Analysis of Rarely Known Tourist Attractions by Geo-tagged Photographs

Jhih-Yu Lin
Graduate School of Systems Design
Tokyo Metropolitan University
Tokyo, Japan
lin-jhihyu@ed.tmu.ac.jp

Shu-Mei Wen
Department of Statistics and Information Science in Applied Statistics
Fu Jen Catholic University
Taipei, Taiwan
126531@mail.fju.edu.tw

Masaharu Hirota
Department of Information Science
Faculty of Informatics
Okayama University of Science
Okayama, Japan
hirota@mis.ous.ac.jp

Tetsuya Araki
Graduate School of Systems Design
Tokyo Metropolitan University
Tokyo, Japan
araki@tmu.ac.jp

Hiroshi Ishikawa
Graduate School of Systems Design
Tokyo Metropolitan University
Tokyo, Japan
ishikawa-hiroshi@tmu.ac.jp

Abstract—**Today, with the advancement of the Internet and transportation, we can readily travel around the world using diverse modes of travel. On these journeys, many people use various mobile devices to obtain the latest tourist information from the Internet. However, most of the information focuses on popular tourist attractions and leads to crowds flocking there. Unlike existing studies, which concentrate on analyzing popular tourist attractions, we attempt to disperse crowds from popular tourist attractions and provide more spots for travelers to choose by analyzing rarely known tourist attractions. For this study, we propose a formula for ranking tourist attractions by analyzing geo-tagged photographs on Flickr. The results of our questionnaire survey successfully revealed tourist locations that were unfamiliar to the majority of respondents, but which were attractive to them.**

Keywords-Flickr; geo-tagged photograph; rarely known tourist attractions.

I. INTRODUCTION

In this era of the Internet and smartphones, most people can readily share and record their touristic experiences on Social Networking Services (SNSs) such as Facebook and Flickr. Numerous studies have analyzed user records of tours on SNS to elucidate user hobbies and preferences. It is possible to discover popular tourist attractions and recommend some tour plans for a user according to their preferences [1]–[4]. Using SNSs, we can immediately obtain the newest status of our friends, particularly using well-known functions check-ins and "geo-tagged" photographs, which are useful when one wants to share a location with friends.

Aside from geolocation, diverse information is available from different people using SNSs. That information includes many important and useful data for research. For instance, Hausmann et al. [5] pointed out that social media contents might provide a swift and cost-efficient substitute for traditional surveys. Furthermore, Liu et al. [6] proposed an approach for the discovery of Areas of Interest (AoIs) by analyzing "geo-tagged" photographs and "check-in" information to supply popular scenic locations and popular spots with travelers. Another study with similar aims to our own used SNS users' information and "geo-tagged" photographs to discover obscure sightseeing spots [7].

Most tourists have received sightseeing information through travel websites. However, these websites only present well-known tourist attractions. Consequently, although the attractions are crowded and congested, visitors will be led there. We conducted a preliminary investigation which showed that the great majority of tourists do not like crowded spots that make them feel uncomfortable.

As the number of tourists continue to increase, they will bring huge revenues for tourism-related industries. Nevertheless, benefits from tourists are accompanied by latent crises as well, which we should face. Kakamu et al. [8] discovered that when the number of foreigners and the police force increase, the rate of crime will also increase. However, if criminal rates increase, it will reduce visiting willingness and tourism income will be lost [9].

Most earlier studies have specifically addressed analyses of popular tourism attractions or AoIs and neglected other unnoticed places. Therefore, for the present study, through dispersing crowds from more popular tourist attractions, our goal is to improve several aspects: (1) crowded popular tourist attractions make visitors feel uncomfortable; (2) foreigners are too numerous at popular tourist attractions, engendering higher rates of crime; and (3) supporting tourist industries of regions apart from popular regions.

To accomplish our aim, we analyzed scenic "geo-tagged" photographs taken in Japan from Flickr. Thereby, we discovered worthwhile and rarely known tourist attractions. We studied this topic based on scenic photographs to assess tourism in many categories such as human landscape, ecotourism, and natural landscape. For this study, we specifically examine natural landscapes. Therefore, we used scenic photographs to reach our aim of making travelers realize natural landscape intuitively. In addition, it is clearer to define the research scope. Moreover, we can provide more tourist attractions options for tourists and reduce crowding at well-known tourist attractions.

The rest of the paper is organized as follows: Section II presents an overview of the method. Section III explains the method used for scenic photograph evaluation. In Section IV, we present rarely known tourist attraction estimation and explain our questionnaire results. In Section V, we discuss

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improvements to the survey questionnaire and present conclusions and future works.

II. OVERVIEW OF THE METHOD

This section introduces an overview of our method, as shown in Figure 1. Our method comprises two components: definition of rarely known tourist attractions and data construction.

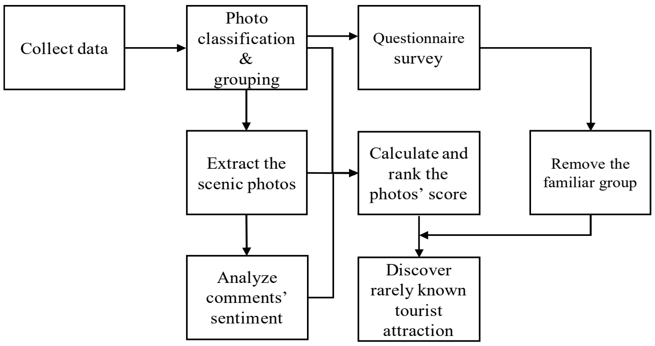


Figure 1. Overview of the method.

A. Definition of Rarely Known Tourist Attractions

To differentiate well-known and rarely known tourist attractions, we adopt two definitions of rarely known tourist attractions.

Definition 1: Only some people know about this tourist attraction.

Definition 2: That tourist attraction deserves to be visited and it is attractive for tourists.

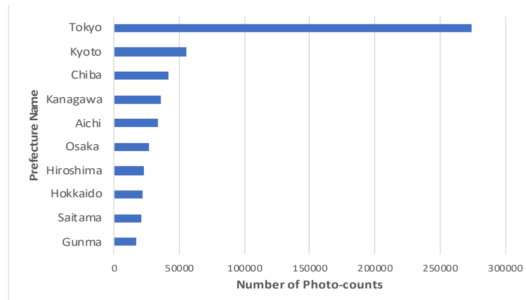
B. Data Construction

Using Flickr API, we collected 769,749 photographs shot in 2017 with geolocation in Japan. After extracting the photographs' latitude and longitude to gather details of addresses through Google geocoding API, we sorted the 47 prefectures and 1,159 cities by the number of photo-counts in descending order. Finally, we used a grouping method of unequal class interval to divide prefectures and cities into eight groups, as shown in Table I. This grouping method is presented in the next section. However, 309 photographs had no details of addresses because these photographs were shot in the sky or on the ocean.

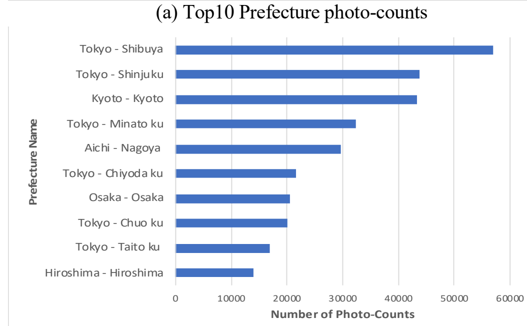
TABLE I. GROUP OF PREFECTURE

Group	***Prefectures***
Group 1	Tokyo, Kyoto, Chiba, Kanagawa, Aichi
Group 2	Osaka, Hiroshima, Hokkaido, Saitama
Group 3	Gunma, Nara, Nagano, Okinawa
Group 4	Hyogo, Fukuoka, Mie, Tochigi, Shizuoka
Group 5	Yamanashi, Oita, Okayama
Group 6	Ibaraki, Aomori, Miyagi, Gifu, Ishikawa, Wakayama, Kagawa, Niigata, Shiga, Ehime, Kumamoto, Akita, Toyama, Fukushima, Nagasaki
Group 7	Yamagata, Kagoshima, Tottori, Saga, Fukui
Group 8	Tokushima, Kochi, Yamaguchi, Iwate, Shimane, Miyazaki

We classified these photographs into different prefectures and cities according to the photographs' address details. We calculated the photo-counts in every prefecture and city. Figure 2 presents the Top 10 prefectures and cities for the photo-counts. Furthermore, we extracted 2,671 scenic photographs with tags which mean scenic in English and Japanese (e.g., "風景", "景色", "scenery"), and collected these photographs' comments and favorite counts.



(a) Top10 Prefecture photo-counts



(b) Top10 City photo-counts

Figure 2. Numbers of photo-counts.

III. SCENIC PHOTOGRAPH EVALUATION

A. Grouping Method of Unequal Class Interval

In this subtask, we present that the unequal class interval is a kind of statistical grouping method. This method applies uneven index values and class intervals of group as dissimilar. We used a slightly modified method similar to the one reported by Arjunan et al. [10]. We used this method to divide the 47 prefectures and 1,159 cities into different groups according their respective photo-counts.

To complete this grouping method, we employed two methods.

1) Reduction rate: By calculating the rate of increase and reduction, we can observe the numerical change that is usually used to calculate the mortality rate, rainfall rate, unemployment rate, etc. [11]–[13]. For this study, we sorted the prefectures and cities in descending order. The reduction rate of prefectures and cities was calculated using equation (1) in the equation, x_i represents the count of photographs. Then, after dividing the data into different groups through observation of the reduction rate variation, the reduction rate variation needs to meet two conditions: first is that the reduction rate must be more than 10%; second is that the reduction rate must be decreased gradually, then the next reduction rate is increased. Figure 3 presents the reduction rates of the respective prefectures.

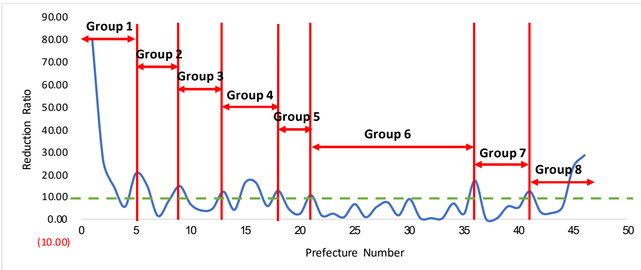


Figure 3. Photo-counts of reduction rate.

$$y = (x_i - x_{i+1})/x_i \times 100\ ,(x_i > x_{i+1}) \qquad (1)$$

In Table II, we can use the conditions above to divide the data. Although the second reduction rate meets the conditions, we still allocate it into group 4 because the city count of every group must contain at least three cities. The third and fifth reduction rates of prefecture are gradually decreased. However, the sixth reduction rate is increased and it is greater than 10%. We determined the sixth row is the period with abrupt change and divided the second row to sixth row into the group 4.

TABLE II. PARTIAL PREFECTURE LIST

Prefecture name	Photo-count	Reduction rate	Group
Okinawa	14,823	12.29%	3
Hyogo	13,001	4.21%	4
Fukuoka	12,454	16.36%	4
Mie	10,416	16.13%	4
Tochigi	8,763	5.93%	4
Shizuoka	8,218	12.64%	4
Yamanashi	7,179	4.49%	5
Oita	6,857	2.42%	5
Okayama	6,691	10.69%	5

2) Standard Deviation (STDEV): In statistics, the standard deviation (s) is usually used to measure dispersion of a set of data values. A greater standard deviation and greater magnitude will indicate greater deviation of values. In the following equation, $\overline{x}$ represents the x sample average.

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2} \qquad (2)$$

3) Z-score: z-scores are also called standard scores. In statistics, z-scores are used to compare an observation to a standard normal deviate. In the following equation (3), x, $\overline{x}$ and s represent the count of photographs, x sample average, and the standard deviation, respectively.

$$Z = \frac{x - \overline{x}}{s} \qquad (3)$$

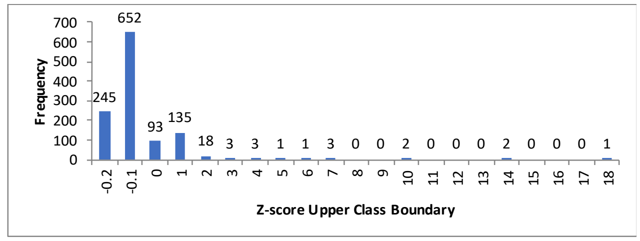


Figure 4. Z-score analysis of all city data.

4) Application: The change of the reduction rate might be readily apparent in the prefectures. Therefore, we only used the method of reduction to divide them into groups. For the group method of city data, in Figure 4, we can observe that about eighty percent cities' data center on -0.2 to 0, which means these photograph count of data less than the photograph count of average (656 photos). However, the data with z-score between 3 and 18 means that the data are excessively different and that many outliers exist. If we use only the z-score to group cities' data, that will show deviation, thereby we synthesized the methods above to group the cities' data. In the first to second group, the reduction rate of data might be readily apparent. We used the method of the reduction rate to group.

The reduction rate change might not be readily apparent (there is little discrepancy of photo-count in group 8). Groups 3–8 were grouped using their z-scores. Considering the class interval size of each group, we judged where z-scores are more than 4 that were divided into the same group, where z-scores are less than 4 and more than 3 as a group, where z-scores are less than 3 and more than 2 as a group , and so on (see Table III). Finally, we used these methods to divide prefectures and cities into eight groups. We also defined scores of the respective groups: group 1 can get 8 points, group 2 can get 7 points, and so on.

TABLE III. SCORE OF CITY GROUP

Group	Z-scores	Score	City counts
Group 1		8	17
Group 2		7	17
Group 3	Z > 4	6	20
Group 4	4 > Z > 3	5	16
Group 5	3 > Z > 2	4	23
Group 6	2 > Z > 1	3	50
Group 7	1 > Z > 0	2	162
Group 8	Z < 0	1	854

B. Comments' Sentiment

Only viewers' emotions need to be considered. Therefore, we collected the scenic photographs' comments; owner's replies are eliminated from the total comments. We analyzed the comments and extracted the positive comments, as shown in Table IV.

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TABLE V. A PART OF RANKING RESULT

Address	Neighboring tourism attraction	Prefecture group	City group	Favorites	Positive comments	Total comments	Score
2871, Onna, Onna-son Kunigami-gun, Okinawa, 904-0411, Japan	Resort	3	3	1548	56	68	1297.63
Yunohama hotel, 1-2-30, Yunokawacho, Hakodate-shi, Hokkaido, 042-0932, Japan	Hot spring street	2	3	337	13	16	283.94
14-16, Suehirocho, Hakodate-shi, Hokkaido, 040-0053, Japan	Kanemori Red Brick Warehouse	2	3	306	5	10	257.67
510, Tangocho Takano, Kyotango-shi, Kyoto, 627-0221, Japan	---	1	7	187	4	7	157.72
Kendou 388sen, Inuma, Kawanehon-cho Haibara-gun, Shizuoka, 428-0402, Japan	---	4	8	126	46	56	106.66
Sinkawagensi 58, Fukuoka Yatsumiya, Shiroishi-shi, Miyagi, 989-0733, Japan	---	6	8	123	2	4	103.72
Ryuuanzi, Ryoanji Goryonoshitacho, Ukyo-ku Kyoto-shi, Kyoto, 616-8001, Japan	Temple of the Dragon at Peace	1	1	100	6	8	85.76
156, Fumoto, Fujinomiya-shi, Shizuoka, 418-0109, Japan	---	4	7	99	32	39	84.16

TABLE IV. COMMENT COUNTS

	Viewer comments	Owner comments	Sum
Positive comments	1,602	248	1,850
Total comments	2,417	572	2,989

We specifically examine English and Chinese comments by using TextBlob [14] and SnowNLP [15]. The scores of English comments' sentiments were -1 to 1. The Chinese sentiment scores were 0 to 1. The score represents the probability of positive meaning. Moreover, we discovered the English comments' sentiment score of more than 0.3 as best. It can get higher accuracy. Chinese sentiment scores should be greater than 0.4.

C. *Formula of Evaluation*

Considering the definitions of rarely known tourist attractions and data construction, we propose a formula to calculate and rank the photograph scores (S_i).

$$S_i = \sum_{p=1}^{3} F_{pi} W_p + \frac{R_i}{T_i}, 0 < W_p < 1 \; and \; \sum_{p=1}^{3} W_p = 1 \quad (4)$$

In equation (4), F_{1i} represents the prefecture group point; and W_1 is F_{1i} weight. F_{2i} represents a city group point; and W_2 is F_{2i} weight. F_{3i} represents the photographs' favorite counts and W_3 is the F_{3i} weight. R_i represents the positive comment count of the photographs. T_i represents the total comment count of the photographs. In this formula, R_i/T_i is regarded as an additional score because most photographs do not have comments. We supposed the photographs' favorite counts and positive comments as factors of attracting someone to visit. Therefore, we can rank all scenic photographs by this formula, as shown in Table V.

Table V presents some ranking results. The first column is the GPS address of the photograph from Google API. The second column is the neighboring popular tourist attraction. The third and fourth columns are photograph groups (not the group score). The fifth column is the favorite count of photographs. The sixth and seventh columns are counts of the photograph's comments. The last column is the photograph's score calculated using our formula. A high score means that the place deserves travelers to visit. In this table, the address of the first row is a famous resort in Okinawa. Additionally, the second row is a hotel on a famous hot spring street. The third row is a well-known tourist attraction in Hokkaido. The place of the seventh row is a renowned and historical temple in Kyoto. Others are obscure places.

D. *Entropy Weight Method (EWM)*

For this study, we used EWM to set the weights used for the formula. EWM is an objective set weight method because it depends only on the discreteness of data. Actually, EWM is used widely in the fields of engineering, socioeconomic studies, etc. [16]–[18].

In information theory, entropy is a kind of uncertainty measure. When information is larger, uncertainty and entropy will be smaller. Based on the properties of entropy information, we can estimate the randomness of an event and the degree of randomness through calculation of the entropy value. Furthermore, entropy values are used to gauge a sort of discreteness degree of index. When the degree of discreteness is larger, the index affecting the integrated assessment will be greater.

To complete the setting of the formula weights, we require some steps, as described below.

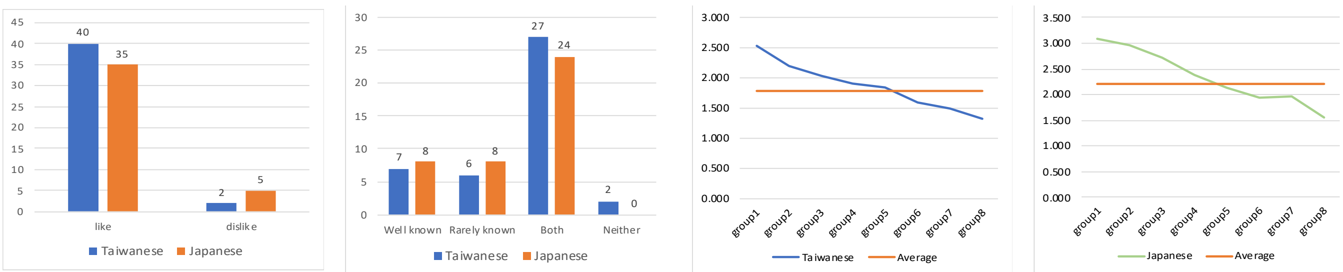
Calculate the ratio (P_{ij}) of the *i*-th index under the *j*-th index. Therein, x_{ij} means the *j*-th index of the *i*-th sample.

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}}, (i = 1, \ldots, n; \; j = 1, \ldots, m) \quad (5)$$

Calculate the entropy value (e_j) of the *j*-th index.

$$e_j = -k \sum_{i=1}^{n} P_{ij} \ln(P_{ij}), (j = 1, \ldots, m; \; k = \frac{1}{\ln(n)} > 0) \quad (6)$$

Calculate the discrepancy of information entropy (d_j).



(a) Travel preference (b) Preference of travel spot (c)Taiwanese score of groups (d) Japanese score of groups

Figure 5. Result of Japanese city questionnaire.

$$d_j = 1 - e_j, (j = 1, \dots, m) \tag{7}$$

Calculate the weight (w_i) of each index.

$$w_i = \frac{d_j}{\sum_{j=1}^{m} d_j}, (j = 1, \dots, m) \tag{8}$$

We analyzed the prefecture group score (F_{1i}), the city group score (F_{2i}), and the favorite counts (F_{3i}) of 2,671 scenic photographs and determined the weight of formula in this research by EWM. In the equations, W_1 is equal to 0.0491; W_2 is equal to 0.1136 and W_3 is equal to 0.8371.

IV. RARELY KNOWN TOURIST ATTRACTION ESTIMATION

A. *Familiarity Level of Japanese City*

We designed a questionnaire and administered it to 42 Taiwanese and 40 Japanese participants to ascertain their level of familiarity with Japanese cities between different nationalities. Surveying levels of familiarity of cities from respondents is difficult. For that reason, we grouped the prefecture and city data. In this way, we were able to select a city's name randomly from each group to decrease the number of questions in the questionnaire. It is easier to investigate which city is unfamiliar to respondents. A rarely known tourist attraction might be included in unfamiliar groups.

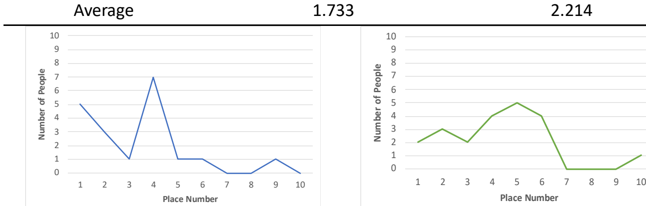
According to the scale of each group, 23 cities' names were selected randomly in this questionnaire. In addition, a few background questions of travel were proposed for respondents (e.g., frequency of travel, age, occupation). We especially investigated respondents' preferences of tourist attractions (e.g., well-known, rarely known).

For these respondents, as shown in Figure 5(a), we observed that 75 respondents like to travel. More than half of the respondents like well-known tourist attractions and rarely known tourist attractions (Figure 5(b)). Respondents were provided with four choices to answer the city questions: (1) I have absolutely no idea; (2) I have heard of this city, but I do not know the relevant tourist attractions; (3) I have heard of this city and know the relevant tourist attractions; (4) I have been to this city. If a respondent chooses option (1) the respondent is assigned 1 point in this question; option (2) can get 2 points, and so on, with higher scores indicating greater familiarity with this city.

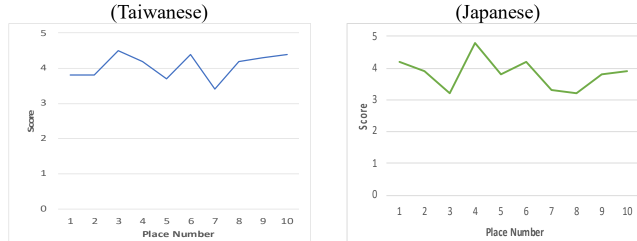
Finally, we calculated the average scores of respective groups, as shown in Table VI. The average represents the city question score (23 questions) average. When the score of a group is less than average, we categorize this group as the rarely known one. Figure 5(c) shows that group 6 – group 8 are unfamiliar to Taiwanese people. Figure 5(d) shows that Japanese people are unfamiliar with group 5 – group 8. We removed the familiar groups from the ranking of Section III as our aim.

TABLE VI. SCORE OF GROUP

Group	Taiwanese	Japanese
Group 1	2.536	3.075
Group 2	2.190	2.950
Group 3	2.204	2.725
Group 4	1.913	2.375
Group 5	1.841	2.125
Group 6	1.595	1.950
Group 7	1.488	1.975
Group 8	1.321	1.544
Average	1.733	2.214



(a) Cognitive level of each place (Taiwanese) (b) Cognitive level of each place (Japanese)



(c) Average score of each place (Taiwanese) (d) Average score of each place (Japanese)

Figure 6. Result of verfication questionnaire.

B. *Verification Experiment*

Based on the discussion presented above, we can ascertain which group is unfamiliar to the Taiwanese (groups 6–8) and to the Japanese (groups 5–8). In this section, we use the questionnaire to verify these rarely known tourist attractions, which are obscure but attractive to respondents.

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For the verification experiment, we extracted the top 10 rarely known tourist attractions (from Taiwanese and Japanese unfamiliar groups) to investigate 10 Taiwanese (who have touristic experience in Japan) and 10 Japanese. Two questions were asked for each attraction: "Do you know this place according to the address?" If respondents probably know this attraction, then the answer is "Yes". The second question is "According to this photograph, do you want to visit this place?" For the second question, respondents can score 1–5 for the attraction, with a higher score indicating greater attraction.

Figure 6 portrays the survey results. Figures 6(a) and 6(b) present how many people know this place. Figures 6(c) and 6(d) explain the level of attractiveness to respondents. In this questionnaire, we observed that each respondent knows two places out of ten on average. For Taiwanese participants, the average score of the places was 4.07. Furthermore, for Japanese participants, the average was 3.83. This result demonstrates that these places were known by a minority of respondents, but they still want to visit there. Results demonstrate that our research was successful.

V. DISCUSSION AND CONCLUSION

People from different countries have distinct familiarity with Japanese cities. We proposed a novel method to ascertain rarely known tourist attractions for people of different nationalities. By collecting and analyzing Flickr photograph information, we classified them into different prefectures and cities. Subsequently, we classified these prefectures and cities into eight groups.

Additionally, we used a questionnaire to survey Taiwanese participants and Japanese participants. We obtained the unfamiliar city groups of Taiwanese and Japanese participants. The scenic photographs were ranked using the formula for this research. We then removed the familiar city groups in the result of ranking for respondent. By a second questionnaire survey, we verified our results. Consequently, through this research, we were able to discover rarely known tourist attractions for travelers.

From the questionnaire survey, we obtained the surprising result that Taiwanese participants are more familiar with Japanese cities than Japanese participants are. The reason might be that Taiwan and Japan are neighboring countries. In addition, air travel from Taiwan to Japan is cheaper, which might lead to higher frequency of Taiwanese taking trips to Japan. We also discovered that most Taiwanese respondents prefer individual travel in Japan to travelling with groups. Furthermore, the questionnaire results demonstrated that income has little to do with travel frequency.

As future work, we expect to collect and analyze more photographs taken in distinct years. Then, we will try to use different methods of grouping and comparing them. Considering more factors of discovering rarely known tourist attractions, we expect to improve the formula used for this research. Rarely known tourist attractions will be classified into different seasons, weather, days, and nights according to photograph times and contents. We also want to provide a personal recommendation service using Collaborative Filtering (CF).

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