Research on Learning Path Recommendation Algorithms in Online Learning Community

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Abstract. Aiming at the problem of “learning defiance” and “information overload” brought by educating big data to learners, this paper proposes an online learning community personalized learning path recommendation algorithm based on ant colony algorithm: in terms of computing pheromone, it combines individuality. Based on the characteristics of the learning path, a learning path scoring method based on multi-factor fuzzy evaluation is proposed to quantify the learning path evaluation as a score to solve the problem that it is difficult for the subjective score to accurately represent the pheromone concentration; in terms of pheromone updating rules, The introduction of pheromone restriction intervals avoids the problems associated with excessive or small learning path pheromone concentration in global updating; in the calculation of the selection probability of local search, the positive and negative feedback effects of pheromones can be better used. Search for a local optimal solution. The related experiments show that this algorithm can effectively solve the recommendation of the personalized learning path of the online learning community.

Introduction

In the learning process of online learning communities, educators collect and record in real time many data (such as behaviors, trajectories, performance, etc.) generated by learners during the learning process, and provide targeted learning resources or best learning solutions for learners. Helps meet the actual needs of learners' individualized learning and the development of higher-order thinking skills, and promote learner learning effectiveness.

On the study of learning path recommendation, domestic and foreign related work: Considering the dependence on learning ability between learning objects, a model based on graph theory to establish a learning design recommendation system is proposed [1]. The influence of learner's ability on the learner's recommendation path was studied [2]. By applying Markov chain and classification algorithm to provide personalized recommendation recommendations, each student's question questioning method is optimized [3]. A learner-oriented learning recommendation method based on hybrid concept mapping and immune algorithm is proposed to provide learners with a suitable learning path [4].

Ant colony algorithm applied to learning path recommendation has been proved to be a feasible idea. Therefore, based on the above research, this paper proposes a learning path recommendation algorithm based on online learning community based on ant colony algorithm. The main tasks include:

(1) In terms of pheromone calculation, a learning path scoring method based on the multi-factor fuzzy evaluation is proposed in combination with the characteristics of the individualized learning path. This method quantifies the learning path evaluation of the online learning community through
the fuzzy calculation method as a score. To solve the problem that it is difficult to accurately represent
the pheromone concentration with subjective ratings.

(2) In terms of pheromone update rules, a pheromone restriction interval was introduced in the
design of global update rules to limit the related problems caused by excessive or too small
pheromone concentrations in the learning path.

(3) In the calculation of the selection probability of local search, the similarity learners use the
pheromone to implement positive feedback and the dissimilar learners implement negative feedback
through pheromone. The problem of local optimal solution is explored.

Personalized Learning Path Recommendation Framework

Based on the research of literature [5-7], this paper proposes a personalized learning path
recommendation algorithm for online learning community. The algorithm simulates the ant colony
seeking process to carry out the learning path recommendation. That is, during the foraging process,
the ants usually use the pheromone as the medium for indirect communication (pheromone
calculation). The ant colonies work together to find the target. The more ants passing through a path,
the greater the concentration of pheromone in the path over time, and the higher the probability that
subsequent ants will select the path (calculation of transition probability formula). However, the
amount of information on other paths will decrease with time (pheromone updates), so there will be
an optimal path chosen by the ant colony. Its framework is shown in Figure 1.

The algorithm is an improvement to the traditional ant colony path recommendation algorithm: (1)
pheromone computation, combined with the characteristics of a personalized learning path, proposes
a learning path scoring method based on multi-factor fuzzy evaluation, which will learn online
learning community. Path assessment is quantified into scores by means of fuzzy calculations to solve
the problem that it is difficult for subjective scores to accurately represent pheromone concentrations;
(2) pheromone update strategy, introducing pheromone restriction intervals, and limiting the
maximum value of pheromone accumulated on the learning path. The minimum value, where the
minimum pheromone concentration increases the possibility of exploring for better solutions, the
maximum pheromone concentration guarantees the heuristic of the experience for the ant colony; (3)
Formulate the local search strategy, according to the learning style of the same learner. The principle
of mutual "attracting" and learning styles among "learning" between different learners makes use of
pheromone to implement positive feedback between similar learners and the difference between
learners' mutual suppression through pheromones. Solve the problem of local optimal solution.

Figure 1. Learning Path Recommendation Framework in Online Learning Community.
Key Technologies in the Algorithm

Heuristic Information Calculation

In the principle of ant colony routing, heuristic information and pheromone are used to calculate learners' path selection probability, which directly influences path selection decision. There are two types of heuristic information in this article, namely, cognitive heuristics and preference heuristic information. The cognitive heuristic information represents the matching degree between the learner's cognitive level $v$ and the degree of difficulty of the knowledge point $d$. Its calculation formula is shown in formula (1); The preference heuristic information refers to the matching degree between the learner resource preference $c$ and the knowledge point representation $o$, and the calculation formula is shown in Formula (2).

$$h_{v-d} = 1 - |v - d|$$  \hspace{1cm} (1)

$$h_{c-o} = 1 - |c - o|$$  \hspace{1cm} (2)

Pheromone Calculation

This section is based on the multi-factor fuzzy evaluation method [8], which translates the evaluation of the learning path into score and uses the score as the pheromone for the calculation of the personalized learning path. The specific steps of this method are as follows:

1. Establish an evaluation index system. Based on the analysis of the characteristics of personalized learning paths, a personalized learning path assessment system is designed. The system is composed of three levels, which are evaluation objects, evaluation criteria, and evaluation factors. The evaluation object is the learning path $l_{ij}$, which involves three evaluation criteria ($U_1 = \text{Applicability}$, $U_2 = \text{Experience}$, $U_3 = \text{Purpose}$). Each evaluation criterion involves several evaluation factors, and a total of 8 evaluation factors ($U_1 = \{U_{11}, U_{12}\}$, $U_2 = \{U_{21}, U_{22}\}$, $U_3 = \{U_{31}, U_{32}, U_{33}, U_{34}\}$), if applicability $U_{11}$ under $U_1$ is to play a personal advantage, $U_{12}$ is whether the two factors meet the current cognitive level.

2. Determine the evaluation set V. The evaluation set $V = \{v_1 (\text{excellent}), v_2 (\text{good}), v_3 (\text{middle}), v_4 (\text{difference}), v_5 (\text{very bad})\}$ is a set of evaluation levels, and different scores can be quantified according to different levels, such as Graded = 9 and good = 7 for equal variance assignment.

3. Establish a weight set of evaluation factors. Using the Analytic Hierarchy Process (AHP) method [9] to calculate the weights of the evaluation factors within each evaluation criterion $W = \{W_1, W_2, W_3\}$, where $W_1 = \{W_{11}, W_{12}\}$, $W_2 = \{W_{21}, W_{22}\}$, $W_3 = \{W_{31}, W_{32}, W_{33}, W_{34}\}$ to describe the relative importance of each evaluation index for evaluation purposes.

4. Based on the correspondence between evaluation index system T and evaluation set V, a fuzzy evaluation matrix A is constructed. $A = (A_1, A_2, A_3)$, where $A_i$ is the i-th criterion fuzzy evaluation matrix, $A_i = (a_{ij})$ $p \times n$, where $p$ is the number of comment grades, $n$ is the number of evaluation indicators in the layer and $A_i = v_{ij} / n$, $n$ is the total number of reviews of evaluation criteria i.

5. The pheromone value is obtained by using the evaluation criteria and the weights and fuzzy matrix of the evaluation factors. The membership degree vector $P$ is calculated according to the formula (3) (4), and the maximum value is selected as the pheromone value according to the principle of maximum membership degree.

$$P_i = W_i \circ A_i = (b_{i1}, b_{i2}, ..., b_{im})$$  \hspace{1cm} (3)
\[ P = W \circ \left[ P_1, P_2, P_3 \right]^{-1} = (b_1, b_2, b_3) \] (4)

Where \( P_i \) is the score of the \( i \)th evaluation criterion, "\( \circ \)" is a fuzzy operator, and this paper selects a weighted average type fuzzy operator to perform the operation. The calculation formula (5) of the weighted average type fuzzy operator is shown.

\[ b_j = \sum (w_i \times a_{ij}) (j = 1, 2, \ldots, p) \] (5)

**The Introduction of Pheromone Limit Intervals**

In this paper, the pheromone restriction interval is introduced on the basis of the traditional pheromone update rule [9] of the ant colony algorithm to solve two problems: (1) the role of legacy pheromone covering the heuristic information; (2) Excessive pheromone is too small, leading to the failure of pheromone guidance. Therefore, the pheromone restriction interval is introduced to solve the above problems by solving the ant colony algorithm too early. The specific approach is to use the formula (6) to limit the pheromone during the global updating of the algorithm pheromone.

\[
R^k_{ij}(t,u) = \begin{cases} 
R_{max}^k, & R^k_{ij}(t,u) \geq R_{max} \\
R_{min}^k, & R^k_{ij}(t,u) \leq R_{min} \\
R^k_{ij}(t,u), & R_{min} < R^k_{ij}(t,u) < R_{max} 
\end{cases}
\]
(6)

Where \( R^k_{ij}(t,u) \) represents the concentration of pheromone left by the \( k \)-th ant (learner) of class \( u \) in the path \( l_{ij} \).

**Local Search Transfer Probability Calculation**

The selection probability of the local search refers to the probability that the learner \( k \) selects the \( l_{ij} \) path in the same set of similar learners \( A_k (1 \leq n \leq m) \). This article uses the idea of literature [9] to use the negative feedback effect of pheromone (that is, to add the influence of alien ant colony in local search selection) to solve the problem of local optimal solution.

For this purpose, \( x \) learners are divided into \( m \) classes by a binary k-means clustering algorithm, ie learners are divided into ant colonies \( A_1, A_2, \ldots, A_m \). First, at \( t \) time, the corresponding pheromone concentrations on the learning path \( l_{ij} \) are respectively \( R^k_{ij}(t,1), \ldots, R^k_{ij}(t,m) \), and the pheromone influences the pheromone for others (ie positive feedback for similar learner scores and negative feedback for dissimilar learner scores). Secondly, based on the learner characteristics and knowledge point matching degree as heuristic information, the heuristic information and pheromone concentrations can be combined to calculate the learning path selection probability, as shown in formula (7).

\[
P^k_{ij}(t,n) = \begin{cases} 
\frac{[h_{\alpha_1}]^{\beta} \times [h_{\alpha_2}]^{\beta} \times [R^k_{ij}(t,n)]^\beta}{\sum_{l_{ij} \in \text{allowed}_k} [h_{\alpha_1}]^{\beta} \times [h_{\alpha_2}]^{\beta} \times [R^k_{ij}(t,l)]^\beta} & (l_{ij} \in \text{allowed}_k) \\
0 & (l_{ij} \notin \text{allowed}_k)
\end{cases}
\] (7)

Which \( \text{allowed}_k \) represents the set of knowledge points that the learner \( k \) can select; \( \beta \) is the pheromone influence factor; \( \alpha_1, \alpha_2 \) is the corresponding information heuristic factor, and \( \sum_{l_{ij} \in \text{Learn}} \delta_{ij}(t,u) \) represents the sum of probability inhibitors of the path \( l_{ij} \) selected by the learners of other classes for similar learners. This suppressor is called an alien repulsion factor in this paper and its calculation is...
shown in formula (8).

\[
\delta_y(t, u) = \begin{cases} 
\sum_{s \in \text{allowed}_y} [h_{y,s}^{(1)}] \times [h_{y,s}^{(2)}] \times [R_y(t, u)]^y & (l_y \in \text{allowed}_y) \\
0 & (l_y \notin \text{allowed}_y)
\end{cases}
\]  

(8)

**Personalized Learning Path Recommendation Algorithm**

Based on the above research, this paper proposes a personalized learning path recommendation algorithm. The preparatory work of the algorithm includes: (1) Construct a learning object association diagram based on learning objectives and domain knowledge models, and construct a domain knowledge state space G; (2) Construct all possible learning paths based on the domain knowledge state space G. The algorithm shown in Figure 2.

The algorithm degenerates into a personalized learning path recommendation algorithm based on traditional ant colony algorithm when n learners are similar learners, and the time complexity is the same if the learner's goal is the same; but the worst case is considered. N learners' learning goals are inconsistent and their time complexity is \(Nc\) iterations, \(m\) is the total number of path nodes, and \(n\) is the number of learners.
This paper selects the "Data Structure" course in a school cloud classroom as the main learning content of the learner. A total of 197 learners in the four classrooms are the subjects of the study. Experiments are conducted in the experimental environment constructed in this study. Analysis of the organization structure of the course, which consists of nine chapters a total of 40 sections, involving a total of 457 related video and audio resources, a total of 63 sets of exercises. At the same time, it provides a learning forum related to this course. The forum contains various text types of learning resources such as posts, summaries, etc.; simulates the personalized learning process during the experiment and requires each learner to complete the learning style in the learning community. And knowledge level testing and independent learning and other links.

This paper first analyzes the contents of the "Data Structure" on the basis of the division of knowledge points, the construction of domain knowledge table and analysis of learner learning characteristics to construct the learner database table. At the same time, using Java Web related technologies, a learning platform is set up as a test environment with Java + Spring + MySQL as the framework. The learning resources such as course materials are presented in the form of HTML files.

Empirical Research

Experiment Instructions

This paper selects the "Data Structure" course in a school cloud classroom as the main learning content of the learner. A total of 197 learners in the four classrooms are the subjects of the study. Experiments are conducted in the experimental environment constructed in this study. Analysis of the organization structure of the course, which consists of nine chapters a total of 40 sections, involving a total of 457 related video and audio resources, a total of 63 sets of exercises. At the same time, it provides a learning forum related to this course. The forum contains various text types of learning resources such as posts, summaries, etc.; simulates the personalized learning process during the experiment and requires each learner to complete the learning style in the learning community. And knowledge level testing and independent learning and other links.

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The recommended algorithm is developed on the server side by Java language. Learner behavior data is stored in log files and used as input for the recommendation algorithm.

**Analysis of Results**

In order to verify the experimental results of the algorithm, this paper randomly selects 98 learners from 197 students and does not provide any recommendation service when performing autonomous learning. Another 97 learners provide a personalized path recommendation algorithm based on an online learning community. And learners can choose to accept the results of the recommendation, or they can choose not to accept but ask them to submit their results. Analyze the results of relevant data generated by learners in the experimental environment.

1) Learning efficiency analysis

Receiving the recommended learner's learning efficiency can prove the effectiveness of the recommendation algorithm. This paper randomly selects the learner's learning situation of 10 knowledge points and compares and analyzes the learning efficiency of the learner's knowledge point accepted by the proposed algorithm and the unreceived recommended algorithm, as shown in Figure 2. The results show that the learning efficiency of the learners who accepted the algorithm recommendation results is higher than that of the learners who did not accept the algorithm, and the more the knowledge content involved in the knowledge points is, the more complex the improvement effect is.

![Learning efficiency comparison](image)

Figure 2. Learning efficiency comparison.

2) Satisfaction analysis

This article analyzes the degree of personalization (satisfaction) of the recommendation results by the average learning time after the recommendation and the coincidence of the learning trajectory and the recommendation result.

**The Time of Learning after Receiving the Recommendation.** This study collected the learning time of the learners who did not receive the recommended learner and the time period of the week that they did not accept the recommended learner, and randomly selected a week for statistics. The average length of time for the recommended learner was 11.3 (hours) /week). The average length of learning for learners who did not receive any recommendation was only 8.5 (hours/week).

**The Coincidence Degree Between the Recommended Learning Trajectory and the Recommendation Results.** This article also counts the coincidence degree between the learner's learning trajectory and the recommendation results after receiving the recommendation. The results showed that the number of learners with a coincidence of more than 80% accounted for 86% of the total number of recommenders. Therefore, the experimental results show from the side that the results of the algorithm proposed in this paper are easily accepted by learners and are willing to be used as future learning plans.
Conclusion

This paper introduces in detail the principle and key technologies of personalized learning path recommendation algorithm based on ant colony algorithm and improves it from three aspects. First, the pheromone calculation is optimized based on a multi-factor fuzzy evaluation method. Second, the pheromone restriction interval is introduced to limit the value of the pheromone when the information is updated globally. Finally, according to similar learners' "attracting" to each other, different learners choose the principle of "repulsion" to each other, adjust the concentration of pheromone in the path through pheromone inhibitors, and fully utilize the positive and negative feedback effects of pheromones to improve the accuracy and degree of personalization of the recommended path. Experiments were conducted on data collected from the self-constructed platform to demonstrate the effectiveness of the proposed algorithm.

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References


