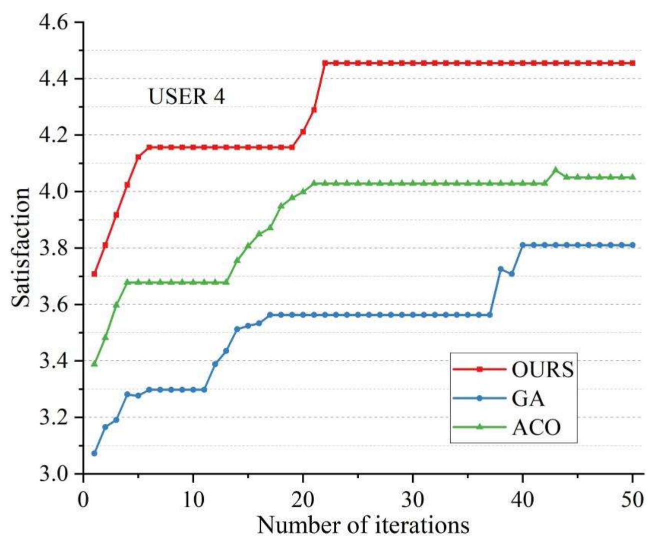

Figure 6: The iterative result of the learning path of User 4

This paper's method significantly outperforms the comparison algorithm (GA/ACO) in all users. For the application-oriented user 2, the satisfaction level of this method is 4.07, which is 9.7% higher than the 3.71 of GA and 4.6% higher than the 3.89 of ACO, and its matching degree reaches 0.91 (the highest in the whole group), which indicates that the algorithm is the best fit for the users with “high coverage but weak foundation”. For analytical users3, the satisfaction level of this method is 4.33, which is 5.4% and 2.6% higher than that of GA's 4.11 and ACO's 4.22, respectively. For the framework user 4 with features (0, -7, 2, 5), the satisfaction of this paper's method is 4.75, which is 24.7% higher than GA's 3.81, and 17.3% higher than ACO's 4.05, which verifies that the method can effectively support users with “weak feature decomposition ability”.

The path matching degree (0.79-0.91) of this paper's method comprehensively outperforms that of GA (0.58-0.67) and ACO (0.69-0.76), and the matching degree of user 2 (0.91) highlights the algorithm's ability to capture complex cognitive structures. And the satisfaction of this paper's method is stabilized at a high level (>4.07) in all 50 iterations, while GA/ACO fluctuates, which proves that the planning strategy based on learning state features has stronger convergence and robustness. By integrating dynamic learning state features and knowledge graph topological relations, the method in this paper achieves significant improvement in both satisfaction and matching, which is especially suitable for differentiated cognitive structures such as high coverage of pattern knowledge or weak knowledge of feature points.

V. Conclusion

This study proposes an artificial intelligence-driven personalized learning path optimization framework, which realizes the closed-loop optimization of “diagnosis-image-intervention” by integrating fuzzy cognitive diagnosis, dynamic learning state modeling, and knowledge graph topology analysis. Based on the experimental data of Advanced Mathematics for 237 students and the validation of 4 types of differentiated users, the following conclusions are drawn:

In the cognitive diagnosis of 10 core knowledge points, the model accurately quantifies group weaknesses. The mastery rate of Curve Integration (A3) is only 31.71% (mastered by 62/237 people), and the application of reintegration (A8) is as low as 27.42% (mastered by 27/237 people); the mastery rate of strong knowledge points, such as infinite series (A4), reaches 90.55% (mastered by 230/237 people), reflecting the validity of the model's successive fine-grained assessment of cognitive level.

User 2 (-3,1,-5,7), characterized by “high coverage but weak foundation”, achieves a satisfaction level of 4.07 with the highest match of 0.91 for the whole group through knowledge graph-driven miss rate updating. User 4 (0,-7,2,5) is characterized by “weak feature point decomposition ability”, and the satisfaction level is increased to 4.75, which is 24.7% higher than that of the GA algorithm, which verifies the adaptability of the model to the dynamic modeling of tacit knowledge. Comparing the GA and ACO algorithms, the average satisfaction of this paper's method after 50 iterations reaches 4.49, which is 13.7% higher than the 3.95 of GA, and 9.5% higher than the 4.10 of ACO, and the average matching degree is 0.85, which is 32.8% higher than the 0.64 of GA, and 16.4% higher than the 0.73 of ACO.

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