An Extraction Method of Well-Matched Spot Pairs based on Co-occurrence of Experiences in Travel Plans

Junsaku Takada, Daisuke Kitayama

Abstract—**When travellers go sightseeing, they often know the main sightseeing spots to visit, but deciding on other interesting spots to visit can be time-consuming and difficult. Therefore, in this study, travellers input the main tourist spots that they want to visit and recommend other sights that are well-matched with those spots. In this study, well-matched is defined as a high rate of co-occurrence between experiences that appear in existing travel plans. The probability of co-occurrence is calculated based on the amount of mutual information. In this study, spot recommendations are based on the cosine similarity between the vector created by the probability of co-occurrence of experiences appearing in travel records of tourist sites and the vector created from the review texts of tourist sites. In this study, we use travel records generated from Flickr for trip planning. The combination of spots with well-matched experiences is perceived to be selected from the travel records. The experiences in this study are extracted from review texts available on travel websites. For the extraction of experiences, we referred to the work of Ikeda[1] et al.**

Index Terms—**Tourist spots, experience extraction, mutual information content, recommendation system.**

I. Introduction

In recent years, it has become possible to obtain information on tourist attractions from a variety of sources; the sources include tourist information websites such as Jalan[1] and reviews on Google Maps[2], in addition to tourist guidebooks. From these sources, sufficient information about the desired tourist destinations can be obtained. In general, when planning a travel itinerary, travellers often choose the major tourist attractions first. We believe that this information can be easily collected from the sources mentioned above. However, after deciding on the main tourist attractions, choosing other attractions to visit is a challenging task. Because the main sightseeing spots are generally well known and tourists easily have a wealth of information about them at their disposal, finding other spots requires more effort. In addition, there may be many sightseeing spots in the vicinity, making it extremely difficult to examine all of them. For example, if a person decides to visit a hot spring and then visits other sightseeing spots, it increases the time taken to create a satisfactory sightseeing plan; this could pose problems when trying to focus on the details. In addition, visitors may become weary of making sightseeing plans, reducing the number of sightseeing spots they visit during their trips. In the case of non-famous tourist spots, it is even more difficult to make travel plans based on travel records and tours.

To solve these problems, we propose a method of recommending sightseeing spots, which are well-matched with the main sightseeing spots that the travellers intend to visit. By recommending sightseeing spots that are well-matched with the main sightseeing spots, the effort of making a travel plan can be saved. The travel record contains sites that were selectively determined by actual travellers, suggesting that there was a reason to visit them. The travel record is created from the Flickr photos. Therefore, in this study, we focus on experiences at the tourist spots and assume that the experiences at the other spots in the travel records are the reasons for visiting those spots together. Experiences that tend to emerge in these travel records are considered to be well-matched experiences. This can be used to recommend spots that offer experiences that are well-matched with those available at a particular spot. Examples of well-matched experiences include “mountain climbing” and “hot spring bathing”. After climbing a mountain, one may want to go to a hot spring to soothe one’s tired body and wash away the sweat. The contributions of this study are:

- We focused on the experiences at the tourist spot and defined well-matched experiences.
- Clarified the characteristics of tourist spot recommendations based on well-matched experiences.

II. Related Research

A. Extracting features of tourist spot

There are several studies on feature extraction for tourist spots. We introduce our research on feature extraction from documents such as user reviews. Ikeda[1] et al. extract experiences from texts, such as blogs. Morphological analysis is performed on the documents, and the experiences are extracted according to the rules for expressing the experiences defined in their study. In our method, we extract experiences, based on these experience rules. The details are explained in Section III-C.

Park et al.[2] proposed a method for mining personal experiences from large-scale weblogs. Experience is the knowledge embedded in a collection of activities and events that the individual or group did actually experience.

Cuizon et al.[3] presented a sentiment analysis to predict the numerical rating of text reviews in a web-based travel journal application. The application allows users to record and provide text reviews on tourist spots visited. Reviews undergo part-of-speech (POS) tagging, rule-based phrase

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[1]https://www.jalan.net

[2]https://www.google.co.jp/maps/

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chunking, and dependency parsing to extract opinion phrases in noun-adjective and noun-verb pairs from the original text.

Guy et al.[4] proposed to extract short practical tips from user reviews. It extracts information from user reviews posted on TripAdvisor.

Lao et al.[5] proposed travel information with high regional characteristics by extracting regional features. They proposed travel recommendation information sought by users by satisfying two conditions: the localized score and the content category of the travel blog. They used TF-IDF for words appearing in blogs to create a localized score. This study also uses TF-IDF for spot review. In this study, however, experiences are considered rather than words.

B. Travel recommendation using geotagged photos

Many travel and tourism-related papers use geotagged photos.

Kumari et al.[6] focused on the weather in geotagged photos. Previous travel recommendation methods did not consider user preferences and weather conditions. In their paper, we propose a travel recommendation system for tourists based on user preferences, weather conditions, and live events.

Cheng et al.[7] focused on personalized travel recommendations using photos posted in freely available communities. Furthermore, we propose a personalized travel recommendation by considering the profile and attributes (gender, age, race, etc.) of a particular user. Santos et al.[8] helped tourists choose points of interest (POIs), organize itineraries, manage activities, and enhance the tourist experience when visiting unfamiliar cities.

Li et al.[9] developed a new travel planning system that integrates new techniques in data mining and operations research to create multi-day, multi-stay travel plans based on geotagged photos. A modified iterative local search heuristic algorithm was developed to find approximate optimal solutions to multi-day and multi-stay travel planning problems using points of interest (POIs) and recurrence weights between POIs in a travel graph model discovered from photographs. In this study, we use geotagged photos to make a Flickr trip via the photographer's id, posting date, and latitude and longitude of the photo. This geotagged photo method has not been used before.

III. Extraction of well-matched spot pairs based on co-occurrence of experiences

In this study, two types of vectors are generated by two methods. An overview of this study is shown in Figure 1. The two vectors are generated from "Generating experience vectors that are well-matched with tourist spots using mutual information content" and "Generating experience vectors for tourist spots using TF-IDF" in Figure 1. The cosine similarity of the two vectors is used to recommend a spot.

A. Targeted data structures

We created the travel record by extracting photos with the same location information as the photographer's id and the date when the photo was taken. The visited places are those where the photo's latitude and longitude and the tourist spot's latitude and longitude coincide. First, as the data structure of the target travel record, a travel record tr consists of a set of visited spots $[s_1, s_2, s_3, ..., s_n]$. Here, s_i denotes the visited spot. Let s_i have the experience set $[e_1, e_2, e_3, ..., e_m]$. In this study, travel records were obtained from Flickr[3], a photo posting site, and the experience was obtained from Jalan, a tourism review site.

B. Extraction of travel record from photos

For extracting visited spots as travel records from photos. Photos were extracted with latitude and longitude from Flickr and summarized by the photographer's id and date. Subsequently, the visited spots were extracted from the compiled photos. We considered all the spots where the error between the latitude and longitude of the area where the photo was taken and the latitude and longitude of the area where the photo was taken was within 0.002 as visited destinations.

C. Experience extraction of tourist attractions

For the extraction of experiences, we refer to the experience extraction of Ikeda et al. [1]. The experience expressions are summarized in Table I. There are five main types of experiences. We indicate the experience known in the description field of the expression type. For Jalan's spot reviews, we extract words that are applicable to the experience expression rule. Let the extracted word be X. Next, we extract the words that occur within five words before and after word X. Let the extracted word be Y. Next, the word Y is counted by spot, and the word Z is defined as the word that appears more than 50 times. Finally, the pairs of words Z and X that appear within five words before and after Z are saved as experiences. This is the manner in which experiences are extracted in our method.

D. Generating experience vectors that are well-matched with tourist spots using mutual information content

In this study, we use the co-occurrence probability between experiences to recommend well-matched spots with the input spots. Therefore, we use the mutual information content. To use mutual information, it is necessary to obtain the probability of an experience occurring in the travel record for each experience. The probability of occurrence of an experience is $P(e_i)$ and is defined by Equation (1). where $trf(e_i)$ is the number of travel records containing spots with a certain experience e_i, and TR is the total number of travel records.

$$P(e_i) = \frac{trf(e_i)}{TR} \tag{1}$$

We extract experiences from the input spots and generate a vector for each extracted experience. We generate vectors that are well-matched with the input spot by averaging all generated vectors.

Using the mutual information in this study enables researchers to express the extent to which one experience occurs along with another. Thus, experiences with high values are said to be experiences that occur with each other and therefore, are well-matched. We generate a vector based on the obtained mutual information. We determined

[3]https://www.flickr.com/

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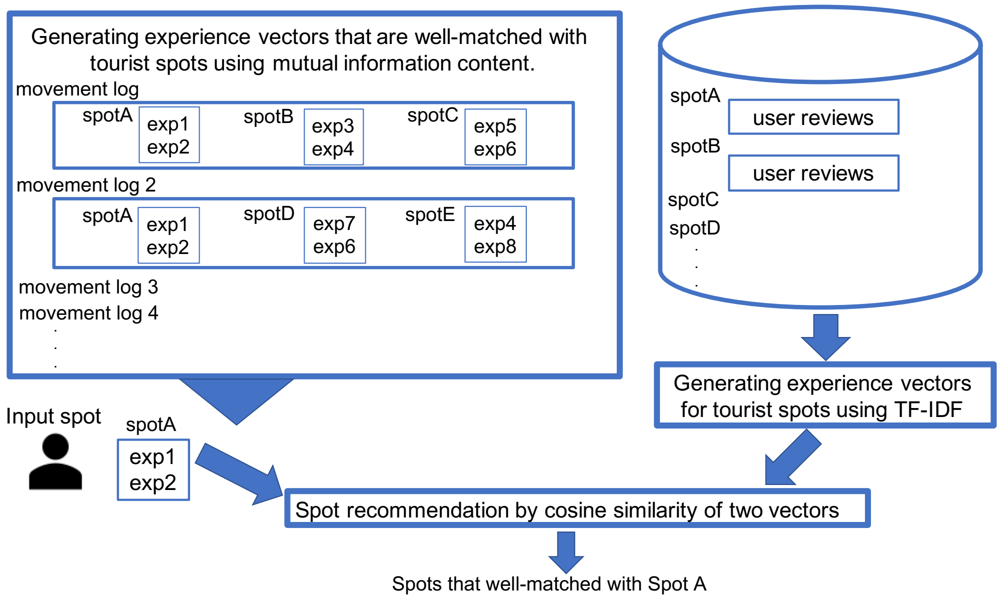

Fig. 1. Overview of the proposed method

TABLE I
EXPERIENCE EXPRESSION RULES. IN THIS STUDY, THE TARGET WAS JAPANESE EXPERIENTIAL EXPRESSIONS, SO THIS TABLE IS WRITTEN IN JAPANESE.

	Explanation of expression types	Examples of expressions
①	Expressions of self trial, such as “〜してみる”	Verb + subjunctive particle“て/で”+auxiliary verb“み た”,Noun that expresses action + verb “する (し)” + conjunctive particle “て” + auxiliary verb “みた”etc.
②	Expressions that describe the experience of “〜したことがある” itself	Verb + Noun “こと” + Gerund “が” + Verb “ある/あった”,①+Noun “こと” + Gerund “が” Verb “ある/あった”etc.
③	Expressions that express the writer’s own actions among verbs.	Verb + Verb Suffix End “た”,Noun: action + Judge: conjunction/termination “だった”etc.
④	Verbs (including words that describe the action of nouns) that express the writer’s own ongoing action	Verb + subjunctive particle “て/で” + auxiliary verb “いる/いた”etc.
⑤	Adjectives (including words that describe the action of nouns) that express impressions based on the writer’s experience	Adjective + adjective suffix: ending “かった”,Noun:Adjective + Judge:Conjunction/Final “だった”etc.

the co-occurrence values of other experiences for a given experience, and a vector for a given experience was generated based on these values. The dimension of an experience vector is the experience taken from the travel record, and the value is that obtained from the mutual information. This is expressed in the equation (2). Let experience e_i be the experience appearing at the input spot, and experience e_j be an arbitrary experience. The value of experience e_j, an element of the vector of experiences e_i, is $f(e_i, e_j)$, and the probability of co-occurrence of experiences e_i and e_j is $c(e_i, e_j)$. Co-occurrence here is defined as appearing in different spots of the same travel record. Two pairs that appear in the same spot are considered to be co-occurrences because they have the same kind of experience, so they were excluded. These are defined by the equation (2). The defining equation of the experience vector is shown in equation (3).

$$f(e_i, e_j) = \log \frac{c(e_i, e_j)}{P(e_i) \times P(e_j)} \tag{2}$$

$$V_{e_i} = [f(e_i, e_1), f(e_i, e_2), \cdots, f(e_i, e_m)] \tag{3}$$

We generate a vector of the top 10 experiences E_{s_i} from all the experiences extracted from the input spots. The average vector of all the vectors generated from the input spot is the vector that matches well with the input spot. This vector is denoted by a well-matched spot vector $V_{s_i}^{(wm)}$, and is shown in equation (4).

$$V_{s_i}^{(wm)} = \frac{1}{10} \sum_{e \in E_{s_i}} V_e \tag{4}$$

E. Creating experience vectors for tourist spots using TF-IDF

We extract experiences from Jalan’s spot reviews. We generate vectors $V_{s_j}^{(TFIDF)}$ from the extracted experiences. We use TF-IDF to generate vectors. The expression (5) is TF, the expression (6) is IDF, and expression (7) is TF-IDF. The TF-IDF value of a spot expresses the importance of the experience available at the spot. In equation (5), let $tf(e_i, s_j)$ be the frequency of a certain experience e_i appearing in the spot review of a certain spot s_j, and let the importance be the proportion of that experience in that spot. Equation (6) takes the total number of spots as $|S|$ and the number of spots containing experience e_i as $df(e_i)$. This value is higher when a certain experience e_i appears in other spots. By multiplying equation (7) by equation (5) and equation (6), we can express the importance of the experience that can be enjoyed at a spot.

$$TF(e_i, s_j) = \frac{tf(e_i, s_j)}{\sum_{e_k \in s_j} tf(e_i, s_j)} \tag{5}$$

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$$IDF(e_i) = \log \frac{|S|}{df(e_i)+1} \tag{6}$$

$$TFIDF(e_i, s_j) = TF(e_i, s_j) \times IDF(e_i) \tag{7}$$

$$V_{s_j}^{(TFIDF)} = [TFIDF(e_i, s_j) | 1 \leq i \leq m] \tag{8}$$

IV. Experiment

We conducted comparative experiments to show the effectiveness of the proposed method and found two key elements.

Effectiveness A
: The effectiveness of the proposed method is demonstrated, in that the spots recommended by the proposed method are well-matched with the input spots.

Effectiveness B
: We demonstrate the effectiveness of the experience used in the proposed method. To confirm this effectiveness of the experience, we created a system that extracts nouns from spot reviews and recommends spots based on the amount of mutual information.

To demonstrate the effectiveness of these two methods, we prepared two conventional methods for comparison—the association rule method and the noun method. The association rule method is prepared to show the effectiveness A. The noun method is prepared to show the effectiveness B. A questionnaire was conducted based on the recommendation results of the proposed method and the comparison method, and the effectiveness of each method is shown. We used four input spots for recommendation: Yokohama Chinatown, Asakusa Hanayashiki, Hokanji Temple, and Entokuin Temple. Yokohama Chinatown is a Chinatown, Asakusa Hanayashiki is a theme park, Hokanji Temple is a temple, and Entokuin Temple is a temple. The data used were the number of spots in Jalan: 29322, number of Flickr trips: 27429, and number of types of experiences: 13109.

A. Association Rule

The association rule is a spot recommendation method based on association rule mining using travel records. In the association rule, we treat the travel records in which the visited spots are close to each other as one spot. This one spot is called the visited place. Figure 2 shows an image of how to create a place for a visit. All sightseeing spots whose latitude and longitude errors were within 0.002 were considered visited places. If several photos are taken nearby and the same tourist spot appears between the visited areas, those areas are treated as one visited place. If place A has eight attractions, place B has two attractions, and place C has one attraction, then the number of places visited and attractions in those places are represented in Figure 2. We use confidence as a measure. Let $conf(s_i, s_j)$ be the confidence of a certain recommendation spot s_j for a certain input spot s_i, and equation (9). Let $f(s_i)$ be the number of travel records in which s_i is included. Let $f(s_i, s_j)$ be the number of travel records, which includes both s_i and s_j. Here, if s_i and s_j do not exist in the same place, the travel records are included together. This prevents the candidate

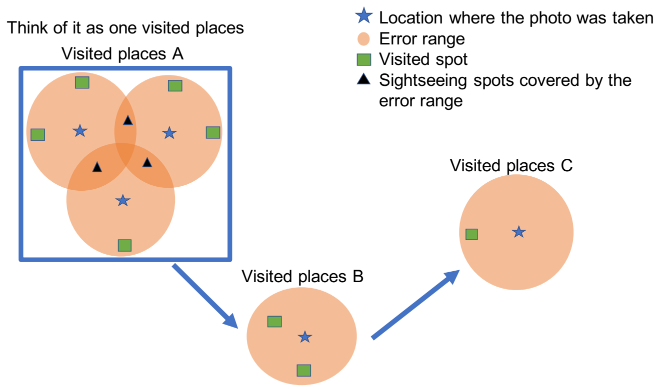

Fig. 2. Extraction of visited locations from photos.

spot confidence values near the input spot from becoming too high.

$$conf(s_i, s_j) = \frac{f(s_i, s_j)}{f(s_i)} \tag{9}$$

We based this system on the association rule method of the travel record.

B. Noun-based recommendation method

The proposed method uses location data and experience feedback to produce recommendations for the user. The noun method differs from the original method, in that experience is replaced by the desired noun. The nouns used are the noun parts of the experiences used in the proposed method. The number of nouns is 532. The program makes recommendations, using the Noun-based recommendation method created from these nouns.

C. Recommendation results by the three methods

The recommendation results of the proposed method, the association rule method, and the noun method are shown in Table II, Table III, Table IV, and Table V. The recommendation results of the proposed method and the noun method are listed in the table from the top with the top five cosine similarities. The top five confidence values for the association rule method are also listed in the table. The recommended spot area was defined as a spot in the same city as the input spot.

D. Recommendation results of the proposed method

The Yokohama Landmark Tower and Yokohama Red Brick Warehouse are at the top of the list for the proposed method in Table II. Being famous places with an abundance of reviews, the Yokohama Landmark Tower and Yokohama Red Brick Warehouse top the list of reviews on Jalan. It can be considered as a spot to visit together with Yokohama Chinatown. The Ueno Zoo and Sensoji Temple top the list for the proposed method in Table III. A theme park and a zoo or a theme park and a temple all represent the possible spots to visit together. The proposed methods in Tables IV and V recommended almost the same spots. This is probably because Hokanji Temple and Entokuin Temple represent similar spots, located in the same city. In the proposed methods in Table IV and Table V, temples and shrines, such

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as Kiyosuji Temple, come at the top of the list. Temples and shrines can be considered as possible spots to visit together with the Hokanji Temple and Entokuin Temple.

V. EVALUATION

A. Experimental settings

We used the results of the proposed method, the association rule method, and the noun method to create a questionnaire. The content of the questionnaire is “When you travel to a certain place, please indicate the places you think you should visit together and the degree to which you should visit them”. We use Yokohama Chinatown, Asakusa Hanayashiki, Hokanji Temple,and Entokuin Temple as a certain place. We show the recommendation results of the input spots that are the same in the proposed method, the association rule method, and the noun method. This means that the sum of Table II, Table III, Table IV, and Table V are the contents of the questionnaires of “tourist attractions that should be visited together”. The spots that should be visited together were evaluated on a five-point scale: “Should not be visited together,” “Somewhat should not be visited together”, “Neither”, “Somewhat should be visited together”, and “Should be visited together”. We administered questionnaires to “Yokohama Chinatown,” “Asakusa Hanayashiki,” “Hokanji Temple,” and “Entokuin Temple.” Therefore, we created four questionnaires, and 50 people answered each questionnaire, out of a total of 200 people. This section presents the results of a questionnaire survey conducted using the proposed method, the association rule method, and the noun method. The number of respondents who answered “Yokohama Chinatown”, “Asakusa Hanayashiki”, “Hokanji Temple”, and “Entokuin Temple” was 50, 50, 49, and 50, respectively. One respondent was not suitable for “Hokanji Temple” and was excluded from the list. We evaluated the ranking of each method using a five-point scale of evaluation of spots to be visited along with the recommendation results of the proposed method, the association rule method, and the noun method. Normalized Discounted Cumulative Gain (NDCG)[10] is used to evaluate the ranking. First, we changed the five-point scale of the evaluation of “spots that should be visited together” to one (1) for “should not be visited together,” two (2) for “somewhat should not be visited together,” three (3) for “neither should be visited together,” four (4) for “somewhat should be visited together”,and five (5) for “should be visited together”. Subsequently, we assigned a score for each of the “places we should visit together”. We calculated each score, by multiplying the number of subjects in each evaluation by the value of the evaluation in the five evaluation levels. The ideal rankings in Table II,III,IV,V were determined in order of the total score of the “must-visit spots” in the questionnaires for “Yokohama Chinatown,” “Asakusa Hanayashiki,” “Hokanji Temple,” and “Entokuin Temple.” The spots shown in the table are the top five spots with the highest scores, sorted from the top. This is the order of the spots evaluated by the users in the questionnaire. Therefore, this order is an ideal ranking of “places to visit together”. Using these, the DCG@5 formula for a certain spot is given as equation (10). Let $score_i$ be the score of the rank i-th spot. Let the expression of $NDCG$@5 for a spot be equation (11). Let DCG_{ideal}@5 be the DCG@5 of the ideal ranking. Spots outside the ideal ranking for each spot are treated as score 0. The values of $NDCG$@5 for each method are shown in Table VI. In all spots, the proposed method has the highest value, followed by the noun method and the association rule method. This result shows the effectiveness of “the spots recommended by the proposed method are spots that are well-matched with the input spots” and “the experiences used in the proposed method”.

$$DCG@5 = score_1 + \sum_{i=2}^{5} \frac{score_i}{\log_2 i} \tag{10}$$

$$NDCG@5 = \frac{DCG@5}{DCG_{ideal}@5} \tag{11}$$

VI. DISCUSSION

From the results of section V, we showed the effectiveness of “Effectiveness A” and “Effectiveness B”. In addition, the proposed method can recommend spots even when the input spots are “spots or areas that have not been visited by many people”. For example, when an “Ousenn waterfall” is used as an input spot, the association rule method cannot recommend a spot because there is no data. However, the proposed method can make recommendations as shown in Table VII. Table VII shows the top five cosine similarities from the top. As the proposed method recommends spots based on the co-occurrence of experiences, it is possible to recommend spots even in places where there are few reviews, in other words, “areas visited by few people.” There are only 49 reviews of the Ousenn waterfall in Jalan. Using the proposed method, we extract experiences from spot reviews and recommend spots. Therefore, it is possible to recommend spots, even when the input spot is an area or region that many people have not visited.

VII. CONCLUSION

In this study, we input the main sightseeing spots that we want to visit and recommend sightseeing spots that are well-matched with those spots. The proposed method extracts experiences from travel records, uses mutual information and TF-IDF to generate two kinds of vectors from the experiences, and recommends spots that are well-matched with the input spots, based on the cosine similarity of the generated vectors. To demonstrate the effectiveness of the proposed method and a questionnaire was used to compare the recommended spots whit two conventional methods. The results show the effectiveness of the proposed method. In this paper, we can only recommend one spot. In the future, we would like to be able to recommend more than one spot.

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TABLE II
TOP FIVE RANKING OF EACH METHOD IN YOKOHAMA CHINATOWN

	Ideal ranking	Association rule method	Noun method	Proposed method
1	Yokohama Red Brick Warehouse	Hotel New Grand Main Building	Yokohama Red Brick Warehouse	Yokohama Landmark Tower
2	Yokohama Landmark Tower	Marine Rouge	Sankeien Garden	Yokohama Red Brick Warehouse
3	Yokohama Port Osanbashi International Passenger Boat Terminal	Sea Bus	Yokohama World Porters	Yokohama World Porters
4	Yokohama World Porters	Marine Shuttle	Odori Park	Yokohama Port Osanbashi International Passenger Boat Terminal
5	Main Street Park	Rush	Ellisman House	Sankeien

TABLE III
TOP FIVE RANKING OF EACH METHOD IN ASAKUSA HANAYASHIKI

	Ideal ranking	Association rule method	Noun method	Proposed method
1	Sensoji Temple	Asakusa Sightseeing Federation	Ueno Onshi Park	Ueno Zoo
2	Ameyoko	Fujiya	Sensoji Temple	Ueno Onshi Park
3	Ueno Zoo	Bentenyama Bell Tower	Ameyoko	Sensoji Temple
4	Ueno Onshi Park	Sensoji Temple	Asakusa ROX	National Science Museum
5	Ebisuya Asakusa Store	Ebisuya Asakusa Store	Yanaka Cemetery	Ameyoko

TABLE IV
TOP FIVE RANKING OF EACH METHOD IN HOKANJI TEMPLE

	Ideal ranking	Association rule method	Noun method	Proposed method
1	Kiyosuji Temple	Kiyosuji Temple	Jionwon Temple	Kiyosuji Temple
2	Yasaka Shrine	Jishu Shrine	Yasaka Shrine	Yasaka Shrine
3	Shionin	Meiji Kobo	Kyoto National Museum	Shionin
4	Maruyama Park	Museum of Contemporary Art Kyoto	Kiyomizu Temple	Kenninji Temple
5	Kenninji Temple	Kanji Museum	Maruyama Park	Maruyama Park

TABLE V
TOP FIVE RANKING OF EACH METHOD IN ENTOKUIN TEMPLE

	Ideal ranking	Association rule method	Noun method	Proposed method
1	Kiyomizu Temple	Jizo Shrine	Jiyonin Temple	Kiyomizu Temple
2	Yasaka Shrine	Kiyomizu Temple	Yasaka Shrine	Yasaka Shrine
3	Kodaiji Temple	Limited Corporation Mori Pottery Museum	Kyoto National Museum	Shionin
4	Jiyonin Temple	Meiji Kobo	Kiyomizudera Temple	Keninji Temple
5	Kenninji Temple	Kimono Rental Hana Komachi	Maruyama Park	Kodaiji Temple

TABLE VI
EVALUATION VESULTS OF EACH METHOD BY NDCG@5

spot name	Association rule method	Noun method	Proposed method
Yokohama Chinatown	0.00	0.57	0.89
Asakusa Hanayashiki	0.26	0.75	0.82
Hokanji Temple	0.30	0.81	0.99
Endokuin	0.29	0.70	0.99

TABLE VII
RESULTS OF THE PROPOSED METHOD USING OUSENN WATERFALL AS INPUT

1	Shima Hot Spring
2	Shimagawa Dam
3	Shimanoouketsu
4	Sekizenkan
5	Shima Tamura

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