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*Retraction*

# Retracted: Precision Marketing Strategy for Ecotourism Based on Data Mining and User Images

**Mobile Information Systems**

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] X. Chen, Q. Li, F. Zou, D. Wang, T. Li, and M. Hu, "Precision Marketing Strategy for Ecotourism Based on Data Mining and User Images," *Mobile Information Systems*, vol. 2022, Article ID 1104633, 8 pages, 2022.

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*Research Article*

# Precision Marketing Strategy for Ecotourism Based on Data Mining and User Images

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With the continuous development of ecotourism industry, it has become a common concern in ecotourism industry to utilize the available data to realize the change of ecotourism industry and promote the product development and business expansion of ecotourism industry. To this end, we propose a personalized ecotourism route recommendation (PTIR) algorithm based on the popularity of points of interest (POI) and users' interest preferences. First, we analyze the real historical ecotourism footprints of users, propose a time-based user interest preference, and design a method to calculate the best ecotourism route given the travel time limit, departure point, and end point. Experiments were conducted on a real dataset of the Flickr social networking site, and the results showed that this personalized ecotourism route recommendation algorithm has greatly improved accuracy and recall compared with the traditional algorithm that only considers POI popularity, and the results were visualized through specific experimental cases based on user image clustering.



## 1. Introduction

With the development of society, the ecotourism industry is strong in the global development, and the industry is ranked first in terms of scale [1–4]. With the improvement of people's consumption level, ecotourism industry has become the spiritual pillar of people's development in life and the pillar industry of China's economy on the road of development; the demand of ecotourism service is expanding; the issue of how the enterprises in ecotourism industry should effectively use the existing data to develop, expand, and innovate their ecotourism products has become the common concern of each ecotourism. This issue has become a common concern for all ecotourism companies [5–8].

Due to the precision of precision marketing, it is easier to clarify the target customers, so the marketing effect is more obvious, and marketing costs will be reduced. A significant advantage of precision marketing is controllability, because the audience is accurate, so companies can track their research and adjust their marketing strategies through the feedback, so as to achieve better marketing results. The characteristics of precision marketing are mainly in the following aspects: firstly, effective market segmentation, secondly, targeting customers, thirdly, target customer interaction, and fourthly, increasing customer value [9, 10]. In this paper, we propose the precise marketing of ecotourism constructed in the way of user image and realize the user segmentation by user clustering algorithm; secondly, we realize the personalized recommendation algorithm of ecotourism attractions by feasibility experiment method.

Before recommending an ecotourism itinerary, people want to know which POIs are of interest, and generally this can be regarded as POI recommendation. The system takes into account five factors: weather, time of day, day of the week, user's location, and user's emotion to personalize user's interest preferences, and evaluates a generalized matrix decomposition of the scoring prediction model to recommend POIs that satisfy user's interest preferences [10]. By analyzing the semantic, temporal, and spatial check-in data of users, a probabilistic generation model, i.e., the Topic-Region Model (TRM), is proposed. This model solves the problem of sparse data and recommends the top-k POI sets for users considering their interests and spatial movement patterns. Paper [11] proposed an active recommendation system based on a context-aware model, which predicts a score for each POI in terms of user interest preferences and different contextual factors (e.g., time required to visit two POIs, POI tour time, weather, user availability, and user's historical ecotourism footprint) and thus recommends POIs suitable for the current context for the target user.

Developing products and expanding business has become a common concern in the ecotourism industry. To this end, we propose a personalized ecotourism route recommendation (PTIR) algorithm based on POI popularity and user interest preferences. The results show that an optimal ecotourism route calculation method is designed given travel time constraints, departure, and destination points, and the results are visualized by a specific experimental case based on user image clustering. The accuracy and recall of this personalized ecotourism route recommendation algorithm are improved compared with the traditional algorithm that only considers POI popularity.

## 2. Related Work

Ecotourism route recommendation is to plan one or more reasonable ecotourism routes for users that meet their interests and expectations. In recent years, a large number of studies on ecotourism route recommendation have emerged. Paper [12] analyzed ecotourism photos shared by users on social networking sites to recommend ecotourism routes. Paper [13] used the tags and titles in the photo data to obtain the frequent visit pattern of different ecotourism theme categories. The Markov and theme models are combined to propose a probabilistic behavioral model to obtain the probability of a user's visit to the next attraction under the theme and find the top-k ecotourism routes that satisfy the user's interests and time constraints; paper [14] proposes a Bayesian learning model using user-contributed community photos to recommend personalized ecotourism routes for users based on their characteristics (e.g., gender, age, race) and their group ecotourism styles (e.g., family, friends, couples). Although these early studies have successfully used users' shared ecotourism photos to recommend routes for users, [15] did not consider user interests or POI types, and [6, 8] modeled user interests with a theme model but did not consider users' tour starting and ending points.

Among various ecotourism route recommendation algorithms, the route recommendation algorithm based on the orientation problem has been very widely used. Literature [16] is one of the early studies on ecotourism route recommendation based on the orientation problem, which recommends routes for users to maximize the target score when the starting POI and ending POI are known; [17] recommends the best ecotourism route that satisfies both user interest and POI type to users under the travel constraints (e.g., time budget, starting and ending locations); [18] improves the orientation problem using POI types, so that the recommended routes are limited by the order of POI type access (e.g., art gallery-park-church); [19] combines the POI type access with the POI type access order (e.g., art gallery-park-church). With [17] combining the user's chosen destination and input requirements (e.g., departure date, expected time spent, starting location, and ending location), we use multiobjective criterion functions and other optimization methods to find the activities that meet the user's requirements and constraints and generate ecotourism routes that are closest to the expected time spent, have the shortest ecotourism time, and have the highest activity value and recommend these routes to the user.

Compared with the above work, the ecotourism route recommendation studied in this paper mainly uses the user's access time to a certain type of POI to obtain time-based user interest and uses the orientation problem to return an optimal ecotourism route for the user under the comprehensive consideration of user interest preference and POI popularity.

## 3. Ecotourism Route Recommendation Method

*3.1. Recommended Framework for Ecotourism Routes.* As shown in Figure 1, the user based on the orientation problem is using our proposed PTIR algorithm that integrates the user's interest preference and POI popularity.

*3.2. Construction of POI Association Diagram.* The construction of POI association graph is carried out offline; in this paper, the POIs in the ecotourism sequence of all users are used as nodes in the graph, representing ecotourism locations, and the successive visits of users in the ecotourism sequence generate the edges in the graph.

In this paper, the POI prevalence is calculated as follows:

$$\text{Popular}\,(p) = \frac{N\,(p)}{N_{\max}}, \tag{1}$$

where $N\,(p)$ denotes the number of photos taken by all users in $\text{POI}_P$; $N_{\max}$ denotes the maximum number of photos taken by users in all similar POIs.

*3.3. User Interest Preferences.* In this paper, the average visit time for any user at $\text{POI}_P$ is denoted by $\overline{V}\,(p)$ in the ecotourism route recommendation. The average visit time required for each $POI_P$ is given by the following equation:

$$\overline{V}\,(p) = \frac{1}{n}\sum_{u\in U}\sum_{p_x\in S_u}\left(t_{p_x}^{d} - t_{p_x}^{a}\right)\sigma\left(p_x = p\right);\ \forall p \in P, \tag{2}$$

where $U$ denotes all users; $n$ denotes the number of users in $U$ who visited $p$:

$$\sigma\left(p_x = p\right) = \begin{cases} 1, p_x = p \\ 0, \end{cases}, \tag{3}$$

calculated by the following equation:

$$\text{Int}\,(u, c) = \sum_{p_x\in S_u}\frac{\left(t_{p_x}^{d} - t_{p_x}^{a}\right)}{V\left(p_x\right)}\sigma\left(\text{Cat}_{p_x} = c\right);\quad \forall c \in C, \tag{4}$$

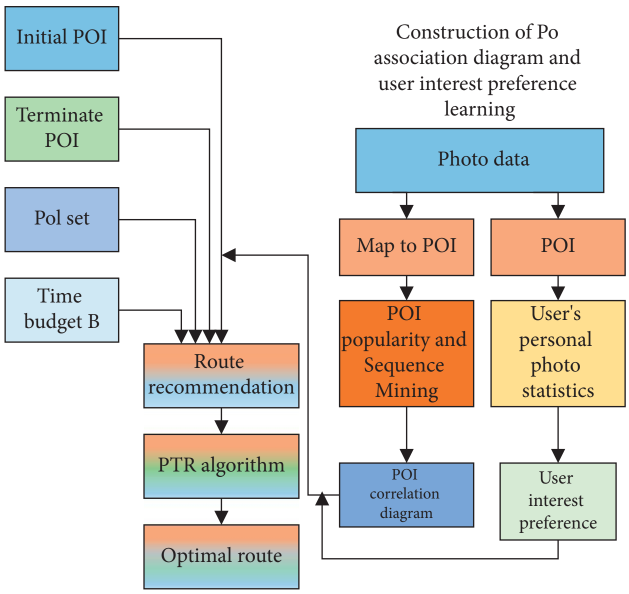


FIGURE 1: Route recommendation framework.

where $\mathrm{Cat}_p$ represents the category attribute of $\mathrm{POI}_P$:

$$\sigma\left(\mathrm{Cat}_{p_x} = c\right) = \begin{cases} 1, \mathrm{Cat}_{p_x} = c \\ 0, \end{cases}. \tag{5}$$

Equation (5) is calculated based on the time spent by the user at each POI with category attribute $c$.

*3.4. PTIR Algorithm.* Orientation problem (OP) has been widely used in ecotourism route recommendation. On the basis of orientation problem, this paper proposes a PTIR route recommendation algorithm considering POI popularity as follows:

$$\mathrm{Max} \sum_{i=2}^{N-1} \sum_{j=2}^{N} x_{i,j} \mathrm{score}\left(P_i\right), \tag{6}$$

where $x_{i,j} = 1$ means the route goes from $i$ to $j$, i.e., via edge $(p_i, p_j)$; otherwise $x_{i,j} = 0$.

Equation (6) satisfies the following constraints:

$$\begin{aligned} &\sum_{j=2}^{N} x_{1,j} = \sum_{i=1}^{N-1} x_{i,N} = 1, \\ &\sum_{j=2}^{N} x_{k,j} = \sum_{i=1}^{N-1} x_{i,k} \leq 1;\ \forall k = 2, 3, \ldots, N-1, \\ &\sum_{i=1}^{N-1} \sum_{j=2}^{N} \mathrm{Cost}\,(i, j) x_{i,j} \leqslant \mathrm{B2} \leqslant u_i \leqslant N, \\ &u_i - u_j + 1 \leqslant (N-1)\left(1 - x_{i,j}\right);\ \forall i, j = 2, 3, \ldots, N\mathrm{POI}_x P_n. \end{aligned} \tag{7}$$

This paper uses the lpsolve linear programming package proposed in [18] to solve the proposed integer programming problem.

*3.4.1. Route Planning.* To better illustrate the proposed algorithm, given the set of POIs, the information of each POI is shown in Table 1.

There is a user $u_1$ and the set of POIs he visited Su1. The POIs visited by user $u_1$ and the visit time (i.e., stay time) at each POI are shown in Table 2, and the average visit time at each POI calculated from the user's historical data according to equation (3) is shown in Table 3. The weights of the edges in Figure 2 indicate the time required for a user to $u_1$ access two POIs consecutively, and the values of the vertices indicate the scores of POIs. $p_1$ (Central Station) is the starting location, $p_2$ (Columbia University) is the ending location, and user $u_1$'s playtime budget is 6 hours; specific parameters are shown in Table 4. Suppose $a = 0.5$. The user's interest preference vector can be calculated from formula (4), then according to the PTIR algorithm, the user's $R_3$ time budget are obtained, and the three routes are scored by the formula (1), and the score of the route $R_3 = \left\{p_1, p_4, p_{3,} p_2\right\}$ is 0. 45; the score for route $R_1$ is 0.5. The score for route is 0.95. Finally, the route with the highest score $u_1$ is recommended to user 999, and the route {Central Station, Statue of Liberty, New York Stock Exchange, Columbia University} is recommended to user $u_1$.

## 4. User Image Architecture

In the process of realizing accurate recommendation, companies usually use user image modeling to mine key valuable information such as users' behavioral preferences and interest habits. The core of user image modeling is to refine and organize the user's basic information and behavior information, and this process is to label the user information. The implementation framework of ecotourism user images mainly includes combining the user data about the ecotourism system, obtaining and researching user basic information, user interaction information, user behavior information, classification/clustering analysis, establishing a label system for users, user division, and clustered image presentation of individual users and group users. The implementation framework model of the user image is shown in Figure 3.

In the modeling of user images, it is realized by processing user data through various algorithms. Machine learning algorithm is to process user data to form features of the same dimension and use feature tags to enrich user images. Clustering analysis is also an important algorithm in data mining. In the absence of prior knowledge, data can be divided into different types and aggregated according to the similarity between the data. The similarity of similar elements is high. The segmentation of ecotourism users in this paper is mainly based on clustering algorithm to implement. In addition, data mining also includes a large number of technical and statistical algorithms, such as text retrieval, natural language processing, prediction algorithms, recommendation algorithms, similarity calculation, correlation rules, etc. [20–24].

Ecotourism user images can be divided into two levels: static and dynamic. Static data includes user base and external attributes, and dynamic data includes behavior attribute analysis and purchase consumption attributes, as shown in Figure 4.

Table 1: POI category attributes and coordinate information.

| POI | Category properties | Latitude | Longitude |
|---|---|---|---|
| Central station $p_1$ | Historical architecture $c_{3,}$ | 40.752506 | −73.977477 |
| Columbia university $p_2$ | University $c_2$ | 40.807537 | −73.962570 |
| New York stock exchange $p_3$ | Historical architecture $c_{3,}$ | 40.706877 | −74.011265 |
| Statue of liberty $p_4$ | Sculpture/statue $c_1$ | 40.689249 | −74.044501 |
| Charging bull $p_5$ | Sculpture/statue $c_1$ | 40.705552 | −74.013444 |

Table 2: POIs visited by user $u_1$.

| POI | Access time/h |
|---|---|
| $p_1$ | 0.51 |
| $p_5$ | 0.42 |

Table 3: Average access time per POI.

| POI | Average access time/h |
|---|---|
| $p_1$ | 1.1 |
| $p_2$ | 0.31 |
| $p_3$ | 0.79 |
| $p_4$ | 0.81 |
| $p_5$ | 0.99 |

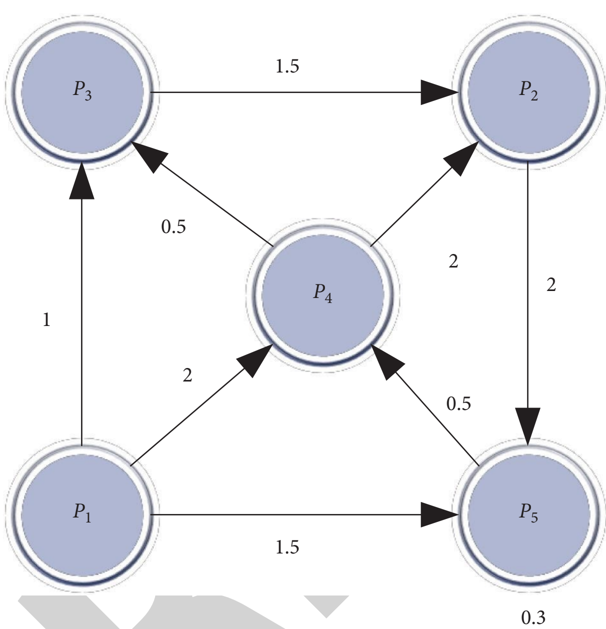


Figure 2: An example of route recommendation.

Table 4: POI popularity.

| POI | Popularity |
|---|---|
| $p_1$ | 0.21 |
| $p_2$ | 0.32 |
| $p_3$ | 0.39 |
| $p_4$ | 0.59 |
| $p_5$ | 0.21 |

User image refers to the understanding and visualization of target users in the big data environment. It is a tool for clarifying service goals. Its role is to use big data to fully interact among users, resources, and services. The ecotourism accurate recommendation system links the relationship between user data and ecotourism product data and fully connects the two types of data. The user image activates the role of traditional ecotourism enterprises in services by predicting the behavior and needs of users and promotes ecotourism enterprises to achieve precision and intelligence. Its functions are shown in Figure 5.

The results of clustering are shown in Figure 6. As the number of clusters increases, the overall silhouette coefficient also increases. When the number of clusters increases to 30, the growth of the silhouette coefficient tends to be stable, and it reaches the inflection point of growth. The clustering relationship in this chapter is determined based on the similarity between users, and the end users with high similarity will be regarded as a class of users with similar feature preferences and will be clustered into one class.

After user clustering algorithm processing and clustering result analysis, users are selected to be divided into 30 categories. It can also be seen from Figure 6 that the effect of clustering discovery is better at this time.

Based on the force-directed layout diagram of the Echarts library, the data visualization of the clustering results was carried out. Echants provides an intuitive, rich, and highly personalized graphical interface. It is an open-source visualization library based on JavaScript. It has a good display effect and can run smoothly on both PC and mobile based on HTML5.

## 5. Simulation and Analysis

To measure the performance of the system, metrics such as precision, recall, $F1$-score, and mean precision (MAP) are used. Table 1 shows the comparison between our method and traditional data mining algorithms such as Apriori, Eclat, decision tree, and logistic regression. It can be seen from Table 5 that all models will decrease the accuracy and increase the recall rate with the increase of the recommendation list, and the model of this paper is better than other methods, achieving 53% $F1$ and 74% MAP, while the worst is the Apriori method that achieves an $F1$ of 48% and a MAP of 58%, with a 16 percentage point difference in MAP between the two.

This study further considers the dimension of the label vector. The test dataset is divided into 6 groups according to the size of the label vector, and each group is evaluated with correspondingly sized itemset proposals. Figure 7 shows the final test results. As can be seen from Figure 7, the method in this paper, logistic regression, and decision tree methods are basically better than the Apriori and Eclat algorithms. The

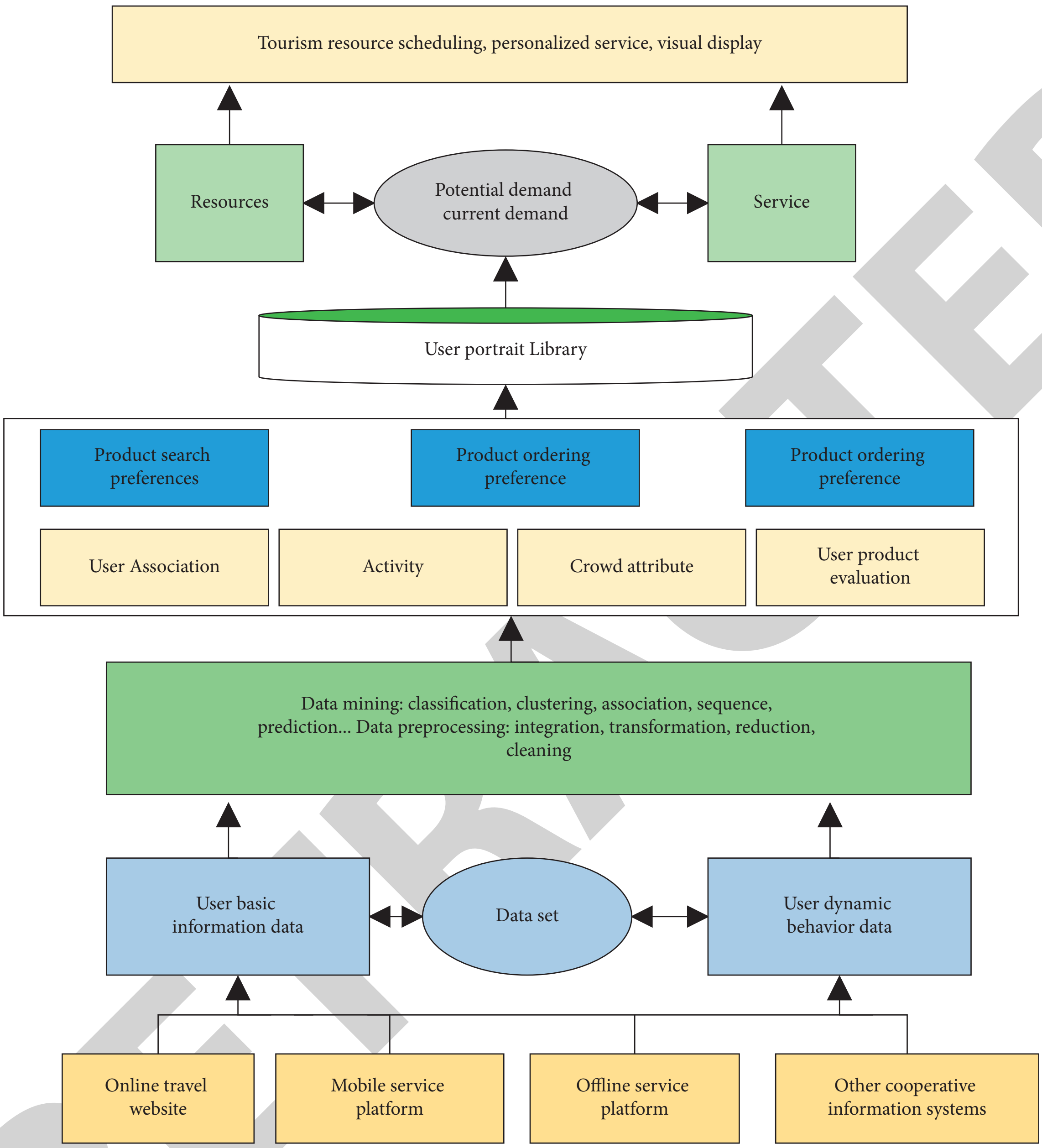


Figure 3: Implementation framework model of user image.



final average recommendation accuracy of this method can reach about 80%.

Echarts is driven by data, and data is the basis of graphical representation, so data organization and parameter configuration need to be handled well. For data, there are two main data items nodes and links. Nodes, as a list of node data in the clustering graph, has the following key data item attributes: name attribute, id attribute, value data item value attribute, and layout style attribute. Links is a list of node data relationships in the clustering relationship graph, including two string attributes, source and target, source is the name of the source node of the edge, and target is the name of the target node of the edge. The values attribute of links refers to the value of the edge. In order to make the display more intuitive, this section expands the user similarity value represented by the edge by 45 times and rounds it up, so that the value of the attribute is represented by the length of the edge. At the same time, configure the layout position and style attributes of links according to the requirements. Since there are 30 types of clusters, in order to avoid confusion and display clearly, a single representative cluster is selected for display. After the data and parameters of the force-oriented layout are configured, the generated force-oriented layout with weights is shown in Figure 8.

When the mouse hovers over a user node in the force-oriented layout diagram, the transparency of other edges and nodes is increased and faded, and the prompt box shows the user attributes of the user of the node and other information. Figure 9 shows the effect when the mouse is hovered over the

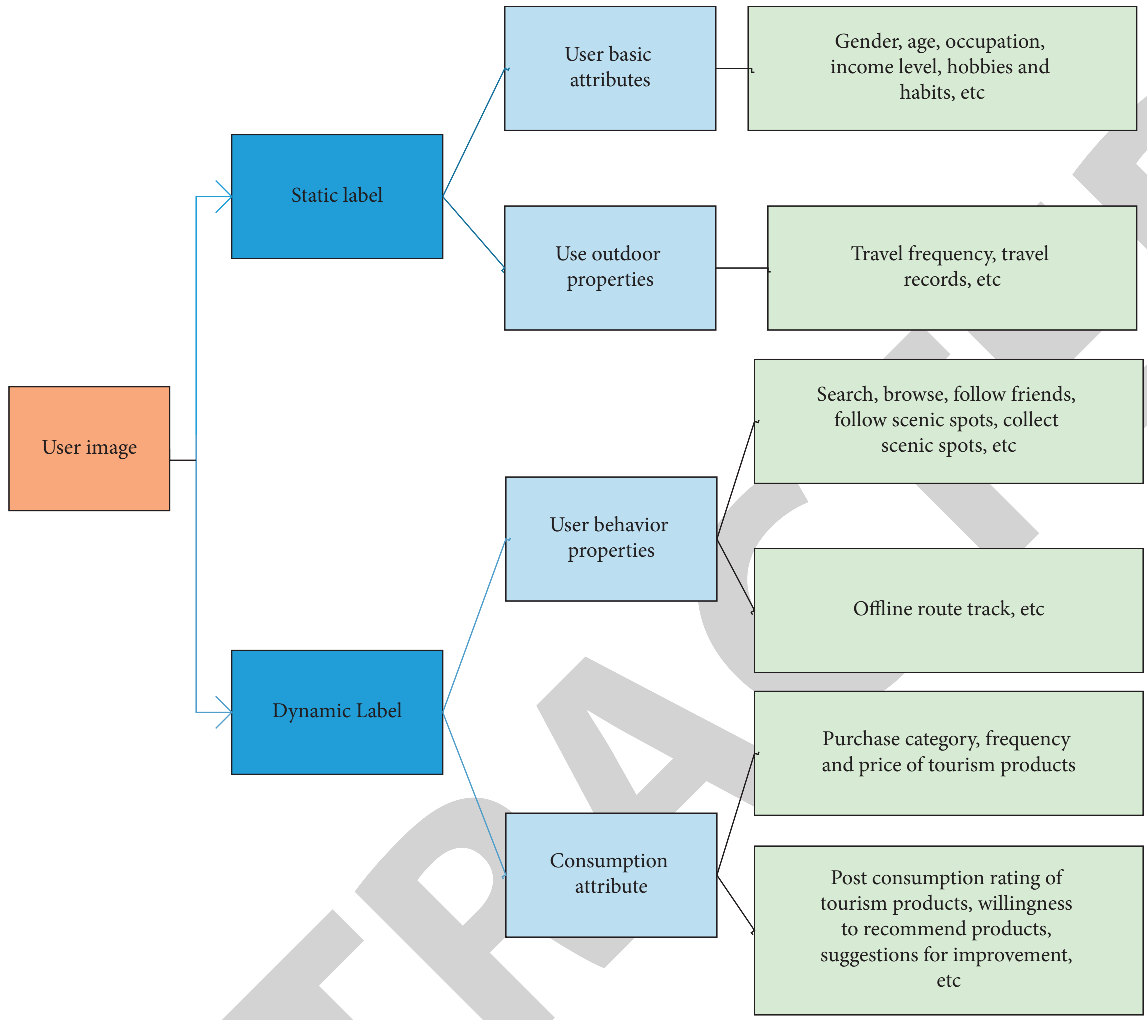


Figure 4: Panorama of travel user portraits.

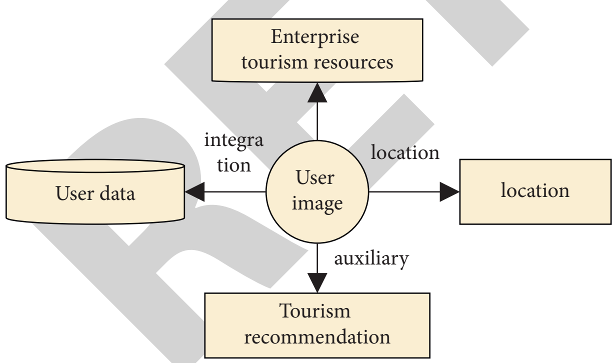


Figure 5: User portrait function of travel recommendation system.

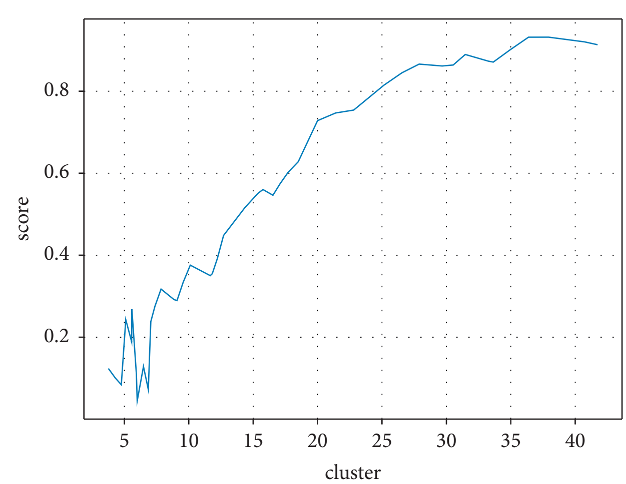


Figure 6: Contour coefficient map of clustering results.

user 386. When the mouse is hovered over each connected edge, the edge is bolded and highlighted.

The two associated user nodes are also highlighted, and the prompt box shows the weight information of the edge. The rest of the nodes and connected edges are faded, as shown in Figure 9:

By visualizing the clustering results and observing the hierarchical structure of the user relationship network and the key information of the user network, it can be clearly seen that the user clustering example implemented in this section has divided the users with the same characteristics into classes with distinctive characteristics each. The

Table 5: Comparison of network security verification packages (unit: %).

| Method | Accuracy | Recall | $F1$ score | MAP |
|---|---|---|---|---|
| Apriori | 41 | 63 | 49 | 59 |
| Eclat | 42 | 63 | 49 | 60 |
| Decision tree | 33 | 51 | 39 | 70 |
| Logistic regression | 36 | 58 | 42 | 70 |
| This paper | 45 | 70 | 52 | 75 |

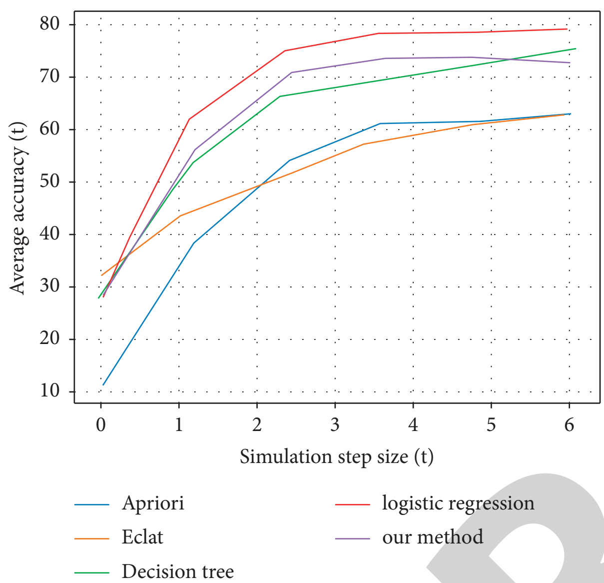


Figure 7: Comparison results of the average accuracy of different algorithms.

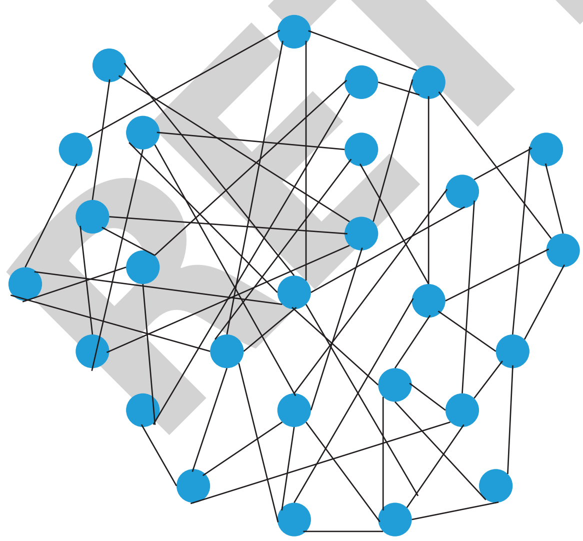

Figure 8: Layout of force guidance with weights.

clustering results realized based on user images are applied to the ecotourism precision recommendation process and combined with collaborative filtering algorithm to realize the recommendation of ecotourism attractions.

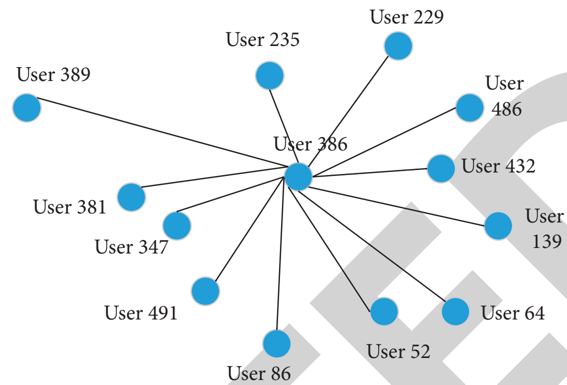


Figure 9: Mouse hover user 386 effect.

## 6. Conclusions

In order to promote the ecotourism industry in a better direction, contemporary ecotourism enterprises must grasp the follow-up work of ecotourism big data, fully excavate its value, obtain valuable information, and occupy a favorable position in the ecotourism market. In this paper, we propose a POI (point-of-interest) based system that can be used for the development of ecotourism. In this paper, we propose a personalized ecotourism route recommendation (PTIR) algorithm based on the popularity of points of interest (POI) and users' interest preferences. The results show that the accuracy and recall rate of this personalized ecotourism route recommendation algorithm are improved compared with the traditional algorithm that only considers POI popularity.

## Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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