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RESEARCH

Research on Tourism Route Planning Based on Matrix Decomposition and an Improved Ant Colony Algorithm

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Abstract

The goal of the tourism planning studied in this paper lies in the comprehensive development and overall deployment of the tourism system within the territorial complex. In the planning process, to consider the overall optimization of the system comprehensively, the complex structure of the tourism system is handled correctly. Related problems are effectively solved from a developmental and multi-perspective perspective. Our tourism planning is based on a holistic view and provides clear guidelines for realizing tourism objectives. Improve the drawbacks of the basic ACO algorithm that takes a long time and is prone to deadlocks. The basic ant colony algorithm is improved by adopting the state transfer rule of the pseudo-random scale rule, invoking the dynamic parameter adjustment mechanism, and proposing the optimization method of local search based on a genetic algorithm. At the same time, to get the maximum and most comfortable travel experience as the goal, using matrix decomposition to get the user's satisfaction degree for the attractions, the user's satisfaction degree for the attractions as the goal, constructed an improved ant colony algorithm travel route planning model and used the model to solve the planning scheme. Finally, we applied the model to a real case and derived the optimal travel path that meets the requirements through calculation and analysis.

Keywords: Ant colony algorithm; Tourism planning; Traveler Issues; Mathematical Modeling; matrix decomposition

Introduction

According to the annual report for 2022-2023 issued by the National Tourism Board [8], domestic tourism is showing some significant trends in 2022.The travel distance and destination recreation radius have shrunk significantly, and the tourist flow is characterized by localization and proximity. This means that today's travel patterns favor shorter distances, shorter trips, and a greater focus on finding attractions that match personal preferences [1].

In this context, travel planning becomes essential. Travelers want an ideal travel itinerary to maximize their satisfaction. Therefore, finding the correct travel route becomes a problem while traveling. To meet this challenge, we can use a method based on matrix decomposition and an improved ant colony algorithm for travel route planning. It can help travelers quickly and accurately find a tour that meets their needs in today's diverse travel patterns. By rationally planning travel routes, travelers can better enjoy travel and get the most enjoyable experience.

Based on current social needs [17]. The paper's tourism route planning research is based on the user's preference, aiming to achieve the goal of a shorter travel distance and a shorter travel time to meet the user's maximum satisfaction. By optimizing the transfer probability function and pheromone update rule of the ant colony algorithm, Lee [5] significantly improved the algorithm's optimization-seeking ability. Yang [18] proposed a recommendation algorithm based on matrix decomposition for obtaining a matrix of user ratings for attractions. Luo [9] and Sun Qiong [14] et al. Proposed an optimization method for pseudo-random scaling rules in the ant colony algorithm, which significantly enhanced the performance and convergence performance of the ant colony algorithm. The travel route planning method of Wan Huiyun [16] et al. Needs to take into account the personal preferences of travelers. However, it considers factors such as time, cost, distance, and comfort. Hong Y [3] et al. Dynamically set heuristic factors and information volatility coefficients and applied the improved algorithm to the path optimization design of tourism products. Zhou Y [20] et al. Introduced a stochastic meeting algorithm into an ant colony system, and improving the distance calculation method is helpful for travel route-planning.Verbeeck and Schilde [11,15] et al. utilize an ant colony algorithm to plan travel routes for tourists butdo not consider the temporal context of tourists and attractions. Li X [7]et al. established a new evaluation system for tourist attractions from the perspectives of both domain experts and users.

This paper obtains the scenic spot rating matrix by studying the matrix decomposition and synthesizing tourists' travel preferences. An improved ant colony algorithm (IACA) is constructed by adopting a state transfer rule with a pseudo-random proportionality rule, introducing a dynamic parameter adjustment mechanism and a local search optimization method based on a genetic algorithm. The algorithm enables more efficient planning of travel routes, taking into account the user's personal preferences and preferences.

The experimental results show that the model proposed in this paper can generate more reasonable travel routes. By considering the user's travel preferences and optimizing using an improved Ant colony algorithm, travelers can have a travel experience that better matches their needs and preferences. This study provides a viable approach to tourism route planning that can improve traveler satisfaction and the quality of the tourism experience.

Scoring Matrix Based on Funk-SVD Algorithmat

Currently, standard recommendation algorithms include collaborative filter-based recommendation algorithms, content-based recommendation algorithms, and hybrid recommendation algorithms [2, 13]. This paper analyzes these recommendation algorithms for matrix decomposition-based approaches, focusing on a matrix decomposition-based recommendation algorithm proposed in Literature 5.

The algorithm employs the Funk-SVD (Singular Value Decomposition) algorithm, [6, 19], which aims to construct a scoring matrix that satisfies the user's needs. Matrix decomposition is a technique that decomposes a rating matrix into implicit feature representations of users and items. The relationship between the user and the entity can be obtained by decomposing the rating matrix, and the user's preference for an unknown item can be predicted.

The Funk-SVD algorithm is a classical matrix decomposition algorithm that fits the scoring matrix through iterative optimization, which minimizes the error between predicted and actual scores. The algorithm can effectively capture the implicit characteristics of users and items, thus improving the accuracy and personalization of recommendations.

By analyzing the matrix decomposition-based recommendation algorithm proposed in the literature5, this paper provides an in--depth understanding of the principles and implementation steps of the method. At the same time, combined with the Funk-SVD algorithm, a scoring matrix can be constructed to satisfy the user's needs and provide more accurate and personalized recommendation results for the recommender system. This is important for improving user experience and promoting the development of recommender systems.

Core Idea of Funk-SVD Algorithm

The Funk-SVD algorithm is a classical matrix decomposition algorithm widely used in recommender systems aiming at personalized recommendations. The core idea is to realize the prediction and recommendation of unknown ratings by decomposing the rating matrix into the product of the user matrix and the item matrix, thus capturing the implicit features between users and items. The user-item rating matrix is decomposed into the development of the user matrix and the item matrix by singular value decomposition. These feature vectors are learned to capture the relationship between users and items, and these feature vectors are used for personalized recommendations.

The core goal of the algorithm is to fit the rating matrix to an optimal state by learning the implicit features of users and items. By decomposing the rating matrix into two low-rank matrices, the dimensionality of the data can be reduced, and correlations between users and items can be captured. In this way, when making recommendations, unknown ratings can be predicted from the feature vectors of users and objects. Through iterative optimization and parameter updates, the Funk-SVD algorithm continuously improves the elements in the user and item matrices to fit the actual rating matrix better. As iterations proceed, the algorithm can gradually improve its ability to model the relationship between users and items, improving the accuracy of the predicted ratings.

Construction of the Scoring Matrix

Constructing a rating matrix is essential in a recommender system, representing the user's rating or degree of preference for an item. In recommender systems, the rating matrix is based on the user's and the object's interactive behavior or feedback data.

According to different tourists on the further evaluation of tourism routes, we synthesize the views of tourists to give travelers a better experience; the tourism routes are categorized and provide a reasonable recommendation for new tourists. The following data is a matrix consisting of attractions and tourists scoring part of the content, as shown in Table 1, with a rating of 1 to 5 points; 0 represents not being there. Scoring Matrix 36 attractions near Chaohu Lake were selected, and the scores of each interest were assigned through questionnaires and online comments to obtain the final scoring matrix.

Table 1: The original tourist attraction scoring matrix (Partial Schematic)

	user1	user2	user3	user4	user5	user6	user7	user8	user9	user10
Anhui Hall of Fame	5	5	4	5	0	5	4	4	4	5
Dujiang Zhanyi Memorial Hall	3	4	2	3	3	4	4	0	0	4
Binghu National Forest Park	3	4	3	4	4	4	5	4	3	3
Changlinhe Ancient Town Scenic Spot	0	3	4	4	1	4	0	5	2	5
Baima Mountain Tourist Attractions	5	4	3	4	2	5	3	3	4	3
Six Famous Residences	3	4	4	0	4	5	5	3	3	5
Siding Mountain National Forest Park	5	5	4	5	5	4	5	3	3	4
Cai Yongxiang Memorial Hall	5	3	4	4	2	4	4	3	4	3
basking island	4	3	3	2	4	5	4	5	4	3
ZhangZhizhong's former residence	0	3	0	5	4	4	5	3	0	5

Basic Flow of Recommendation Algorithm Based on Matrix Decomposition

In the recommendation algorithm of Funk-SVD, we need to utilize the user-attraction rating matrix R to predict how users rate unknown attractions. Suppose R is a rating matrix, where the rows represent users' ratings, and the columns represent users' ratings of attractions. In the process of matrix decomposition, we decompose R into a user matrix P and an item matrix Q. By matrix factorization, R can be approximated as the product of matrix P and matrix Q, as shown in equation (1):

$$\mathrm{R}_{\mathrm{m}\times\mathrm{n}} \approx \mathrm{P}_{\mathrm{m}\times\mathrm{k}} \times \mathrm{Q}_{\mathrm{k}\times\mathrm{n}} \quad (1)$$

Q is a size matrix denoting the k-dimensional feature vectors of n users. P is a matrix of size indicating the k-dimensional feature vectors of m attractions. k is the dimension of the implicit feature set. The matrix decomposition allows us to predict the ratings of unknown attractions by the product P * Q. Specifically, for the ith user and the jth appeal, the expected rating value is the inner product of the ith row of matrix P and the jth column of matrix Q. Through optimization algorithms, such as gradient descent, we can iteratively adjust the elements of matrix P and matrix Q to minimize the error between the predicted and actual rating values. During the iteration process, the details in matrix P and matrix Q are updated according to the size of the error to gradually improve the accuracy of the prediction. With this matrix decomposition, the Funk-SVD algorithm can predict unknown ratings using the implicit features of the user and the attraction to personalized recommendations. By capturing the relationship between users and interests, the algorithm can provide more accurate and customized recommendation results, enhancing the performance and user experience of the recommender system.

Here, the linear regression idea is applied to decompose R into reasonable P and Q. We use the mean square deviation as a loss function to find the final P and Q.Assuming that a certain user u rates item i, the corresponding implicit feature vector of user u is projected into the k-dimensional space after matrix decomposition, and the related implicit feature vector of object i is, and the elements in the two vectors indicate the degree of compliance of user u and item i with the implicit factors respectively, both positively and negatively. The original values before matrix factorization can be approximated by using the dot product of the two implicit eigenvectors, which expresses the overall interest of user u in item i,

Step 1: First, let $\hat{r}_{ui}$ be denoted as:

$$\hat{r}_{\mathrm{ui}} = \mathrm{q}_{\mathrm{i}}^{\mathrm{T}} \mathrm{p}_{\mathrm{u}} \quad (2)$$

In step 2, the objective function is obtained by taking $\hat{r}_{ui}$ in (2) as the true rating and $\hat{r}_{ui}$ as the predicted rating for all the samples with existing ratings, where k is the sample set of pairs of users and samples with existing ratings, and λ is the regularization coefficient, which is a hyperparameter.

$$J(p,q) = \min_{q^*,p^*} \sum_{(u,i)\in k} (r_{ui} - \hat{r}_{ui})^2 + \lambda\left(P_u{}^2 + q_i{}^2\right) \quad (3)$$

Step 3: With the objective function, optimization is done by the gradient descent method to get the final result.

$$\frac{\partial J}{\partial P_u} = -2(r_{ui} - \hat{r}_{ui})q_i + 2\lambda P_u \quad (4)$$

$$\frac{\partial J}{\partial q_i} = -2(r_{ui} - \hat{r}_{ui})p_u + 2\lambda q_i \quad (5)$$

$$P_u = P_u + \alpha[(r_{ui} - \hat{r}_{ui})q_i - \lambda P_u] \quad (6)$$

$$q_i = q_i + \alpha[(r_{ui} - {}_{ui})P_u - \lambda q_i] \quad (7)$$

By iterating, we can finally get P and Q, which can be used for recommendation.

Step 4: Using the above process, write a program to make predictions by dividing the dataset into dividing the original dataset and dividing into a training set (80% of the original dataset), a validation set (10% of the original dataset), and a test set (10% of the original dataset) dataset, and after several iterations, the optimal k-value can be obtained, which predicts the ratings that tourist i will give to the attraction j that he has not been to.

Algorithm Implementation

According to the algorithmic idea and programming in Python, the matrix of ratings of tourists for the attractions that have not been visited can be obtained.It is finally concluded that k=5, the loss function value is minimized at 1,000,000 iterations, and the program is optimal. When k=5, the predicted partial rating matrix is:

Table 2: Modified Tourist Attraction Scoring Matrix (Partial Schematic)

	user1	user2	user3	user4	user5	user6	user7	user8	user9	user10
Anhui Hall of Fame	4.9	4.2	5.3	4.7	4.6	4.7	4.9	4.3	4.8	5.0
Dujiang Zhanyi Memorial Hall	3.4	3.6	2.9	3.1	2.4	3.7	3.5	3.5	3.6	2.7
Binghu National Forest Park	3.7	3.5	3.7	3.7	3.1	3.6	3.9	3.6	3.7	3.7
Changlinhe Ancient Town Scenic Spot	2.6	3.3	2.5	4.7	1.6	1.7	4.7	2.9	2.6	3.9
Baima Mountain Tourist Attractions	3.6	3.5	3.1	2.5	2.8	4.2	3.1	3.3	3.9	2.4
Six Famous Residences	3.5	3.5	3.9	5.2	3.0	2.5	5.1	4.1	3.3	4.9
Siding Mountain National Forest Park	3.9	3.1	4.6	4.2	4.0	3.4	4.2	3.4	3.7	4.6
Cai Yongxiang Memorial Hall	3.8	3.3	4.1	3.4	3.6	3.8	3.6	3.3	3.8	3.7
basking island	3.9	3.7	3.5	2.5	3.1	4.6	3.1	3.4	4.1	2.6
ZhangZhizhong's former residence	3.8	3.0	4.8	4.9	4.1	2.9	4.6	3.6	3.5	5.3

Software programming is used for the above algorithm to make the loss function iteratively smaller, as the k value is controllable, different k values are used to observe the convergence curve when k=3; the convergence curve is shown in Figure 1. When k=5, the convergence curve is shown in Figure 2. When k=10, the convergence curve is shown in Figure 3.

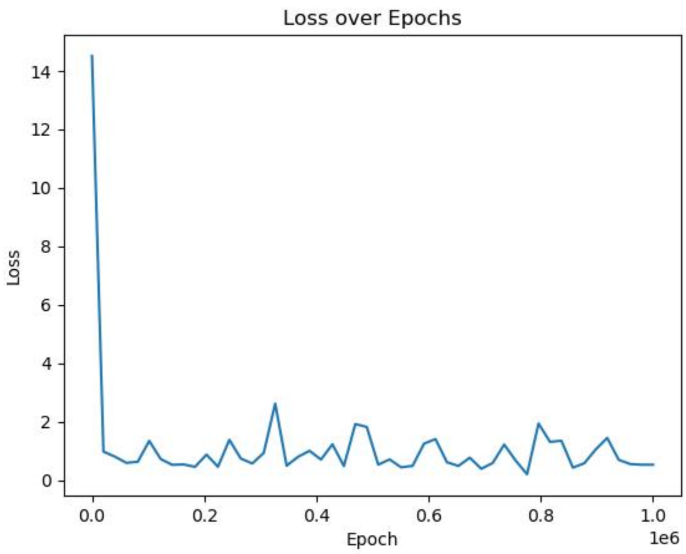

Figure 1: Convergence curve of loss function

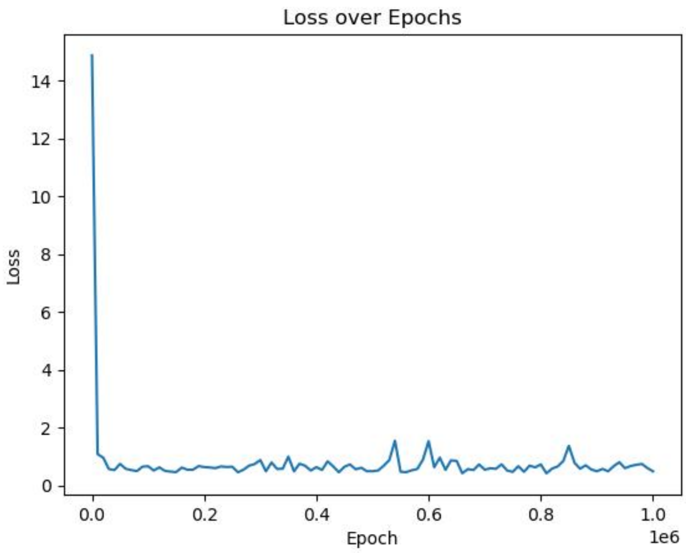

Figure 2: Convergence curve of loss function

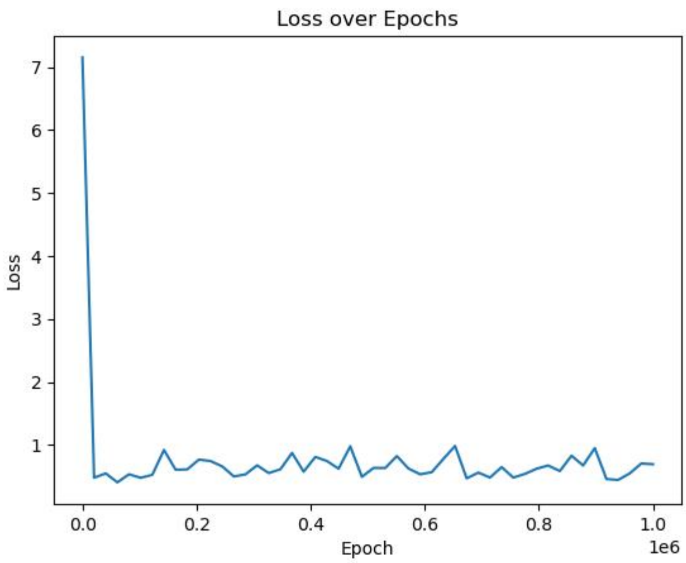

Figure 3: Convergence curve of loss function

Improved ant Colony Algorithm

Description of the Problem

This paper studies tourism route planning for 36 attractions around Chaohu Lake. It proposes the following specific steps for tourism route planning:

1) The user defines the scope of the tour and determines the range of attractions around Chaohu Lake of interest.

2) The user selects the number of tourist attractions and determines the number of attractions to be included in the program.

3) Based on the location of the sights, the distances between the sights are calculated to get a distance matrix or map.

4) Construct a scoring matrix for attractions.

5) Based on the distance between attractions and the scoring matrix, a travel route planning algorithm determines a reasonable travel route. This is done to provide the best travel experience.

These steps will help users choose the correct tour route among the many attractions around Chaohu. They will consider distance, attraction ratings, and user preferences to optimize tour route planning and experience.

Heuristic Functions

A heuristic function is an evaluation function used in heuristic search algorithms to estimate the cost or distance from the current state to the goal state. It guides and directs the search direction during the search process and helps the algorithm find the optimal solution faster.

Based on the above concept, the distance d_{ij} between attraction i and attraction j is the actual distance through the map, and attraction i is rated:

$$\mathrm{r_i} = \frac{\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{r'_{ij}}}{\mathrm{n}} \quad (8)$$

(8) where n denotes the number of users chosen to rate, and r'_{ij} means the rating of user j for attraction i.Users are more inclined to choose Attraction i when Attraction i has a high rating and is a short distance away. From this, the objective function is:

$$Max\left(\sum_{(j=1)}^{L} \frac{r_j}{d_{ij}}\right), (j = i + 1) \quad (9)$$

(9) where L denotes the set of selected sights.

The heuristic function is positively proportional to the objective function, i.e.:

$$\eta_{\mathrm{ij}} = \mathrm{r_j} \quad (10)$$

Pheromones

Pheromones are a critical concept in ant colony algorithms for modeling information exchange and cooperative behavior among ants. It guides ant search and path selection and acts as a global information transfer in the Ant Colony algorithm.

The algorithm's positive feedback mechanism and memorization path are completed by releasing the pheromone. This is where a denotes the pheromone volatilization rate. For the pheromone B, it has been updated as shown in (11) and (12) below:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{best} \quad (11)$$

$$\tau_{ij}(t+1) = \begin{cases} \tau_{max}, \tau_{ij}(t+1) \geq \tau_{max} \\ \tau_{min}, \tau_{ij}(t+1) \leq \tau_{min} \end{cases} \quad (12)$$

Where t is the number of iterations, a denotes the increase in pheromone concentration on the globally best path. It optimizes the ant colony algorithm, helping the ants focus their search and select the globally optimal way.So $\Delta\tau_{ij}^{best}=1/F(L)$ where F(L) is the satisfaction of the current global optimal solution route L.

Improved State Transfer Rules

Any ant k in the process of action is based on the size of the amount of pheromone and the path-inspired information to determine the direction of the movement of the ant, t moment ant k from the attraction i transferred to the attraction j path selection probability is $P_{ij}^{k}(t)$ for:

$$P_{ij}^{k}(t) \begin{cases} \dfrac{\tau_{ij}(t)^{\alpha}\eta_{ij}(t)^{\beta}}{\sum_{s\in L_k}\tau_{is}(t)^{\alpha}\eta_{is}(t)^{\beta}}, j \in L_k \\ 0 j \notin L_k \end{cases} \quad (13)$$

(13) where L_k denotes the set of attractions that a nt k can choose from.α and β represent the influence factors of the pheromone and heuristic functions, respectively.A state transfer rule with pseudo-randomized proportionality rules invokes a dynamic parameter tuning mechanism for selecting paths. As shown in equations (14) ,(15) below:

$$q_0 = \begin{cases} a + b * \left(\dfrac{t}{N}\right), 0 \leq t < \dfrac{2}{N} \\ 0.9, \dfrac{2}{N} \leq t \leq N \end{cases} \quad (14)$$

$$j = \begin{cases} argmax\left(P_{ij}^{k}\right), q \leq q_0 \\ argmin\left|q - P_{ij}^{k}\right|, q \geq q_0 \end{cases} \quad (15)$$

The dynamic adjustment function q0 is designed to ensure pathfinding aggressiveness and diversity during the algorithm in Eq.In the algorithm, the algorithm's search space is increased to avoid a local optimum, and decreasing q0 makes the algorithm more random.Later in the algorithm, the probability of the algorithm searching for an optimal solution decreases, and increasing A brings the algorithm closer to the current optimal solution more quickly. A,b, and q are constant between [0, 1], a+b≤1。 j∈L_k

Local Search

In the iterative ant colony algorithm, it is easy to reach the local optimum. To overcome the limitations of the ant colony algorithm in neighborhood search, we use the genetic algorithm's crossover and mutation to increase the algorithm's exploration ability. In this way, the algorithm jumps out of the local optimum. The algorithm is divided into two steps.1) Crossover operation: after each iterative process, each ant selects a path L, a section of course Lm is randomly selected from the L path, and the way L is removed from Path Lm and retained by Path L_a is indicated. Insert Lm at $L_{a's}$ head and tail to form two distinct paths. The path with the highest level of user satisfaction becomes the optimal path. (2) Mutation operation: a randomly selected point in the path chosen L is mutated, and the end is replaced with any point in the set of selectable tracks L_k to form another course Lb.The path with the highest level of user satisfaction becomes the optimal path.

Setting of Parameters

The setting of parameters significantly impacts the algorithm's efficiency in solving the problem, so the set of parameters needs to be reasonable and scientific.Also, in the literature review [12], the influence of pheromone factor α, heuristic factor β, and pheromone volatility coefficient ρ on the Ant colony algorithm is more significant.In this paper, the dynamic adjustment function, the parameter a b, has a more significant influence. Therefore, this paper compares the above parameters.

Setting of α、β and ρ

Literature [10] was discussed for the parameters pheromone factor ρ and heuristic factor β. It was determined that the pheromone factor α is in the range of [1, 3], and the heuristic factor β is in the range of [1,5].To select the appropriate parameters, the maximum number of iterations is g_{max}=500, the number of ants M = 35, the number of selection attractions L = 10, and the volatilization coefficients of the pheromone to be determined are 0.3, 0.5, and 0.7, respectively. Each combination is solved ten times and averaged; the results are below.

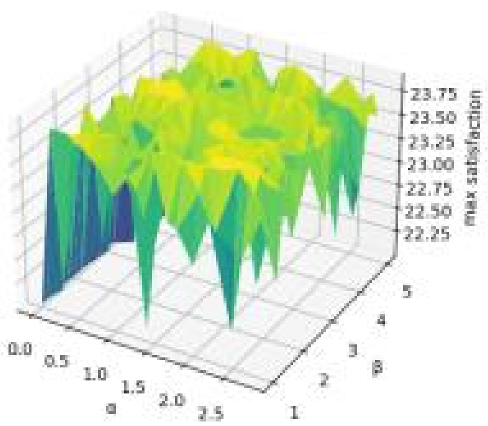

Figure 4: ρ= 0.3

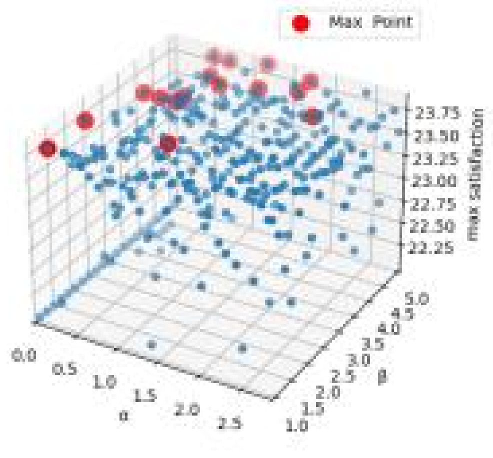

Figure 5: Scatterplot for ρ =0.3

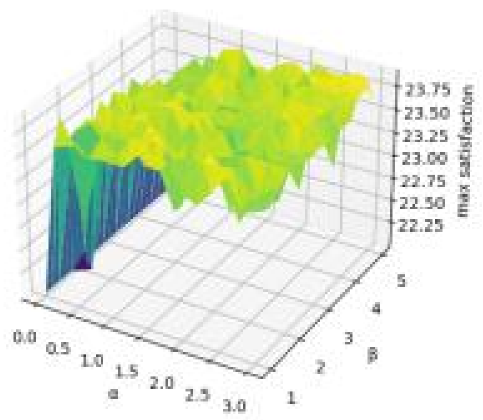

Figure 6: ρ= 0.5

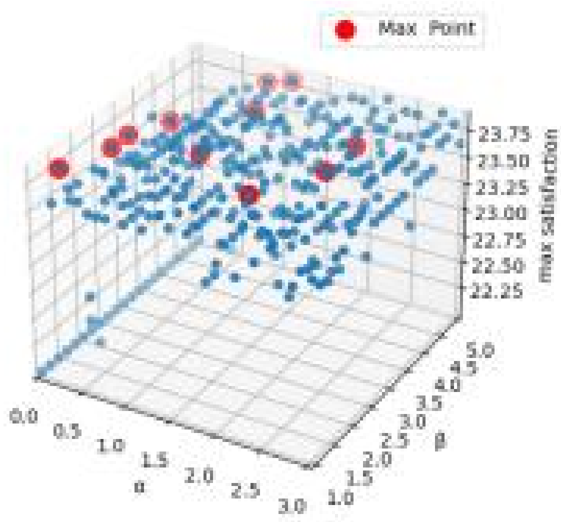

Figure 7: Scatterplot for ρ =0.

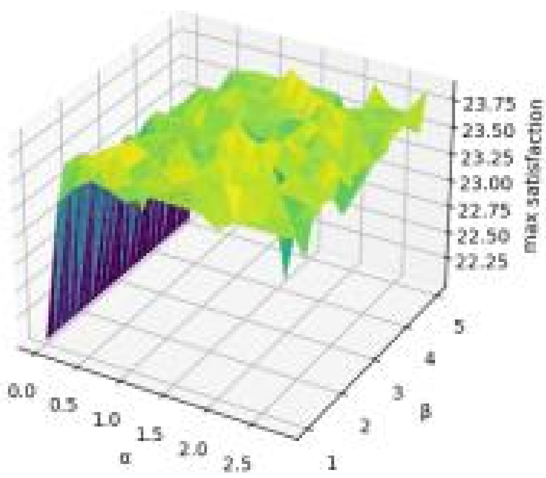

Figure 8: ρ= 0.7

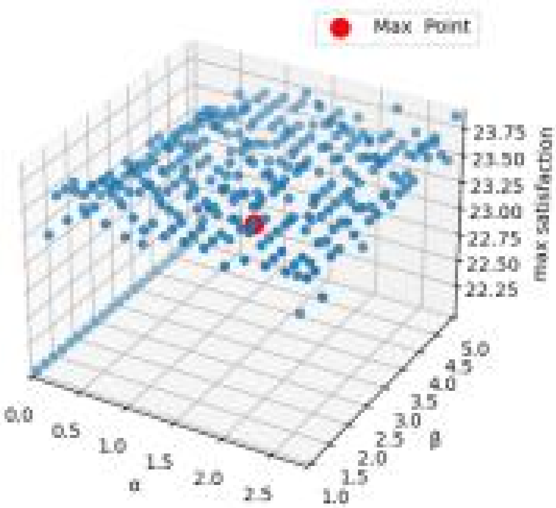

Figure 9: Scatterplot for ρ =0.7

For the 4-6 figures shown, the optimal combination of parameters is the average of the results of the three sets of data above, which gives α = 2 and β = 4.

Each combination is solved ten times with the pheromone factor α as 2, the heuristic factor β as 4, the maximum number of iterations to g_{max}=500, the number of ants M=35, and the number of choice attractions L=10. Choose the pheromone ρ= {0.1，0.2，0.3，0.4，0.5，0.6，0.7，0.8，0.9 }; each data set is solved ten times and averaged, and the solution results are shown in Fig. 10 below. And averaged; the results are below.

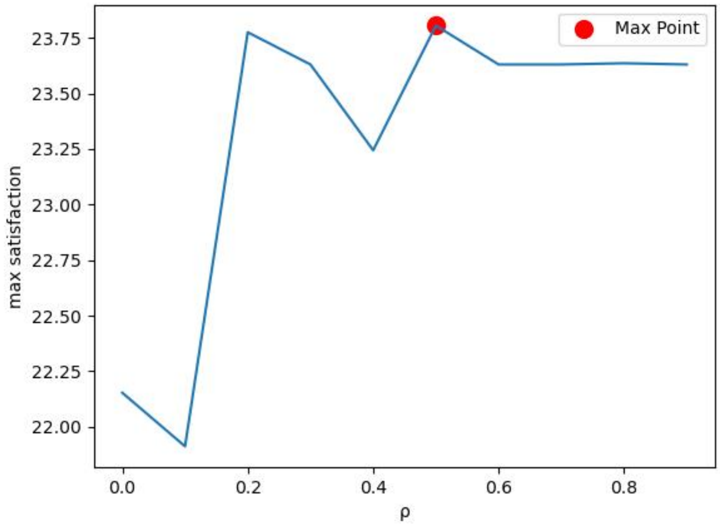

Figure 10: Relationship between and maximum satisfaction

The graph above shows user satisfaction is most significant when ρ is at 0.5.

Setting of a and b parameters

Figure 10 shows that α = 2, β = 4, ρ = 0.5 when the algorithm works best, and then set a and b of the dataset for {0.1，0.2，0.3，0.4，0.5，0.6，0.7，0.8，0.9 } and a+b≤1, a total of 55 sets of [a,b], and each group of [a,b] applied to the IA-CA algorithm to conduct ten sets of experiments, and take the average value to get the user satisfaction. The solved data are shown in Figures 11 and 12.

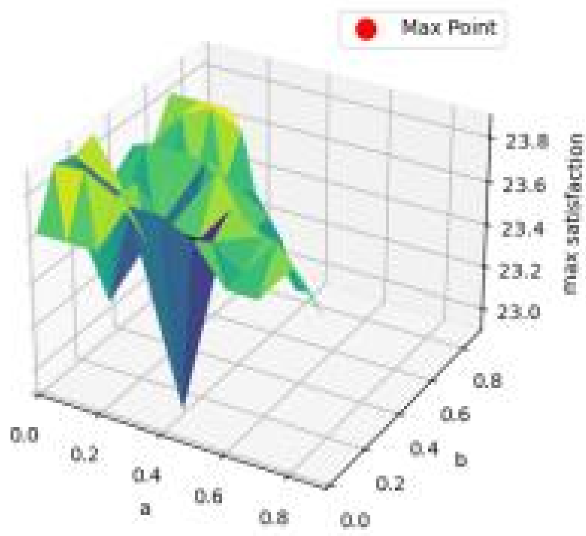

Figure 11: Relationship between parameters a, b a=0.2 , b=0.2

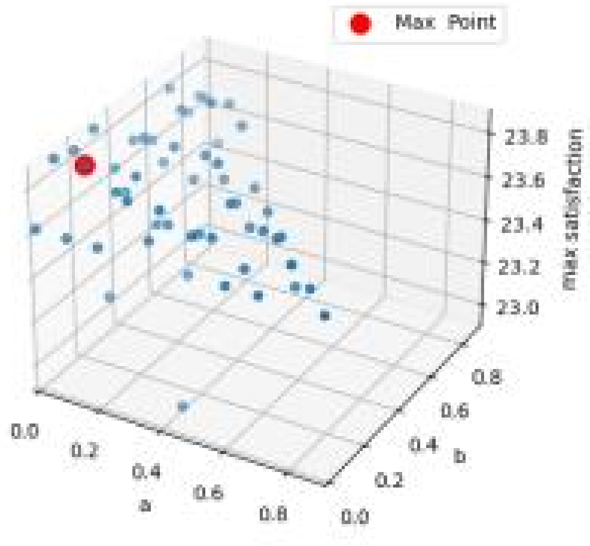

Figure 12: Scatterplot of parameters a, b a=0.2 , b=0.2

Input: g_{max}

Output: q_0

(1) While （$g \le g_{max}$）

(2) {

(3) If $g \le g_{max} / 2$

(4) $q_0 = a + (b * g) / g_{max}$

(5) Else

(6) $q_0 = 0.9$;

(7) Ant(q_0)

(8) g++

(9) }

Algorithm 1: Dynamic adjustment strategies

Input: L_n, L_k, q_0

Output: L_n

Random one L in L_k -> L_n

Random one q in [0,1]

While ($x \leq n$)

{

If $q \leq q_0$

L = $\arg\max(P_{ij})$ -> L_n

Else

L = $\arg\min|q - P_{ij}|$ -> L_n

X++

}

Algorithm 1: Ant()

Experimental Simulations

This experiment uses 36 attractions around Chaohu Lake as simulation objects to verify the algorithm's performance.

Suppose the user starts from any point and selects 10 points of interest. Parameter setting g_{max}=500, α=2, β=4, ρ=0.5, L =10.

The SRPAS algorithm with improved pheromone updating state transfer rules was proposed by Yu-Hsin Huang [4] et al. It is used to realize load balancing of the number of people in each attraction of the scenic spot.In order to compare the performance with its algorithm, the improvement strategy proposed by Huang Yuxin is used in the tourism model of this paper. The average of ten data runs was calculated as the result of this experiment, and the comparison structure is shown below. The standard of ten data runs was calculated as the result of this experiment, and the comparison structure is shown below.

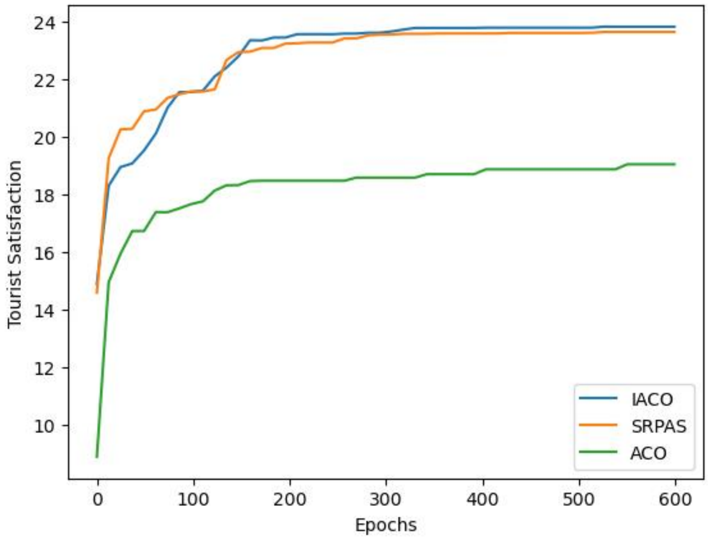

Figure13: Comparison of data

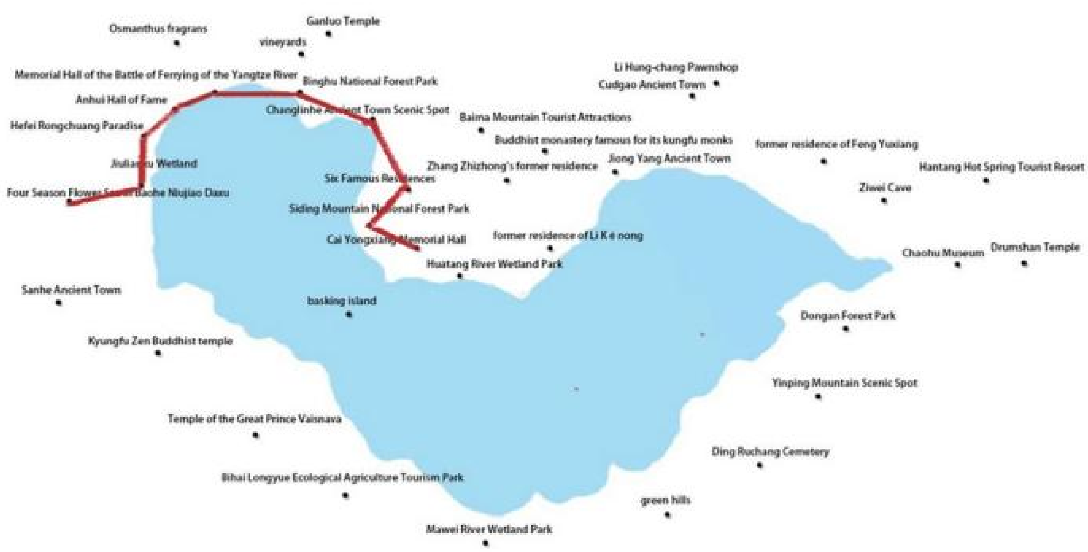

Figure 14: Actual path planning

As can be seen from Fig. 14, the SRPAS algorithm converges around the local optimum of 23.78 at around 300 generations.The IACO algorithm converges around the local optimum 23.88 at around 320 generations.The main reason why IACO converges worse than the SRPAS algorithm is that the SRPAS algorithm uses a small number of iterations to increase the search space of the algorithm. In contrast, the remaining number of iterations brings the algorithm into the neighborhood of the current optimal solution more quickly.It is easy to see in Figure 14 that the satisfaction of the SRPAS algorithm rises significantly around generation 150. The IACO algorithm increases the number of iterations to avoid the algorithm falling into a local optimum, increasing the algorithm's search space for the first 300 generations and converging to a local optimum for the next 300 generations.Although the IACO algorithm converges slightly worse than the SRPAS algorithm, the IACO algorithm can find better and better paths.

Table 3: Algorithm performance comparison

algorithm	Number of iterations	Count times	Optimal solution	Worst solution	average value
IACO algorithm	320	10	24.07	23.63	23.88
SRPAS algorithm	300	10	23.98	23.63	23.73
ACO algorithm	550	10	19.93	17.72	18.89

Conclusion

Ant colony algorithms are a popular research direction in information technology nowadays, and they play an essential role in personalized recommendation, information filtering, and decision support. The text centers on the recommendation algorithm based on matrix decomposition and an improved ant colony algorithm for travel route planning in recommendation algorithms, and the two aspects are introduced and analyzed in detail.

This paper focuses on matrix decomposition-based recommendation algorithms, using the Funk-SVD algorithm as an example. The algorithm realizes the prediction and recommendation of unknown ratings by decomposing the rating matrix into the product of the user matrix and the item matrix, capturing the implicit features between users and items. Specifically, the algorithm uses iterative optimization to adjust the elements in the matrix to minimize the error between predicted and actual scores. The Funk-SVD algorithm has the advantages of better recommendation accuracy, computational efficiency, and simplicity of implementation. Still, it has limitations, such as its inability to deal with the cold-start problem and capture auxiliary information. Meanwhile, for the issue of tourism route planning, this paper introduces research into tourism route planning based on an improved ant colony algorithm. This study obtained the user's satisfaction level of attractions through matrix decomposition, synthesized the user's satisfaction level of interests as an objective, and established a travel route planning model with an improved ant colony algorithm. In the improved ant colony algorithm, the state transfer rule with pseudo-random scale rule is used, and the optimization method of dynamic parameter adjustment mechanism and genetic algorithm-based local search is invoked. The experimental results show that the improved ACO algorithm can get more reasonable traveling routes.

Analyzing the two studies together, we can draw the following conclusions:

First, a recommendation algorithm based on matrix decomposition is an effective personalized recommendation method. By decomposing the rating matrix, the implicit features between users and items can be captured to predict unknown ratings accurately. In practical applications, we can choose suitable matrix decomposition algorithms according to the characteristics of specific problems and combine other data sources and feature information for comprehensive recommendations to improve the accuracy and personalization of the request.

Secondly, the improved ant colony algorithm has good application prospects in tourism route planning. By combining matrix decomposition and an improved ACO algorithm, users' travel preferences and information about attractions can be connected to realize more reasonable and comfortable travel route planning. The enhanced ant colony algorithm is optimized for state transfer rules, parameter adjustment, and local search, improving the algorithm's performance and search efficiency. In practical applications, we can optimize the algorithm according to different travel needs and constraints to obtain optimal travel path planning that meets the user's needs.

However, both research directions still need to address some challenges and issues. In recommendation algorithms, the cold-start problem, data sparsity, and the interpretability of algorithms are still hot and challenging research topics. Considering more constraints and diversity, addressing the complexity of path searching and solving efficiency are concerns in travel route planning.

In conclusion, recommendation algorithms and travel route planning are essential in current research and application areas to provide personalized and satisfying services to users. Research on matrix decomposition-based recommendation algorithms and improved ant colony algorithms has significantly progressed in advancing recommender systems and travel planning. Through a recommendation algorithm based on matrix decomposition, accurate prediction of user preferences and personalized recommendations can be achieved to enhance user satisfaction and experience. Improved ant colony algorithm in travel route planning combines user's preferences and attraction information, which can generate more reasonable and comfortable travel paths and provide users with a better travel experience.

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