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Design and Implementation of an Adaptive Learning Path Planning Platform for Multi-Level Instructional Needs

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Abstract: To address the personalized and diverse needs of students during instruction, this paper integrates the concept of fit into reinforcement learning algorithms to meet multi-level learning demands and develops an adaptive learning path planning platform. First, the concept of “fit” is introduced, focusing on analyzing the relationship between learners and learning content. This relationship is then represented through data across three dimensions: educational, technological, and subject-related. Second, an adaptive learning path generation mechanism based on reinforcement learning was designed. This mechanism can automatically generate learning paths according to learner characteristics and existing learning resources and adaptively adjust them based on individual learner needs. Finally, an adaptive learning path platform was designed using reinforcement learning algorithms and the concept of fit. Experiments confirmed that the designed platform can apply adaptive learning path planning mechanisms to real personalized teaching needs, demonstrating the feasibility and effectiveness of the adaptive algorithmic mechanism.

1. Introduction

Learners, guided by teachers, can integrate and assimilate knowledge resources during the course instruction process [1]. However, two major challenges arise in this process. First, significant differences exist among students in terms of prior knowledge, learning ability, and learning styles, leading to multi-level and dynamic variations within instructional settings. Second, learners increasingly demand personalized learning experiences, yet they often lack the ability to design appropriate learning paths based on their characteristics [2-4].

Researchers have looked into different ways to plan adaptive learning paths because information technology is changing so quickly. Existing studies mainly focus on learner modeling and recommendation algorithms; however, limited attention has been paid to quantitatively modeling the relationship between learners and learning resources [5].

To address this issue, this paper introduces the concept of “fit” into the learning path planning process. Integrating learner characteristics with knowledge resource attributes establishes a quantitative relationship between the two [6-8]. Furthermore, reinforcement learning is employed to simulate learner behavior and iteratively optimize learning paths, allowing for adjustments based on individual progress and preferences. The proposed method provides a systematic approach for supporting multi-level instructional needs and personalized learning, ensuring that the learning paths are tailored to individual learner characteristics and knowledge resource attributes [9-11].

2. Research Content

2.1. Model Analysis

2.1.1. Learner Model

The learner model analyses learner characteristics primarily based on their knowledge level, learning style, and learning preferences, in addition to basic learner information.

(1) Level of knowledge. The learning process involves the interaction and integration of new information acquired by learners with their existing knowledge, while knowledge level reflects the breadth and depth of concepts already mastered in the learner's mind. Factors considered in assessing a learner's knowledge level include both objective and subjective elements. Among these, objective factors refer to prior course performance, reflect the breadth and depth of knowledge already acquired in the learner's mind, and constitute quantitative data. Subjective factors include learning ability and motivation, which reflect the learner's capacity and willingness to acquire new knowledge, and constitute qualitative data [12]. These can be obtained through methods such as surveys or tests and converted into quantitative data.

Knowledge level is represented by vector $z = (z_1, z_2, z_3)$, where z_i (i=1,2,3) takes values in the range $[0,1]$. Here, z_1 reflects the excellence of prior course performance; z_2 , z_3 respectively denote the learner's learning ability and learning motivation.

(2) Learning Styles. Typically, each learner's learning style is a combination of multiple learning types. Learners exhibit different learning styles, including convergent, divergent, assimilative, and accommodative types.

Quantitatively describe learners' preferences for acquiring various types of knowledge using vector $c = (c_1, c_2, c_3, c_4)$ .Here, c_1, c_2, c_3, c_4 represent the extent to which a learner prefers text-based theory, graphic knowledge, video content, and case studies, respectively, Moreover, there is $0 \le c_j \le 1 (j = 1,2,3,4)$.

(3) Learning Preferences. Learning tends to favour vectors $h = (h_1, h_2, h_3, h_4, h_5, h_6)$, $0 \le h_t \le 1$ (t=1,2,3,4,5,6) to quantitatively describe knowledge representation methods. Here, h_1, h_2, h_3, h_4, h_5 represent the presentation formats of knowledge resources as text, symbols (charts, animations, etc.), audio/video, case studies, and experiments, respectively. h_6 indicates other display methods.

2.1.2. Knowledge Resource Model

(1) Knowledge Evaluation. Knowledge evaluation primarily involves teachers assessing knowledge resources based on the breadth and depth of content, drawing on long-term teaching experience and historical student learning outcomes. Key factors include difficulty level, importance, and relevance to other knowledge areas. Knowledge evaluation is represented by $p = (p_1, p_2, p_3)$, where $p_i (i = 1,2,3)$ takes values in the range $[0,1]$. Here, the difficulty coefficient is denoted by p_1. Importance is represented by p_2. The association degree is denoted by p_3. The closer it is to 0, the more independent the knowledge point is.

Matrix $\boldsymbol{P} = [p_{i1}, p_{i2}, ..., p_{ig}]$ represents the evaluation information for all knowledge points, where g denotes the number of knowledge points in the course.

(2) Knowledge Representation. Knowledge point relationships primarily include three types: predecessor, successor, and related. These are typically depicted using diagrams that show knowledge point associations. This paper's knowledge representation is evaluated from perspectives such as “theoretical nature, visualizable, experimental feasibility, and practicality.” Among these, the knowledge representation of knowledge points is quantified by vector $b=(b_1,b_2,b_3,b_4)$,where b_1 , b_2 , b_3 and b_4 respectively denote the theoretical, visual, experimental, and practical aspects of knowledge resources, with $0 \le b_j \le 1 (j=1,2,3,4)$. Knowledge representation uses matrix $\boldsymbol{B}=[b_{j1},b_{j2},...,b_{jg}]$ to express the features of all knowledge points, and knowledge relationships are represented by knowledge point association diagrams.

(3) Knowledge Presentation. Knowledge presentation refers to the manner in which knowledge resources are presented during the course teaching process, such as text, video, images, case studies, etc. Multiple formats (e.g., text + video) present many knowledge resources. The knowledge points in this article are expressed using vector $d=(d_1,d_2,d_3,d_4,d_5,d_6), 0 \le d_t \le 1 (t=1,2,3,4,5,6)$ is a quantitative description of knowledge representation methods. Where, d_1, d_2, d_3, d_4, d_5 represent the presentation formats of knowledge resources as text, symbols (charts, animations, etc.), audio/video, case studies, and experiments, respectively. d_6 indicates other display methods. The knowledge representation $\boldsymbol{D}=[d_{t1},d_{t2},...,d_{tg}]$ represents all possible expressions of knowledge points.

2.2. Learner-Knowledge Resource Matching and Quantification

The fit between learners and knowledge resources is modeled using a fuzzy balance operator. This paper analyses the concept from three dimensions: educational fit, technological fit, and subject fit.

(1) Educational alignment primarily reflects the degree of correspondence between a learner's proficiency level and the evaluation of knowledge resources. Proficiency level serves as an assessment of a learner's academic capabilities, primarily measuring their capacity for acquiring knowledge. Meanwhile, knowledge evaluation focuses on providing learners with guidance to enhance learning outcomes by assessing the importance, difficulty level, and relevance of knowledge content.

(2) Technological fit primarily reflects the degree of alignment between learners' learning preferences and the presentation of knowledge resources. Learning preferences refer to learners' inclinations toward specific modes of knowledge presentation during the learning process, while knowledge expression primarily reflects the instructional resources used to present key knowledge points.

(3) Subject-Learning Style Alignment primarily reflects the degree of compatibility between a learner's learning style and the representation of knowledge resources. Learning style embodies the learner's intrinsic learning tendencies and strategies, serving as a key indicator of their motivation and interest in learning. Knowledge representation captures the interconnections between knowledge points, comprehensively describing aspects such as the theoretical nature, practical applicability, and testability of knowledge content.

Definition: Given fuzzy sets A and B, after applying the balancing operation, the resulting set C satisfies: $\mu_C(x)=[\mu_A(x)\cdot\mu_B(x)]^{1-\gamma}\cdot[1-(1-\mu_A(x))\cdot(1-\mu_B(x))]^{\gamma}$. Among these, γ takes values within the range of $[0,1]$.

When $\gamma=0$, $\mu_C(x)=\mu_A(x)\cdot\mu_B(x)$ corresponds to the algebraic product operator at

$A \cap B$;when $\gamma = 1$, $\mu_C(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x)$ corresponds to the algebraic sum operator at $A \cup B$. The balanced operator γ adapts automatically based on the learner's progress and learning outcomes.

According to Definition, the relationship between learners and knowledge resources is determined using the balance operation of fuzzy matrices, yielding educational fit values, technical fit values, and subject fit values. A weighted average method is employed to convert the fuzzy results into precise values, which serve as the fit values.

$$y = \frac{\sum_{k=1}^{3} y\mu_k(y)}{\sum_{k=1}^{3} \mu_k(y)} \tag{1}$$

3. Research on Adaptive Learning Path Planning Algorithms for Multi-Level Instructional Needs

Knowledge resource planning focuses on determining the compatibility between learner characteristics and knowledge resources, while incorporating the effectiveness value of knowledge resources based on teachers' pedagogical experience and historical teaching outcomes into the planning process. Reinforcement learning iteration primarily utilizes iterative learning algorithms to determine multi-level instructional needs based on alignment, simulate learners' learning processes, and identify optimized knowledge pathways through repeated iterative learning. Figure 1 illustrates the knowledge pathway recommendation algorithm employing reinforcement learning iteration to address multi-level instructional needs during course teaching.

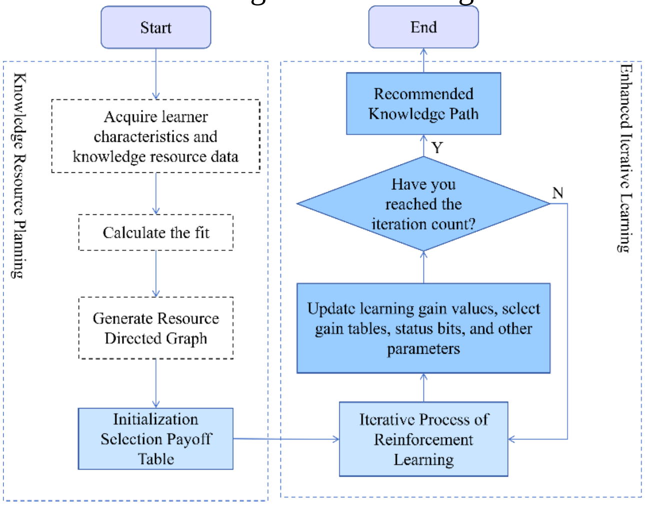


Figure 1. Knowledge Path Recommendation Mechanism Based on Reinforcement Learning Iterative Process

The process of knowledge path generation based on reinforcement learning involves the following steps:

Step1. Fit Calculation: Learner characteristics and other information are obtained through methods such as questionnaires, while knowledge resource characteristics are primarily derived from teachers' instructional experience and historical teaching outcomes. The fit between learners and knowledge resources is quantified using fuzzy algorithms across three dimensions: educational fit (Q_Y), technical fit (Q_J), and subject fit (Q_T). Defuzzification algorithms are then applied to obtain the final fit value

(Q_H).The learning effectiveness (L_E) of each knowledge point in a resource is determined by expert knowledge or instructor experience. The learning benefit (R) gained by learners after selecting and studying the resource is calculated as:

$$R = F_W * Q_H + L_W * L_E \tag{2}$$

Step.2 Enhanced Iterative Learning: Calculate the past return value R_{inM} based on the maximum value within the learning resource returns.

$$R_{inM} = D_c * Max(SRT(R_{ij})) \tag{3}$$

The calculated result value R_t equals the sum of the current learning resource benefit value C_R and the past benefit value R_{inM}. If the result value reaches the learning target value D, the end state bit F_{sb} is true.

Step.3 Parameter Adaptive Adjustment: Update the learning selection reward table SRT. The calculation method for the new value $SRT(R_{ij})$ in the table is:

$$SRT(R_{ij}) = SRT(R_{ij}) + SS * (R_t - P_{re}) \tag{4}$$

Step.4 Generate knowledge path recommendations: Starting from the first row of the table, sequentially read the learning selection benefit table SRT. The system selects the row with the maximum learning benefit value and pushes it into the learning path recommendation queue (PRQ). This process is repeated until the last row of the table is reached, thereby generating the PRQ. The main process of the reinforcement learning iterative algorithm is illustrated in Figure 2.

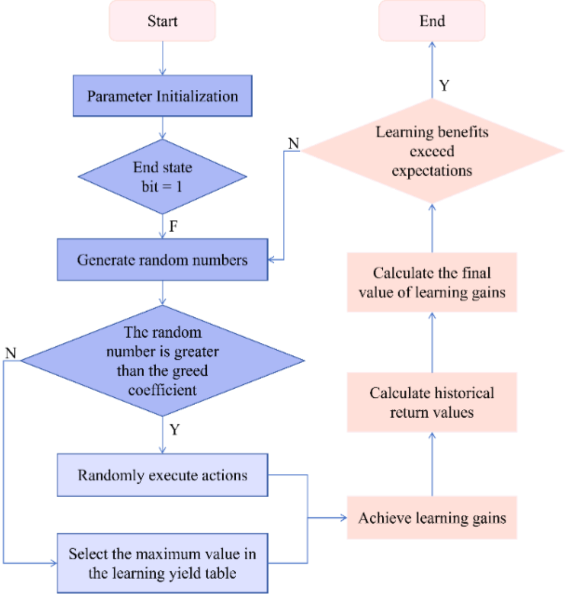
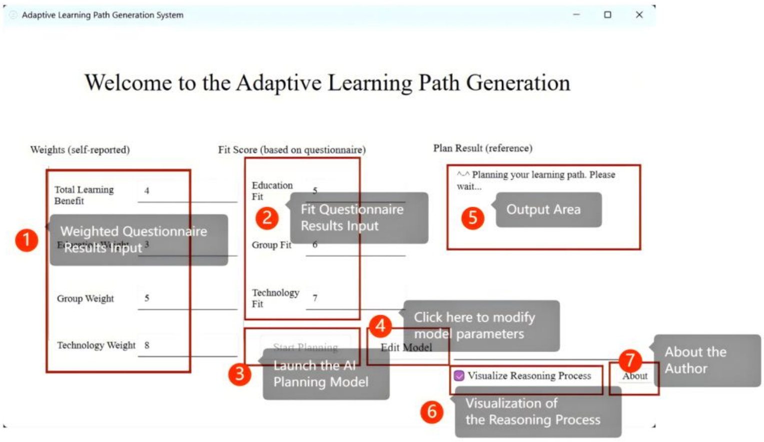


Figure 2. Main Process of the Reinforcement Learning Iterative Algorithm

4. Adaptive Learning Path Platform Design

4.1. Main Interface Features

Figure 3 below illustrates the platform's functional modules and corresponding operational interfaces.



Adaptive Learning Path Generation System

Welcome to the Adaptive Learning Path Generation

Weights (self-reported)

Total Learning Benefit: 4
Education Weight: 3
Group Weight: 5
Technology Weight: 8

Fit Score (based on questionnaire)

Education Fit: 5
Group Fit: 6
Technology Fit: 7

Plan Result (reference)

^-^ Planning your learning path. Please wait...

① Weighted Questionnaire Results Input

② Fit Questionnaire Results Input

③ Launch the AI Planning Model

④ Click here to modify model parameters

⑤ Output Area

⑥ Visualization of the Reasoning Process

⑦ About the Author

Figure 3. Adaptive Learning Path Platform Interface

4.2. Functional Testing

Experiments were conducted on a university course dataset. Figure 4 shows the directed graph of learning resources, where nodes represent learning resources and the numbers within nodes indicate resource IDs. Connecting lines between knowledge points denote resource connectivity, while arrows indicate unidirectional learning paths influenced by knowledge support relationships.

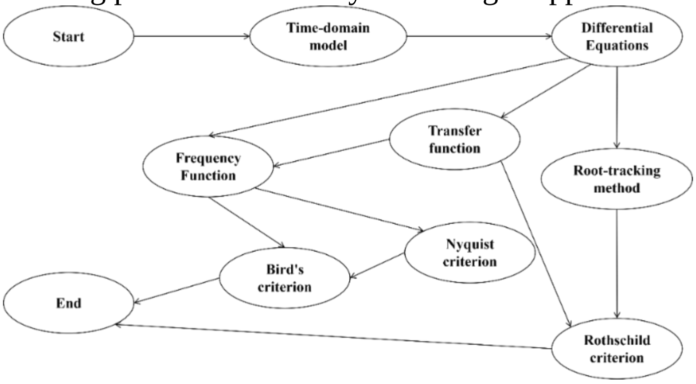
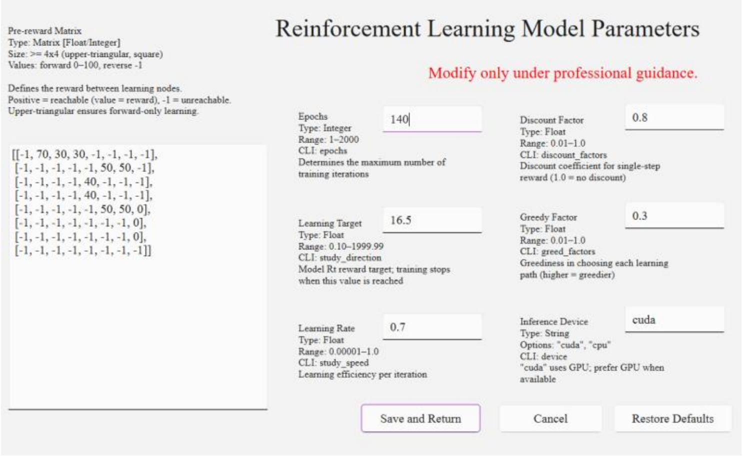


Figure 4. Example of a Learning Resource Directed Graph

The parameter settings for the reinforcement learning algorithm are shown in Figure 5:



Reinforcement Learning Model Parameters

Pre-reward Matrix
Type: Matrix [Float/Integer]
Size: >= 4x4 (upper-triangular, square)
Values: forward 0–100, reverse -1

Defines the reward between learning nodes.
Positive = reachable (value = reward), -1 = unreachable.
Upper-triangular ensures forward-only learning.

```
[[-1, 70, 30, 30, -1, -1, -1, -1],
 [-1, -1, -1, -1, -1, 50, 50, -1],
 [-1, -1, -1, -1, 40, -1, -1, -1],
 [-1, -1, -1, -1, 40, -1, -1, -1],
 [-1, -1, -1, -1, -1, 50, 50, 0],
 [-1, -1, -1, -1, -1, -1, -1, 0],
 [-1, -1, -1, -1, -1, -1, -1, 0],
 [-1, -1, -1, -1, -1, -1, -1, -1]]
```

Modify only under professional guidance.

Epochs: 140
Type: Integer
Range: 1–2000
CLI: epochs
Determines the maximum number of training iterations

Discount Factor: 0.8
Type: Float
Range: 0.01–1.0
CLI: discount_factors
Discount coefficient for single-step reward (1.0 = no discount)

Learning Target: 16.5
Type: Float
Range: 0.10–1999.99
CLI: study_direction
Model Rt reward target; training stops when this value is reached

Greedy Factor: 0.3
Type: Float
Range: 0.01–1.0
CLI: greed_factors
Greediness in choosing each learning path (higher = greedier)

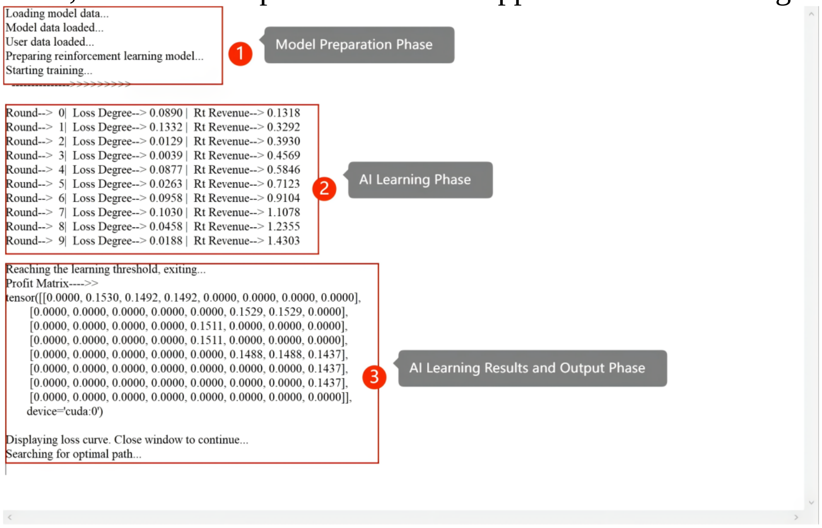
Learning Rate: 0.7
Type: Float
Range: 0.00001–1.0
CLI: study_speed
Learning efficiency per iteration

Inference Device: cuda
Type: String
Options: "cuda", "cpu"
CLI: device
"cuda" uses GPU; prefer GPU when available

Figure 5. Reinforcement Learning Model Parameter Configuration Interface

After entering relevant data based on actual conditions, users can click Run to obtain the platform's operational results. The results of adaptive learning path planning demonstrate that it can effectively align with students' learning characteristics and knowledge content.

You can control the display of the reinforcement learning model's learning process by selecting or deselecting the "Visualize Inference Process" option. Developers recommend enabling this feature during model parameter debugging to closely observe parameter suitability. This feature is disabled during normal user operation to conserve computational resources and accelerate processing. When visualization is enabled, the inference process interface appears as shown in Figure 6.



```
Loading model data...
Model data loaded...
User data loaded...
Preparing reinforcement learning model...
Starting training...
  ---------------->>>>>>>>>>

Round-->  0|  Loss Degree--> 0.0890 |  Rt Revenue--> 0.1318
Round-->  1|  Loss Degree--> 0.1332 |  Rt Revenue--> 0.3292
Round-->  2|  Loss Degree--> 0.0129 |  Rt Revenue--> 0.3930
Round-->  3|  Loss Degree--> 0.0039 |  Rt Revenue--> 0.4569
Round-->  4|  Loss Degree--> 0.0877 |  Rt Revenue--> 0.5846
Round-->  5|  Loss Degree--> 0.0263 |  Rt Revenue--> 0.7123
Round-->  6|  Loss Degree--> 0.0958 |  Rt Revenue--> 0.9104
Round-->  7|  Loss Degree--> 0.1030 |  Rt Revenue--> 1.1078
Round-->  8|  Loss Degree--> 0.0458 |  Rt Revenue--> 1.2355
Round-->  9|  Loss Degree--> 0.0188 |  Rt Revenue--> 1.4303

Reaching the learning threshold, exiting...
Profit Matrix---->>
tensor([[0.0000, 0.1530, 0.1492, 0.1492, 0.0000, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1529, 0.1529, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.1511, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.1511, 0.0000, 0.0000, 0.0000],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1488, 0.1488, 0.1437],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1437],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.1437],
        [0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000]],
       device='cuda:0')

Displaying loss curve. Close window to continue...
Searching for optimal path...
```

Figure 6. Adaptive Path Planning Reasoning Process

5. Conclusions

This paper proposes an adaptive learning path planning method by integrating the concept of fit with reinforcement learning. By modeling the relationship between learners and knowledge resources, the proposed approach enables dynamic and personalized path generation. Experimental results verify its effectiveness in supporting multi-level instructional needs and improving learning adaptability.

Acknowledgement

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