Shih, JL. et al. (Eds.) (2023). Proceedings of the 31st International Conference on Computers in Education. Asia-Pacific Society for Computers in Education

A Bio-Inspired Method for Personalized Learning Path Recommendation Problem

Yaqian ZHENG[a, b], Deliang WANG[c], Yaping XU[a, b], Ziqi MAO[a, b], Yaqi ZHAO[a, b] & Yanyan LI[a, b*]

[a]*School of Educational Technology, Beijing Normal University, China*
[b]*Research Center for Knowledge Engineering, Beijing Normal University, China*
[c]*Faculty of Education, The University of Hong Kong, Hong Kong*
*liyy@bnu.edu.cn

Abstract: The recommendation of personalized learning paths is recognized as one of the most challenging aspects in the field of e-learning. In the existing literature, numerous approaches have been proposed to identify appropriate learning paths for e-learners, taking into consideration multiple perspectives. However, the current state of research lacks a unified framework that effectively integrates the most vital parameters associated with the learner, learning object (LO), and domain knowledge to generate optimal learning paths. To address this challenge, a novel bio-inspired approach is proposed for solving the personalized learning path problem. In this method, we initially incorporate the learner, LO and domain knowledge models into a unified mathematical model. Then an enhanced ant colony optimization algorithm is utilized to determine the optimal personalized learning paths for learners. To investigate the effectiveness of the proposed method, we performed several computational experiments based on six simulation datasets. The results indicate that the proposed method surpasses other competing methods in terms of performance and robustness, showcasing its superior effectiveness.

Keywords: E-learning, learning path recommendation, unified model, ant colony optimization algorithm

1. Introduction

E-learning has gained significant prominence in the education sector, providing remarkable opportunities for learning (Al-Fraihat et al., 2020). However, e-learners, particularly those with limited experience in a specific domain, may face challenges such as information overload and learning disorientation when confronted with a wide range of resources (Meng et al., 2021). In order to tackle this issue, several methods have been proposed for the automated generation of personalized learning paths for e-learners. These methods aim to optimize learning paths from various perspectives, including domain knowledge structure and learning preferences, among others. Nevertheless, there is currently no unified framework that effectively incorporates the most significant parameters linked to the learner, learning object (LO), and domain knowledge in order to create optimal learning paths. To this end, a novel bio-inspired approach is proposed to discover personalized learning paths for e-learners, in which the important parameters associated with learner, LO and domain knowledge are formulated as a unified mathematical model and an enhance improved ant colony optimization (EACO) algorithm is utilized to identify the optimal personalized learning path.

2. Problem Formulation

The personalized learning path recommendation problem (PLPRP) is represented by a three-tuple consisting of a learner model, LO model, and knowledge graph. Figure 1 presents a description of the problem formulation.

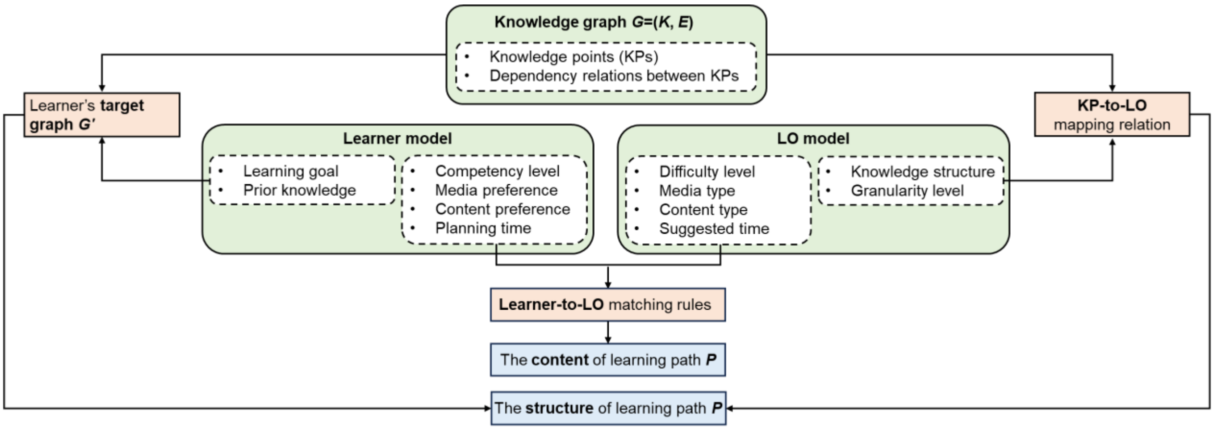

Figure 1. Description of the problem formulation for the PLPRP.

Here, the PLPRP is considered as a constrained optimization problem. The unified mathematical model is expressed as follows:

$$Minimize\ F = w_{match}F_{match} + w_{continuity}F_{continuity} \quad (1)$$

Subject to

$$KP\_set(G') \subseteq KP\_set(P) \quad (2)$$

$$(KP_i, KP_j) \in E, \forall KP_i, KP_j \in KP_{set}(P), 1 \leq i < j \leq KP\_number(P) \quad (3)$$

where F_{match} assesses the matching degree between the learner and LOs based on Learner-to-LO matching rules and $F_{continuity}$ evaluates the path's continuity based on the dependency relations between KPs. Constraint (2) is employed to ensure the path's completeness, while constraint (3) is utilized to guarantee its legality.

3. A Bio-Inspired Method for Solving the PLPRP

To solve the model of PLPRP, a bio-inspired algorithm, i.e., an enhanced ant colony optimization algorithm (EACO) is proposed.

- Problem representation. The problem space is transformed into a KP space and LO space. Once an ant selects a node, the KP and LO space undergo dynamic updates. When the KP space becomes empty, a feasible learning path solution is constructed.
- Heuristic information. The matching degree between the learner and LO is leveraged to design the new heuristic information.
- Pheromone initialization. Following prior work (Yu et al., 2018), the value of pheromone is initialized by a *greedy nearest-neighbor algorithm*.
- Dynamic candidate set strategy. To generate feasible solutions of learning path, a *dynamic candidate set strategy* is presented, which constructs the candidate set for each element based on the dependency relations.
- Selection of the initial node. The heuristic information and the *roulette selection rule* are utilized to determine the initial positions of the ants.
- Selection of the next node. The selection of the next node is determined using the *pseudorandom-proportional rule* (Ma et al., 2021).
- Pheromone Update. After an ant finishes constructing a solution, the pheromone levels on the edges visited by the ant in the obtained solution are locally updated. Once all the ants have completed their solutions, the pheromone trails are evaporated, and only the best-so-far ant is permitted to release pheromone on all the edges along its traveled path.

4. Computational Experiments

We generate multiple simulation datasets to perform computational experiments and assess the effectiveness of our proposed algorithm. The datasets are defined based on the number of KPs and LOs. The specific settings are as follows: (10, 30), (15, 45), (25, 75), (40, 120), (60, 180), and (90, 270). For the purpose of comparison, three widely used algorithms, namely random algorithm (RA), genetic algorithm (GA), and standard ant colony optimization algorithm (SACO), are employed. Considering the inherent stochastic nature of these algorithms, each of them is independently executed 20 times for every dataset.

Table 1 provides a summary of the computational results, presenting the average objective function value over 20 runs (labeled as *Obj*) and the standard deviation of the objective function values across different trial runs (labeled as *Std*). The values of *Obj* obtained by RA are always the highest, so its performance is the poorest. This indicates that learners encounter challenges when attempting to independently explore suitable learning paths. GA, SACO, and EACO obtain better solutions than RA, demonstrating that employing heuristic algorithms can effectively guide the search process toward more promising areas. In all scenarios, EACO demonstrates the highest level of performance, and its superiority becomes increasingly prominent as the problem dimension expands. In comparison to other algorithms, RA exhibits significantly larger values of *Std*, which imply its limited stability. On the other hand, IACO consistently achieves the smallest *Std* values across all scenarios, highlighting its remarkable robustness.

Table 1. *Performance of the Proposed Algorithm and Other Competitors on Six Datasets*

Dataset	RA		GA		SACO		EACO	
	Obj	*Std*	*Obj*	*Std*	*Obj*	*Std*	*Obj*	*Std*
1	1.2530	0.1745	0.5339	0.0514	0.3430	0.0188	0.3250	0.0000
2	1.1626	0.1589	0.5141	0.0585	0.3106	0.0199	0.2250	0.0000
3	1.2734	0.1728	0.9649	0.0426	0.7035	0.0231	0.2170	0.0024
4	1.3364	0.1497	0.9888	0.0224	0.6915	0.0210	0.1966	0.0065
5	1.6351	0.1262	1.3335	0.0474	1.0830	0.0199	0.1308	0.0022
6	1.7216	0.1375	1.1698	0.0159	1.1670	0.0342	0.2112	0.0059

5. Conclusions

In this work, we propose a bio-inspired algorithm to address the personalized learning path recommendation problem (PLPRP). The experimental results indicate that compared with other competitors, the proposed algorithm achieves better performance and robustness when dealing with the PLPRP across varying sizes and levels of complexity.

Acknowledgements

This work has been supported by the National Natural Science Foundation of China (Grant No: 62277006), the Beijing Natural Science Foundation (Grant No: 9222019), the Science and Technology Research Youth Fund Project of Higher Education Institutions of Hebei Province (Grant No: QN2018261) and the Student Research Fund of the Faculty of Education at Beijing Normal University (Grant No: 2212216).

References

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67–86.

Meng, L., Zhang, W., Chu, Y., & Zhang, M. (2021). LD–LP generation of personalized learning path based on learning diagnosis. *IEEE Transactions on Learning Technologies*, 14(1), 122-128.

Nabizadeh, A. H., Leal, J. P., Rafsanjani, H. N., & Shah, R. R. (2020). Learning path personalization and recommendation methods: A survey of the state-of-the-art. *Expert Systems with Applications*, 159, 113596.

Yu, X., Chen, W. N., Gu, T., Yuan, H., Zhang, H., & Zhang, J. (2018). ACO-A*: Ant colony optimization plus A* for 3-D traveling in environments with dense obstacles. *IEEE Transactions on Evolutionary Computation*, *23*(4), 617-631.

Ma, W., Zhou, X., Zhu, H., Li, L., & Jiao, L. (2021). A two-stage hybrid ant colony optimization for high-dimensional feature selection. *Pattern Recognition*, 116, 107933.