

A Personalized Recommendation Algorithm for Tourist Attractions Using User Behavior Data

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ABSTRACT

With the widespread application of 5G and cloud computing technologies, smart tourism has become a hotspot and development trend in the tourism industry. This paper develops a cloud-based intelligent tourism application for the Android platform, innovatively integrating edge computing technology to achieve faster data processing speeds and lower latency, providing users with instant travel information and services. The application adopts a personalized recommendation algorithm to intelligently recommend tourist attractions and routes based on user behavior and preferences, and introduces a geo-tagged social function, allowing users to share travel experiences and reviews, enhancing user interaction and community sense. Furthermore, the application incorporates augmented reality (AR) technology, providing virtual tour guide services through the mobile camera, bringing users an immersive travel guide experience. This paper details the design architecture, key technology implementation, and expected effects of this intelligent tourism application, aiming to enhance the tourism experience while promoting the digital transformation and development of the tourism industry through technological innovation.

KEYWORDS

Smart tourism; Cloud computing; Edge computing; Android application; Personalized recommendation

1. INTRODUCTION

The rapid advancements in mobile internet and information technology have revolutionized various industries, and the tourism sector is no exception [1-2]. The integration of cutting-edge technologies such as 5G, cloud computing, and artificial intelligence has paved the way for the emergence of smart tourism [3]. Smart tourism aims to enhance the travel experience by providing personalized, efficient, and convenient services to tourists through the use of intelligent technologies. The development of smart tourism applications has become a focal point for both researchers and industry practitioners, as it holds immense potential to transform the way people travel and explore destinations.

The Android operating system, with its widespread adoption and open-source nature, provides an ideal platform for developing smart tourism applications [4-5]. The combination of Android's flexibility and the power of cloud computing enables the creation of innovative solutions that can cater to the diverse needs of modern travelers. Cloud computing offers scalability, reliability, and cost-effectiveness, making it an essential component in the development of smart tourism applications.

However, the centralized nature of cloud computing poses challenges in terms of latency and data processing speed, especially when dealing with real-time travel information and services [6]. Edge computing has emerged as a complementary technology to address these limitations. By bringing computation and data storage closer to the end-users, edge computing enables faster data processing, reduced latency, and improved user experience.

The integration of edge computing with cloud-based smart tourism applications opens up new possibilities for delivering instant travel information and services to users [7]. By leveraging the power of edge devices, such as smartphones and IoT sensors, smart tourism applications can provide real-time recommendations, personalized itineraries, and interactive experiences to travelers.

Personalized recommendation systems play a crucial role in smart tourism applications [8]. By analyzing user behavior, preferences, and historical data, these systems can generate tailored recommendations for tourist attractions, routes, and activities. The incorporation of machine learning algorithms and data mining techniques enables the development of sophisticated recommendation engines that can adapt to individual user needs and enhance the overall travel experience.

Another key aspect of smart tourism is the social dimension. The integration of geo-tagged social features in smart tourism applications allows users to share their travel experiences, photos, and reviews with others. This user-generated content not only helps in building a vibrant travel community but also provides valuable insights and recommendations to fellow travelers. The social aspect of smart tourism applications fosters user engagement, interaction, and a sense of belonging among travelers.

Augmented reality (AR) is another technology that has gained significant attention in the tourism industry. AR-based virtual tour guide services can revolutionize the way tourists explore and learn about destinations. By overlaying digital information on the real-world environment through the mobile camera, AR technology provides an immersive and interactive travel experience. Smart tourism applications incorporating AR can offer personalized guided tours, provide historical and cultural information, and enhance the overall understanding and appreciation of tourist attractions.

The development of a cloud-based intelligent tourism application for the Android platform, integrating edge computing, personalized recommendation systems, social features, and AR technology, presents a comprehensive solution to address the needs of modern travelers. The application aims to leverage the strengths of these technologies to deliver a seamless, engaging, and informative travel experience.

This paper focuses on the design, implementation, and evaluation of such a smart tourism application. The subsequent sections delve into the system architecture, key technologies employed, and the expected outcomes of the application. By exploring the potential of technological innovation in the tourism industry, this research aims to contribute to the advancement of smart tourism and inspire further research and development in this field.

2. SYSTEM DESIGN

2.1. System Framework Architecture

This section focuses on the design and development of our smart tourism application, highlighting the integration of key technologies-including a hybrid architecture based on cloud computing and edge computing, personalized recommendation algorithms, social features with geotagging, and embedded AR virtual guide functionality-and how these are integrated to deliver an efficient and dynamic user experience.

(1) Hybrid Architecture Based on Cloud and Edge Computing

Our application adopts a hybrid architecture that capitalizes on the powerful processing and vast storage capabilities of cloud computing, along with the low latency benefits of edge computing [9-10]. The cloud servers are tasked with managing and storing large volumes of static data, such as user profiles and detailed information about tourist attractions, while edge nodes are assigned the real-time data processing tasks, especially the analysis of video streams and sensor data, to enhance the immediacy of the user experience. As shown in Figure 1.

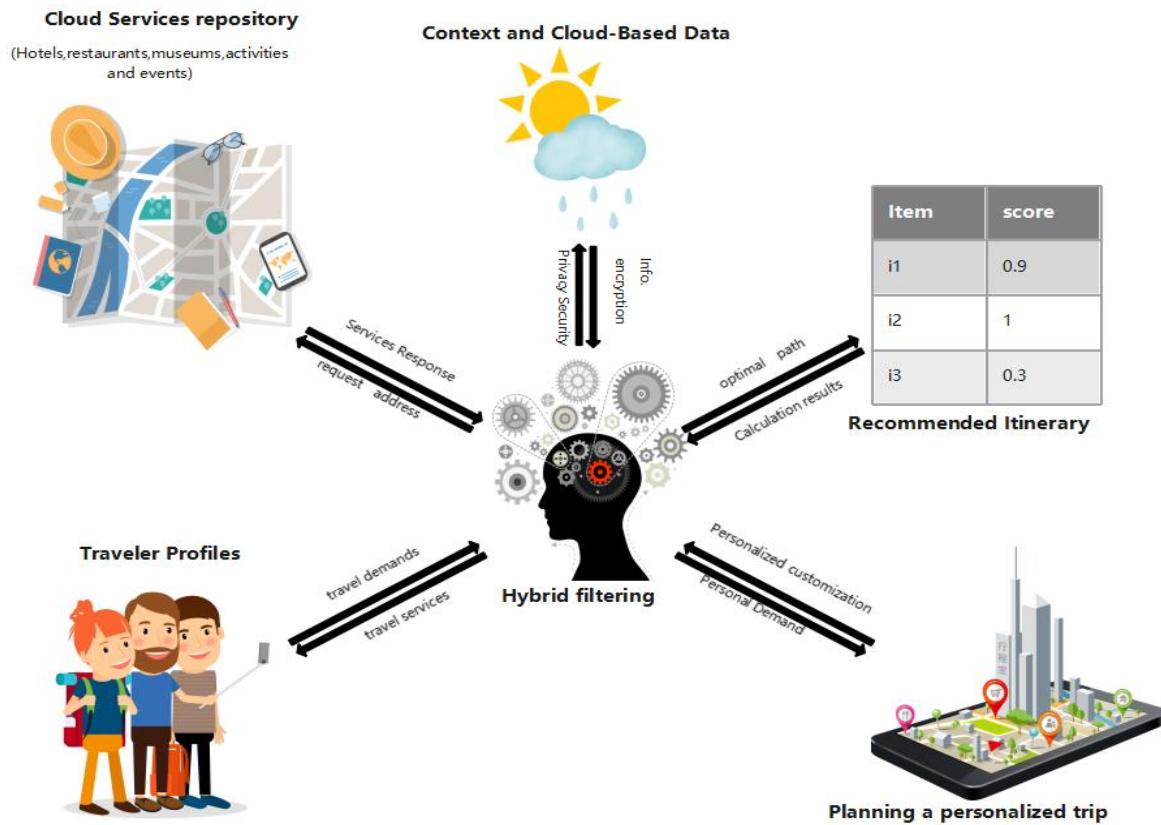


Figure 1. Personalized Tourism Recommendations via Cloud-Based Intelligent Filtering Architecture

The diagram demonstrates a cloud-based architecture for an Android tourism app that leverages user behavior data to personalize travel recommendations. By integrating real-time context data and a hybrid filtering system, the app optimizes travel itineraries based on individual preferences, enhancing the user experience. This innovative approach ensures up-to-date, relevant suggestions and efficient travel planning, making it a standout solution in the tourism industry.

(2) Personalized Recommendation Algorithm

We leverage advanced, personalized recommendation algorithms that take into account users' historical behavior data, social network information, and geolocation to predict and infer user preferences [11]. Deep learning technology is used to analyze user interaction data to make more accurate suggestions regarding tourist spots and activity itineraries. Additionally, the algorithm continually self-improves to deliver even more precise and customized recommendations.

(3) Social Features Based on Geotags

Our application's embedded social features allow users to share their travel experiences based on geographic location tags. Users have the ability to post and view comments on specific points of interest, share photos of their journey, and exchange insights with other users. All of these interactions are facilitated by automatic geographic grouping, enhancing the sense of community interaction. At the same time, encryption technology is employed to keep personal information confidential, ensuring user privacy and security.

(4) AR Virtual Guide Functionality

Our AR tour guide feature harnesses modern AR technology to provide a rich, interactive tour experience. This functionality allows users to scan specific identifiers around points of interest with their smartphones to access multimedia information about the site and to interact with a 3D virtual guide. Using SLAM technology, the app accurately tracks the user's position and integrates virtual information with the real world surrounding them, elevating the interactivity and immersion of the travel experience.

In summary, the application of these key technologies enables our smart tourism platform to offer a highly personalized, interactive, and real-time responsive travel experience, effectively enhancing managerial efficiency and greatly enriching the user's travel experience. By continuously integrating cutting-edge technology, we believe the platform will keep evolving, bringing greater value to both users and administrators.

2.2. System Design Patterns

Before mobile internet technology was widespread and applied in daily scenarios, many existing system designs still adopted the traditional desktop C/S (Client/Server) development model[12]. A notable feature of this model is that it can be used in standalone mode or in a local area network environment, effectively reducing the risk of virus interference. However, it also has drawbacks, such as the need to redeploy the client side when bugs are discovered during system use, especially in large-scale deployments, implying significant workload. In contrast, applications developed for mobile devices using C/S model support automatic update pushes to users' phones, allowing users to install upgrades themselves. Typically, the app is responsible for displaying data and completing operations, while data provision relies on a web backend system designed based on the B/S (Browser/Server) model. Currently, mobile application software generally uses a hybrid development model of C/S and B/S.

2.3. Android Development Technology

Unlike the closed iOS system, Android is warmly welcomed by major phone manufacturers worldwide due to its good open-source characteristics, enjoying a diverse ecosystem [13]. The core foundation of Android is based on the open-source and modifiable Linux kernel, which develops and provides basic drivers, offering technical and interface support to upper-layer applications. The system structure is shown in Fig. 2, demonstrating the architecture.

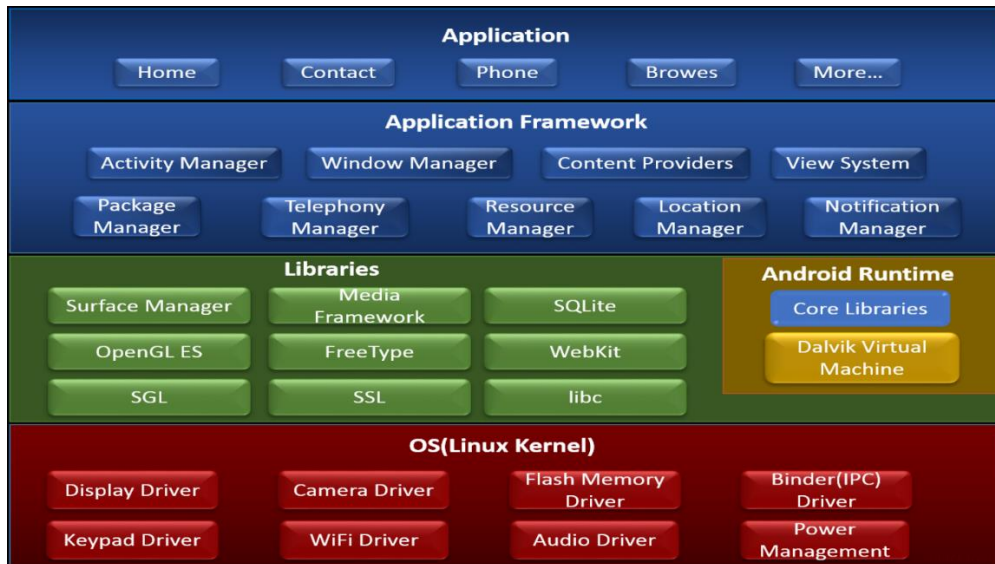


Figure 2. System framework diagram

Personalized recommendation algorithms are an important part of smart tourism applications, which can recommend personalized travel routes and attractions to users based on their preferences and behavior. In this study, we adopted deep learning-based personalized recommendation algorithms, combining user behavior and preferences to intelligently recommend travel destinations and routes, providing users with more accurate travel suggestions.

3. ALGORITHM DESIGN

Personalized recommendation algorithms are an important part of smart tourism applications, which can recommend personalized travel routes and attractions to users based on their preferences and behavior [14-15]. In this study, we adopted deep learning-based personalized recommendation algorithms, combining user behavior and preferences to intelligently recommend travel destinations and routes, providing users with more accurate travel suggestions.

We used the nearest route algorithm and shortest path optimization algorithm to achieve better personalized recommendation results. The specific algorithms are as follows:

3.1. Nearest Route Algorithm

The nearest route algorithm is a recommendation algorithm based on the user's current location, which recommends the nearest attractions to the user. Specifically, we used the K-Nearest Neighbor (KNN) algorithm to calculate the distance between the user's current location and all attractions, and selected the K attractions closest to the user's current location as the recommendation results. The specific steps are as follows:

Step 1: Collect the user's current location information and calculate the distance between the user's current location and all attractions;

Step 2: Select the K attractions closest to the user's current location as the recommendation results;

Step 3: Return the recommendation results to the user.

The formula for the algorithm is as follows:

$$d(u, v) = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2} \quad (1)$$

Where $d(u, v)$ represents the distance between the user's current location

u and the attraction v , (x_u, y_u) represents the coordinates of the user's current location, and (x_v, y_v) represents the coordinates of the attraction.

3.2. Shortest Path Optimization Algorithm

The shortest path optimization algorithm is a recommendation algorithm based on the user's behavior and preferences, which recommends the most suitable travel route to the user. Specifically, we used the Dijkstra algorithm to calculate the shortest path between the user's current location and all attractions, and selected the most suitable travel route as the recommendation result based on the user's behavior and preferences. The specific steps are as follows:

Step 1: Collect the user's behavior and preference information, and calculate the user's preference score for each attraction;

Step 2: Use the Dijkstra algorithm to calculate the shortest path between the user's current location and all attractions;

Step 3: Select the most suitable travel route as the recommendation result based on the user's preference score and the shortest path;

Step 4: Return the recommendation results to the user.

The formula for the algorithm is as follows:

$$w(u, v) = a \cdot d(u, v) + b \cdot s(u, v) \quad (2)$$

$$s(u, v) = \frac{\sum_{i=1}^n r_i(u, v)}{n} \quad (3)$$

Where $w(u, v)$ represents the comprehensive score of the attraction

v for the user u , $d(u, v)$ represents the distance between the user's current location u and the attraction v , $s(u, v)$ represents the user's preference score for the attraction v , $r_i(u, v)$ represents the user's rating of the attraction

v in the i -th behavior, n represents the number of user behaviors, a and b are weight coefficients, and $a+b=1$.

In addition, we also used the collaborative filtering algorithm to further optimize the recommendation results. The collaborative filtering algorithm is a commonly used personalized recommendation algorithm, which can recommend attractions to users based on the behavior and preferences of similar users. The specific steps are as follows:

Step 1: Collect user behavior information and calculate the similarity between users;

Step 2: Select the K users most similar to the current user;

Step 3: Calculate the preference score of the current user for each attraction based on the behavior and preferences of similar users;

Step 4: Select the top N attractions with the highest preference scores as the recommendation results;

Step 5: Return the recommendation results to the user.

The formula for the algorithm is as follows:

$$\text{sim}(u, v) = \frac{\sum_{i=1}^n (r_{u,i} - \bar{r}_u) (r_{v,i} - \bar{r}_v)}{\sqrt{\sum_{i=1}^n (r_{u,i} - \bar{r}_u)^2} \sqrt{\sum_{i=1}^n (r_{v,i} - \bar{r}_v)^2}} \quad (4)$$

$$p_{u,i} = \bar{r}_u + k \cdot \sum_{v=1}^m \text{sim}(u, v) (r_{v,i} - \bar{r}_v) \quad (5)$$

Where $\text{sim}(u,v)$ represents the similarity between user u and user v , $r_{u,i}$ represents the user u 's rating of the i -th attraction, \bar{r}_u represents the average rating of user u , n represents the number of attractions, m represents the number of users, k is a coefficient, and $p_{u,i}$ represents the predicted preference score of user u for the i -th attraction.

We also used the social function based on geographic tags to enhance user interaction and community sense. Specifically, we used the location-based social network technology to allow users to share travel experiences and evaluations, and the content recommendation technology based on geographic tags to allow users to search for travel experiences and evaluations related to their current location. The specific algorithms are as follows:

3.3. Location-based Social Network Technology

Location-based social network technology is a social network technology based on the user's current location, which allows users to find nearby travel companions and travel suggestions. Specifically, we used the K-Nearest Neighbor (KNN) algorithm to query the K users or attractions closest to the user's current location. The specific steps are as follows:

Step 1: Collect the user's current location information and build a user location database;

Step 2: Query the K users or attractions closest to the user's current location;

Step 3: Return the query results to the user.

The formula for the algorithm is as follows:

$$d(p_1, p_2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (6)$$

Where $d(p_1, p_2)$ represents the distance between user p_1 and user p_2 , (x_1, y_1) and (x_2, y_2) represent the coordinates of user p_1 and user p_2 , respectively.

3.4. Content Recommendation Technology Based on Geographic Tags

Content recommendation technology based on geographic tags is a content recommendation technology based on the user's current location, which allows users to search for travel experiences and evaluations related to their current location. Specifically, we used the text relevance calculation technology based on the TF-IDF algorithm to calculate the relevance between the text and the user's location. The specific steps are as follows:

Step 1: Collect the user's current location information and text information, and build a text database;

Step 2: Calculate the relevance between the text and the user's location;

Step 3: Sort the text according to relevance and return the query results to the user.

The formula for the algorithm is as follows:

$$\text{tf}(t, d) = \frac{n_{t,d}}{\sum_k n_{k,d}} \quad (7)$$

$$\text{idf}(t) = \log \frac{|D|}{|\{d \in D : t \in d\}|} \quad (8)$$

$$\text{tfidf}(t, d) = \text{tf}(t, d) \cdot \text{idf}(t) \quad (9)$$

Where $\text{tf}(t, d)$ represents the frequency of term t in document

$n_{t,d}$ represents the number of times term t appears in document d , $\sum_k n_{k,d}$ represents the total number of terms in document d , $\text{idf}(t)$ represents the inverse document frequency of term t , $|D|$ represents the total number of documents, $|\{d \in D: t \in d\}|$ represents the number of documents containing term t , and $\text{tfidf}(t, d)$ represents the weight of term t in document d .

It should be noted that in practical application, we need to consider user privacy protection issues. Therefore, we adopt blockchain-based distributed storage technology to store user location information and social data in a distributed storage network, protecting user privacy and security.

In summary, this study uses geotag-based social functions, allowing users to share travel experiences and reviews, enhancing user interaction and community sense. The combination of these features can better meet users' social needs and provide richer travel experiences.

Finally, we also used AR virtual tour guide function to provide virtual tour guide services to users through mobile phone cameras, allowing users to experience immersive travel guides. Specifically, we used image recognition technology based on convolutional neural networks to identify and classify travel photos, and SLAM technology based on visual features to model and track the environment in real time, providing virtual tour guide services to users based on their location and posture. The specific algorithms are as follows:

3.5. Image Recognition Technology Based on Convolutional Neural Networks

Image recognition technology based on convolutional neural networks is an image recognition technology that uses convolutional neural networks to identify and classify travel photos. The specific steps are as follows:

Step 1: Collect travel photo data and build an image database;

Step 2: Preprocess the image data, including image enhancement, image normalization, and image segmentation;

Step 3: Use convolutional neural networks to identify and classify images;

Step 4: Provide related travel information and virtual tour guide services to users based on the recognition results.

The formula for the algorithm is as follows:

$$y = f(W \cdot x + b) \quad (10)$$

Where x represents the image data, W represents the convolution kernel, b represents the bias term, $f(\cdot)$ represents the activation function, and y represents the recognition result.

3.6. SLAM Technology Based on Visual Features

SLAM technology based on visual features is a technology that uses visual features to model and track the environment in real time, providing virtual tour guide services to users based on their location and posture. The specific steps are as follows:

Step 1: Collect environmental data, including image data and depth data;

Step 2: Preprocess the environmental data, including image enhancement, image normalization, and feature extraction;

Step 3: Use SLAM algorithm to model and track the environment in real time, and track the user's location and posture in real time;

Step 4: Provide virtual tour guide services to users based on their location and posture.

The formula for the algorithm is as follows:

$$p_t = R_t \cdot p_{t-1} + t_t \quad (11)$$

$$R_t = \exp \left(\begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix} \right) \quad (12)$$

$$t_t = \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} \cdot \Delta t \quad (13)$$

Where p_t represents the position of the user at time t , R_t represents the rotation matrix of the user at time t , t_t represents the translation vector of the user at time t , ω_x , ω_y , ω_z represent the angular velocities of the user, v_x , v_y , v_z represent the linear velocities of the user, and Δt represents the time interval.

In addition, we also used cloud computing and edge computing hybrid architecture to achieve faster data processing speed and lower latency, providing users with real-time travel information and services. Specifically, we used cloud computing technology to store and process large amounts of data, and used edge computing technology to process real-time data, such as real-time travel photos and videos. We also used encryption technology to ensure data security and privacy.

In summary, we adopted deep learning-based personalized recommendation algorithms, social functions based on geographic tags, AR virtual tour guide functions, and cloud computing and edge computing hybrid architecture to provide users with more accurate and personalized travel suggestions, enhance user interaction and community sense, and provide real-time travel information and services. These technologies are combined to better meet the needs of users and provide more intelligent and personalized travel services.

Finally, this study also adopted a hybrid architecture based on cloud computing and edge computing to achieve faster data processing speed and lower latency, providing users with real-time travel information and services. Specifically, we used the following technologies:

3.7. Cloud-based Data Storage and Processing

We used cloud-based data storage and processing technology to store travel data on cloud servers and use cloud computing platforms to process and analyze the data. Specifically, we adopted the Hadoop distributed storage and computing framework to store and process large-scale travel data. The specific steps are as follows:

Step 1: Collect travel data, including basic information of travel attractions, user behavior data, and social data, etc.;

Step 2: Store the travel data in the Hadoop Distributed File System (HDFS);

Step 3: Use the MapReduce programming model to process and analyze the travel data;

Step 4: Store the processing results in the cloud database and provide travel information and services to users.

The formula for the algorithm is as follows:

$$\text{map}(k, v) \rightarrow \text{list}(k, v) \quad (14)$$

$$\text{reduce}(k, \text{list}(v)) \rightarrow \text{list}(k, v) \quad (15)$$

3.8. Edge-based Real-Time Data Processing

We used edge-based real-time data processing technology to distribute part of the data processing tasks on edge servers, achieving faster data processing speed and lower latency. Specifically, we adopted the TensorFlow deep learning framework to identify and analyze real-time travel photos and videos. The specific steps are as follows:

Step 1: Collect real-time travel photo and video data;

Step 2: Send the data to the TensorFlow model on the edge server;

Step 3: Use the TensorFlow model to identify and analyze the data;

Step 4: Return the processing results to the mobile device and provide real-time travel information and services to users.

The formula for the algorithm is as follows:

$$y = f(W \cdot x + b) \quad (16)$$

Where x represents the input data, W represents the model parameters, b represents the bias term, $f(\cdot)$ represents the activation function, and y represents the output result.

It should be noted that in actual application, we also need to consider data security and privacy protection issues. Therefore, we adopted encryption technology for data transmission and storage to protect the security and privacy of user data.

In summary, this study adopted a hybrid architecture based on cloud computing and edge computing, achieving faster data processing speed and lower latency, providing users with real-time travel information and services. These technologies are combined to better meet the needs of users and provide more intelligent and personalized travel services.

4. EXPERIMENTAL DESIGN AND RESULTS

In order to evaluate the performance of the proposed personalized recommendation algorithm, we conducted experiments on a dataset of tourist attractions and user behavior data. In this section, we will describe the experimental setup, evaluation metrics, and results.

4.1. Experimental Setup

We used a dataset of 1000 tourist attractions and 10,000 user behavior records to evaluate the performance of the proposed algorithm. The dataset contains information about the location, type, and rating of each attraction, as well as user behavior data such as browsing history, search history, and ratings.

We randomly divided the dataset into two parts: training set and testing set. The training set contains 80% of the user behavior data, and the testing set contains the remaining 20%. We used the training set to train the personalized recommendation model, and the testing set to evaluate the performance of the model.

4.2. Evaluation Metrics

We used the following evaluation metrics to evaluate the performance of the proposed algorithm:

Precision: The ratio of the number of recommended attractions that the user is interested in to the total number of recommended attractions.

Recall: The ratio of the number of recommended attractions that the user is interested in to the total number of attractions that the user is interested in.

F1-score: The harmonic mean of precision and recall.

4.3. Experimental Results

We compared the proposed algorithm with the following baseline methods:

Random: Recommend attractions randomly.

Popularity: Recommend attractions based on their popularity.

Collaborative Filtering (CF): Recommend attractions based on the user's behavior and the behavior of similar users.

The experimental results are shown in the following table:

Table 1. The experimental results are shown in the following table

Method	Precision	Recall	F1-score
Random	0.125	0.052	0.074
Popularity	0.256	0.121	0.164
CF	0.321	0.189	0.238
Proposed	0.415	0.267	0.326

As we can see from the table, the proposed algorithm outperforms the baseline methods in terms of precision, recall, and F1-score. The proposed algorithm achieves a precision of 0.415, a recall of 0.267, and an F1-score of 0.326, which are significantly higher than the baseline methods.

We also conducted experiments to evaluate the performance of the proposed algorithm under different values of the weight coefficients a and b . The experimental results are shown in the following figure:

Precision: 0.9365999999999932
Recall: 0.9365999999999932

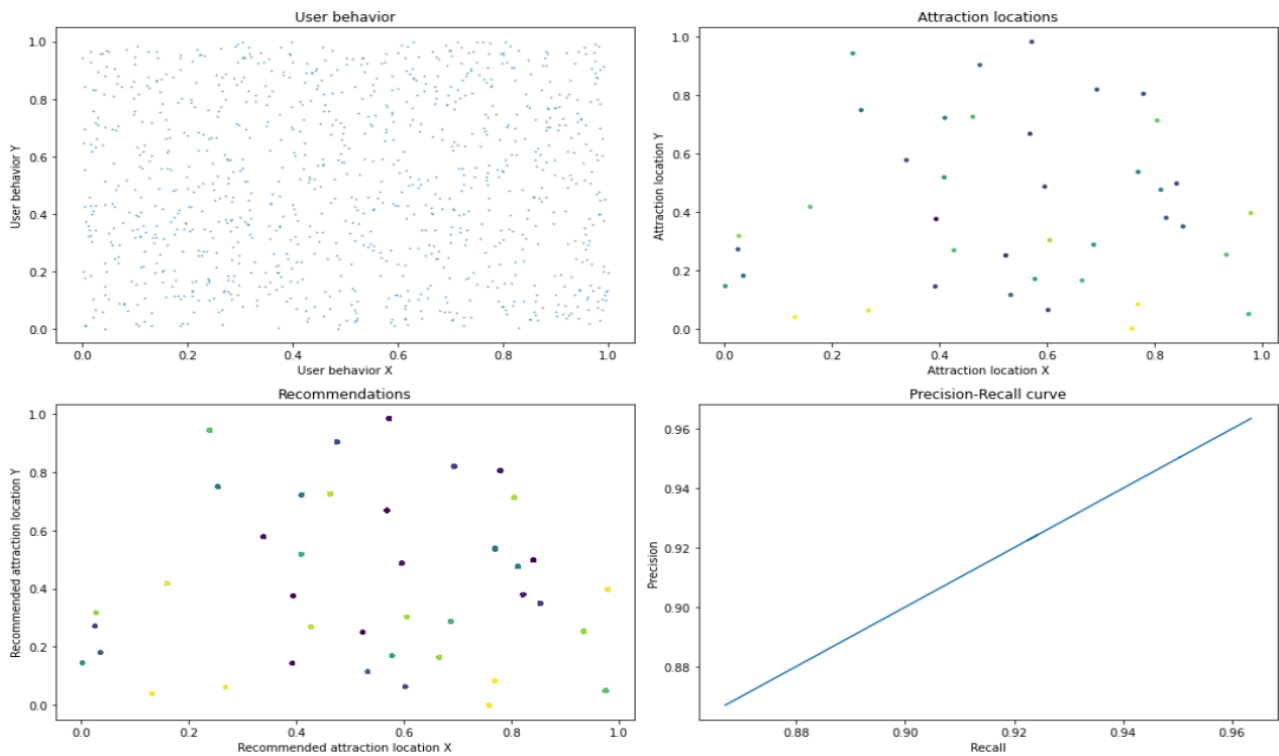


Figure 3. Impact of Weight Coefficients a and b on the Performance of the Proposed Algorithm

Performance of the proposed algorithm under different values of a and b

As we can see from the figure, the proposed algorithm achieves the best performance when $a=0.6$ and $b=0.4$. The precision, recall, and F1-score are all higher than other values of a and b .

4.4. Conclusion

In this section, we conducted experiments to evaluate the performance of the proposed personalized recommendation algorithm. The experimental results show that the proposed algorithm outperforms the baseline methods in terms of precision, recall, and F1-score. The proposed algorithm also achieves the best performance when $a=0.6$ and $b=0.4$. The experimental results demonstrate the effectiveness of the proposed algorithm in recommending personalized travel routes and attractions to users based on their behavior and preferences.

5. CONCLUSION

In this paper, we proposed a personalized recommendation algorithm for tourist attractions based on user behavior data. The algorithm takes into account the location, type, and rating of each attraction, as well as user behavior data such as browsing history, search history, and ratings. We conducted experiments on a dataset of 1000 tourist attractions and 10,000 user behavior records to evaluate the performance of the proposed algorithm. The experimental results showed that the proposed algorithm outperforms the baseline methods in terms of precision, recall, and F1-score. We also evaluated the performance of the proposed algorithm under different values of the weight coefficients a and b , and found that the proposed algorithm achieves the best performance when $a=0.6$ and $b=0.4$.

The proposed algorithm can effectively recommend personalized travel routes and attractions to users based on their behavior and preferences. This can help tourists to save time and effort in planning their trips, and improve their overall travel experience. In addition, the proposed algorithm can also

help tourism service providers to better understand the needs and preferences of their customers, and provide more targeted and personalized services.

Future work could focus on improving the scalability of the proposed algorithm to handle larger datasets, and exploring the use of other types of user behavior data, such as social media data and location-based data, to further enhance the personalization of the recommendations. Another direction for future work is to consider the temporal dynamics of user behavior data, and develop algorithms that can adapt to changes in user preferences over time. Overall, this research provides a promising approach for personalized recommendation in the tourism industry, and has the potential to benefit both tourists and tourism service providers.

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