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Tour Concierge: Tour Route Recommendation System Based on User Short-Term and Long-Term Preference Models

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Abstract:
This chapter introduces Tour Concierge, an interactive system that learns each user's preferences and suggests optimal tour plans. A user preference model that is continuously optimized over time is proposed to recommend personalized tour routes. This model distinguishes between the user's short-term and long-term preferences and combines them with a tour route generation algorithm to increase user satisfaction. Twenty-six university students were asked to evaluate the use of this system and were surveyed. The survey results showed that 70.5% of the subjects felt that the tour routes generated by the system were compatible with their preferences. In addition, in a comparison experiment with ChatGPT, 64.1% of the subjects answered that the tour routes generated by the system were better. The experimental results suggest that this system has the potential to significantly improve the user's tour experience.

Keywords:
Tour route, Recommendation system, Preference model, Short-term, Long-term, Interaction

1. Introduction

As people's lives have become more affluent in recent years, traveling has become a familiar leisure activity. There are two kinds of tours: group tours and independent tours. Independent tours allow more flexibility, but require a considerable amount of time and effort to plan. According to an article in NYC Design [1], travelers spend an average of 20-30 hours planning their tours.

Tour route recommendation systems are attracting attention as a solution to these independent tour challenges. However, most existing systems are limited to suggesting tourist spots based on user preferences and lack the ability to interact with users and improve user satisfaction. More attention needs to be paid to user interaction when recommending tour plans. These systems simply give the results to the user without caring whether the user is satisfied with the recommendation results. However, if the user is not satisfied with the recommendation results, the process becomes meaningless. In addition, when users travel to different cities, they often need to re-enter their preferences.

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This chapter introduces Tour Concierge, a new tour route recommendation system that provides a more personalized tour route by emphasizing user interaction and continuous improvement. This system includes the following features:

(i) Interactive: The system not only suggests fixed plans, but also interacts with the user to create a more optimal plan through conversation.
(ii) Continuous optimization: The system continuously improves the plan based on user feedback.
(iii) Personalization: The system takes into account the user's past travel history and what he or she wants to focus on during the tour, and proposes a personalized plan for each individual.

The system considers two factors: the user's long-term preferences and short-term preferences. Long-term preferences are latent travel needs that are shaped by an individual's past experiences and are not tied to a specific purpose or location. Short-term preferences are the specific types of destinations that individuals want to visit during the tour. Based on these preferences, an optimal tour is generated. In addition, user feedback can be used to suggest more accurate plans.

2. Tour Recommendation System and Issues

This section introduces tour spot recommendation systems and tour route recommendation systems as related studies. After identifying issues with the existing system, it reveals design goals for Tour Concierge to address them.

2.1 Tour Spot Recommendation Systems

Tour spot recommendations suggest tour spots that match the user's preferences. These systems first obtain user preferences, then match user preferences with tour spots, and finally recommend suitable tour spots for the user.

Yudai Kato et al. [2] proposed a recommendation system that combines user visit frequency and tour spot attributes/user preferences. Pravinkumar Swamy et al. [3] proposed a recommendation using collaborative filtering by computing similarities between users and tour spots. Hend Alrasheed [4] proposed a destination ranking system that considers similar user preferences and user constraints. Joseph Coelho et al. [5] proposed a personalized recommendation based on social media analysis using Twitter data. Zahra Abbasi-Moud et al. [6] proposed a recommendation system using semantic clustering and sentiment analysis to extract user preferences from tourism website reviews. Mickael Figueredo et al. [7] proposed a system that detects tourists' implicit preferences from social media photos and recommends tour spots. These studies aim to achieve more accurate tour spot recommendations by using a variety of data, including user behavior history, social media data, and review data.

2.2 Tour Route Recommendation Systems

Tour route recommendation is more complex than tour spot recommendation in that it not only suggests destinations, but also generates optimal travel routes by connecting multiple spots. Tour route recommendation systems dynamically generate routes considering user preferences and constraints such as time and transportation.

Pattara Leelaprute et al. [8] support planning by suggesting similar routes based on past travel history to reflect user preferences. Ying Xu et al. [9] aim to generate more practical routes by considering not only personal preferences but also real-time traffic conditions. Remigijus Paulavičius et al. [10] proposed a system that can meet diverse needs by flexibly incorporating user constraints using genetic algorithms. Xiao Zhou et al. [11] combine clustering and spatio-temporal inference models for efficient route generation. Chieh-Yuan Tsai et al. [12] generate routes based on more visual information by using image data from social media. Chenzhong Bin et al. [13] generate personalized routes based on real-time location information by connecting smartphones with IoT devices. Sajal Halder et al. [14] use reinforcement learning to generate more satisfying routes by optimizing the selection and sequencing of sights. These studies lay the foundation for a more personalized travel experience.

2.3 Issues

Existing tour route recommendation systems mainly generate routes based on the known preferences of users and have the following issues

(i) Insufficient exploration of latent preferences: insufficient route suggestions based on new interests that the user is not yet aware of.
(ii) Non-permanence of preference information: users need to re-enter their preferences each time, which is time consuming.
(iii) Lack of interactivity: The system unilaterally suggests routes and lacks a mechanism to actively incorporate user feedback.

Tour Concierge, described in this chapter, has the following three goals to address these issues.

(i) Discover latent preferences: In addition to the users' known interests, the system discovers latent interests and suggests more diverse routes.
(ii) Persistence of preference information: Stores user preference information in the system and makes it available for future use.
(iii) Interactive recommendation: Through user interaction, the system continuously improves recommendation results and suggests more personalized routes.

3. Tour Concierge: Interactive Travel Route Recommendation System

This section details Tour Concierge, a travel route recommendation system that emphasizes user interaction to achieve a high degree of personalization. The basic concept of the system is described, followed by the system architecture based on it.

3.1 Basic Concept

The most important feature of this system is that it continuously learns the user's preferences by interacting with the user and can propose more personalized plans. Figure 1 shows the process of continuously learning user preferences and proposing more personalized plans through user interaction. In this example, a user first travels to Bangkok and then to Tokyo. When traveling to Bangkok, the user first creates a personalized plan by telling the system his or her desired sights and budget. The system will modify the plan based on the user's evaluation and feedback, and make more satisfactory suggestions. In addition, by accumulating past travel history, the system stores the user's preferences over time. The next time the user travels to Tokyo, the system can suggest a faster and more accurate plan by referring to the user's preferences.

This system includes the following features

(i) Interactive communication: The system collects real-time feedback from the user and uses this information to improve the recommendation results, thereby gaining a deeper understanding of the user's preferences and suggesting more satisfying travel plans.

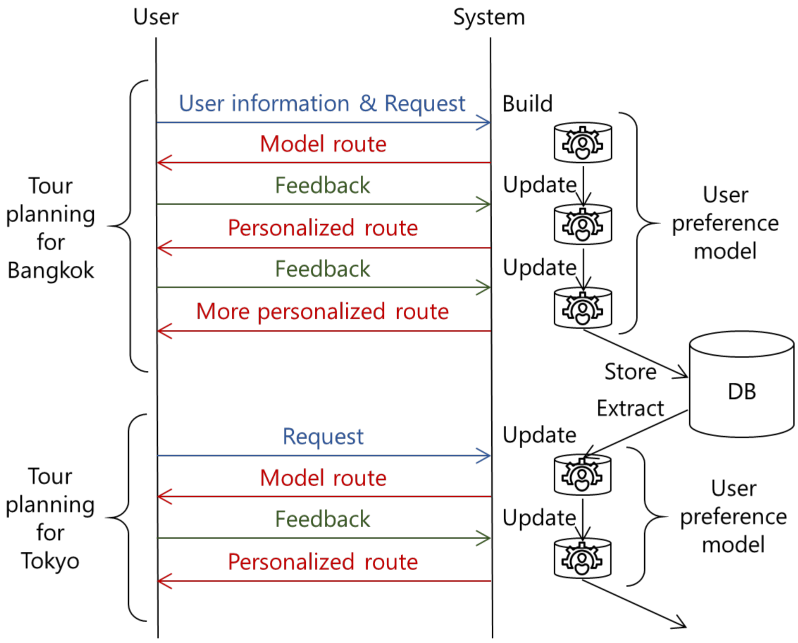


Figure 1: User-system interaction

(ii) Leverage historical data: By accumulating past travel history and recommendation ratings, the system can learn user preferences over time and provide more personalized suggestions for future trips.

(iii) Adaptability to different travel styles: The system can flexibly respond to changes in the user's travel style and the emergence of new interests, and can suggest a variety of travel plans.

This allows users to efficiently create their own ideal travel plans by interacting with the system.t a faster and more accurate plan by referring to the user's preferences.

3.2 System Architecture

As shown in Figure 2, the system consists of two parts: the part that builds user preferences and the part that suggests personalized routes.

(1) Building user preference models:
   (i) Initial setup: Users register basic information, such as travel style and sights of interest, when they register an account.
   (ii) Interactive learning: The system gradually learns the user's preferences based on the feedback it receives as the user selects and evaluates travel routes.
   (iii) Historical data: By analyzing past travel history, search history, etc., the system can discover the user's latent interests and make more accurate recommendations.

(2) Suggesting personalized tour routes:
   The system recommends travel routes based on the following criteria.
   (i) Selecting model routes: The system presents multiple candidates from several model routes that best match the user's preference model.
   (ii) User interaction: The user is free to select the spots of interest and the spots of dislike for the suggested routes.

(iii) Real-time optimization: Based on user feedback, the travel route is modified in real-time and a more personalized plan is proposed.

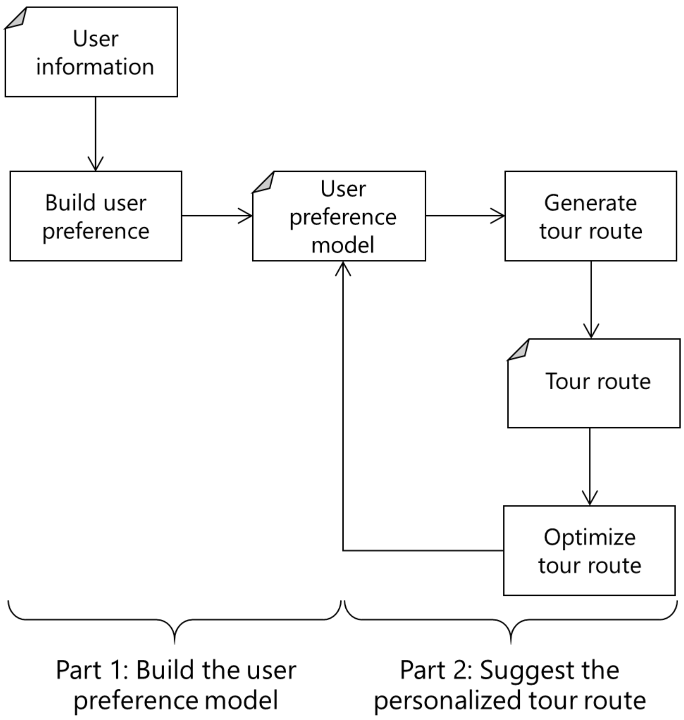


Figure 2: Overall structure of the system

4. User Preference Models

4.1 Short-term and Long-term Preferences

Tour Concierge uses a continuously optimizable user preference model proposed in Reference [15] to capture user travel preferences. This user preference model classifies user travel preferences into long-term and short-term preferences. Figure 3 shows the structural relationship between long-term and short-term preferences in the user preference model.

Long-term preferences are latent needs for tours that are formed from past travel experiences. For example, travelers who frequently visit history museums and monuments during their trips tend to have a strong interest in history, while travelers who frequently visit aquariums and zoos tend to have a strong interest in nature. In this study, we categorize long-term preferences into five themes: History, Culture, Art, Nature, and Leisure, and quantify the degree to which individual travelers are interested in these.

Short-term preferences are the specific types of places one would like to visit on a particular tour. Examples are museums and theme parks. Unlike long-term preferences, short-term preferences are highly dependent on the destination of the tour. For example, you may be interested in temples when visiting Thailand and shrines when visiting Japan, because different countries and regions attract different types of places. To represent short-term preferences, we used data provided by the Place API of the Foursquare platform [16]. From the 1233 place types provided by this API, 25 tourism-related place types were extracted.

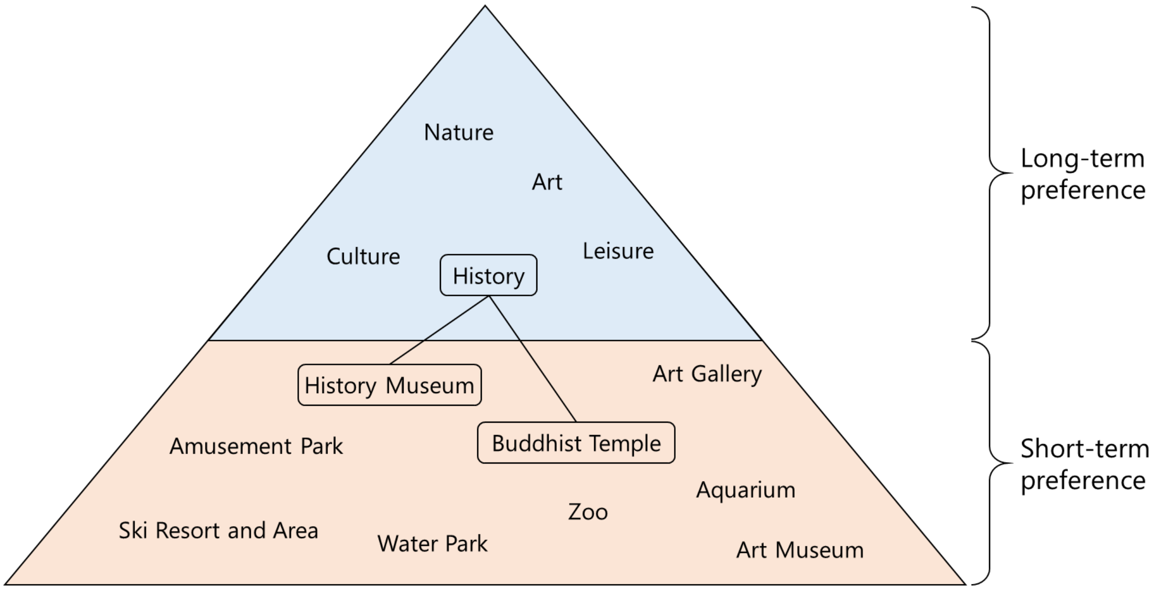


Figure 3: Structure of the user preference model

Five themes of long-term preferences and 25 place types of short-term preferences are mapped. For example, the place type "History Museum" corresponds to the theme "History," and the place types "Aquarium" and "Zoo" correspond to the theme "Nature. The place type "Buddhist Temple" correspond to both the themes "Culture" and "History". Table 1 shows the correspondence between themes in long-term preferences and tourist attraction types in short-term preferences.

Table 1: Correspondence between place type in short-term preferences and theme in long-term preferences

Short-Term Preference		Long-Term Preference				
Place Type ID	Place Type Label	History	Culture	Art	Nature	Leisure
10001	Amusement Park					✓
10002	Aquarium				✓	
10004	Art Gallery			✓		
10028	Art Museum	✓		✓		
10030	History Museum	✓				
10055	Water Park					✓
10056	Zoo				✓	
12099	Buddhist Temple	✓	✓			
⋮	⋮					
18061	Ski Resort and Area					✓

4.2 Mutual Transformation Between Long-term and Short-term Preferences

Long-term and short-term preferences can be mutually transformed by mapping place type to travel theme. The weight of each theme in the long-term preferences is calculated by dividing the sum of the weights of the place types in the short-term preferences associated with that theme by the number of associated place types. Conversely, the weight of each place type in the short-term preferences is calculated by dividing the weights of the themes in the long-term preferences associated with that place type by the number of associated themes.

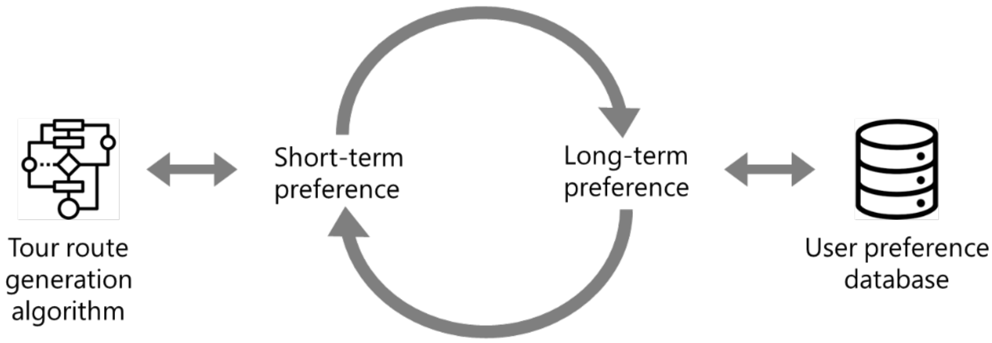


Figure 4: Tour route generation mechanism based on mutual transformation between long-term and short-term preferences

Figure 4 shows the tour route generation mechanism based on the mutual conversion of long-term and short-term preferences. For a first-time user, the system first predicts the travel theme of interest to the user and builds the long-term preferences of the user preference model. Then, when recommending a trip, the system searches for sights from place types based on the user's short-term preferences and builds a travel route for the user. After the user uses the system, the system converts the short-term preferences into long-term preferences and stores them in the database. The next time the user uses the system, he/she can directly use the historical data stored in the database without having to build the user preference model again. The system converts the long-term preferences stored in the database into short-term preferences and generates travel routes for the user.

5. Tour Route Generation and Optimization Based on User Preference Model

This section describes an algorithm for generating tour routes based on a user preference model. It also describes the optimization of tour routes by adjusting the user preference model based on the feedback and repeating the re-generation and evaluation.

5.1 Generation

When using the system for the first time, the user must register and enter tour destinations and other relevant information. Figure 5 shows the travel information input screen. This interface allows the user to enter information such as destination, mode of transportation, and travel time.

Figure 6 is a screen that allows the user to evaluate a model route. In this screen, the route information is displayed on the map, and the user can click on each tourist spot on the map to obtain more detailed information. Users can rate model routes and select spots they like and dislike on their travel routes. Based on the user's evaluation of the model route and the spots in the route, the system constantly modifies the weight of each place type in the user preference model.

Tour Concierge uses an algorithm to generate optimal tour routes based on user preferences and travel needs. The algorithm calculates the shortest route using the Google Maps API under constraints of the user's travel time and transportation, and sequentially selects sights that match the user's preferences from among 25 place types obtained from the Foursquare Places API [17].

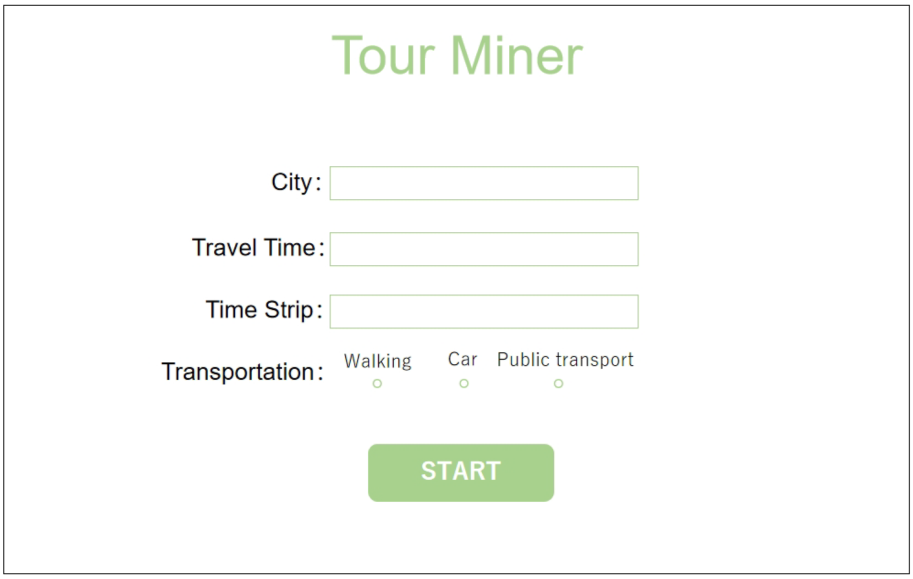


Figure 5: Tour information entry screen

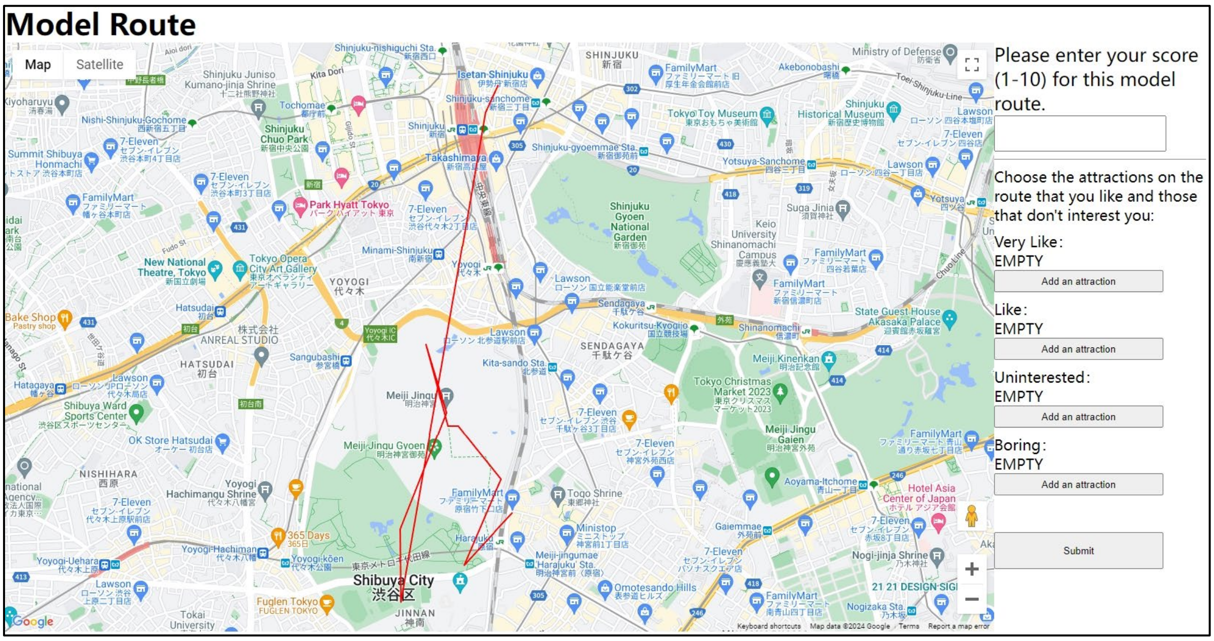


Figure 6: Model route evaluation screen. The user can review detailed information about each spot on the route, indicated by red lines, and request changes to the route

The starting point can be freely set by the user or automatically determined by the system based on a user preference model. If the system decides automatically, it selects the most popular starting points in the current city based on the place types with the highest weight in the user's preference model.

For spot selection, the system searches for spots within a certain range of the current location and incorporates the best spots into the route, taking into account the balance between user preferences and the overall route. This process is repeated to complete the final route. Algorithm 1 shows this process in more detail.

Input: User preference model, Destination, Travel time, Transportation mode Output: Tour route
Step 1: If no starting point is specified, use the spot that the user is most interested as the starting point. Step 2: Set the direct route between the starting point and the destination as the initial. Step 3: Repeat the following while the current route meets the specified travel time requirement. (i) Search for nearby spots using the last spot other than the destination on the current route as the center point. (ii) Calculate the score of each spot, considering the travel time according to the transportation mode, and select the spot with the highest score and insert it into the tour route. Step 4: Output the current route as the tour route.

Algorithm 1: Tour route generation algorithm

5.2 Optimization

Tour routes are generated based on a user preference model, but this model is not perfect and may differ from the user's actual preferences. Therefore, Tour Concierge dynamically updates the user preference model by actively incorporating user feedback to generate more accurate travel routes.

Users can provide feedback such as “Very Like”, “Like”, “Uninterested”, and “Boring” for the travel routes generated by the system. Based on this feedback, the system adjusts the parameters of the user preference model and generates a new tour route. By repeating this process, the system gradually learns the user's preferences and can suggest more personalized tour plans.

As an example, consider a user with the long-term preferences shown in Table 2 for a two-day trip to Tokyo. Obviously, this user is interested in theme “History” and “Nature”. The system transforms the user's long-term preferences into short-term preferences as shown in Table 3. From the table, we can see the place type “History Museum” or “Zoo” related to the theme “History” or “Nature” have a higher weight.

Table 2: A user's long-term preferences

Theme	History	Culture	Art	Nature	Leisure
Weight	0.3	0.15	0.15	0.3	0.1

Table 3: Short-term preferences obtained by transforming the long-term preferences

Place Type	Weight	Place Type	Weight	Place Type	Weight
Amusement Park	0.1	Aquarium	0.3	Art Gallery	0.15
Art Museum	0.225	History Museum	0.3	Science Museum	0.3

Concert Hall	0.15	Opera House	0.15	Theater	0.15
Water Park	0.1	Zoo	0.3	Outdoor Sculpture	0.15
Buddhist Temple	0.225	Shrine	0.225	Temple	0.225
Beach	0.3	Botanical Garden	0.3	Historic and Protected Site	0.225
Memorial Site	0.3	Palace	0.225	National Park	0.3
Natural Park	0.3	Roof Deck	0.1	Scenic Lookout	0.1
Ski Resort and Area	0.1				

Based on the short-term preferences, the system proposed tour route A, shown in Figure 7, which would include a history-related museum and a nature-related zoo. Table 4 shows the details of route A.

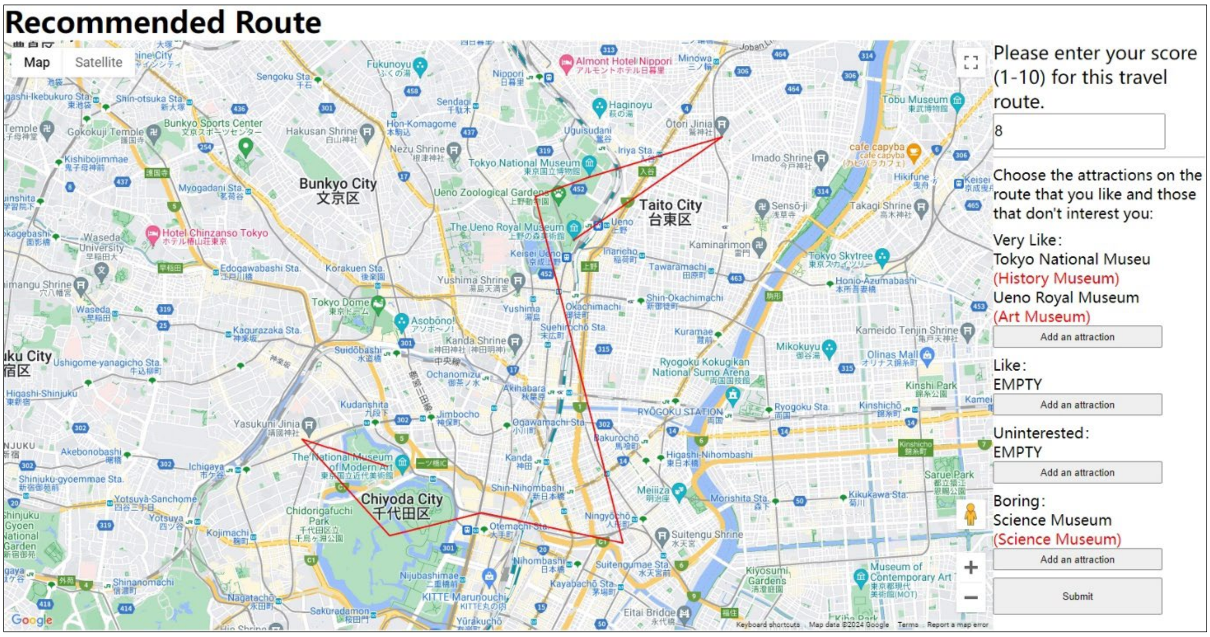


Figure 7: Tour route A, which is initially proposed by the system

Table 4: Details of tour route A

No	Place Name	Place Type
1	Science Museum	Science Museum
2	Yasukuni-jinja Shrine	Historic and Protected Site
3	Imperial Palace	Historic and Protected Site
4	Yomiuri Otemachi Hall	Concert Hall
5	Koami-jinja Shrine	Shrine
6	Ueno Zoo	Zoo
7	Tokyo National Museum	History Museum
8	Washi Shrine	Shrine
9	Ueno Royal Museum	Art Museum

However, the user may not be interested in all the suggested spots. In this screen, the route information is displayed on the map, and the user can click on each tourist spot on the map to obtain more detailed spot information. Users can rate model routes and select spots they like and dislike on their travel routes. Based on the user's evaluation of the model route and the spots in the route, the system constantly modifies the weight of each place type in the user preference model.

As mentioned before, the user can give feedback to the system by selecting "Very Like" or "Like", "Uninterested", or "Boring" for each spot using the on-screen controls. For example, suppose that the user gives feedback that he/she likes the Tokyo National Museum and the Ueno Royal Museum very much but is not interested in the Science Museum. Based on this feedback, the system dynamically updates the user's preference model. The system will assume that the user is not interested in the travel theme corresponding to that place type and will reduce the weight of that theme. For details, see Reference [15]. In this example, the system reduces the weight of the science museum and increases the weights of the history museum and art museum to more accurately reflect the user's actual preferences. Table 5 shows the updated user preference model.

Table 5: Short-term preferences updated based on user feedback. Values in red cells have been changed compared to Table 3

Place Type	Weight	Place Type	Weight	Place Type	Weight
Amusement Park	0.1	Aquarium	0.3	Art Gallery	0.15
Art Museum	0.305	History Museum	0.38	Science Museum	0.22
Concert Hall	0.15	Opera House	0.15	Theater	0.15
Water Park	0.1	Zoo	0.3	Outdoor Sculpture	0.15
Buddhist Temple	0.225	Shrine	0.225	Temple	0.225
Beach	0.3	Botanical Garden	0.3	Historic and Protected Site	0.225
Memorial Site	0.3	Palace	0.225	National Park	0.3
Natural Park	0.3	Roof Deck	0.1	Scenic Lookout	0.1
Ski Resort and Area	0.1				

Based on the short-term preferences, the system regenerates tour route B, shown in Figure 8.

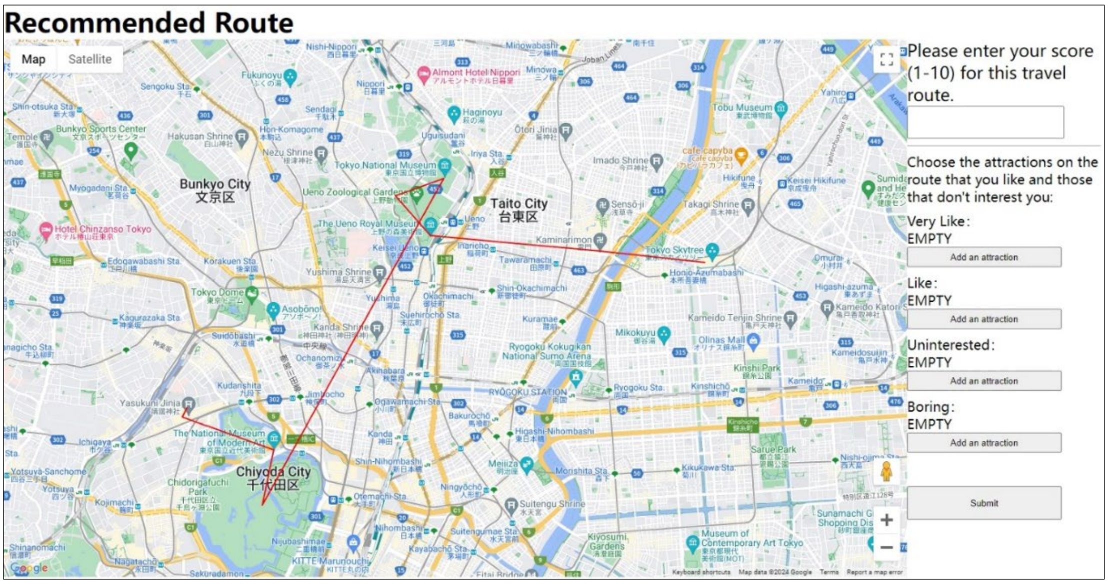


Figure 8: Tour route B which is optimized by the system based on the user feedback

Table 6 shows the details of route B.

Table 6: Details of tour route B

No	Place Name	Place Type
1	Yushukan	History Museum
2	Yasukuni-jinja Shrine	Historic and Protected Site
3	National Museum of Modern Art	Art Museum
4	Imperial Palace	Historic and Protected Site
5	Tokyo National Museum	History Museum
6	Ueno Zoo	Zoo
7	Ueno Royal Museum	Art Museum
8	Kaminarimon Gate	Shrine
9	Sumida Aquarium	Aquarium

In response to feedback from users that they were more interested in the History Museum than the Science Museum, the system updated the user preference model and changed the first spot on route A, the Science Museum, to the History Museum, the Yushukan.

In this way, Tour Concierge flexibly adjusts tour routes based on users' real-time feedback to provide a more personalized travel experience. Even if users are not satisfied with the initial suggestion, they can get a tour plan that suits their preferences through feedback.

6. Evaluation

6.1 Experiment

An evaluation experiment was conducted to verify the effectiveness of Tour Concierge. The subjects were 26 university students. Subjects were asked to have the proposed system recommend travel routes according to a given scenario. For comparison, they also received travel route recommendations from ChatGPT according to the same scenario. Three scenarios were used for generality

(1) Scenario 1: A user interested in history and art travels to Tokyo for two days.
(2) Scenario 2: A user has visited the Jade Buddha Temple (Temple), Golden Buddha Temple (Temple), Grand Palace (Thai Imperial Palace), Siam Ocean World (Aquarium), and Bangkok Safari Park (Zoo), and Bangkok Safari Park (Zoo) during a previous trip to Thailand, and now travels to Tokyo for two days.
(3) Scenario 3: A user has visited the Forbidden City (Palace), the Great Wall of China (Historic and Protected Site), and the Central Television Tower (Scenic Lookout) during a previous trip to China, and now travels to Tokyo for two days.

After the recommended travel routes were obtained, a questionnaire was administered to the subjects. The two questions in the questionnaire were, for each case, as follows

(1) Question 1: Do you think that the tour route generated by Tour Concierge will be able to match the user's preferences?
Answer 1: (i) I think so, (ii) I somewhat think so, (iii) Neutral, (iv) I don't think so, (v) I don't think so at all.
(2) Question 2: Do you think that the travel routes generated by Tour Concierge are better than the routes generated through ChatGPT?
Answer 2: (i) I think so, (ii) I somewhat think so, (iii) Neutral, (iv) I don't think so, (v) I don't think so at all.

6.2 Result

(1) Scenario 1

Subjects become travelers interested in history and art, and are asked to recommend travel routes for a 2-day trip to Tokyo using Tour Concierge and ChatGPT. The tour routes recommended by Tour Concierge are shown in Table 7 (a), and those recommended by ChatGPT are shown in Table 7 (b).

The results of the questionnaire are shown in Table 8. Numbers represent the number of respondents. 76.9% of subjects responded that the route generated by Tour Concierge routes met their preferences. In addition, 73.1% of the subjects responded that the routes generated by Tour Concierge routes were superior to the routes generated by ChatGPT.

Table 7: Tour routes proposed for Scenario 1

(a) Tour Concierge

No	Place Name	Place Type
1	Yushukan	History Museum
2	Yasukuni Shrine	Shrine
3	Yomiuri Otemachi Hall	Concert Hall
4	Imperial Palace	Palace
5	Imperial Theatre Tokyo	Theatre
6	Hulic Hall Tokyo	Theater
7	Gyoko-dori Underground Gallery	Art Gallery
8	Tokyo Takarazuka Theatre	Theater
9	Hibiya Open-Air Concert Hall	Concert Hall

(b) ChatGPT

No	Place Name	Place Type
1	Sensoji Temple	Buddhist Temple
2	Edo-Tokyo Museum	History Museum
3	Tokyo Imperial Palace and East Gardens of the Imperial Palace	Park
4	Kabuki-za Theater, Shinjuku	Theater
5	Mori Art Museum	Art Museum
6	Ueno Onshi Park	Park
7	The National Art Center, Tokyo	Art Museum
8	Roppongi Art Area	Art Museum

Table 8: Results of the survey for the recommended route for Scenario 1

	Q1: User preferences match?	Q2: Better than ChatGPT?
I think so	6	5
I somewhat think so	14	14
Neutral	3	1
I don't think so	0	2
I don't think so at all	3	4

(2) Scenario 2

Subjects become travelers who have previously visited Thailand, and are asked to recommend travel routes for a 2-day trip to Tokyo using Tour Concierge and ChatGPT. The tour routes recommended by Tour Concierge are shown in Table 9 (a), and those recommended by ChatGPT are shown in Table 9 (b).

The results of the questionnaire are shown in Table 10. 69.2% of subjects responded that the route generated by Tour Concierge routes met their preferences. In addition, 61.5% of subjects responded that the routes generated by Tour Concierge routes were superior to the routes generated by ChatGPT.

(3) Scenario 3

Subjects become travelers who have previously visited China, and are asked to recommend travel routes for a 2-day trip to Tokyo using Tour Concierge and ChatGPT. The tour routes recommended by Tour Concierge are shown in Table 11 (a), and those recommended by ChatGPT are shown in Table 11 (b).

The results of the questionnaire are shown in Table 12. 65.4% of subjects responded that the route generated by Tour Concierge routes met their preferences. In addition, 57.7% of subjects responded that the routes generated by Tour Concierge routes were superior to the routes generated by ChatGPT.

Table 9: Tour routes proposed for Scenario 2

(a) Tour Concierge

No	Place Name	Place Type
1	Tsukiji Honganji Temple	Buddhist Temple
2	Imperial Palace	Palace
3	Museum of Science and Technology	Science Museum
4	Yasukuni Shrine	Shrine
5	Shinjuku Gyoen	Garden
6	Hanazono Shrine	Shrine
7	Sunshine Aquarium	Aquarium
8	Ueno Zoo	Zoo
9	Hibiya Open-Air Concert Hall	Concert Hall

(b) ChatGPT

No	Place Name	Place Type
1	Sensoji Temple	Buddhist Temple
2	Edo-Tokyo Museum	History Museum
3	Tokyo National Museum	History Museum
4	Shinjuku Kabukicho	Neighborhood
5	Ueno Onshi Park	Park
6	Tsukiji Market	Market
7	Inokashira Onshi Park	Park
8	Tokyo Bay Aqualine and Odaiba Seaside Park	Park

Table 10: Results of the survey for the recommended route for Scenario 2

	Q1: User preferences match?	Q2: Better than ChatGPT?
I think so	9	9
I somewhat think so	9	7
Neutral	3	3
I don’t think so	3	3
I don’t think so at all	2	4

Table 11: Tour routes proposed for Scenario 3

(a) Tour Concierge

No	Place Name	Place Type
1	Tokyo City View	Scenic Lookout
2	Zojoji Temple	Buddhist Temple
3	Atago Shrine	Shrine
4	Imperial Palace	Palace
5	Yasukuni Shrine	Shrine
6	The National Museum of Modern Art, Tokyo	Art Museum
7	Tokyo National Museum	History Museum
8	Sensoji Temple	Buddhist Temple
9	Ueno Royal Museum	Art Museum

(b) ChatGPT

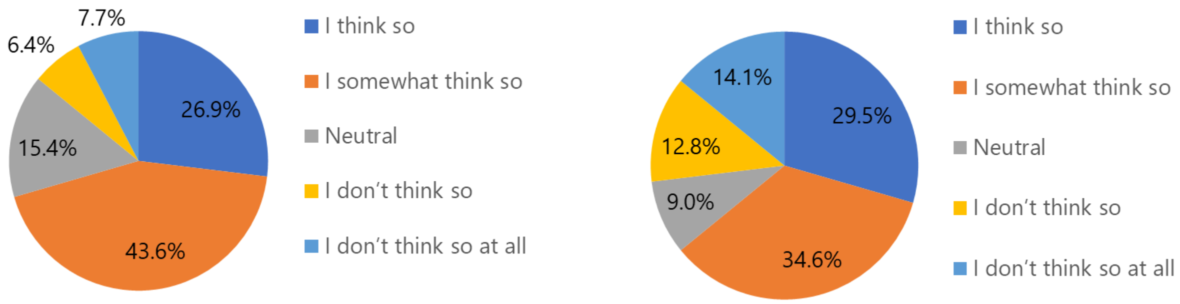
No	Place Name	Place Type
1	Sensoji Temple	Buddhist Temple
2	Edo-Tokyo Museum	History Museum
3	Tokyo National Museum	History Museum
4	Tokyo Tower	Monument
5	Shinjuku Gyoen	Garden
6	Yoyogi Park	Park
7	Roppongi Hills	Mall
8	Daiba Seaside Park	Park

Table 12: Results of the survey for the recommended route for Scenario 3

	Q1: User preferences match?	Q2: Better than ChatGPT?
I think so	6	9
I somewhat think so	11	6
Neutral	6	3
I don’t think so	2	5
I don’t think so at all	1	3

6.3 Discussion

Figure 9 shows the overall evaluation results. 70.5% of subjects found the routes generated by Tour Concierge to be consistent with their preferences. In addition, 64.1% of subjects rated these routes as superior to those generated by ChatGPT. These results suggest that Tour Concierge can suggest tour routes that match user preferences in situations where users have different travel experiences and requirements.



(a) Q1: User preferences match? (b) Q2: Better than ChatGPT?

Figure 9: Results of evaluation by questionnaire

Comparing Tour Concierge and ChatGPT, ChatGPT tends to give priority to famous spots for recommendation. While this is an attractive option for many travelers, further personalization is needed to provide travel routes that are fully tailored to the user's individual preferences. On the other hand, Tour Concierge was able to generate a wider variety of travel routes compared to ChatGPT. However, this experiment also resulted in similar initial recommended spots. This may be due to the experimental setting (using the Imperial Palace as the starting point) and the fact that the route generation algorithm considers the distances between sights.

Through feedback to the system, users can adjust the weights of the tourist attraction types to match their own preferences and obtain more optimal tour routes. However, developing an algorithm that effectively utilizes user preference information to generate more accurate tour routes is an important topic for future research.

7. Conclusion

This chapter presented Tour Concierge, an interactive recommendation system that continuously learns user preferences and suggests more personalized travel routes. This system is a concierge that learns the user's travel history and preferences and suggests optimal travel plans. It comprehensively analyzes past travel experiences and what the user wants to emphasize in this trip, and creates a detailed plan tailored to everyone. In a user evaluation experiment with 26 university students, approximately 70.5% of subjects indicated that the routes generated by the system matched their preferences. In comparison to ChatGPT, 64.1% of subjects rated the route generated by Tour Concierge as superior.

The research and development of Tour Concierge have just begun. Future challenges to upgrade this system include the following. First, the introduction of AI is prospective to accurately understand the preferences of various types of users and suggest optimal plans. Another future challenge is to improve the sophistication of the algorithm so that it can generate tour plans that simultaneously satisfy multiple conditions that in some cases contradict each other. These will make it possible to respond more intelligently to users' potential needs when formulating tour routes.

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