Research Article

Simulation Path of Network Microvideo Personalized Recommendation Based on Improved Ant Colony Algorithm

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With the rapid development of Internet technology, network information not only brings many conveniences to the majority of users but also brings about the problem of information overload. It is increasingly difficult for users to accurately obtain the information they need from the vast ocean of information. This problem has led to the research of recommendation technology, especially the simulation path of online microvideo personalized recommendations. The video recommendation model in this study adopts the idea of an ant colony algorithm. The evaluation data and browsing record data generated by users are the basis of video recommendation, and the microvideo feature model and user preference model are abstracted from the original data by improving the ant colony algorithm. The recommendation algorithm is then used to recommend online microvideos that meet users' preferences. There are two recommendation methods, one is to find similar students through the user preference model of each student, and find the microvideo content that the students have not learned; the other is to use the user preference model and the content feature model to match the content that conforms to the user's preference. Compared with the traditional BP neural network algorithm, GA-BP algorithm, and PSO-BP algorithm, the mean square error MSE value of the ACO algorithm for microvideo scoring classification is reduced by 11.41%, 5.93%, and 2.41%, respectively. It can be seen that the classification of video ratings by the improved ACO algorithm has lower average errors than other algorithms. The network microvideo personalized recommendation scheme designed in this study has very practical significance.

1. Introduction

With the continuous upgrading of Internet technology, video shooting equipment is becoming more and more simple and easy to learn, which has spawned many netizens who love video shooting, and accelerated the development and dissemination of microvideos. With the wide application of a new generation of smart mobile terminals, especially smartphones, microvideos, which used to be very popular on mobile phones but lacked in operation, have once again become a hot spot for people. In general, the development of microvideo in the mobile era is still in its initial stage, but microvideo has the potential to subvert the development of the original media ecology. The "micro" feature of microvideo makes it very dependent on social networking sites to share, only on social networking sites can a large number of viewers be assembled, and at the same time, the traffic of social networking sites itself is increased. Due to the short content of microvideos, if there is no social networking site or video platform, it is difficult to cultivate a stable user group, so the personalized recommendation of online microvideos is very important.

With the continuous maturity of personalized recommendation technology and the continuous development of artificial intelligence algorithms, online microvideo personalized recommendation algorithms have begun to enter people's field of vision. Aiming at complex choice and travel problems, Kotiloglu et al. [1] proposed a "filter first, travel second" framework for generating personalized travel recommendations for tourists based on information from social media and other online data sources. Karidi et al. [2] proposed an efficient semantic recommendation method to help users filter interesting content in Twitter streams. Xiao and Benbasat [3] constructed and empirically tested a theoretical

model that examines how Prudential Regulation Authority bias advice affects consumers' decision quality and decision-making effort. Zhou et al. [4] designed an ensemble learning model based on a deep neural network (DNN) to analyze and describe potential behavioral influences hidden in multiple modalities [4]. Liu et al. [5] proposed the Bayesian Mallows (BMCD) method for click data. He used the Mallows ranking model to learn user preferences. They did not give an optimal path for the simulation of personalized recommendations of online microvideos. This study will add an improved ant colony algorithm to optimize it.

The biggest feature of the improved ant colony algorithm is local optimization, which enables us to optimize the path without mastering all the information. In order to improve the efficiency of non-contact power distribution and improve user satisfaction, Wu [6] proposed a non-contact power distribution path optimization algorithm based on an improved ant colony algorithm. Lv and Chen [7] proposed an improved heterogeneous ant colony algorithm. By introducing the alternate search strategy of regional ants and common ants, the convergence speed of the algorithm is accelerated. He et al. [8] established an optimization model of dangerous goods transportation based on an improved ant colony algorithm. Li and Yu [9] proposed a path planning method for rescue and coal detection robots based on an improved ant colony algorithm. Yi et al. [10] studied the scheduling and conflict-free routing problems of AGVs and made an empirical evaluation of the improved ant colony algorithm. However, the improved ant colony algorithm proposed by them has two shortcomings: the search time is too long and the search is easy to fall into the flat part optimum. The personalized recommendation technology proposed by them is not the optimal result. Therefore, the method in this study is not only fast but also obtains a large amount of information.

In this study, the improved ant colony algorithm is combined with a personalized recommendation engine to improve the accuracy of the microvideo recommendation function. By constructing a personalized video recommendation system based on the improved ant colony algorithm, the data collection of the whole process of user learning can be realized, the user's dynamics can be fully grasped, and their personality characteristics and practical needs can be grasped. In order to better guide students' initiative and creativity, it provides help for targeted guidance. Through effective personalized recommendations, users can enjoy more personalized services that meet their own needs, and it is also convenient for users to extract useful information from massive information and improve the efficiency of resource utilization. At the same time, efficient personalized recommendations can improve the adhesion between users and the network. About 39% of users watch microvideos every day; 33.9% watch them once every two or three days, and 15.2% watched them for a week or more. The main research framework of this study is as follows.

This study first introduces the idea of using the ant colony algorithm.

Second, the method part abstracts the microvideo feature model and user preference model from the original data by improving the ant colony algorithm.

The experimental part uses recommendation algorithms to recommend online microvideos that meet users' preferences.

The analysis results partly use the user preference model of each student to find similar students and find microvideo content that the students have not learned.

2. Network Microvideo Personalized Recommendation Simulation Path

2.1. Network Microvideo. Microvideo contains two elements: picture and sound. Learning through video means that the visual channel and the auditory channel work together and at the same time receive information stimulation and process the information. The visual microvideo emphasizes the dynamic and figurative nature of the content. The screen uses animation to present the content, visualizes the abstract text, and uses graphics, icons, cartoon characters, etc. to present the content. The audio selects the commentary with commentary.

By improving the determination of the ant colony function, the updated user interest degree can be obtained [11, 12]:

$$\text{new weight} = \text{new weight} - \text{fibo}(t). \tag{1}$$

The user interest degree generally refers to the user's interest in a certain web page or a certain resource. The larger the value, the more interested the user is in a certain thing. The value of interest degree is often related to some key factors that affect user interest. In this study, the user interest degree can also be called the user interest weight. This study mainly considers the user behavior set of seven dimensions. The user interest degree $I(i)$ of a certain user i can be expressed as the sum of the interest degrees of seven influence factors, namely:

$$I(i) = a(i) + b(i) + c(i) + d(i) + e(i) + f(i) + g(i). \tag{2}$$

In the formula, $a(i)$ represents the interest degree of the number of times user i clicks on the network microvideo; $b(i)$ represents the interest degree of the time user i watches the video case; $c(i)$ represents the interest degree of the number of video cases downloaded by the user i [13].

In this study, the in-degree statistics of user nodes are used to represent, and the global trust degree of user v_i is defined as follows:

$$T_{v_i} = \sum_{v_j \in I_{v_i}} \frac{w_{ij}}{\text{in}(v_i)}. \tag{3}$$

User v_i trusts v_j as follows:

$$W_{ij}^p = W_{v_i v_1} \times \prod_{k=1}^{n-1} W_{v_n u}. \tag{4}$$

Among them, $n + 1$ is the length of the path Path.

The similarity of interest between v and U is as follows [14]:

$$\text{sim}_{vu} = \partial_1 c_{uv} + \partial_2 \beta_{uv}. \tag{5}$$

2.2. Personalized Recommendations. Microvideo can simultaneously provide visual and auditory channel information through picture and sound, and provide an information source for dual-channel information processing. When learners prefer a certain type of information, they recommend the corresponding type of information in a personalized way, which makes their information processing process more efficient and effective. For example, visual learners prefer to memorize information in the form of pictures, charts, flowcharts, etc. When designing video resources for visual learners, the content should be presented in the form of pictures, icons, or cartoon animations to highlight the information of the visual channel.

When $t > 0$, the trust value that user u should have on user v is calculated as follows [15]:

$$W_{vu}^t = \beta^t W_{vu}^1 + \left(1 - \beta^t\right) \sum_{n=1}^{t} \frac{f_{vu}^n(i)}{\left[\text{item}_{vu}^n\right]}. \tag{6}$$

In order to measure the accuracy of prediction, in each round of testing, the absolute value of the average difference between the predicted value and the actual rating value of each user's test set is calculated, and then the average value of the group of test users is obtained, which is calculated as follows:

$$\text{MAE} = \frac{1}{m} \sum_u \sum_j \left| r_{u,j} \right|. \tag{7}$$

Among them, m is the total number of all ratings, and $r_{u,j}$ is the actual ratings [16].

Each piece of content in each text content collection is treated as a document. Among them, N is the number of documents, N_m is the number of words in document d, and the similarity value $P(d_m)$ of document dm is as follows.

$$P(d_m) = \sum_{j=1}^{T} \left(\varepsilon_{j,w} \times \theta_{d,j}\right)^{n(w_n,d)}. \tag{8}$$

Among them, $n(w_n, d)$ is the number of occurrences of word w in document d. In microvideo recommendation, the importance of each topic in the text content set is calculated based on the text-topic distribution, and the calculation formula is as follows.

$$P(z_i|D) = \frac{\sum_{n=1}^{N} \delta_{z_i}^{d_n}}{\sum_{i=1}^{T} \sum_{n=1}^{N} \delta_{z_i}^{d_n}}. \tag{9}$$

Usually, when designing microvideos, designers and producers will add some animations, sounds, or pictures, and even add background music in order to enhance the dynamic effect. According to the different characteristics of learning styles, the visual microvideos are presented in the form of animation, highlighting the visualization of abstract content, and the rest of the auditory, writing-reading, and kinesthetic microvideos are in the form of a combination of PPT screen recording and explanation. Generally, in the production process of PPT, many animation effects will be designed in order to be dynamic, and too many animation effects will distract the learners' attention. According to the principle of avoiding redundant information interference, the use of complex animation effects should be minimized when designing PPT. It is only necessary to set simple animation effects such as fade-in and fade-out for some texts and pictures, without setting subtitles, without adding music, and reducing the interference of irrelevant information to learners [17]. This study believes that the design of microvideo should reduce redundant information and avoid interference. The picture does not need to present the same subtitles as the audio again, nor does it need to add background music.

The historical score of user k on item j can be obtained from the item score in NE. The calculation method of users who have scored item j in NE is as follows:

$$\rho_{ij}^H(t) = \frac{\sum_{n \in NE} \text{sim}(k,s)\left(\rho_{sj}^H(t) - \overline{\rho_s^H(t)}\right)}{\sum_{n \in NE}(|\text{sim}(k,s)|)}. \tag{10}$$

When the pheromone of each segment of the learning path is updated globally, a pheromone restriction interval is introduced, and the maximum and minimum limits are set to avoid the above situation. The restriction formula is as follows [18]:

$$R_{ij}^k(t) = \begin{cases} R_{\max}, & R_{ij}^k(t,u) \geq R_{\max}, \\ R_{\min}, & R_{ij}^k(t,u) \leq R_{\min}, \\ R_{ij}^k(t,u), & R_{\min} < R_{ij}^k(t,u) R_{\max}. \end{cases} \tag{11}$$

2.3. Personalized Recommendation for Online Microvideos. The picture material of the microvideo is selected from the multimedia courseware used in the teachers' traditional classroom, and the same picture is used to establish the association between the microvideo and the courseware, so as to help students recall the content of the microvideo. Learners use the network platform to watch microvideos to learn before class. When teachers show courseware or ask questions in class, this design helps learners to quickly recall the content of microvideos and give teachers timely and accurate feedback. At the same time, online learning is effectively connected with the traditional classroom. The production process of microvideo is shown in Figure 1 [19]. Except for visual microvideos that are presented in the form of animations, the rest are presented in the form of PPT screen recordings v.

2.3.1. Identification of the Learner. If the learner is logging in to the system for the first time, the system will determine the learner's hobbies, interests, and study habits according to the basic information when the learner registered the account, the history records browsed by the system this time. The historical access time of the interface and other historical record information make a preliminary determination, so as to initially construct the learner's learning style model and realize the push of learning information.
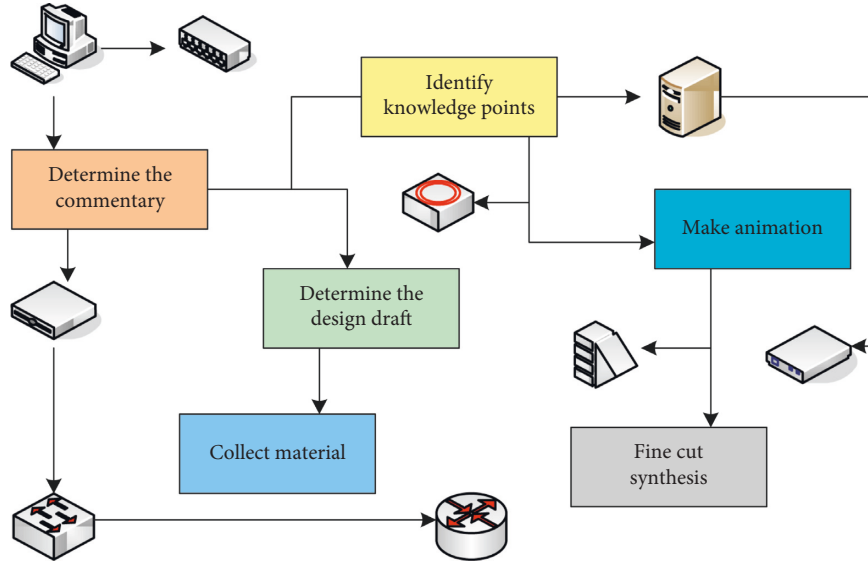
FIGURE 1: Production process of microvideo.

2.3.2. Data Processing. After collecting the learner's source data in the early stage, through the processing and analysis of the source data, the sample data set for building the learning style model can be obtained, such as the texts browsed by the learners, audio and video information, test scores, page stay time. The information collected above is the learner's behavior information automatically collected by the system after the learner logs in to the system and stored, while the learning index of text learning is obtained by the learner through the text test. Therefore, in the process of establishing the training sample data set, the data can be distinguished and stored by means of discrete attributes.

2.3.3. Model Instantiation. With the advancement of the data collection process, after the system has accumulated an appropriate amount of learning data, the system will pass the collected basic data (such as forum posting topics, the total number of posts, and module stay time). It analyzes and mines the characteristic data that needs to be derived, such as the learning goals of the learners at the current stage, to instantiate the personalized learner model based on the online learning community. At the same time, various resource information updates and instantiated domain knowledge models are collected, and both are used as the core basis and data input for the recommendation.

2.3.4. Personalized Recommendation. The learner can obtain the recommended result by actively applying for the personalized learning path recommendation service or when the starting conditions of the recommendation algorithm are met (e.g., the accumulation of learning data reaches the threshold requirement for starting, etc.). However, it still needs to be presented to learners in a visual form (such as a visual recommendation interface, animation display) to guide learners to carry out learning activities with clear goals, clear organization, and easy to play the learners'

individual advantages. At the same time, the system records its feedback information (such as the comment data on the path, the learning status, and the change data of the learning goal), and realizes the adaptive updating of the personalized learning model based on the online learning community through data-driven technology. Obtaining the updated learner model instance can not only be used for self-evaluation and recommendation effect evaluation but also can accumulate historical data for the next recommendation service to further optimize the recommendation result.

The similarity between microvideos A and B is as follows:

$$J(A, B) = \frac{|A \cap B|}{\left|A \bigcup B\right|}. \tag{12}$$

The frequency of microvideo features in user comments is as follows:

$$N(f_i, u) = \frac{B_i(u) - A_i}{A_i + 1}, \tag{13}$$

where N is the number of comments for u. The ACO algorithm generally has an advantage over scheduling methods such as simple inspiration algorithms, and the method of improving the ACO algorithm will also make some better improvements than the original algorithm.

2.4. Improved Ant Colony Algorithm. Through a multifactor-based microvideo personalized recommendation framework, specific microvideos can be recommended to individuals instead of relying on global recognition (that is, personalization). Although matrix factorization methods have been shown to successfully mitigate sparsity, they are ultimately limited to 2D data (for example, user microvideo matrices). Sparsity means that the energy of most channel coefficients is small, and several parts with large energy are distributed far apart [20]. In contrast, user-preferred microvideos are affected by multiple modes, including the

social relationship between users and publishers, whether users' emotions are consistent with the emotions contained in microvideos, and themes. First, a representative microvideo dataset is captured from a microvideo social network (such as vine), and an algorithm for the personalized recommendation of microvideos is extracted from the three modes of social network trust, sentiment analysis, and topic.

Under the regulation of pheromone (referring to chemical substances that interact between individuals of the same species), the ants between the nest and the food source will be distributed on the planned path with increasing probability [21]. After a certain period of time, almost the entire ant colony will eventually travel along the planned path, thus searching for the optimal path between the nest and the food source. The heuristic information plays a role in ants choosing paths, the larger the value, the closer the ant colony algorithm is to the traditional greedy algorithm [22]. Therefore, the performance of the ant colony algorithm is jointly determined by these two factors. The corresponding relationship is as follows:

$$\sigma_{ij} = \frac{1}{d_{ij}}. \tag{14}$$

At the moment $(t + n)$, the amount of information on the microvideo optimization path (i, j) needs to be adjusted accordingly. The adjustment formula is as follows:

$$\theta_{ij}(t + n) = (1 - \varepsilon)\theta_{ij}(t) + \Delta\theta_{ij}(t),$$
$$\Delta\theta_{ij}(t) = \sum_{k=1}^{m} \theta_{ij}(t + 1). \tag{15}$$

The search rules of the improved ant colony algorithm can be determined by the transition formula, and the algorithm assumes that there may be two types of search behaviors in the search process of ants. One possibility is domain search, and the other is to move from node i to node j with probability. The selection probability is calculated as follows.

$$P_{ij}^{k}(t) = \frac{[h_{i-d}]^{\alpha_1} \times [h_{s-c}]^{\alpha_2} \times [R(t)]}{\sum_{t=1} [h_{i-d}]^{\alpha_1} \times [h_{s-c}]^{\alpha_2} \times [R(t,n)]^{\beta}}. \tag{16}$$

At the same time, in order to avoid the situation that the accumulated pheromone concentration in the path is too large with the passage of microvideo time, which will cause the residual information to cover the heuristic information. It is necessary to perform a global update on the microvideo pheromone in a certain period of time (for example, after completing a cycle). The update formula is as follows:

$$R_{ij}(t + 1, u) = (1 - Q) \times R_{ij}(t, u). \tag{17}$$

The formula for calculating the increment of pheromone is

$$\Delta R_{ij}(u) = \sum_{k=n} \Delta R_{ij}^{k}. \tag{18}$$

In the basic improved microvideo recommendation ant colony algorithm, the global update method of pheromone is that when the algorithm completes an iterative operation, all ants release a pheromone to participate in the global update of pheromone. But doing so will make the search process of the algorithm interfered by some bad information so that the search direction of the ant colony will change due to the influence of the interference information, slow down the search speed of the algorithm, and finally affect the generation of the global optimal solution. Its expression is as follows:

$$\tau_{ij} = (1 - \mu)\tau_{ij} + \frac{\sum_{k=1}^{m} \Delta\tau_{ij}^{k}}{Z_B}. \tag{19}$$

Personalized learning path recommendation is not only a specific solution to the problems of information overload and cognitive trek but also an effective auxiliary means for the development of personalized education in online learning communities. It can enhance the learning experience of learners in online learning communities and enhance the level of personalized learning support services in online learning communities. The personalized recommendation engine is the core component of personalized learning path recommendation and the carrier of the personalized learning path recommendation algorithm. Its function is to calculate a personalized learning activity plan or plan suitable for the learner, and according to the learning characteristics and personality characteristics of the individual learner described in the learner model, it filters (searches) the appropriate learning activity from the state space of the domain knowledge model resources and learning content, visualize it to individual learners, providing them with personalized learning paths that conform to their learning styles, and meet their actual learning needs. This recommendation is in line with constructivist learning theory (emphasis on learning based on one's own understanding), which changes the passive learning style of learners in the past. Through analysis and calculation, learners can obtain personalized learning paths that are consistent with their own goals at various stages and in line with their characteristics, and solve problems such as learning loss and information overload. The microvideo personalized recommendation path framework is shown in Figure 2.

ACO microvideo recommendation step:

Step 1. Initialized pheromone matrix.

Step 2. According to the pheromone matrix (carrier) and the city distance, a new solution is generated as the current species (current video solution).

Step 3. Calculate the length of the video recommendation path length (target function value) of each solution in the current species (current solution).

Step 4. According to the current species (currently optimal video recommendation solution set), update the pheromone matrix (carrier). (When it meets the iterative termination conditions, jump out of the iterative link and execute Step 5).

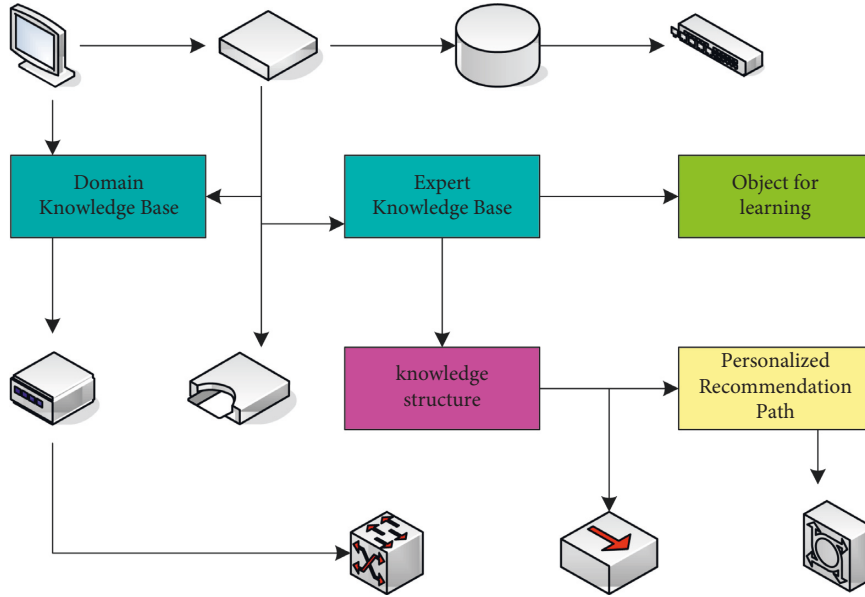Step 5. Output the optimal solution (optimal video recommendation solution).

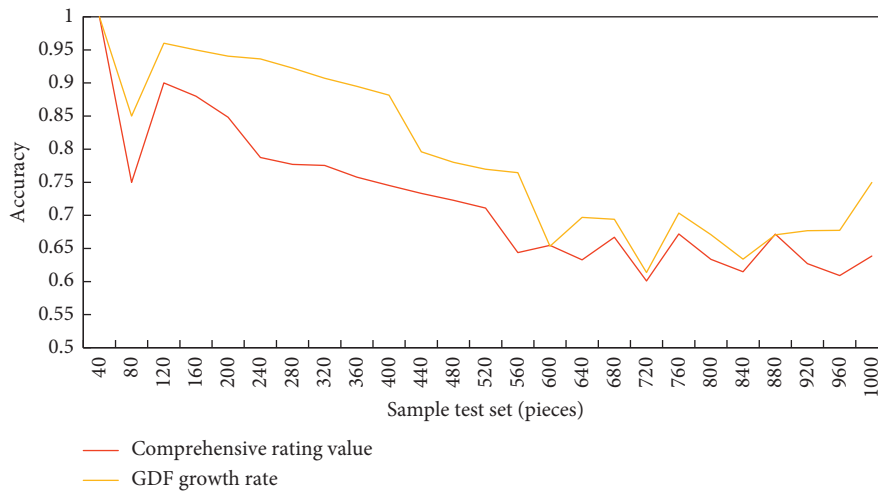FIGURE 2: Microvideo personalized recommendation path framework.

FIGURE 3: ACO and improved ACO algorithm network microvideo personalized recommendation accuracy experimental results.

3. Simulation Results of Online Microvideo Personalized Recommendation

Figure 3 shows the experimental results of ACO and improved ACO algorithm network microvideo personalized recommendation accuracy. The classification accuracy of the improved ACO (ant colony optimization) algorithm for user ratings is higher than that of the traditional ACO. Compared with the traditional ACO, the improved ACO algorithm improves the accuracy of microvideo personalized recommendations by 12.8%. When the test sample set is relatively small, the fluctuation range based on the improved ACO is much smaller than that of the ACO, and with the continuous increase of the sample test set, the improved ACO is more stable than the traditional ACO.

MSE reflects the degree of difference between the estimator and the estimator. The MSE (mean squared error) of

the improved ACO algorithm and the ACO algorithm is shown in Figure 4. The mean square error (MSE) of the improved ACO algorithm for network microvideo scoring classification is about 0.35, which is 12.5% lower than the mean square error of the traditional ACO algorithm (≈0.4). It can be seen that the classification of video ratings by the improved ACO algorithm has a lower average error than the ACO algorithm.

This section mainly introduces the improved ACO algorithm. The MovieLens1M dataset is used in the experiment, and a dataset of 3900 videos evaluated by 6040 users can be obtained, which includes: user datasets, video datasets, and datasets where users rate videos. The three datasets are merged through Python tools to obtain a dataset containing user ID, video IDmmc1, user age, user gender, video type, and user rating of the video. Then feature extraction is performed on this dataset. The method of feature
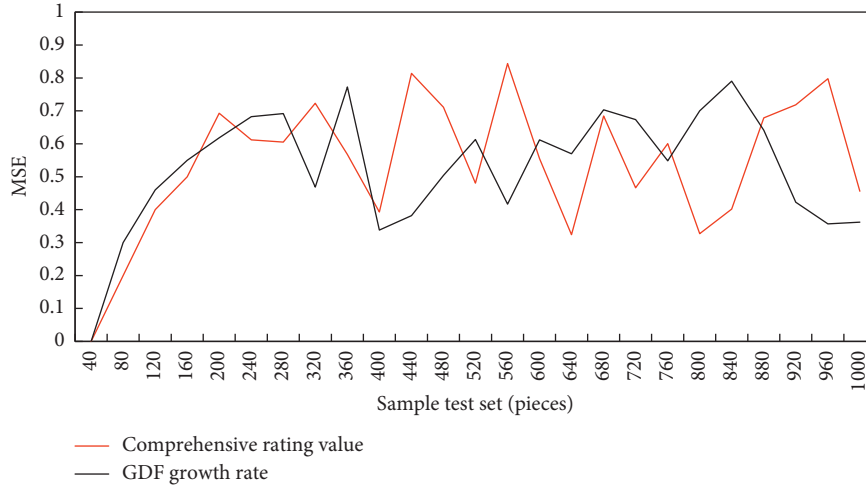
Figure 4: MSE (Mean Squared Error) of improved ACO algorithm and ACO algorithm.

Table 1: Principal component feature set for users' ratings of videos by calculation.

Main ingredient	Contribution rate (%)	Cumulative contribution rate (%)
Video ID	15.6	15.6
Main type of video	17.5	44.1
Video subtype	16.1	46.1
Number of users by age group (6 columns)	12.4	69.5
Number of male users	7.1	77.7
Number of female users	7.1	75.7

extraction is as follows: the feature set takes the video ID as a column vector, and the average of the ratings of users who have watched the video is used as the label of the video ID, that is, the true value; then the age, gender and type and other data characteristics of the users who have watched the video are extracted. The main features included are average age, maximum age, minimum age, total number, number of men, number of women, the gap between men and women, number of age groups and their variance, standard deviation, median, and other data. As the feature data set of the video, after the feature extraction is completed, the invalid video data feature samples are deleted from the feature data set, and the final valid feature data set is $1966 * 63$. The feature data set (is a statistical method) is further processed by the principal component analysis method, and the eigenvalues and eigenvectors are obtained by using the correlation coefficient matrix, and then the contribution rate of each feature is obtained. When the cumulative contribution rate of some features in the feature set reaches 85%, these features are selected as the data in the principal component matrix, and the principal component feature set of the user's rating of the video is finally obtained through calculation, as shown in Table 1. It can be seen that the cumulative contribution rate of video ID, video type, and user gender and age has reached 85.8% (over 85%). Therefore, these 11 parameters can be used as the input of the neural network to remove the non-principal components from the feature space set. It can be obtained that the data set size of the principal component feature set is $1966 * 11$; then the principal component feature data set is randomized, the first part of the data set is $1000 * 11$ as the training set, and the latter part is $966 * 11$ as the test set. Using the new feature space for algorithm training can reduce the time of algorithm training to a certain extent, and improve the accuracy and time efficiency of the algorithm. After the new feature space set is generated, the new feature space set can be used to test and improve the ACO network video recommendation algorithm.

The comparison of MSE (mean squared error) of BP neural network algorithm, GA-BP algorithm, PSO-BP algorithm, and ACO algorithm is shown in Figure 5. The mean square error can qualitatively judge the "average error" of the algorithm for the classification of the sample set. The smaller the mean square error, the lower the sample classification error. Compared with the traditional BP neural network algorithm, GA (genetic algorithm)-BP algorithm and PSO-BP algorithm, the mean square error MSE value of the ACO algorithm for microvideo scoring classification is reduced by 11.41%, 5.93%, and 2.41%, respectively. It can be seen that the classification of video scores by the improved ACO algorithm has a lower average error than other algorithms, but it is not convincing enough to judge the classification of video scores by the ACO algorithm only from the accuracy and mean square error. The algorithm with better accuracy and mean square error performance can only show that the overall classification accuracy of the algorithm is high. In the real network, the user's rating of the video is a subjective and personalized event, so more refined indicators are needed to test the user rating classification algorithm.

The recall rate and F1_score of the ACO algorithm are better than those of the traditional BP neural network, the
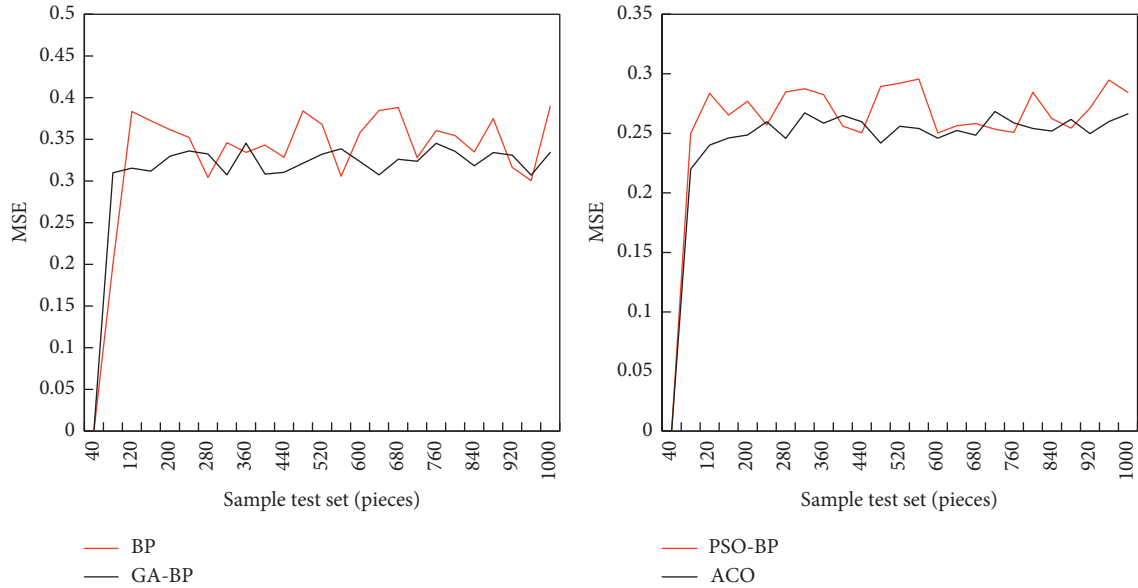
FIGURE 5: Comparison of MSE (mean squared error) of BP neural network algorithm, GA-BP algorithm, PSO-BP algorithm, and ACO algorithm.
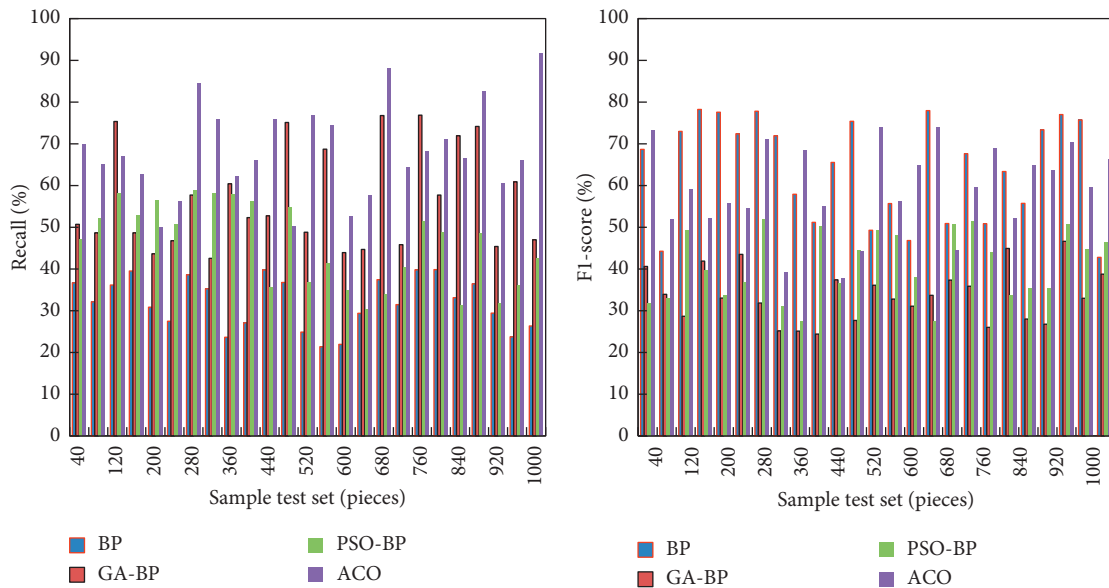

FIGURE 6: Comparison of recall and F1_score.

QA-BP algorithm, and also outperforms the PSO-BP algorithm (videos with a score ≥4 are the videos that users are interested in. Among them, the F1_score of the ACO algorithm is improved by 32.08%, 24.74%, and 3.35%, respectively compared with the traditional BP neural network, QA-BP algorithm, and PSO-BP algorithm. The comparison of recall and F1_score is shown in Figure 6.

The data of this experiment is the user operation behavior log of the Baidu Video App, in which useful behaviors include browsing, playing, and retrieving video data. After the log data is processed by the data preprocessing module, a data structure that can be directly mined is generated, and

the Id of the work is used as the unique identifier of the work. In this simulation, the performance of the improved ACO algorithm and the original algorithm are compared by the difference in the amount of input user data and the minimum support.

The support degree is 0.2, the abscissa is the number of users participating in mining (unit/unit), and the ordinate is the running time (unit/ms) required to mine the final result. As the amount of input data increases gradually, the running time of the two algorithms shows an upward trend. When the number of mining users is 2000, because the improved algorithm requires format conversion preprocessing, the
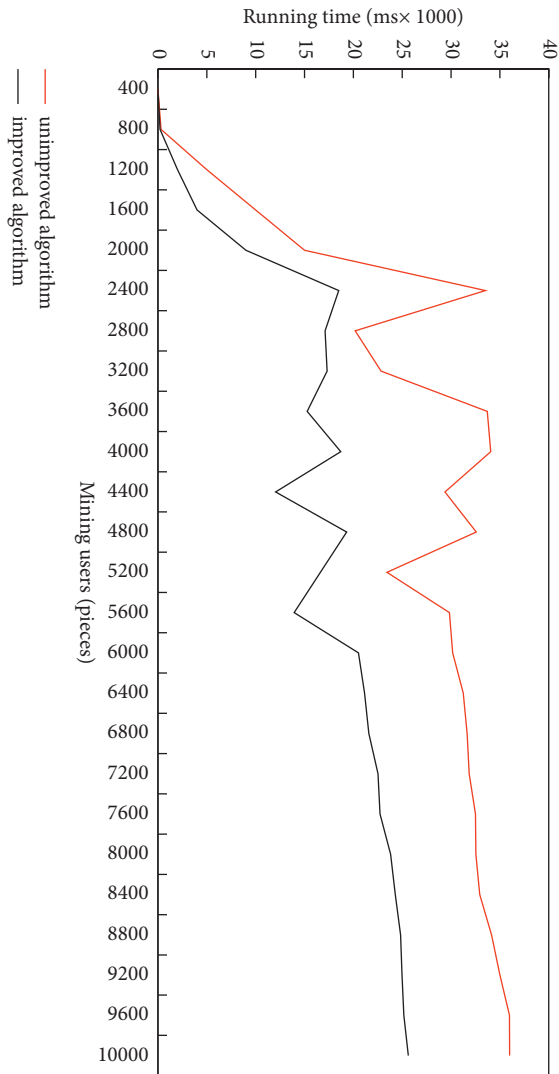
FIGURE 7: Algorithm performance comparison.

running time is higher than that of the unimproved algorithm. However, as the number of mining users increases, the improved algorithm has obvious advantages. The algorithm performance comparison is shown in Figure 7.

The frequency of college students watching and using microvideos is shown in Figure 8, and the following data is obtained by taking days as the standard: 39% watch microvideos every day; 33.9% watch it once every 2 or 3 days; 11.9% watch it once every 4 or 5 days; and 15.2% watch it for a week or more, and these data show that college students have a higher rate of using microvideos.

It was found that watching students watching microvideos for learning mainly wanted to broaden their horizons and expand their knowledge, accounting for 35%. The second is to improve the thinking, the world outlook and the outlook on life, the proportion is 27%. In addition, the number of people who choose to experience the personal charm of professors or actors up close is 22%. The number of people who use microvideo for professional learning is the least, accounting for only 16%. However, there are many

microvideos available for professional learning on the Internet, and there are also many successful examples of applying microvideos to classroom teaching. It can be seen that microvideo can play an auxiliary role in students' professional learning, but the small number of users also exposes some problems. It may be related to the boring curriculum resources, strong professionalism, monotony, and difficulty in understanding, or it may be related to the lack of teacher guidance and lack of learning awareness and ability. The purpose of students watching microvideos is shown in Figure 9.

The course learning module mainly provides students with functions such as viewing a list of all courses, watching instructional videos of a specified course, and jumping to related videos. The data used by the video learning module mainly comes from the course setting module, but there is also a separate table structure that needs to be used to record the learning records of the college. The learning records are shown in Table 2.

The teaching video list lists the representation structure of the teaching video in the database, and the video id is used to uniquely identify a video course stored in the system. The video title and video summary are used to describe the content of the course. The course id is used to associate the course to which the video belongs. The video sequence number is used to organize the video course and make the course logic flow. The video path field stores the path where the video is located, which will be referenced when watching the video. The teaching video is shown in Table 3.

The pheromone increment was fixed at 1.5, $p = 0.3$, to test the effect of pheromone intensity on precision and recall values. The highest accuracy can be achieved when the information strength is 1.9. The effects on precision and recall are shown in Table 4.

When the algorithm proposed in this study uses the powerful cooperation and searchability of the ant colony algorithm, the design of the heuristic function also considers the evaluation properties of the project and the properties of the project itself. The user's evaluation of the recommended content is shown in Table 5.

The results of the algorithm also show a big difference when the ant colony scale takes different values. When the size of the ant colony is 8 and 10, the running time of the algorithm is relatively long, and its variation law is relatively similar. When the ant colony size is 4 and 6, the results show a similar change rule. When the ant colony size is 8 and 10, the algorithm can achieve the optimal scheduling result of 7.4500 s, when the ant colony size is 6, the optimal scheduling length of the algorithm is 7.6000 s, and when the ant colony size is 4, the optimal scheduling length of the algorithm is 8.4467. The number of tasks is 12, which means that the closer the ant colony scale is to the task scale, the better the optimal solution can be achieved, and the smaller the ant colony scale, the poorer the performance of the algorithm. The selection of ant colony size should be close to the number of tasks. The results for different ant colony sizes are shown in Figure 10.
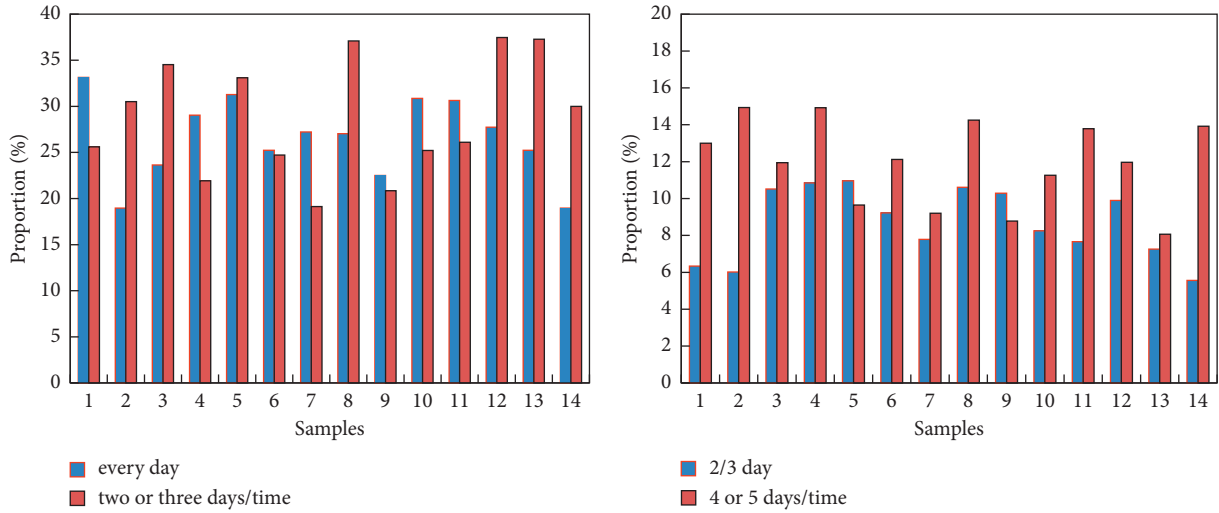
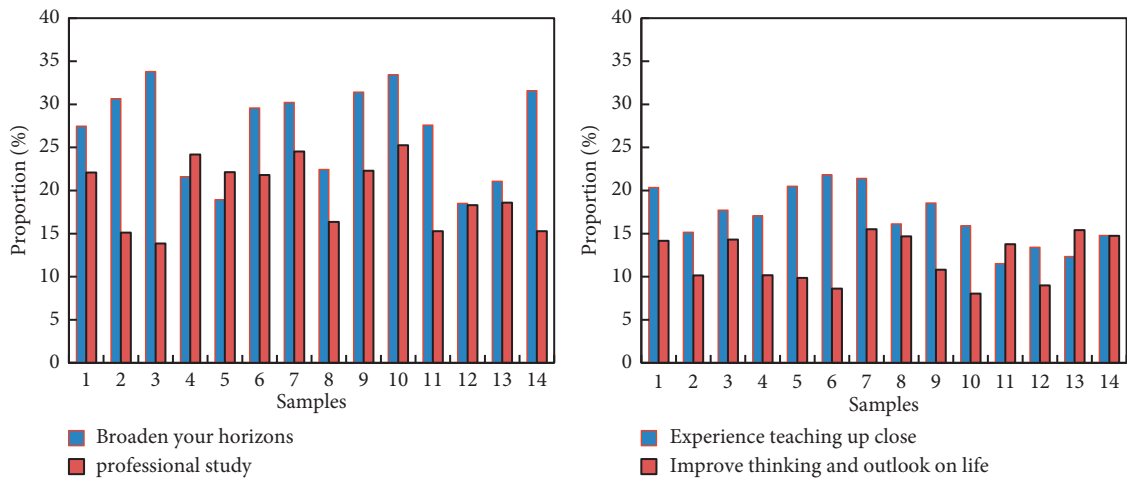Figure 8: Frequency of viewing and using microvideos by college students.

Figure 9: The purpose of students watching microvideos.

Table 2: Learning records.

Field definition	Data length	Type of data
Video id	15	Int
Student id	15	Varchar
Time point	50	Varchar
Learning record	60	Varchar

Table 4: Effects of precision and recall.

The parameter value	Precision	Recall
1	0.3	0.02
1.3	0.4	0.06
1.6	0.3	0.05
1.9	0.2	0.04

Table 3: Instructional videos.

Type of data	Data length
Int	11
Varchar	20
Int	100
Varchar	200

Table 5: User evaluation of recommended content.

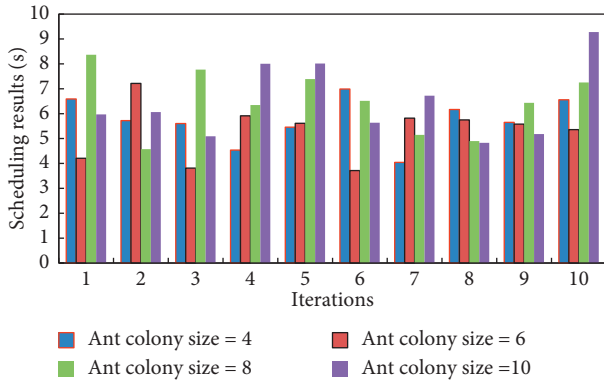| Test times	Best	Good	Bad
1	0.6	0.2	0.2
2	0.7	0.12	0.18
3	0.8	0.1	0.1
4	0.9	0.05	0.05

FIGURE 10: Results for different colony sizes.

4. Conclusion

With the rapid development of artificial intelligence and big data, the microvideo industry has sprung up. In the process of recommendation, it often encounters the problem of data sparsity and the inability to solve the problem of massive data processing. In this study, other video recommendation algorithms are compared and analyzed, and their recommendation effects are analyzed to obtain a better video recommendation model, meet the various needs of users, and improve the click-through rate of videos. The personalized learner model describes the characteristics of the learner, and reflects the learner's learning progress, learning motivation, and goals from the side. Building an operable and reasonable personalized learner model helps the system to mine the associations between various learning-related data in educational big data. Finally, according to the different learning characteristics of learners, different learning paths are recommended for them at different learning stages, which are suitable for their needs and goals, so as to stimulate their learning interest and enthusiasm. Compared with other methods, the ACO proposed in this article has developed from solving one-dimensional static optimization problems to solving the problem of multi-dimensional dynamic combination optimization problems, and research from the scope of the bulk domain gradually expands to the continuous domain. Optimized algorithms to show the prospects of vibrant and broad development. In the transmission of popular videos, the ant colony algorithm is used to obtain the optimal path for transmission; when watching popular microvideos, the encoding value is compared to obtain the optimal server with real-time performance, and a connection is established to meet the concurrent access of large-scale users. This study fails to comprehensively summarize the factors that affect the online microvideo by college students. In addition, there are many tests such as stability tests that have not been done. The next step in this study is to conduct a more comprehensive test of the short video recommendation system, to improve the short video recommendation system.

Data Availability

This article does not cover data research. No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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