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Artificial Intelligence-based Online Customized Learning Direction Guidance Model

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Abstract

Users' requirements for online teaching platforms are developing in the direction of customization, intelligence and precision. Users urgently need customized learning direction guidance services to help them discover the learning content they need in a timely and accurate way. To address this need, this paper proposes an artificial intelligence-based online customized learning direction guidance model, introduces E-learning behavior analysis into the customized learning direction guidance system, uses artificial intelligence algorithms such as neural networks and ant colony optimization, obtains similar user learning directions by mining user web log data, iteratively calculates probabilistic optimized learning directions, and performs collaborative filtering to guide the direction of compensatory intervention. The experimental results show that the model proposed in this paper can make the learning direction generation more accurate, thus compensating for individual differences and effectively improving learning efficiency and learning quality.

Keywords

E-learning behavior, neural networks, ant colony optimization, learning direction guidance, artificial intelligence.

1. Introduction

With the continuous development of digital technology, online teaching platforms are increasingly developing in the direction of customization, intelligence and precision. In the face of teaching resources with large amount of data, strong specialization and complex knowledge structure, the problem of users getting lost in learning is especially prominent, so there is an urgent need for customized learning direction guidance services to help users discover the required learning content in a timely and accurate way. Customized learning direction is the route of learning activities and knowledge sequence chosen by users in the learning process according to their own learning preferences, learning style and learning level as well as environmental factors[1]. Customized learning direction guidance has been proven to achieve dynamic guidance and effective control of user learning behavior.

At present, there are more and more studies on customized learning direction guidance at home and abroad, which usually use two parts of building user models and directed algorithms to achieve learning direction guidance. In user model building, Madhour and Forte proposed to build a learning group model based on the similarity of users' learning goals and learning attributes[2], And Chen et al. proposed a model for building characteristics of learning members in group learning[3], Lawson builds user models based on the similarity of users' learning plans[4], Zhuo Zhong et al. proposed to build a user model based on user knowledge goals[5]. In learning direction guidance planning, Nearest Neighbor, collaborative filtering, and content-based filtering are usually used to achieve customized guidance[6]. Although combinations of guidance techniques can solve the lack of data and cold start problems, this

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typical guidance technique only provides users with a single online teaching resource or a few continuous learning sequences, ignoring the continuity and sequence of users' E-learning. In addition, it is difficult to explore the actual needs of users by providing them with knowledge items in a superficial way.

In addressing the above problems, this paper proposes an online customized learning direction guidance model based on artificial intelligence. The model contains two stages according to the guidance process, which are establishing similar learning user models and implementing customized learning direction guidance, and artificial intelligence models such as neural networks and ant colony optimization are used in each stage respectively. Considering the differences in learning levels and learning styles of different users, firstly, we use neural networks to analyze users' learning behaviors and establish user models with similar learning characteristics; then, according to the similar user learning sign-in data areas, grid-clustering learning directions and obtains similar user learning directions for collaborative filtering guidance. To reduce individual differences, ant colony optimization is used to compensate for the deficiencies of the collaborative filtering guidance. Learning directions are collections of knowledge items with sequence and continuity, so the relevance calculation of knowledge items is performed in the direction guidance.

2. Theoretical Principle

2.1. E-Learning Behavior

E-learning is a new way of learning that has gradually emerged with the advancement of the Internet and computer technology. Users can freely use the Internet to learn anytime and anywhere with the help of computers or various mobile devices to achieve the purpose of learning knowledge. The most prominent feature in the development of E-learning is that users are extremely free and can use different terminal devices to independently select learning contents to obtain the required knowledge information through different E-learning platforms according to their actual needs. A large amount of data, i.e. learning behavior data, is automatically generated during the process of E-learning by users. These data accurately record various behavioral activities of users in the learning process. Although user learning behavior data is messy on the surface, it may contain the real learning state and learning mindset of users.

The essence of E-learning behavior analysis is to analyze the data generated by users through various types of subject knowledge, to explore the behavioral characteristics and learning rules of users, to gradually improve the construction of the platform according to the research results, and to enhance the experience and efficiency of users' independent E-learning. One of the most important purposes is to develop corresponding teaching strategies and establish effect evaluation models based on the characteristics of users' personal attributes, such as their education level, interests and learning styles. Thus, users are assessed and classified to realize customized independent learning[7].

2.2. Neural Networks

Neural networks are a subset of machine learning and are at the heart of deep learning algorithms. Their name and structure are inspired by the human brain, mimicking the way that biological neurons signal to one another.

Neural networks are comprised of a node layers, containing an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, connects to another and has an associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network[8].

In this paper, it is assumed that one neuron corresponds to one learning behavior, and the neural networks are made up of a large number of interconnected neurons, and the multiple learning behaviors of users constitute an adaptive nonlinear dynamic system, and using the neural networks, a classification for learning multiple learning behaviors of the user can be obtained.

2.3. Ant Colony Optimization

Ant colony optimization is an optimization algorithm which employs the probabilistic technique and is used for solving computational problems and finding the optimal path with the help of graphs.

Ant colony optimization is inspired by the foraging behavior of ants. At the core of this behavior is the indirect communication between the ants with the help of chemical pheromone trails, which enables them to find short paths between their nest and food sources. Ant colony optimization algorithm has strong robustness as well as good dispersed calculative mechanism. Ant colony optimization can be combined easily with other methods; it shows well performance in resolving the complex optimization problem. Ant colony optimization optimizes a problem by having an updated pheromone trail and moving these ants around in the search space according to simple mathematical formulae over the transition probability and total pheromone in the region[9].

With full consideration of individual user characteristics and the relevance of the learning materials, this paper makes full use of the ant colony optimization to iteratively calculate probabilistic optimized learning directions and compensatory interventions for directions of collaborative filtering guidance, taking full account of the correlation between individual user characteristics and learning materials.

3. Artificial Intelligence-based Online Customized Learning Direction Guidance Model

This paper introduces the analysis of E-learning behavior into the customized learning direction guidance system, mine the user web log data, and construct a customized learning direction guidance model based on the guidance process. Among them, the following issues are mainly considered.

(1) How to construct user models with similar learning styles and learning levels based on users' E-learning behaviors.

(2) How to calculate the learning paths of similar learning users to obtain collaborative filtering guidance.

(3) How to optimize the learning direction for customized learning direction guidance.

Therefore, the framework of customized learning direction guidance model consists of two main parts: similar learning user module and customized learning direction guidance module. The similar learning user module is used to obtain the similar learning user model by calculating the similarity of learning style and learning level of learning users. Another core of the model framework is the customized direction guidance module, the main task is to carry out vector mapping, grid-clustering and density-based clustering based on similar learning user sign-in learning module, to calculate learning direction to obtain collaborative filtering guidance TopN-1, and further to obtain probabilistic optimized guidance direction TopN-2 by ant colony optimization, and orderly merge guidance to users, as shown in Figure 1.

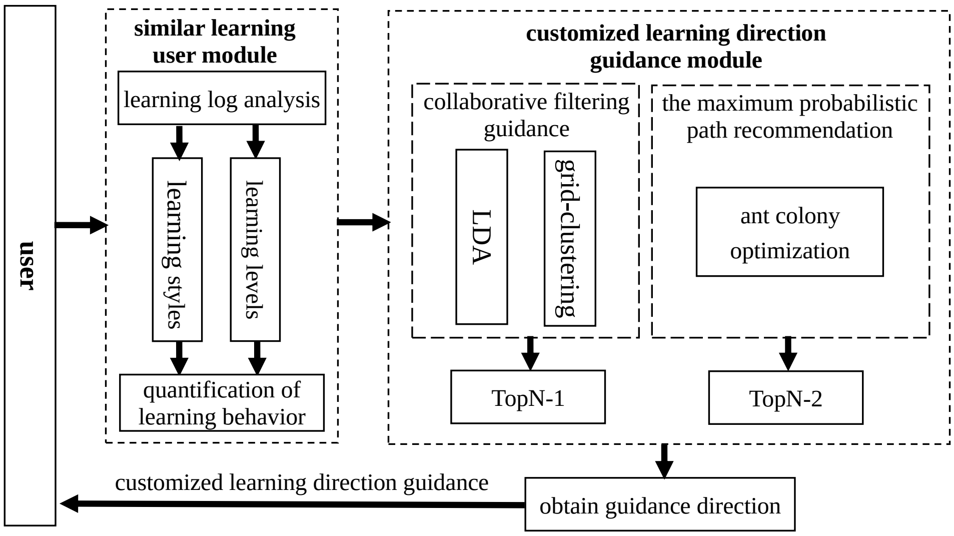

Figure 1. customized learning direction guidance module

3.1. Similar Learning User Module

The learning behavior predicts the characteristics of individual differences in users' learning styles and learning levels, and is an important basis for achieving customized guidance. Therefore, the similar learning user module is constructed in the following steps.

(1) Quantification of users' learning behavior

Users' learning behavior data are saved in the web platform logs, and these learning behavior data are the reflection of users' learning styles, and different groups of users with different learning characteristics can be established by classifying the learning behavior data with neural networks. It is assumed that all learning behavior of the user is a set of input variables $X = \{X_1, X_2, \cdots, X_n\}$, and the data enters from the input layer, which carries out Weighted Analysis, weight values are used as input layer data along with the input variables to the hidden layer. In the hidden layer, the activation function g(z), the independent variable is linear combinations of the learning behavior input variable x and the weight v, $t_j^1 = \sum v_{ij}^1 x_i$, is compared to a predefined threshold $\lambda(t_j^1)$ in the hidden layer, the threshold being the feature value [10]. If $\mathrm{g(z)} > \lambda(t_j^1)$, $\mathrm{g(z)} = 1$, we can determine that the user has a certain learning style, conversely , $\mathrm{g(z)} = -1$, we can determine that the user has the opposite learning style, as shown in Figure 2.

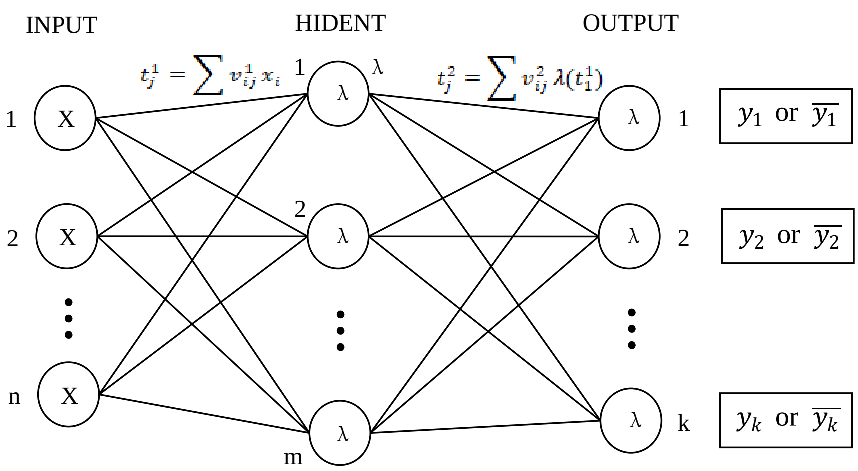

Figure 2. Neural networks discriminant based user learning style

The formula is as follows:

$$\mathrm{g(z)} = \begin{Bmatrix} 1 & \text{if } z \geq \lambda(t_j^1) \\ -1 & \text{otherwise} \end{Bmatrix}$$

$z = v_1x_1 + v_2x_2 + \cdots + v_nx_n = \sum_{j=1}^{n} x_jv_j$, v_j means the weight of the learning behavior, determined using the entropy method, which determines the objective weight according to the degree of difference in the learning behavior.

This formula leads to a learning style consisting of linear array of four dimensions, $T_i = \{1/-1, 1/-1, 1/-1, 1/-1\}$, corresponding to learning style attributes of active/reflective, intuitive/ sensitive, visual/verbal, and global/sequential, respectively.

(2) Calculation and judgment of the predefined threshold $\lambda(\mathrm{t}_\mathrm{j}^1)$

The hidden layer consists of a number of hidden node problems, each with different threshold λ, which is used to indicate the learning style corresponding to different learning behaviors. The predefined threshold $\lambda(\mathrm{t}_\mathrm{j}^1)$ is the weight of the threshold λ for different learning behaviors and is an important criterion for calculating the classification of learning styles, as shown in Table 1.

Table 1. Description of learning styles and learning behaviors and rules for calculating the predefined threshold $\lambda(\mathrm{t}_\mathrm{j}^1)$

Learning Style Types	learning styles	learning behaviors	rules for calculating the predefined threshold $\lambda(\mathrm{t}_\mathrm{j}^1)$
Information processing	active / reflective	Post a topic	The corresponding numbers are compared to the average number , with above average being active and below average being reflective.
		Reply to topic	
		Topic Click	
Information perception	intuitive / sensitive	Visit the example explanation	Efficacy values are calculated for visiting the example explanation and for viewing concept definitions, with above average being sensitive and below average being intuitive.
		View concept definitions	
Information acquisition	visual / verbal	Video Learning	Efficacy values for learning from video/lesson are calculated as above average for the visual, and above average for learning from text for the verbal.
		Lesson learning	
		Text learning	
Information comprehension	global / sequential	Using the Knowledge Index	A ratio of more than 1 using the knowledge index and system navigation is global ,conversely sequential.
		Using the system navigation	

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(3) Similar learning user model construction

Similar learning users refer to a group of users with similar cognitive levels and learning styles. Firstly, the group of users with the same cognitive level of learning is divided according to the test scores of online users in the test module, and then the learning style similarity of this user group is calculated, and the user group with similar preferences is filtered using the Prefix Span, as shown in the following equation:

$$S(a,b)=\frac{\sum_{j\in I_a\cap I_b}(T_a(j)-\lambda_a(j))(T_b(j)-\lambda_b(j))}{\sqrt{\sum_{j\in I_a\cap I_b}(T_a(j)-\lambda_a(j))^2}\sqrt{\sum_{j\in I_a\cap I_b}(T_b(j)-\lambda_b(j))^2}}$$

$S(a,b)$ denotes calculating the learning style similarity between users a and b, $I_a \cap I_b$ denotes the set of resources visited jointly by users a and b[11], Referring to the above, $T_a(j)$ and $T_b(j)$ denote the learning style scale values of two users, $\lambda_a(j)$ and $\lambda_b(j)$ denote the learning style thresholds of the two users, respectively. The Prefix Span uses the quotient of the covariance and standard deviation between two users to measure the linear correlation between the two users. If the value of the quotient is in the range of -1 to 1, we determine that users a and b are similar.

3.2. Customized Learning Direction Guidance Module

The main task of the customized learning direction guidance module is to calculate the learning directions and form the learning direction guidance list. The calculation of learning directions is divided into two parts: firstly, the collaborative filtering guidance direction TopN-1 is formed based on the similar learning user model, and then the probabilistic optimized direction TopN-2 is found by ant colony optimization, and calculation of relationship degree is done to form the customized guidance directions.

3.2.1. Collaborative Filtering Guidance Learning Direction

Collaborative Filtering is one of the most classic types of guidance, and it is an algorithm to guide similar users to jointly selected knowledge items by calculating the learning direction of similar users. The implementation of similar user learning direction is an offline calculation process, based on the sign-in data of similar learning users, using LDA to projects area map, and then using grid-clustering to obtain similar learning user learning direction.

(1) Similar learning user data classification

Learning direction is the sequence of learning content or learning activities, the presentation or guidance of learning steps, reflecting the dynamic information of the learning process. Not only does the sign-in data reflect the semantic information about the content of the user's E-learning, but the order in which it is presented also reflects the chronological nature of the sign-in data. Thus, learning direction is a string of browsing knowledge item data arranged in chronological order. We represent the knowledge item sign-in data in three dimensions: timing data, semantic data and trajectory data. For timing data with grid-clustering, and the grid is divided using horizontal axis reflecting the sequence of data positions and vertical axis reflecting the order of data. Semantic data is used to calculate topic probability distributions through text semantic mining, while trajectory data is the basis for establishing area addressing.

(2) Acquisition of learning direction for similar learning users

First, the learning module sign-in data is classified according to semantic data, text semantic mining is done, and using the LDA, it is projected into a two-dimensional space to form a topic probability area map, as shown in Figure 3.

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Then, the location information of the timing data is used as the horizontal axis and the order is used as the vertical axis to grid the learning module sign-in data, and the probability topic distribution area and the density of the number of sign-ins are clustered by the grid-clustering to obtain the most frequently arrived blocks of cores, as shown in Figure 4.

Finally, all the trajectory data between core regions and high-density grids are found and stored in adjacency list of digraph to establish the learning direction, as shown in Figure 5.

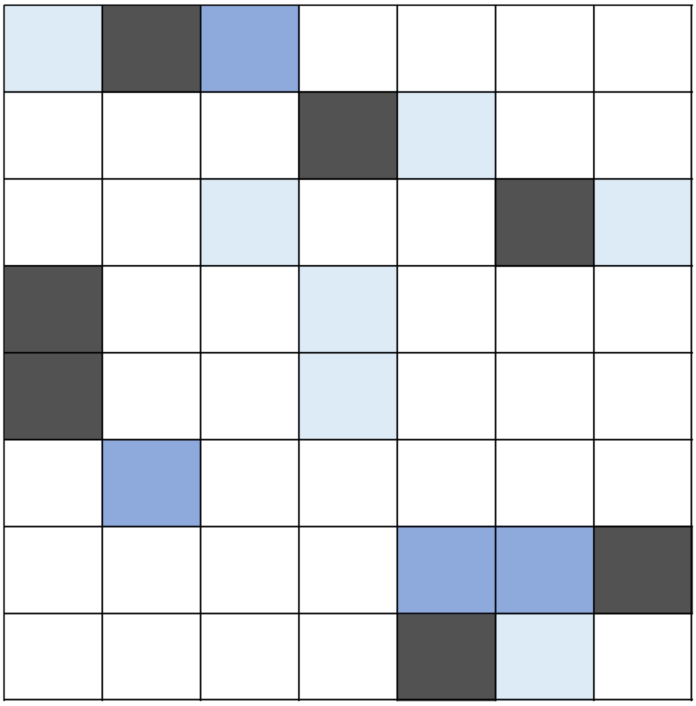

Figure 3. Similar learning user learning direction calculation - regional topic distribution probability

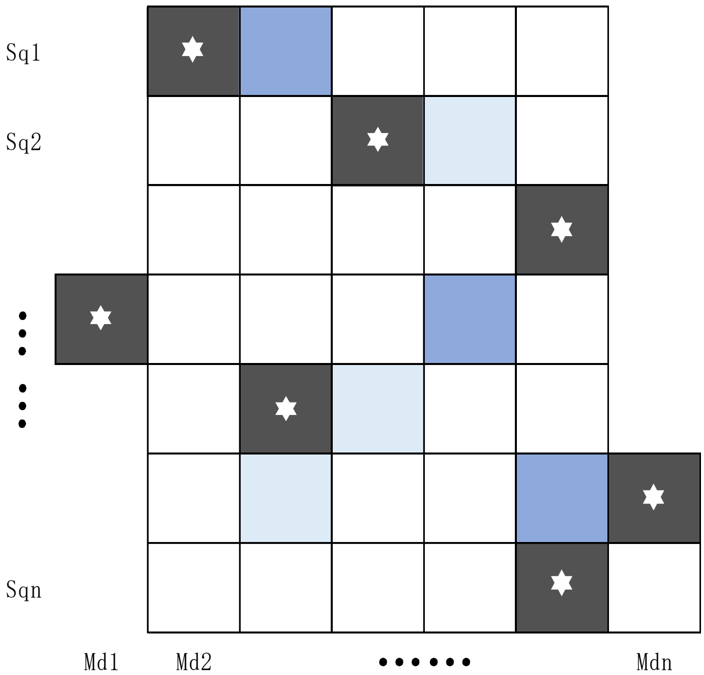

Figure 4. Similarity learning user learning direction calculation – grid-clustering

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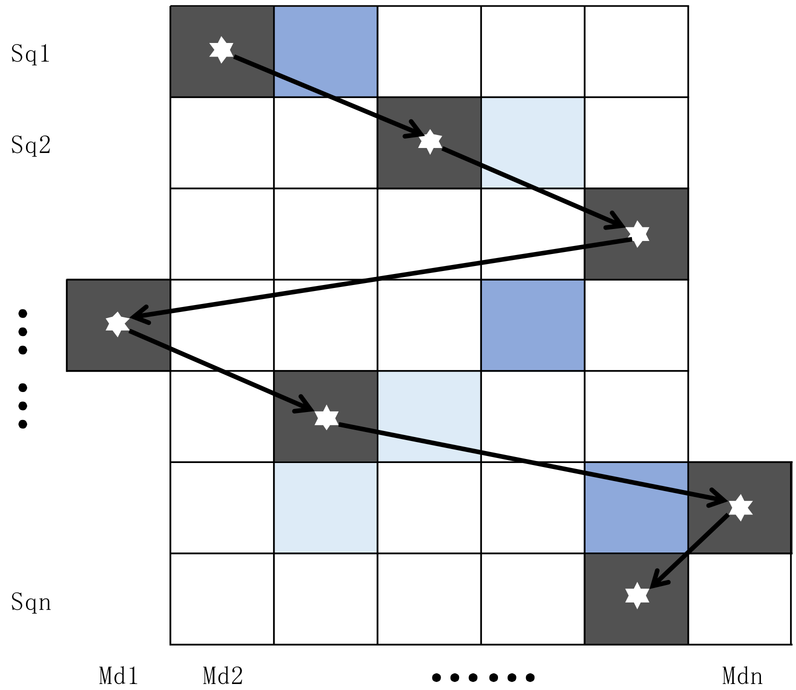

Figure 5. Similar learning user learning direction calculation - area addressing

3.2.2. Learning Direction Guidance Optimization based on Ant Colony Optimization

The correspondence between the parameters of the ant colony optimization and the learning characteristics of the customized network is a prerequisite for the use of the ant colony optimization for customized learning direction guidance. The pheromone and heuristic information, as the most important parameters in the ant colony optimization, determine the final guidance results by the way their values are determined.

(1) Pheromone concentration

Ants judge the source of food by the pheromone concentration left by the ant colony in the direction, and the pheromone concentration$\rho_{ij}(t)$ in the teaching platform can be seen as the sign-in density of learning users, i.e., the sign-in density of knowledge point t, knowledge item i to knowledge item j.

(2) Heuristic information

Heuristic information denotes the degree of transfer from knowledge item i to knowledge item j expectation. For the to-be-selected knowledge item Q_k, there are n-1 knowledge items in Q_k at the initial moment, i.e., the knowledge item where the learning user is located at the beginning is excluded, and there are fewer and fewer to-be-selected knowledge items as time passes until it is empty, indicating that all knowledge items are traversed.

(3) Probabilistic optimized guidance direction

The probabilistic selection of the ant colony optimization is the core element of the guidance algorithm. The probability of selecting the knowledge items is:

$$F_{i,j}^{k}(t) = \frac{\left[\rho_{i,j}(t)\right]^{\sigma}\left[\theta_{i,j}(t)\right]^{\gamma}}{\sum_{w \in Q_k}[\rho_{iw}(t)]^{\sigma}\left[\theta_{i,w}(t)\right]^{\gamma}}, \quad w \in Q_k$$

$F_{i,j}^{k}(t)$: knowledge point t, the probability of transferring learning user k from knowledge item i to knowledge item j. The pheromone factor σ is the pheromone concentration index and the heuristic function factor γ is the heuristic function index, and these two parameters determine the importance of sign-in density and transfer expectation, respectively, for the probability of transferring learning user k from knowledge item i to knowledge item j.

4. Experiments and Analysis

This paper introduces E-learning behavior analysis into the customized learning direction guidance system, mines user web log data, and constructs customized learning directions based on the guidance process.

4.1. Experimental Platform Design

Considering the characteristics of customized learning direction guidance and the current research status, this paper takes the teaching platform of Computer Information Literacy course as the experimental object and analyzes the experimental effect of the constructed customized learning direction guidance model.

4.1.1. Overview of the Course Teaching Platform

The E-learning platform of Computer Information Literacy course consists of four modules, which are resource navigation, teaching resources, problem solving and inquiry, and the interactive learning module. The knowledge items in the modules are classified by knowledge chapters. Among them, resource navigation module consists of learning objectives, knowledge index and key points; teaching resources module consists of videos, electronic courseware and textbooks; problem solving and inquiry module consists of example problem analysis, exercises and quizzes; the interactive learning module consists of discussion forum.

4.1.2. Knowledge Item Mapping

In order to improve the system's extraction and programming of user access directions, the original log data needed to be further optimized. First, the knowledge items under the learning module were redefined, as shown in Table 2.

Table 2. Knowledge Item Mapping

Learning Modules	Knowledge Item	Mapping
resource navigation	learning objectives	L_1
	Knowledge Index	L_2
	key points	L_3
teaching resources	videos	L_4
	electronic courseware	L_5
	textbooks	L_6
problem solving and inquiry	example problem analysis	L_7
	exercises	L_8
	quizzes	L_9
the interactive learning	Using the Knowledge Index	L_{10}

4.2. Data Acquisition

In this paper, the web data acquisition was used to capture the learning data of 50 users in the web teaching platform logs. Considering the restriction of learning content on the range of learning modules selected by users, the experiment selects the chapter of "Information Processing - Data Statistics and Analysis", which has a comprehensive distribution of learning modules, as the data acquisition area to obtain the number of user node visiting, learning directions and test scores. The number of user node visiting refers to clicks and length on each knowledge item node by users, as shown in Table 3.

Table 3. User node visiting statistics

Knowledge Item	the number of node visiting	
	clicks	length (s)
L_1	107	42647
L_2	88	27710
L_3	109	39242
L_4	476	301206
L_5	433	252633
L_6	238	213318
L_7	361	344106
L_8	580	347395
L_9	309	205081
L_{10}	294	123484

4.3. Data Processing

Based on the similar user model building method, eight groups of similar user groups were established for 50 learning users and collaborative filtering guidance TopN-1 was calculated. parameters were initially calculated according to the ant colony optimization, mainly including the user and learning style similarity value D_j, the heuristic information value θ_{ij} obtained from the learning user's cognitive level and learning material difficulty z_j, and the learning user evaluation optimization information value $\rho_{ij'}$, pheromone factor σ, and heuristic function factor γ, as follows: $\theta_{ij} = 0.4, \sigma = 3, \gamma = 4.5$ The maximum probabilistic knowledge item guidance TopN-2 is calculated, and the customized guidance direction is obtained after the ordered merging of TopN-1 and TopN-2, as shown in Table 4.

Table 4. Learning direction and customized guidance for 8 groups of similar user groups

Learning Level	Similar Learning Users	Similar Study Direction	TOPN-2
90-100	A_1	$L_2, L_3, L_4, L_6, L_5, L_7, L_8, L_9$	L_{10}(65%)
	A_2	$L_1, L_3, L_6, L_5, L_7, L_{10}, L_8, L_9$	L_2(10%)
80-90	B_1	$L_1, L_4, L_6, L_7, L_{10}, L_8, L_9$	L_2(72%)
	B_2	$L_2, L_4, L_5, L_7, L_8, L_9$	L_3(75%), L_{10}(46%)
70-80	C_1	L_4, L_5, L_7, L_8, L_9	L_2(50%)
	C_2	$L_4, L_7, L_{10}, L_8, L_9$	L_2(40%), L_3(75%)
60-70	D_1	L_4, L_{10}, L_7, L_9	L_1(50%), L_2(30%), L_8(64%),
	D_2	L_4, L_8, L_9	L_2(52%), L_6(66%), L_7(75%), L_{10}(40%)

4.4. Experimental Evaluation Index Construction

Based on the target demand of customized learning direction guidance, this paper introduces 2 performance indicators, learning efficiency and learning disorientation guidance effectiveness .Learning efficiency indicates the rate of improvement in learning performance after a period of continuous use of the customized learning direction guidance. learning disorientation guidance effectiveness is measured by the increase in the rate of knowledge item sign-in after the user has used the customized learning direction guidance program compared with the previous one. The higher the concentration of knowledge item sign-ins, the higher the degree to which the user's learning disorientation problem is solved during the E-learning process.

This paper assumes a concept of knowledge volume: an E-learning platform is a network system consisting of multiple knowledge nodes, each of which consists of n knowledge items. The knowledge nodes and knowledge items constitute the knowledge volume, denoted as K. knowledge volume constituted by the knowledge items that have been signed in by student t for a given knowledge point is assumed to be K(t), and knowledge volume constituted by the customized guidance knowledge items used by the user is K(t,s). Thus, guidance effectiveness can be expressed by the following algorithm.

$$\mathrm{E}(\mathrm{P}') = \sum\nolimits_{\mathrm{t} \in \mathrm{P}'} \mathrm{K}(\mathrm{t}) + \sum\nolimits_{\mathrm{t} \in \mathrm{P}'} \mathrm{K}(\mathrm{t}, \mathrm{s}) \frac{\mathrm{P}}{\mathrm{K_e} \cdot \mathrm{P}}$$

$\mathrm{P}' = (\mathrm{t}_1, \mathrm{t}_2, \dots, \mathrm{t}_\mathrm{L})$, denotes the set of learned knowledge points, P denotes the set of all knowledge points in the teaching platform, and $\mathrm{K_e}$ denotes the total amount of knowledge in the teaching platform. From the above formula for guidance effectiveness, it is clear that the more guidance knowledge items which a user has access to when learning a particular knowledge, the more effective the learning disorientation solution will be.

4.5. Results and Analysis

Five users were randomly selected in each of the eight groups of similar user groups for customized learning direction guidance, as shown in Table 5 for the users to get Customized learning direction to guide disorientation control rate respectively, as shown in Figure 6 and Figure 7 for the comparison of knowledge item sign-in density before and after customized learning direction guidance, as shown in Figure 8 for the grades development trend after customized learning direction guidance.

Table 5. Customized learning direction of users to guide disorientation control rate

grades	Similar User Groups	Average disorientation control rate
90-100	A_1	2.5
	A_2	0.9
80-90	B_1	5.8
	B_2	6.4
70-80	C_1	11.1
	C_2	11.3
60-70	D_1	15.6
	D_2	16.4

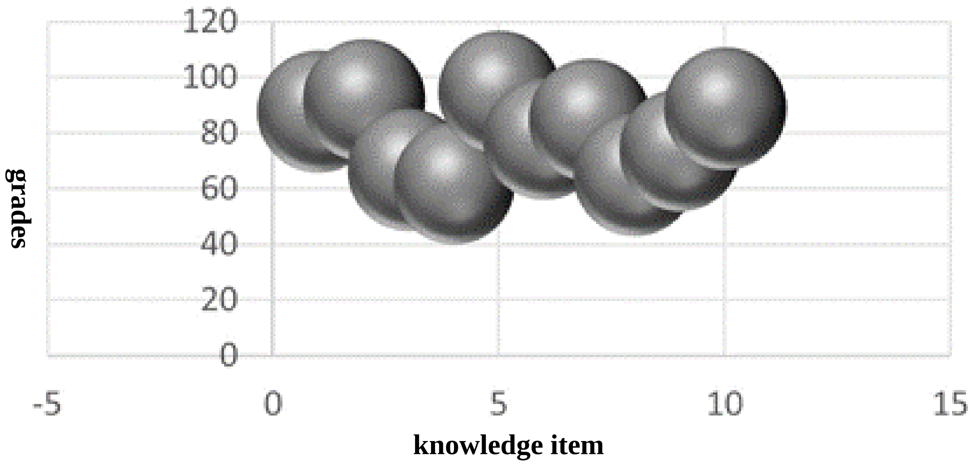

Figure 6. Knowledge item sign-in density before customized learning direction guidance

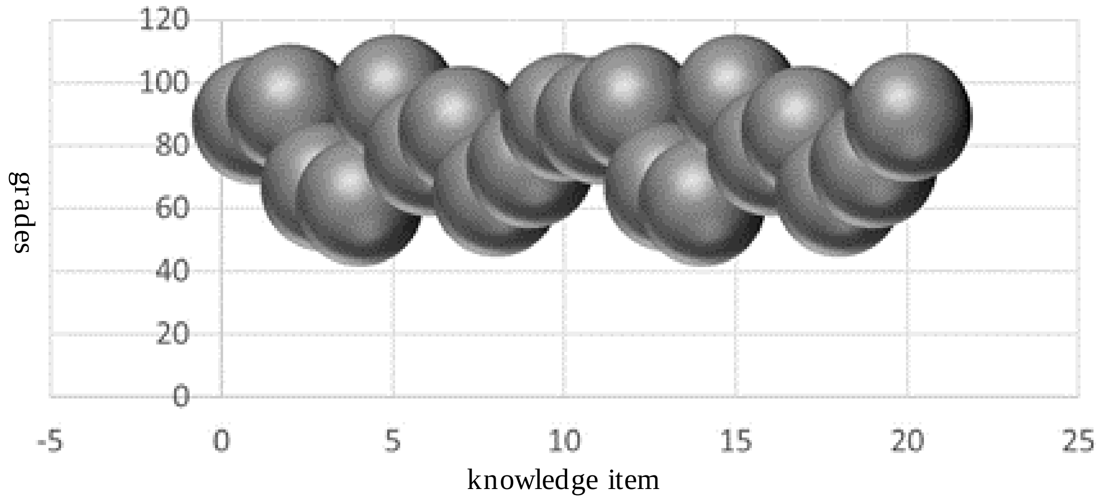

Figure 7. Knowledge item sign-in density after customized learning direction guidance

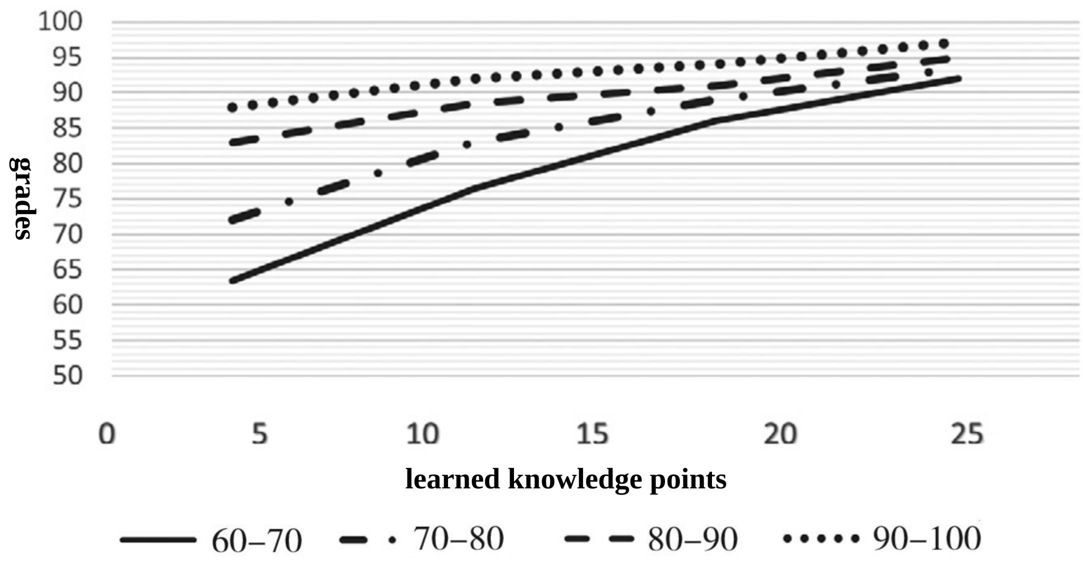

Figure 8. The grades development trend after customized learning direction guidance

According to the experimental results, it can be found that the customized learning direction guidance has a certain degree of control on the learning users' learning disorientation, which shows that the sign-in density of the learning users after the guidance is significantly higher than the sign-in density of the learning users before the guidance. After getting the direction guidance, the users' performance improved, especially for the users with 60-70 and 70-80 grades, their performance improved significantly.

5. Conclusion

With the continuous development of information technology, the deep integration of learning analysis and education makes the teaching platform more and more tends to be precise and customized services. Based on the analysis of E-learning behavior, this paper fully respects the individualized differences in learning style and learning level of learning users, uses artificial intelligence models such as neural networks and ant colony optimization to carry out customized learning direction guidance for users, fully uses group evaluation information of learning directions, learning user sign-in information and the representation information of learning materials to evaluate students' knowledge construction and learning ability, makes learning direction generation more accurate and customized, compensates for individual differences, and thus improves learning efficiency and learning quality, and provides an innovative attempt for the further development of intelligent teaching.

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