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Research on the design of grassland ecological study curriculum and improvement of learning path based on multi-objective optimization algorithm

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Abstract In this paper, we constructed a curriculum design ontology for grassland ecological study for the individual characteristics of learners, learning needs and the logical relationship between knowledge points, and extracted, fused and stored the knowledge mapping data of the discipline. After that, the structural relationship between knowledge points is explained, and the personalized learning path recommendation model is constructed based on the feature information of learners and learning resources in the learning path recommendation solving problem, with personalized learning path as the decision variable and based on the mapping relationship between learners and learning resources. Finally, the basic particle swarm optimization algorithm is improved from the perspectives of inertia weight and variation operator setting to solve the model. The MABPSO model has better convergence ability, stability and adaptability, and it can solve the personalized online learning resources recommendation problem better. In addition, the method in this paper utilizes the learner cognitive level function to calculate the learner's mastery of the knowledge points, and then sets the generation rules of the learning paths, and finally generates the optimal learning paths and recommends them to the learners.

Index Terms Knowledge Graph, Particle Swarm Optimization Algorithm, MABPSO, Personalized Recommendation, Grassland Ecology Study Course

I. Introduction

Grassland ecology research course is a teaching method that combines classroom learning with grassland fieldwork, which provides students with a new way of learning, so that learning is no longer confined between textbooks and classrooms, but closer to real life and social practice [1]-[3]. Grassland ecological research course helps to cultivate students' innovative thinking, practical ability, interpersonal skills and leadership, improve their comprehensive quality, and prepare them for future career development [4]-[6].

The core of grassland ecology research course design is student-centered, starting from the actual needs of students, to determine the theme and tasks of the research [7], [8]. The whole curriculum design should be carried out in strict accordance with the principles of “task-oriented, practical, exploratory and comprehensive”, and even for different study courses on the same theme, flexible adjustments should be made according to the characteristics and needs of students [9]-[12]. In practice, the grassland ecology study program should be designed in a multidisciplinary way, in which students can obtain knowledge and practice in natural sciences, humanities, social sciences and technology [13]-[15]. For this reason, in the design of research courses, teachers should choose practical courses with strong scientific and practicality, and run science and technology education, environmental education and humanities education through them to provide students with diversified experiences and learning opportunities [16]-[19]. At the same time, the design of grassland ecological research courses should try to meet the age characteristics and psychological needs of students, and teachers should pay attention to the physical, psychological and safety issues of students to ensure their physical and mental health in the research activities [20]-[22]. For this reason, in the design of the research course, teachers should set appropriate tasks and challenges according to the age characteristics and actual situation of the students, create a positive and optimistic team atmosphere, so that students can obtain happiness and growth through the research activities [23].

In this paper, we first constructed the knowledge map of grassland ecological research course design, then combined the learners' cognitive characteristics to carry out the knowledge point path planning, sorted and filtered the associated resources based on the sequence of knowledge points and the learner model, and integrated and stored the subject knowledge. After that, starting from the dimensions of learners and learning resources, the problem of multi-objective optimization is transformed into a single-objective optimization problem for finding the minimum value, so as to construct a learning path recommendation model based on students' characteristics. When analyzing the connection between learners and learning resources, the variability between learners' learning styles, ability levels, learning duration and other components are considered. Then the convergence performance of the particle swarm optimization algorithm is optimized using nonlinear incremental and variational operators for binary particle swarm optimization algorithm to solve the personalized learning path recommendation problem. Finally, the learning resource personalization effect of the optimization algorithm is analyzed to further improve the speed and quality of learning path recommendation.

II. Personalized learning path recommendation algorithm based on multi-objective optimization algorithm

II. A. Knowledge Mapping Construction of Grassland Ecology Research Course

II. A. 1) Constructive thinking

In this paper, the construction of disciplinary knowledge map integrates manual and automatic methods, and combines top-down and bottom-up approaches. Firstly, based on the catalog of disciplines and majors established by the Ministry of Education and the teaching standards of majors issued by various teaching committees, we refine the typical work tasks and vocational ability requirements corresponding to the core work areas of different disciplines and majors in accordance with the cultivation specifications of different disciplines and majors, construct the curriculum system based on the work process, clarify the main teaching contents and requirements of the core courses of the majors, and form the logical framework of the knowledge system of the disciplines. On this basis, define the entity class, attribute class and relationship class of the professional core curriculum knowledge map, and complete the construction of the ontology structure from the top down, a process that requires the participation of experts in the disciplinary field. Secondly, using knowledge extraction, knowledge fusion and other technologies, a bottom-up approach is adopted to change multi-source heterogeneous data into structured knowledge triples, forming a specific instance data layer. Finally, the knowledge is stored in the graph database to realize the construction of subject knowledge graph. In the process of subsequent use of the knowledge map, the update aspect is mostly the update of the data layer, while the ontology structure is relatively stable and will not be updated frequently.

II. A. 2) Construction of the disciplinary ontology

The main role of an ontology is to use a formal description language to provide a shared, consistent semantic model for defining and organizing concepts, attributes, and relationships within a domain, as a guide for subsequent knowledge extraction. Constructing a high-quality subject knowledge ontology is a prerequisite for constructing a complete and accurate subject knowledge map, which has extremely stringent requirements for data quality, focusing on consistency and standardization, scalability and updatability, knowledge quality and verifiability in the construction process. In this paper, we use manual construction to define the types of entity types, attributes and inter-entity relationships under the guidance of subject area experts.

II. A. 3) Disciplinary knowledge extraction

Knowledge mapping data sources include semi-structured and unstructured data such as teaching text, video, audio, etc., which are divided into two parts: entity extraction and relationship extraction. Entity extraction is the process of extracting knowledge and skills related to the subject from subject data, and then mining the relationship between entities to form the ternary representation of “entity-relationship-entity”. The professional teaching program contains a number of courses, there is a relationship between the courses, there are a number of different types of teaching resources in the course, and teaching resources are to explain the knowledge and skills points, there are relationships between the knowledge points such as inclusion, juxtaposition, synonymy, antecedent and successor, etc., in this paper, according to the practical needs of the definition of the type of relationship between the entities.

II. A. 4) Integration and storage of disciplinary knowledge

The overall task of knowledge fusion is to calculate the similarity between entities and delineate those entities whose similarity is within a certain threshold as the same entity. Data classification and cleaning and filtering are performed through the BERT model, and the alignment of entities is completed by using Word2Vec to determine the semantic similarity between them through the distance between words. Finally, the ternary knowledge obtained after information extraction and knowledge fusion is persistently stored in the non-relational graph database Neo4j using Cypher language to generate a structured knowledge semantic network, which helps the implementation of the subsequent functions and performance optimization. In this paper, the software engineering professional training program, core work areas, and professional curriculum standards are taken as the main data sources, and the resources of the e-learning platform are used as supplementary auxiliary data sources to construct the disciplinary knowledge mapping. After ontology construction, knowledge extraction and knowledge fusion, it is stored in Neo4j graph database.

II. B. Construction of personalized learning path recommendation model

II. B. 1) Learner Modeling

(1) Define the learner $L = \{L_1, L_2, L_3, \cdots, L_K\}$, K stands for the number of learners, and L_k stands for the kth learner, where $1 \le k \le K$.

(2) Define the learner ability level $A = \{A_1, A_2, A_3, \cdots, A_K\}$, A_k represents the learning ability level of the learner L_k, where $1 \le k \le K$.

(3) Kolb learning styles are categorized into four types: divergent thinking type, absorptive type, convergent thinking type, and adaptive type, so defining the learning styles of K learners $LS = \{ls_1, ls_2, ls_3, \cdots, ls_k\}$, and ls_k denotes the type of style that the kth learner belongs to, $ls_k = \{ls_{k1}, ls_{k2}, ls_{k3}, ls_{k4}\}$, where ls_{k1} denotes the match value of the learner belonging to the divergent thinking type, similarly ls_{k2} is the match value of the learner belonging to the absorptive type, ls_{k3} is the match value of the learner belonging to the convergent thinking type, and ls_{k4} is the match value of the learner belonging to the fitness type, and the learner's bias to Which learning style represents the largest match value in that style and satisfies $\sum_{q=1}^{4} e_q = 1$.

(4) Define the learner target knowledge points $H = \{H_1, H_2, H_3, \cdots, H_K\}$, where H_k denotes the kth learner target knowledge point, and each H_k has M binary values, then $H_k = \{h_{k1}, h_{k2}, h_{k3}, \cdots, h_{kM}\}$, $1 \le k \le K$, $1 \le m \le M$, if $h_{km} = 1$, then the m th knowledge point of the kth learner is the target knowledge point, otherwise $h_{km} = 0$.

(5) Lt is the time period in which the learner wants to master the target knowledge point, $Lt\_l \le Lt \le Lt\_u$, where Lt_l is the minimum value of the target time and Lt_u is the maximum value of the target time.

II. B. 2) Construction of Learning Resource Models

(1) Define learning resource $S = \{S_1, S_2, S_3, \cdots, S_N\}$, with S_n denoting the n th learning resource, where $1 \le n \le N$. The learning resource that the learner starts to learn is ns_i, and the next learning resource that the learner has to learn is ns_j.

(2) Define the knowledge points $U = \{U_1, U_2, U_3, \cdots, U_M\}$, and U_m denotes the m th knowledge point. Each U_m has N learning resources corresponding to it, then $U_m = \{U_{m1}, U_{m2}, U_{m3}, \cdots, U_{mN}\}$, when U_{mn} denotes the value of the difference between the learning of the m th knowledge point and the corresponding learning resources, $1 \le n \le N$, $1 \le m \le M$;

(3) Define the degree of difficulty of learning resources $D = \{D_1, D_2, D_3, \cdots, D_N\}$, where D_n represents the degree of difficulty of the n th learning resource, then the degree of difficulty of ns_i is D_{ns_i} and the degree of difficulty of ns_j is D_{ns_j}.

(4) Learning resource time information $T = \{T_1, T_2, T_3, \cdots, T_N\}$, and T_n denotes the time consumed to learn the n th learning resource.

(5) The media types of learning resources include various types such as text, video, audio, image, interactive learning software, etc., so the media type is defined as $MT = \{mt_1, mt_2, mt_3, \cdots, mt_N\}$, and the resource type to which the n th learning resource is categorized as MT_n, $MT_n = \{mt_{n1}, mt_{n2}, mt_{n3}, mt_{n4}\}$, where mt_{n1}, mt_{n2}, mt_{n3}, mt_{n4} denote the values of the learning resources matched with the four modalities of textual, symbolic, video, and interactive software representations, respectively, and there are $\sum_{q=1}^{Q} mt_{nq} = 1$.

II. B. 3) Decision-making variables

Define the personalized learning path variable as the matrix $X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NN} \end{bmatrix}$, if there is a path between the i th learning resource to the j th learning resource, then $x_{ij} = 1$, otherwise $x_{ij} = 0$.

Define the sequence relation between learning resources as:

$$S_{ij}=\begin{cases}1, & \text{Learning resource } i \text{ is a preorder relation of } j\\ 3, & \text{Learning resource } i \text{ is a subsequence relation of } j\\ 2, & \text{Learning resource } i \text{ is a juxtaposition of } j\end{cases} \tag{1}$$

II. B. 4) Construction of the objective function

Based on the above construction of the learner and learning resource model, the mapping relationship between the two is established, and the following personalized learning path recommendation model is formed [24].

(1) The learner cognitive level function, which reflects the difference between the learner's current learning ability level and the difficulty level of its learning resources. It contains the difference between the difficulty level of the initial learning resources, the target learning resources and the learner's ability level respectively, if the difference is smaller, the learning resource is more likely to be recommended to the learner:

$$F_1=\sum_{j=1}^{N}\left|\frac{\sum_{i=1}^{N}\left[X_{ij}\left(D_{nsi}-A_i\right)+X_{ij}\left(D_{nsj}-A_k\right)\right]}{2\sum_{i=1}^{N}X_{ij}}\right| \tag{2}$$

(2) A learning style function that represents the difference between a learner's learning style and the type of learning resource medium. To wit:

$$F_2=\frac{\sum_{n=1}^{N}\sum_{q=1}^{Q}X_{ij}\left|ls_{kq}-mt_{nq}\right|}{X_{ij}} \tag{3}$$

(3) The desired target expenditure function, which represents the match value between the learner's target knowledge points and their corresponding learning resources, as well as the sequential relationship between the learning resources:

$$F_3=\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}X_{ij}U_{mn}H_{km}S_{ij}}{X_{ij}} \tag{4}$$

(4) A time limit function that indicates the difference between the length of time the learner wishes to learn and the time required to complete the learning resource. If the difference between the time spent on the recommended learning path and the specified upper and lower time limits is smaller, the smaller the value of the function is, indicating that the path between learning resources i and j is more likely to be recommended to the learner. That is:

$$F_4=\left(\max\left(t\_l_k-\sum_{n=1}^{N}t_nX_{ij},0\right)\right)+\left(\max\left(0,\sum_{n=1}^{N}t_nX_{ij}-t\_u_k\right)\right) \tag{5}$$

Above is the objective function for the learner model and the learning resource model representation, because each objective function has a different degree of influence on the learner, so its corresponding weight is different, this paper for the four sub-functions using the weight of 0.3, 0.2, 0.4, 0.1. The total objective function is:

$$\min F(x)=\sum_{i=1}^{4}w_iF_i \tag{6}$$

From the above equation, it can be seen that the objective function is the minimum value of the solution problem, and ultimately a set of optimal decision variables can be found in the solution space, that is, the learner's learning path, the learner's spending on the learning path is the value of its corresponding objective function, so when the smaller the value of the objective function, the learner's spending on the path is smaller, and therefore the generated personalized learning path is more in line with the learner's requirements.

II. C.Personalized learning path recommendation algorithm design

II. C. 1) Analysis of Binary Particle Swarm Optimization Algorithms

In the Binary Particle Swarm Algorithm (BPOS) [25], [26], the update of the particle velocity vector is also composed of three parts: velocity inertia, self-learning and social learning, and the update of the particle's position in the $t+1$ generation is determined by the particle's position in the t generation and the velocity vector in the $t+1$ generation. The details are as follows:

$$v_{ij}^{t+1}=\omega v_{ij}^{t}+c_1r_1(p_{ij}-x_{ij}^{t})+c_2r_2(g_{ij}-x_{ij}^{t}) \tag{7}$$

$$x_{ij}^{t+1}=x_{ij}^{t}+v_{ij}^{t+1} \tag{8}$$

where i denotes the particle, j denotes the dimension of the particle; ω denotes the inertia weight; t denotes the number of iterations; c_1 and c_2 are both positive constants, generally $c_1=c_2=2$, c_1 denotes the self-learning factor, and c_2 denotes the social learning factor; r_1 and r_2 are random numbers distributed between $[0,1]$; p_{ij} denotes the individual optimal solution of particle i; and g_{ij} denotes the global optimal solution found in the population.

In the BPSO algorithm, the state of particle motion is defined from a probabilistic point of view. Each bit x_{ij} of each particle in the state space takes the value of 0 or 1, and v_{ij} represents the probability that x_{ij} takes the value of 1, which is given by the following formula:

$$x_{ij}=\begin{cases}1, & rand()<S(v_{ij})\\ 0, & rand()>S(v_{ij})\end{cases} \tag{9}$$

$$S(v_{ij})=\frac{1}{1+e^{-v_{ij}}} \tag{10}$$

where $rand()$ is a random number distributed within $[0,1]$ and Equation (10) represents the Sigmoid function.

II. C. 2) Personalized learning path recommendation algorithm MABPSO design

(1) Nonlinear Incremental Strategy for Inertia Weights

In the binary particle swarm optimization algorithm smaller inertia weights improve the exploration ability, while larger inertia weights focus on exploitation. Although the linear optimization of inertia weights helps to improve the performance of the algorithm, the strategy cannot effectively meet the algorithm's optimization process, and cannot achieve an effective balance between the development and search performance. Therefore, in order to be closer to the actual evolutionary state of algorithm optimization, this paper carries out non-linear incremental optimization of inertia weights. In each iteration, the inertia weights w are calculated as follows:

$$w=\begin{cases}\omega_{\min}+\dfrac{2}{\pi}\arctan\left(\pi*\dfrac{t(\omega_{\max}-\omega_{\min})}{T}\right), & 0.4<\omega\le 0.9\\ \omega_{\max}, & \omega>0.9\end{cases} \tag{11}$$

where t and T represent the number of iterations and the maximum number of iterations, respectively.

(2) Mutation operator

Since the variation operator has a significant performance in improving the convergence performance of the algorithm, this paper draws on the basis of the genetic algorithm variation idea, the variation operator is integrated into the binary particle swarm optimization algorithm, to prevent the algorithm from the phenomenon of premature convergence, and the binary particle swarm algorithm to improve the formula is as follows:

$$v_{ij}^{k+1}=wv_{ij}^{k}+c_1r_1(p_{ij}-x_{ij}^{k})+c_2r_2(g_{ij}-x_{ij}^{k})+\rho r_3(Random-x_{ij}^{k}) \tag{12}$$

where $Random$ is the random location of the solution space; ρ is the curiosity coefficient of the unknown world, after a large number of experimental observations, the best results can be obtained by setting $\rho=2$, and r_3 is the random number distributed within $[0,1]$. Due to the inclusion of the mechanism of exploring the unknown space, the search range of the particles is enlarged, the population diversity is increased, the ability of the algorithm to escape from the local optimal solution is enhanced, and the algorithm is prevented from prematurely converging to a certain extreme value.

II. C. 3) Personalized learning path recommendation algorithm MABPSO process

By improving the basic particle swarm optimization algorithm from two perspectives of inertia weights and variation operator settings, the personalized learning path recommendation algorithm MABPSO is proposed.The steps of personalized learning path recommendation algorithm MABPSO are as follows:

Step1: Initialize the particle parameters of MABPSO algorithm, including speed, position, individual historical optimum before iteration and global optimum of the population;

Step2: Update the inertia weights by using Eq. (11);

Step3: Realize particle velocity and position update by Eqs. (12) and (9), (10);
Step4: calculate the particle adaptation value;
Step5: The particle updates the individual optimum and global optimum according to the adaptation value;
Step6: If the algorithm reaches the termination condition, output the optimal value, otherwise return to step 2;
Complexity analysis of MABSPO algorithm: assume the population size is N and the number of iterations is T. The complexity is $O(N)$ at initialization; the complexity is $O(NT)$ when calculating the value of particle fitness. Therefore the complexity of the MABPSO algorithm is $O(NT)$.

III. Analysis of the effect of grassland ecology study courses and personalized learning path recommendation

III. A. Analysis of performance comparison results of different models

In order to demonstrate the effectiveness of the personalized e-learning resource recommendation method proposed in this paper, the algorithm in this paper (MABPSO) is compared with the binary particle swarm algorithms BPSO, RPSO, and LPSO in the same personalized recommendation model, and also with the binary particle swarm algorithm VBPSO, which is based on a V-shaped mapping function improved for the mapping function.

The acceleration factors $c1$ and $c2$ are set to 2 for all algorithms; BPSO does not come with inertia weights, the inertia weights are adjusted in the same way in RPSO and LPSO, and the inertia weights of VBPSO and MABPSO are reduced in a linear manner, with the maximum inertia weight value of 0.9 and the minimum of 0.4; the population size of all the algorithms is 20, and the maximum number of iteration is 200; the experiments are conducted with the The weights of the secondary fitness functions are w_1, w_2, w_3 and w_4, all of which are 0.3, 0.3, 0.2, 0.2 in that order.

In order to verify the performance of MABPSO's in the personalized e-learning resource recommendation problem, five sets of experiments were implemented and the experimental data are shown in Table 1.

Table 1: Experimental data

Personalized network learning resource model parameters	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
LM_N	100	200	300	100	100
C_M	5	5	5	5	5
L_K	20	20	20	60	100
A_K	The ability level is divided into five levels, randomly initialized in five levels				
R_N	The value of the random initial chemical binary number R_{NM}				
H_K	The value of the random initial chemical binary number H_{KM}				
D_N	The difficulty is divided into five levels, randomly initialized in five grades				
T_{uk}, t_{ik}, t_n	Stochastic initialization				

The mean and variance data of the convergence values of each algorithm in the five sets of experiments are obtained from 30 independent experiments, and the convergence mean and variance are shown in Table 2. From the comparison results of Experiment I, Experiment II and Experiment III, it can be observed that MABPSO has the best convergence accuracy and shows better stability as the number of learning resources increases. It can be observed from Experiment I, Experiment IV and Experiment V that MABPSO has the best convergence accuracy and with the increase in the number of learners, MABPSO shows the best stability. All the algorithms have a tendency to converge in the five sets of experiments, indicating that particle swarm algorithms are feasible for solving the problem of personalized e-learning resource recommendation.

From the convergence curves of Experiment I, Experiment II and Experiment III, it can be observed that MABPSO has the best convergence speed in all 3 groups of experiments, which indicates that with the increase of learning resources, MABPSO shows the best adaptive ability. It can be observed from Experiment 1, Experiment 4 and Experiment 5 that MABPSO has the best convergence speed in all 3 groups of experiments, indicating that with the increase in the number of learners, MABPSO shows the best adaptive ability.

MABPSO has better convergence ability and stability and shows better adaptability with the increase in the number of learning resources and the number of learners. It shows that MABPSO is very suitable for the personalized e-learning resource recommendation problem, and verifies that the MABPSO proposed in this paper is a method that can better solve the personalized e-learning resource recommendation problem.

Table 2: The mean and variance of convergence

Algorithm	Test index	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5
BPSO	Mean	1.492×106	5.908×106	1.769×107	1.705×107	4.996×107
	Variance	5.993×1010	6.709×1010	1.231×1011	7.9037×1011	1.497×1013
RPSO	Mean	2.176×106	7.197×106	1.997×107	2.078×107	5.606×107
	Variance	0.992×1011	3.396×1010	0.992×1011	7.995×1011	1.514×1013
LPSO	Mean	1.8678×106	6.5973×106	1.8935×107	1.798×107	5.296×107
	Variance	8.9985×1010	1.8047×1010	7.3968×1011	8.795×1011	1.008×1013
VBPSO	Mean	1.9984×106	6.9938×106	1.9981×107	1.909×107	5.494×107
	Variance	1.2413×1011	2.9964×1010	8.0036×1012	1.098×1012	1.202×1013
MABPSO	Mean	1.751×102	3.698×103	6.1012×103	5.504×103	2.495×104
	Variance	1.879×104	1.5005×104	1.6975×107	2.892×107	1.906×107

III. B. Effect of personalized e-learning resources recommendation

III. B. 1) Recommended Path Reliability Assessment

(1) Experimental Setting and Evaluation Indicators

Through learners' learning data and the importance of knowledge points, this paper recommends learning paths for learners. In order to verify the reliability of the recommended paths in this paper, the fixed knowledge point paths contained on the Internet are used as expert paths and compared with the in-depth paths based on containment relationships recommended in this paper. In this paper, the BPSO algorithm is used to calculate the degree of importance of knowledge points, and in order to verify the advantages brought by the binary particle swarm algorithm, a control group is set up to compare the generated paths obtained by calculating the importance of knowledge points using the particle swarm optimization algorithm with the expert paths. Finally, the path deviation value is used as a criterion to evaluate the reliability of the learning path generated in this paper. The specific deviation value is calculated by the formula:

$$Deviation(Tp) = \sum_{i=1}^{n} abs(Gpath\_rank(p_i) - path\_rank(p_i)) \tag{13}$$

where Tp is the target knowledge point, p_i is the knowledge point in the pathpath, $Gpath\_rank(p_i)$ is the ranking of p_i on the recommended path, and $path\_rank(p_i)$ is the ranking of p_i on the expert path.

(2) Analysis of experimental results

In order to verify the reliability of the recommended path, 20 graduate students majoring in grassland ecology research course design were invited to participate in the experiment. The experimental results of calculating the deviation between the recommended path and the expert path are shown in Figure 1. The deviation values of the learning path and the expert path are all within 28.5, which indicates that the order of knowledge points in the recommended learning path is similar to the order of knowledge points in the expert path, thus proving the reliability of the recommended path strategy proposed in this paper. The final path recommendation of the knowledge points, measured by the learner's mastery of the knowledge points, also reflects the personalization of the recommended path in this paper.

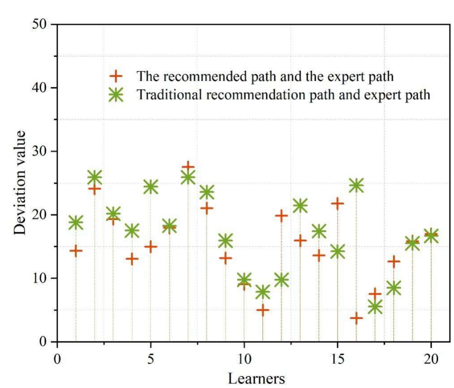


Figure 1: Calculate the deviation of the recommended path and the expert path

III. B. 2) Mastery model assessment

In order to verify the advantages of utilizing the MABPSO model for learners' mastery of knowledge points, this paper uses this model to compare with the baseline models (IRT and DINA) on the public dataset as well as the self-constructed dataset in this paper.

(1) Experimental Setting

In this paper, we use the public dataset Assistments 2023-2024 as well as our own constructed dataset kpoint-exercise to evaluate the model used in this paper, and the basic information of the dataset is shown in Table 3.

Table 3: The basic information of the data set

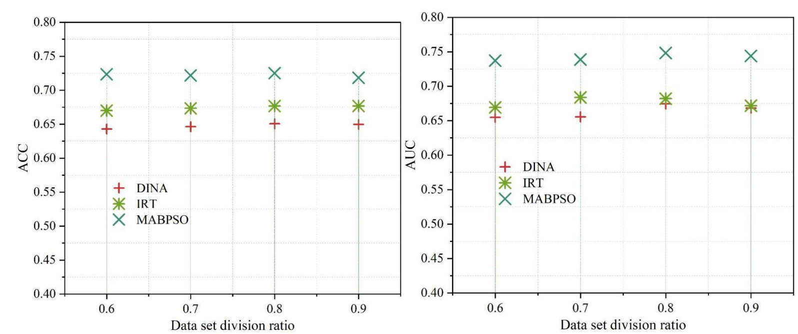
Data set	Item number	Number of knowledge	Student number	Number of records	Each question contains an average of knowledge
Assistments 2023-2024	17763	129	4155	324565	1.2051
kpoint-exercise	366	189	1028	4994	2.8057

In this paper, AUC, ACC and RMSE are used as evaluation indexes.RMSE stands for Root Mean Square Error, which is used to measure the difference between the predicted value and the real value of the model.The smaller the value of the difference between the predicted value and the real value of the model, the better the model performance is. The calculation formula is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_i - \hat{y}_i)^2} \tag{14}$$

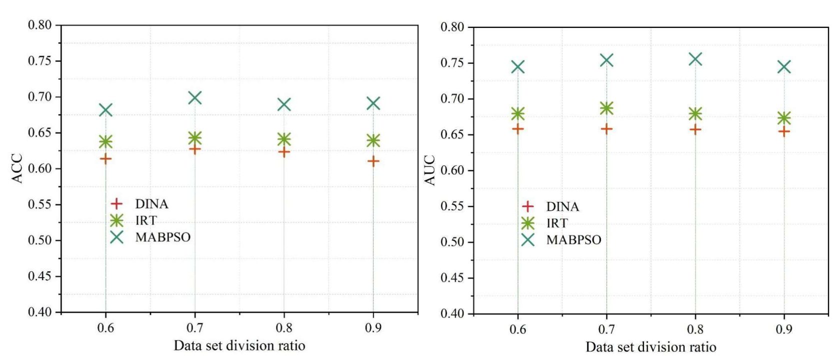
where y_i represents the actual value of student answers and $\hat{y}_i$ represents the model prediction.

In order to better realize the model performance prediction, this paper uses different ratios of 0.6, 0.7, 0.8, and 0.9 to divide the dataset into training set and test set for experimentation. The experimental results on the public dataset Assistments 2023-2024 are shown in Fig. 2. The experimental results on the self-constructed dataset kpoint-exercise are shown in Fig. 3. Through the changes of ACC and AUC of each model in different proportion of data division, using the proportion of 0.7 or 0.8 to divide the data set makes the model work best.



(a)Experimental results of ACC (b)Experimental results of AUC

Figure 2: Experimental results on the public data set of Assistments 2023-2024



a)Experimental results of ACC (b)Experimental results of AUC

Figure 3: The results of the data set kpoint-exercise on the data set

Table 4: Experimental results of different models on different data sets

Model	Assistments 2023-2024			kpoint-exercise		
	AUC	ACC	RMSE	AUC	ACC	RMSE
DINA	0.6817	0.6548	0.4712	0.6594	0.625	0.4752
IRT	0.6778	0.6805	0.4683	0.6854	0.6413	0.4696
MABPSO	0.7448	0.7257	0.4359	0.7491	0.7021	0.4477

III. B. 3) Assessment of Learners' Learning Benefits

(1) Evaluation Indicators

In order to assess whether learners following the path recommended in this paper will bring better learning benefits, this paper sets learning benefit indicators:

$$B_{ij} = \frac{K_{ij} - K_{cj}}{K_{tj} - K_{cj}} \tag{15}$$

B_{ij} represents the learning benefit of the target knowledge point j after the learner i has followed the path, K_{ij} represents the number of questions answered correctly by the learner after following the path, K_{tj} represents the total number of questions associated with the knowledge point j, and K_{cj} represents the number of questions answered correctly by the learner before learning.

(2) Experiment Setting

The experiment was conducted in a combination of online and offline methods, firstly, 20 college students majoring in grassland ecological research course design were invited, 5 of them were divided into a group, and a group was randomly drawn to learn only the target knowledge points as a control group. Group 2 and Group 3 follow the self-organized path and the retrospective path recommended in this paper, respectively. Ultimately, the average benefit of 5 participants in the same group is calculated as the benefit of the group. I.e:

$$E_j = \frac{\sum_{i=1}^{5} B_{ij}}{5} \tag{16}$$

(3) Experimental process and result analysis

Table 5: The results of the learner's earnings

Group	Participant	The number of subjects that you answer before you study	Learn the number of subjects after study	Learning benefits of learners	Revenue per group
Group 1	L1	15	15	0.0706	0.1934
	L2	10	9	0	
	L3	20	22	0.4315	
	L4	13	16	0.2878	
	L5	8	10	0.1602	
Group 2	L6	17	18	0.2004	0.2441
	L7	12	16	0.3284	
	L8	14	16	0.2276	
	L9	15	17	0.254	
	L10	7	10	0.2021	
Group 3	L11	9	19	0.6154	0.514
	L12	10	16	0.4012	
	L13	18	20	0.3262	
	L14	16	23	0.722	
	L15	12	18	0.4712	
Group 4	L16	20	24	0.7158	0.4596
	L17	11	16	0.3754	
	L18	7	12	0.2917	
	L19	19	21	0.368	
	L20	12	19	0.5319	

The results of learners' gains are shown in Table 5. The gain value of the first group is lower than that of the other three groups, indicating that learning only the target knowledge points does not correctly complete most of the topics, reflecting the necessity of learning paths. The learning gain of the third and fourth groups is higher than that of the second group, indicating that the path recommended in this paper is more suitable for completing the learning of the knowledge related to the target knowledge points than the path organized by the learners themselves, which shows the effectiveness of the path recommended in this paper. The comparison of the results of learning gains of the three and four groups reflects that the in-depth learning path based on the inclusion relationship may be more conducive to the learning of the target knowledge points. However, due to the wide range of knowledge points existing in some topics, the retrospective path based on the prior relationship may be more suitable for learning. Thus verifying the necessity of the two paths recommended in this paper, each of which has its own advantages.

III. B. 4) Assessment of user satisfaction

(1) Assessment indicators

In order to assess learners' satisfaction with the recommended learning paths, this paper uses a questionnaire to collect 20 learners' subjective ratings of the recommended paths. We used a Likert scale to quantify learner satisfaction. The ratings totaled 5 points, where 5 represents very satisfied; 4 represents satisfied; 3 represents fair; 2 represents dissatisfied; and 1 represents very dissatisfied. We asked learners to rate the recommended pathways separately. The learners' satisfaction with the recommended paths was assessed as:

$$Satisfied\left(path\right)=\frac{\sum_{j=1}^{M} score\left(Path_r\right)}{M} \tag{17}$$

(2) Experimental results

In order to assess the learners' satisfaction with the results of the recommended path, a satisfaction survey is conducted on 20 students, and the results of the user satisfaction score of the recommended path are shown in Fig. 4, and finally the formula is utilized to obtain a user satisfaction of 4.0217, which indicates that most of the learners are satisfied with the recommended path, and it proves that the learning path recommending method proposed in this paper can provide a satisfactory learning path for users.

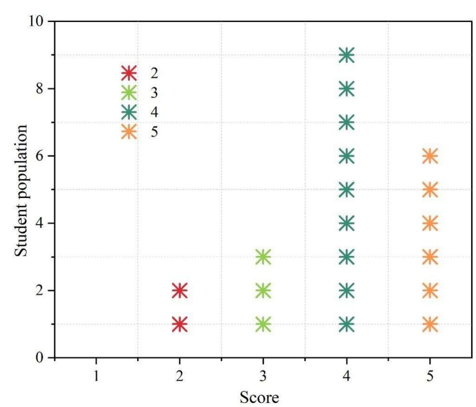


Figure 4: The user satisfaction score of the recommended path

IV. Conclusion

Based on the structural relationship between knowledge points, this paper analyzes the feature information of learners and learning resources in the learning path recommendation solving problem, and constructs a personalized learning path recommendation model based on learner information and learning resource information.

(1) The method MABPSO in this paper has better performance in solving the personalized network learning resources recommendation problem, has the best convergence accuracy, and shows better stability with the increase of the number of learning resources.

(2) This paper calculates the importance degree of knowledge points by adjusting the corresponding weights through the characteristics of knowledge points in the knowledge graph; calculates the learner's mastery degree of knowledge points by utilizing the learner cognitive level function; and sets up the path generation rules to generate the optimal learning paths to be recommended to the learners.

(3) The learning path is evaluated from the perspective of learners' learning benefits, and the effect of the learning path of knowledge points recommended in this paper is better than the self-organized path, which proves the effectiveness of the recommended path.

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