Learning Path Planning Algorithm Based on Career Goals and Artificial Intelligence

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Abstract—With the development of the Internet, various forms of learning resources continue to flood the public, especially the promotion of video learning platforms. More and more people use their spare time to learn what they need. However, there is a general lack of intelligence in online learning platforms at present, which greatly reduced the utilization of online learning platforms and their educational advantages. The innovation of this paper is proposing and explaining that with the integration of big data, online education and artificial intelligence, the contradiction of online education has turned into one between the lack of intelligence in online education and the demand of users. To solve this contradiction, this paper researches from the perspective of an algorithm. Course recommendation is the core algorithm of online education. However, the current recommendation algorithm based on collaborative filtering has the disadvantages of cold start and useless recommendation content. In this paper, Apriori and ACO algorithms in artificial intelligence are studied, and the proposal of an algorithmic framework named Position-Apriori-ACO brings forth new ideas in solving online education problems. The Position-Apriori-ACO algorithm can effectively carry out course recommendation and learning path planning, and also provides a research direction for the intelligent development of online education.

Keywords—learning path planning, course recommendation, online education, vocational education, artificial intelligence, big data

1 Introduction

Big data has impacted every aspect of society, from business technology to healthcare, government, education, economics, humanities and more. In 1980, Alvin Toffler predicted that big data would become the "third wave" in the book "The Third Wave". The Obama administration defined big data as "the new oil of the future." In 2014, Kevin Kelly believed that all businesses are data businesses. Online education has taken "big data" to a new level [1]. The core of education is the dissemination of knowledge. Combining knowledge with big data and continuously improving and optimizing the knowledge dissemination system is as important to the Internet education industry as it is to the traditional education industry.

Big data refers to the collective term for (new) data generated in new technological environments such as cloud computing, the Internet of Things, and smart cities. Compared with traditional data, big data has the following four characteristics:

1. Volume. Compared to existing computing and storage capacity, the volume of big data is enormous, and the temporal distribution of the data volume is not uniform. The volume of data in recent years has accounted for the majority of the total data volume, showing a trend of data explosion.
2. Variety. The data types involved in big data are very diverse and unevenly distributed. The data structure includes structured, semi structured, and unstructured. Unstructured accounts for most of the total data.
3. Value. It is difficult to discover the data value of big data, and the distribution of data value is not linear. It is necessary to dig out the value of big data from massive data.
4. Velocity. The growth and processing speed of data are characterized by "fast". On the one hand, in the era of big data, different data forms such as audio, video, pictures, logs, networks, and locations present a trend of linear growth in data. On the other hand, real time processing is the mainstream form of big data processing, and the requirements for processing speed are becoming more and more stringent [2].

With the advent of the big data era, industries are beginning to integrate with their respective fields to create big data in their specialties [3]. The combination of education and big data has produced education big data. The big data industry is driven by data and produces smart data products [4]. Among many types of data products, path planning is a process of big data optimization through algorithms related to artificial intelligence. The complexity and diversity of education big data have become hotspots and difficulties for scholars [5].

With the development of big data and the Internet, various forms of learning resources continue to flood the public, especially the promotion of video learning platforms. More and more people use their rest time to learn what they need. In recent years, due to the global impact of COVID-19 [6-7], online education has once again become a research challenge in the field of computer and education.

Early research has shown that online education provides the fastest and most effective way of learning for people to compensate for a lack of knowledge and skills [8-9]. However, scholars have found that: online education platforms have long been unacceptable to many Digital Learning Objects (DLS), which greatly reduces the utilization of online learning platforms and their educational advantages[10-11]. In 2021, Stefanos Poultsakis et al. pointed out that the reason was that the existing technology support of online education platforms could not serve users well [12]. Regarding the current development problems of online education, this paper puts forward the following views on the basis of previous research: Before the advent of the big data era, the contradiction of online education was between the lack of information resources and the increasing demand for resources. In the current environment, where big data, online education and artificial intelligence are integrated, the contradiction of online education has changed to one between the lack of intelligence in online education and the needs of users for intelligence. The reason for the contradiction is that the development level of online education does not match the needs of users for autonomous learning.

The current status of online education is:

1. At present, as a new form of education, MOOC is gradually favored by learners for its rich resources, convenience, and low price [13]. In recent years, the number of online learning users has been growing at a rate of more than 20%, and the development of MOOC is in full swing. Online education platforms at home and abroad, such as Blackbord, Moodle, Coursera, edX, Xuetang Online, and NetEase Open Courses, have continued to increase [14]. Nowadays, online learning has become an important trend in the development of education in the information age and has received attention from all walks of life at home and abroad [15-16].
2. The courses of the online education platform exist independently of each other. The online learning platform is an aggregation platform. All courses are recorded and uploaded by different teachers. There is no connection between courses.
3. The online education platform lacks guidance. The platform does not have any plans for users' learning, and users need to find the resources they need from the massive learning resources.
4. The core algorithm of the online learning platform lacks intelligence [17-18]. The platform puts the core algorithm on the course recommendation, but the current course recommendation is based on the collaborative filtering algorithm, which has serious flaws: 1) Cold start problem: The collaborative filtering algorithm recommends courses for you based on content or user similarity. When new users appear, the system lacks historical data and cannot complete the recommendation [19]. 2) The basis for collaborative filtering recommendation is the user's historical data, and such recommendation is often worthless because the user's learning is an advancing process. The collaborative filtering algorithm can only recommend courses similar to the user's historical data, which is of no value to the user's future learning [20]. Therefore, users' perception of the current mainstream course recommendation algorithm is very low.

Current status of user learning needs:

1. The rapid development of online education comes from the needs of users for independent learning: 1) Today's society presents a phenomenon of a knowledge explosion, and the professional skills in different fields are showing constant innovation and progress. Everyone needs to continuously learn new technologies and new knowledge to adapt to work and research needs. 2) The mismatch between the practical skills demanded by enterprises for talents and the theoretical education in schools is becoming increasingly serious. The world is vigorously developing vocational education, opening second classrooms, carrying out educational reforms, and cultivating applied talents. 3) Students need to learn some professional skills required by the target enterprises in advance in order to be competent for their desired employment positions [21]. 4) Many college students may not want to engage in work related to their major after graduation, which requires self-learning some knowledge of other majors which they have never learned before. 5) In recent years,

influenced by COVID-19, online education has become a more important way of knowledge transmission.
2. Difficulties with independent learning: 1) When users learn independently, without the learning guidance of teachers and the training planning of schools in traditional education, students do not know how to plan their learning path. 2) Even for the same occupation, the vocational skills required by each company are very different, and students do not know how to learn in a more general way. 3) There are prerequisite constraints between courses, one course may be the basis for another, so the order of learning between courses is very important, but learners do not have the professional knowledge to know how to choose the order of learning.

The above-mentioned viewpoints for the innovation of this paper—the "contradiction" of online education, and fully explain the causes of the problem, which has never been seen in the academic world. In order to solve the problem expressed by this point of view, this paper believes that we should start with the core algorithm of online education, and give the platform more intelligent algorithms so that users can feel more humane when using it. Collaborative filtering has long been used by online education platforms as a recommendation algorithm. The above points out the shortcomings of the collaborative filtering algorithm applied to online education, which has hindered the intelligent development of online learning platforms. Although scholars have been improving it, there has been no substantial breakthrough.

In order to break through this problem, the following researches have been done in this paper: The problem of learning path planning in online education is transformed into a TSP problem in machine learning, and a learning path planning algorithm based on career goals and artificial intelligence is proposed. The algorithm is named Position-Apriori-ACO. The function of the algorithm is to automatically plan the most effective, fastest and most scientific learning path according to the user's career goals.

The main contributions of this paper are summarized as follows:

1. The current contradiction in online education is proposed: the contradiction between the lack of intelligence in online education and the user's demand for intelligence, and this view is discussed and explained.
2. Convert the learning path problem into the problem of finding the optimal solution for TSP in machine learning, propose a learning path planning algorithm based on career goals and artificial intelligence, and name the algorithm Position-Apriori-ACO.
3. The algorithm proposed in this paper can be applied to many fields such as course recommendation, learning path planning, vocational education reform, second classroom, etc., and contributes the algorithm foundation and solution ideas to the intelligent development of online education in the future.

The rest of this article is organized as follows: Part 2 describes the principles of the basic algorithms of Apriori and ACO and explains the steps of the Position-Apriori-ACO algorithm. Part 3 presents the experimental design and simulation results. Part 4 gives the research results and research significance. Finally, Part 5 discusses future research directions on the intelligence of online education.

2 Methodology

This part will describe the proposed Position-Apriori-ACO algorithm in detail, as well as the related algorithms used: Apriori, ACO.

2.1 Apriori algorithm

Apriori algorithm is a data mining algorithm used to mine frequent itemsets and association rules [22]. Apriori algorithm is an algorithm for mining association rules through frequent itemsets. The algorithm can both discover frequent itemsets and mine association rules between data. The algorithm uses support and confidence to quantify frequent itemsets and association rules, respectively [23].

Description of the problem

Known. There is a data set $X = (x_1, x_2, \ldots, x_n)$, where x_i corresponds to k variables (k statistical indicators). If the value of the variable meets the set conditions, x_i can be converted into classifier data on this variable.

Solve. The frequent itemsets and association rules of the output data set.

Related concepts:

1. item: $item_k(k = 1,2, \ldots, m)$; Such as the course "data structure".
2. itemset: $\{item_1, item_2, \ldots, item_m\}$; Such as {data structure, software engineering, java}.
3. k-itemset: An itemset that contains k items. Such as 2-itemset: {data structure, software engineering}.
4. Support: The degree of support in this data set refers to the proportion of data items in which "A course" and "B course" simultaneously appear in the recruitment requirements of different companies for the same position in the total data items.

   Support:

$$support(A, B) = P(A, B) = \frac{number(A,B)}{number(all\ sample)} \tag{1}$$

5. Confidence: The degree of confidence in this data set refers to the proportion of data items in which "A course" and "B course" simultaneously appear in the recruitment requirements of different companies for the same position to the total data items of "A course".

   Confidence:

$$confidence(A => B) = P(B|A) = \frac{P(A,B)}{P(A)} = \frac{number(A,B)}{number(A)} \tag{2}$$

Algorithm 1 describes the Apriori algorithm and shows the detailed algorithm flow in Figure 1.

Algorithm 1 Apriori

step 1: Enter data set X.

step 2: Determine the set of items contained in the data set X.

step 3: Perform the first iteration, scan and count the items in each item set, regard each item as a member of the candidate 1-item set C_1, and calculate the support of each item.

step 4: Set the minimum support. According to the members, support and minimum support of the candidate 1-item set C_1, the candidate 2-item set C_2 is obtained by combining apriori-gen operation. The support of all proper subsets of the candidate item set is not less than the minimum support.

step 5: Repeat step 4 until it cannot be merged to form a new candidate item set. At this time, the final frequent item set is output and the association rules are given.

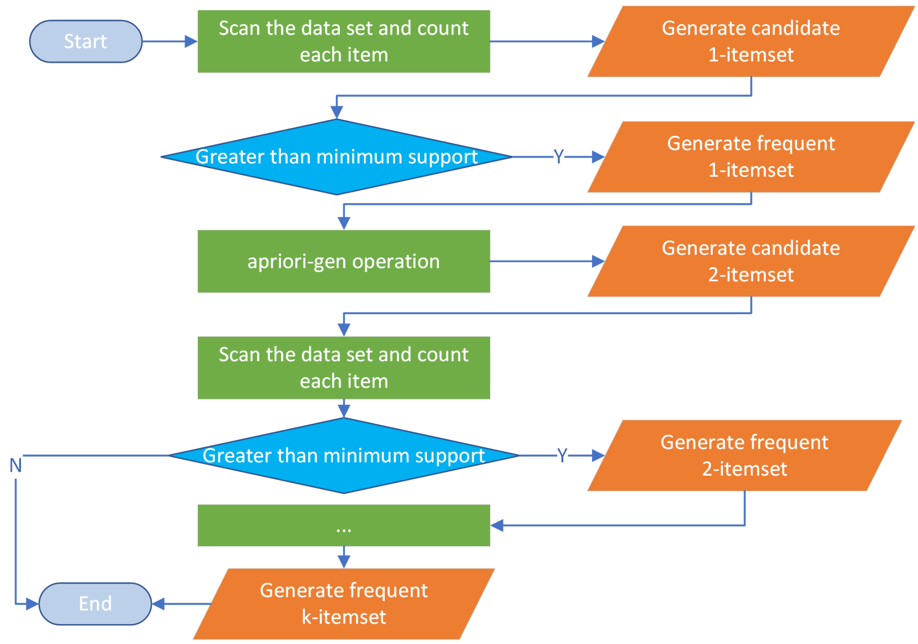

Fig. 1. Flow chart of the Apriori algorithm

2.2 TSP problem and ACO algorithm

TSP problem (Travel Salesperson Problem) is an NP-hard problem. It is difficult to solve optimally using general algorithms, so it is generally solved with the help of heuristic algorithms. For example, genetic algorithm (GA), ant colony optimization algorithm (ACO), particle swarm optimization (PSO), etc [24]. The TSP problem means that a traveler wants to travel n cities, requires each city to experience once and only once, and then returns to the departure city with the mini-mum distance. A TSP problem can be expressed as: solve the traversal graph G= (V, E, C), traverse all the nodes once and return to the starting node. Calculate how to make the connection path cost of these nodes the lowest.

ACO (Ant Clony Optimization) is a swarm intelligence algorithm, which is a group of unintelligent or slightly intelligent individuals (Agents) who exhibit intelligent behavior through cooperation, thus providing a new method for solving complex problems. ACO is a bionic algorithm inspired by the behavior of ants foraging in nature [25]-[26]. In nature, during the ant foraging process, the ant colony can always find an optimal path from the nest to the food source [27]-[28]. ACO was first used to solve TSP problems and has shown great advantages due to its distributed nature, robustness and ease of integration with other algorithms.

The basic principle in solving the TSP problem using the ACO algorithm is that m ants are placed in multiple cities at random. Let these ants start from the cities where they are located, and then return to the starting city after n steps (1 step for an ant from one city to another). If the shortest of the m paths taken by m ants is not the shortest distance for the TSP problem, this process is repeated until a satisfactory shortest path is found. Algorithm 2 gives the detailed process of the ACO algorithm.

```
  Algorithm 2 ACO
  Input: data set.
  Output: the optimal path.
  #Modeling
  step 1: initialization.
  step 2: Choose the next node for each ant.
  step 3: Update the pheromone matrix.
  step 4: Iteration. Check whether the maximum number of
iterations is reached, and
  if the maximum number of iterations is reached, step 5
is executed, otherwise, steps 1-3 are executed in a loop.
  step 5: Output the optimal value.
  The key steps of the ACO algorithm include state tran-
sition and pheromone update [29].
```

1. State transition: The algorithm gives the probability P_{ij}^{k} that the ant k moves from the city i to the next city j.

$$P_{ij}^{k} = \begin{cases} \frac{\tau_{ij}^{\alpha} * \eta_{ij}^{\beta}}{\sum_{s \in allowed_k} \tau_{is}^{k} * \eta_{is}^{\beta}} & j \in allowed_k \\ 0 & otherwise \end{cases} \tag{3}$$

Where $allowed_k$ represents all the cities that ant k could reach in the next step, τ_{ij}^{α} is the pheromone value on the path e_{ij} between cities i and j, and η_{ij}^{β} is the heuristic information value between cities i and j.

2. Pheromone update: Update the pheromone value on the path e_{ij} between cities i and j.

$$\begin{cases} \tau_{ij}(t+1) = \rho\tau_{ij}(t) + \Delta\tau_{ij}(t,t+1) \\ \Delta\tau_{ij}(t,t+1) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t,t+1) \end{cases} \tag{4}$$

Where $\Delta\tau_{ij}^{k}(t,t+1)$ is the pheromone increment contributed by ant k to path e_{ij}, $\Delta\tau_{ij}(t,t+1)$ is the pheromone contributed by all ants passing through path e_{ij}, and ρ is the pheromone residual coefficient.

There are three models for $\Delta\tau_{ij}^{k}(t,t+1)$ update [30]-[31]:

1. Ant-Density model

$$\Delta\tau_{ij}(t,t+1) = \begin{cases} Q, & e_{ij} \\ 0, & otherwise \end{cases} \tag{5}$$

2. Ant-Quantity model

$$\Delta\tau_{ij}(t,t+1) = \begin{cases} \frac{Q}{d_{ij}}, & e_{ij} \\ 0, & otherwise \end{cases} \tag{6}$$

3. Ant-Cycle model

$$\Delta\tau_{ij}(t,t+1) = \begin{cases} \frac{Q}{L_K}, & e_{ij} \\ 0, & otherwise \end{cases} \tag{7}$$

2.3 Position-Apriori-ACO

In this paper, the learning path planning problem is transformed into a TSP solution problem, because as shown in Table 1, their solution ideas are almost the same.

Table 1. Similarities of the problem

Similarities of the problem	
Path planning problem	***TSP solving problem***
The fastest learning route	The shortest travel route
Need to learn courses	Need to pass through the city
Prerequisites between courses	Distance between cities
Course coding	City coordinates

In the face of the "contradictions" in online education pointed out above, this article proposes the Position-Apriori-ACO model, which uses the career goals given by the user to obtain the most important knowledge and skills needed for employment, and then plans the best learning route for the user based on the constraints between the knowledge. The model has the following innovations and utilities:

1. Taking career goals as the characteristic value of course recommendation, which solves the problems of cold start and invalid recommended content when collaborative filtering is used for course recommendation in the industry.
2. Carry out web crawlers on the recruitment information of popular companies in various fields. Use the Apriori algorithm to mine the set of frequent items for job requirements of the same occupation in different companies. The frequently mined itemsets are regarded as the goal of users' learning, so that users' learning can satisfy as many enterprises as possible.
3. According to the design syllabus of college courses, the prerequisites and association rules between courses are obtained, and the courses are coded into two-dimensional coordinates. The problem of curriculum learning path planning is transformed into TSP solving problem, the most efficient learning path is planned for users, and the problem of lack of guidance for users in learning is solved.

Algorithm 3 and Figure 2 describe the implementation of the Position-Apriori-ACO algorithm in detail.

```
  Algorithm 3 Position-Apriori-ACO
  Input: career goals.
  Output: Course recommendation and learning path plan-
ning.
  #Modeling
  Step 1: Obtain recruitment information of popular com-
panies through web crawlers, and obtain the skills re-
quirements of job positions through data cleaning tech-
nology.
  Step 2: Through data cleaning technology, the curricu-
lum design in the talent training program of the univer-
sity is extracted, and the constraints and association
rules of the learning order between the courses are ob-
tained from it.
  Step 3: Using the Apriori algorithm to mine the most
frequently occurring recruitment requirements for the
same position in different companies.
  Step 4: According to the results obtained from steps 2
and 3, encoding the course into two-dimensional coordi-
nates.
  Step 5: Use the ACO algorithm to plan the course and
get the optimal learning path.
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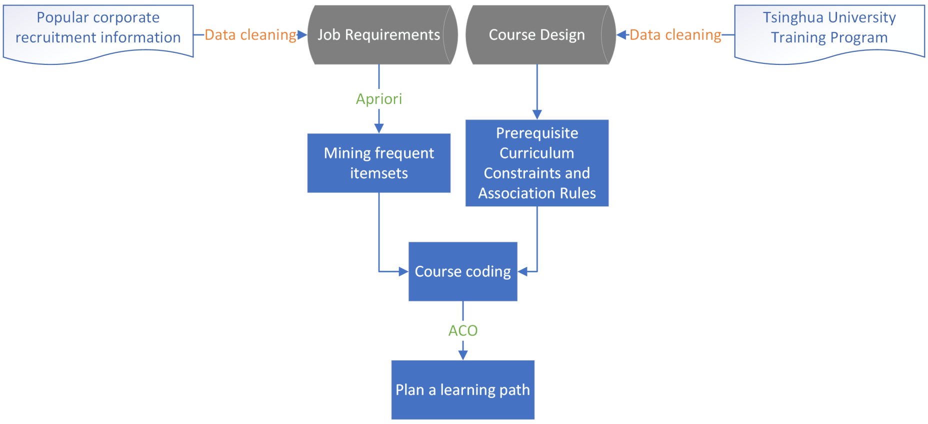

Fig. 2. Position-Apriori-ACO algorithm architecture diagram

The Position-Apriori-ACO algorithm transforms the curriculum planning problem into a TSP solution problem. The key points of conversion are as follows:

1. Encoding rules: 1) The more basic the course, the lower the level. The lower the level of the course, the smaller the coordinate value, the higher the level, the greater the coordinate value of the course. 2) The Euclidean distance between courses with the same level is smaller, and the Euclidean distance between courses with different levels is larger. 3) If course A is a prerequisite course for course B, the Euclidean distance from course A to the origin is less than the Euclidean distance from course B to the origin.
2. Use ACO to solve the learning path planning problem. Figure 3 shows the specific steps to transform the curriculum into a city and the learning path planning problem into a TSP problem.

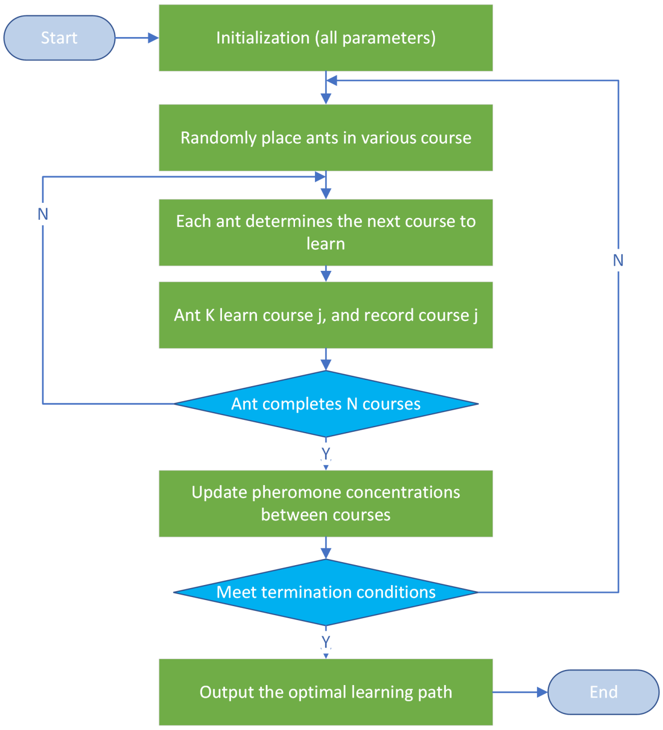

Fig. 3. Learning path planning algorithm diagram

3 Simulation and experiment

3.1 Experimental environment

Both the simulation environment and the modeling environment are Python 3.X. The experimental running platform is: AMD Ryzen 9 5900HX, NVIDIA GeForce RTX 3080, 32.00GB installed RAM.

3.2 Experimental data

In this experiment, 500 pieces of data were obtained through web crawlers, and the data structure included: position, company, and occupational requirements.

3.3 Parameter settings of the model

Through trial and error analysis and consideration of the calculation cost, Table 2 and Table 3 give the model parameters of Apriori and ACO respectively:

Table 2. References Parameter settings of Apriori

Parameter settings of Apriori		
Parameter	***Value***	***Describe***
min_support	0.2	The minimum support is 0.2.
min_conf	0.7	The minimum confidence is 0.7.

Because the source of the data set is from high-influential and representative companies' recruitment requirements, the support of the Apriori algorithm is set relatively low.

Table 3. Parameter settings of ACO

Parameter settings of ACO		
Parameter	***Value***	***Describe***
Job	C++ Software Engineer	The target position of the user.
AntCount	100	The number of ants is 100.
Alpha	1	The important factor of pheromone is 1.
Beta	2	The important factor of the heuristic function is 2.
Rho	0.1	The volatilization rate is 0.1.
Iter	0	The initial value of the iteration is 0.
Max_iter	200	The maximum value of iteration is 200.
Q	1	The initial pheromone is a matrix consisting of 1.

3.4 Results

This article takes a position as a sample to show the results, assuming that the user's career goal is "C++ Software Engineer" and the longest frequent itemset obtained by Apriori algorithm is [‘C language’, ‘computer network’, ‘C++’, ‘data structure’, ‘algorithm design’, ‘Linux’]. The optimal learning path obtained by the ACO algorithm is: [‘C language’, ‘C++’, ‘data structure’, ‘algorithm design’, ‘computer network’, ‘Linux’]. The visual graph of the results of the algorithm is as follows:

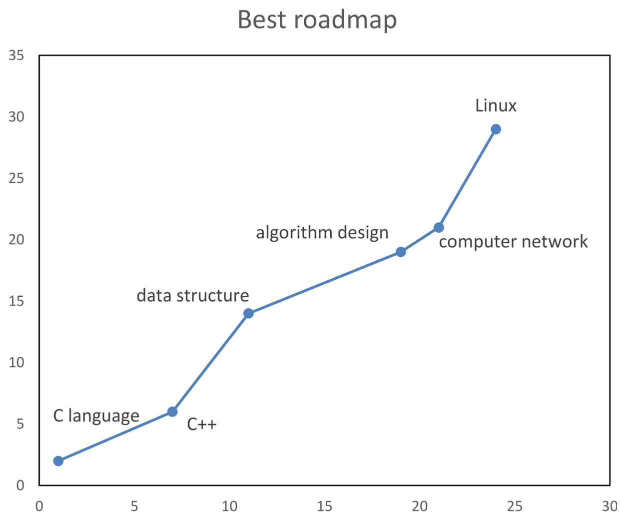

Fig. 4. Planning diagram of the learning path

Through the manual review, it is determined that the above experimental results are the most scientific and fastest learning course path. The effectiveness of the Position-Apriori-ACO algorithm has been fully demonstrated. The system can replace the recommendation algorithm based on collaborative filtering by recommending relevant courses on the learning path to the user. The Position-Apriori-ACO algorithm does not have the shortcomings of cold start and useless recommendation results.

4 Conclusion and discussion

In recent years, online education has always been a hotspot and difficulty in the field of education and computer research. This article points out that in the current environment where big data, online education and artificial intelligence are integrated, the contradiction in online education has turned into the one between the lack of intelligence in online education and the needs of users for intelligence, and explained the reasons. In order to solve this contradiction, this article starts with the course recommendation algorithm of online education, points out the problems of the current course recommendation algorithm, and proposes the Position-Apriori-ACO model. This article conducts simulation experiments on the model, and the experimental results show that the model can plan learning paths according to career goals, and can recommend courses according to the knowledge users need to learn. The model solves the problems of cold start and useless recommendation results in the algorithm based on collaborative filtering. The algorithm can be used well in the following scenarios: 1) Users who need to upgrade their skills; 2) Users who need learn on their own; 3) Users who need job training; 4) Colleges and universities that need to develop vocational education; 5) Colleges and universities that need to develop second classes, etc. The proposal of the learning path planning algorithm has transformed the core algorithm and user experience of online education in the direction of intelligence, and also provided ideas and directions for the research of intelligent algorithms in online education.

During the experiment, the dataset was obtained by web crawler. Network data is described in natural language, so data cleaning is a difficult point in data acquisition. In addition, data needs to be updated in real time, so more intelligent data acquisition strategies need to be developed in the future.

5 Future work

Elementary schools, high schools, universities, networks, training institutions, etc., online learning platforms are increasing in number around the world, but researches show that they are more like a learning management system (LMS) because they lack intelligence [32-33]. Stamatios Papadakis et al. pointed out that online education, despite its strong advantages, is currently underutilized due to the lack of personalization and interactivity, which greatly reduces user interest and perception of use. The reason is that the current online education lacks personalization and interaction, which greatly reduces the interest and perception of users [34]. This paper points out the contradiction between the current development of online education and the needs of users and demonstrates it. This paper proposes to fundamentally solve this problem by giving the online learning platform more intelligent algorithms, which should be designed and innovated according to different times, regions, and target users. In this paper, the Position-Apriori-ACO model replaces the collaborative filtering algorithm, and the good performance of the algorithm is proved by simulation experiments. It is hoped that more outstanding scholars will join this research direction in the future, and use cutting-edge technologies such as artificial intelligence, machine learning, and big data to shape a smarter brain for online education and give users a more intelligent and more humane experience. A smarter online learning platform can improve the utilization, so that the advantages of online education can be reflected to a greater extent, which is the direction of the healthy development of online learning platforms, rather than blindly increasing their number.

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