ANALYSIS OF TOURIST BEHAVIOR AND INTEREST BY GEOTAGGED PHOTOS

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KEY WORDS: geographic information system, tourism, geotagged photos, clustering, topic model

ABSTRACT: Recently, to avoid excessive concentration at tourism spots, the dispersal of tourists has become important. The dispersal of tourists to an alternative tourism spot that has similar tourist attractions to popular tourism spots can be one of the ways to mitigate overcrowding. Understanding tourists' behavior and interest is helpful in solving this problem. Moreover, it is easy today for users to generate and share data that reflects their interests. This research aims to clarify tourists' behavior with respect to their interests and find a method suitable for data classification. To this end, a spatiotemporal distribution of geotagged photos collected from an online photo-sharing service was utilized. Specifically, photo owners were divided into tourists and residents, with the focus on the spatiotemporal information of photos, and only the former were used for analysis. Labels and their reliability scores were applied to photos using Google Cloud Vision application programming interface; the labels were summarized in a label-appearance table. In this research, two methods were applied to the table. One used the R package ClustOfVar and hierarchical clustering, and the other used a topic model based on Latent Dirichlet Allocation. Hotspots, which were found by P-DBSCAN (one of applications of DBSCAN: density-based spatial clustering of applications with noise) were classified according to photo classification. Hotspots and tourists were classified on the basis of two types of photo classification: ClustOfVar and the topic model. The results show the type of tourism spots, including the popularity of spots, historical spots, and natural spots. Moreover, three tourist types can be identified: tourists who take photos mainly at popular tourism spots, tourists who take photos mainly at less popular spots, and those who take photos of various types of spot.

1. INTRODUCTION

1.1 Background

Recently, to avoid excessive concentration at tourism spots, the dispersal of tourists has become important. The dispersal of tourists to an alternative tourism spot that has similar tourism attractions to popular tourism spots can be one of the ways to mitigate overcrowding. For this purpose, an analysis of tourism behavior is essential.

Nowadays, the social network service (SNS) offers a useful tool for finding tourists' interests. One of the important characteristics of an SNS is that it is possible for users to post information, while official organizations send information through conventional media. Users can post photos and text according to their personal experiences. Thus, SNS posts represent the kinds of subjects that impress and interest users. Many tourists use SNSs as information sources during travel. Their posts related to tourism can be a useful tool for finding tourism spots that match the user's interests.

There is a service called Travel Concierge, provided on the website of the Kyoto City tourism association, which is a service that recommends tourism courses in Kyoto City based on the user's interest. In this service, interest is determined by a range of responses from one to five on the following themes: historic and cultural spots, shopping, and eating. The theme is determined by the users themselves, but it is difficult to set their theme properly. Therefore, it will be useful to create a system to determine a user's interests estimated by photos.

1.2. Objective

This research aims to clarify tourists' behaviors with respect to their interests and find a method suitable for data classification. For this objective, the spatiotemporal distribution of geotagged photos collected from an online photo-sharing service was analyzed. The research framework is illustrated in Figure 1. In Section 2, the photos are collected, and tourists are extracted from the photo owners. In Section 3.1, hotspots are extracted from the photos using P-DBSCAN (one of the applications of DBSCAN: density-based spatial clustering of applications with noise for photos). In Section 3.2, photos are labeled using the Google Cloud Vision application programming interface (API) and clustered by two methods: ClustOfVar and hierarchical clustering, and a topic model based on Latent Dirichlet Allocation (LDA). In Section 3.3, hotspots are classified by the k-means method based on photo classification. In Section 3.4, tourists are classified using the k-means method based on the classification of hotspots.

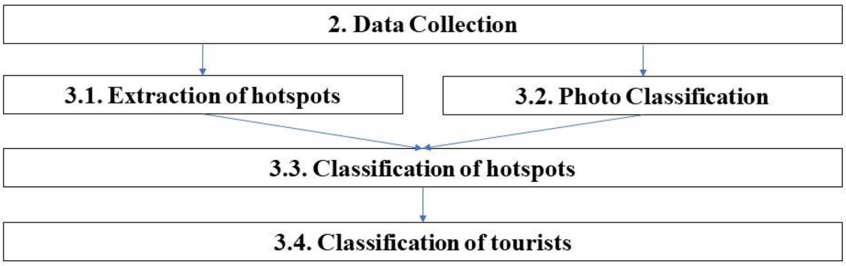

Figure 1: Research Framework

1.3. Related research

Many researchers have analyzed person-trip flows and tourism behavior. Kanno et al. (2018) clarified the difference between international and Japanese tourists on the basis of the places visited. It has been shown that international tourists are more likely to visit popular tourist spots. Kitamura (2019) analyzed where tourists visited by geotagged photos on Flickr with respect to tourists' nationality and tags of posts on Flickr added by users. The tourism characteristics of each prefecture were suggested from the point of view of the characteristics of photos and the visitors' nationalities.

Since SNS has become widespread and users are posting large volumes of data, many researchers have tried to utilize it to explore tourism behavior. Sakuragawa et al. (2015) found places of interest (an area where photos are frequently taken) by using geotagged photos. In that research, tourists and residents were distinguished by certain criteria: one is the length of stay in a certain area. Kurata et al. (2017) created a tourism potential map (plotting hotspots on a map) with respect to the subjects of the photos. The Google Cloud Vision API was used to classify the subjects of the photos. Ishikawa and Kimura (2020) analyzed tourist behavior in the Higashiyama area with respect to tourists' preferences. The research area of our research is the Kansai area, while that of Ishikawa's research area was limited to the Higashiyama area. In small areas such as Higashiyama, tourists' movements and places visited might be affected by chance, affecting the accuracy of the data. The area where tourists intend to visit needs to be determined so that the data reflect their preferences and interests. The novelty of our research lies in the fact that the main target comprises international tourists visiting multiple spots in the Kansai area, with tourism behavior being classified on the basis of tourists' photos.

2. DATA

2.1 Outline

In this study, Flickr was used to collect the photos. Flickr is one of the most popular image-sharing services. Flickr API enables the collection of photos under a variety of conditions. After collecting the photos, photographic subjects were analyzed using the Google Cloud Vision API. This API is an image analysis tool provided by the Google Cloud platform. It has functions for face detection, text detection, and so on. In this study, the label detection function was used to obtain graphical information about the photos.

2.2 Area

Given the background and objectives of the research, the target area needed to be wide and tourism spots dispersed. The Kansai region of Japan is a major tourism area that includes Kyoto, Osaka, and Nara. Tourists do not stay in a single area and move around during travel. International tourists who visit Kyoto also visit Osaka (77.1%) and Nara (51.2%), according to the 2018 Survey on Tourism in Kyoto; such visits can thus be considered part of a popular tourism itinerary in Japan.

In this research, the Kansai region is defined as a rectangular area (from 33.36° to 35.78° north latitude, and from 134.62° to 136.40° east longitude) (Figure 2). Photos taken from 17 popular tourism sites were collected for the extraction of tourists from among the photo owners (Figure 3 and Table 1). The sites were determined by collecting a small number of photos in advance and identifying where many photos were taken. With regard to the date parameters, photos taken between January 1, 2017, and December 31, 2018, were collected on November 25, 2019.

2.3 Extracting tourists

Next, photo owners who were likely to be tourists were selected. To remove photos taken by residents, two conditions were used. The first condition involved the temporal information of the photos, with duration defined as the time difference between the first and last photos taken in a target area. According to a survey by the Japan Tourism Agency (2020), the length of stay of 93.7% of tourists does not exceed 20 days. Users whose duration was longer than 21 days were removed because they were more likely to be residents than tourists. The second condition was the number of areas in which the users took photos. Users had to visit more than two areas for their tourism behavior to be investigated. Users who took photos of a single area were removed.

As a result of data cleansing, the final number of users was 572 (1,528 before the above conditions were applied). These were defined as tourists. To observe their behavior, photos taken in the Kansai region were collected. A total of 45,897 photos were collected by removing photos whose geotags and URLs were missing. Figure 4 shows a heatmap of the photos collected. This shows the areas where many photos were taken.

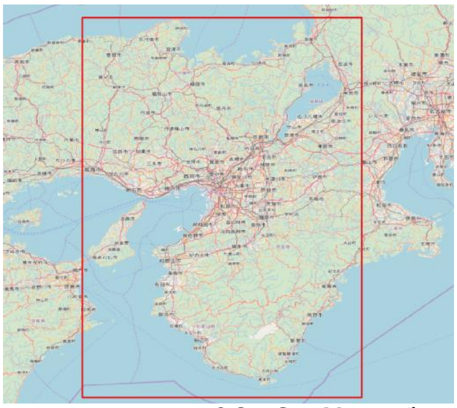

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Figure 2: The research area

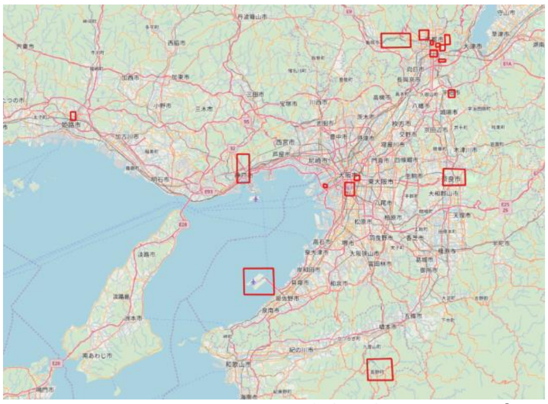

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Figure 3: 17 tourism sites

Table 1: List of tourism sites

Site name	Longitude (°)	Latitude (°)
Himeji	134.68377 - 134.69853	34.82443 - 34.84510
Kōyasan	135.55940 - 135.62920	34.19460 - 34.24710
Kansai International Airport	135.19490 - 135.28080	34.40300 - 34.46600
Kōbe	135.17470 - 135.20940	34.67330 - 34.74290
Namba	135.49240 - 135.52050	34.64230 - 34.67490
Osaka Castle	135.52000 - 135.53570	34.67940 - 34.69160
USJ	135.42920 - 135.43950	34.66190 - 34.67020
Nara	135.78120 - 135.84670	34.66720 - 34.70670
Fushimi-Inari	135.76779 - 135.78888	34.96538 - 34.97139
Higashiyama	135.77193 - 135.78678	34.99230 - 35.00658
Arashiyama	135.60000 - 135.68500	35.00000 - 35.03400
Kawaramachi	135.76110 - 135.77235	35.00126 - 35.01096
Uji	135.79810 - 135.81610	34.88070 - 34.89730
Nanzenji	135.78672 - 135.80037	35.00698 - 35.03073
Nijō Castle	135.74524 - 135.75226	35.00698 - 35.01628
Kinkakuji	135.71096 - 135.73842	35.01891 - 35.04229

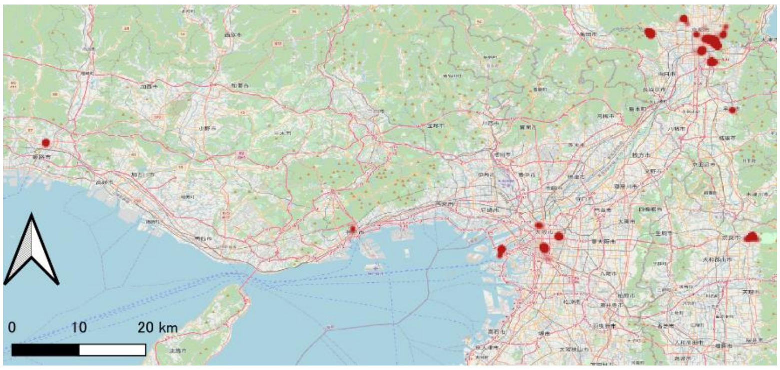


Figure 4: Heatmap of photos, radius=0.01 © OpenStreetMap contributors

3. METHODS

3.1 Extracting hotspots

To analyze tourism behavior, it is essential to identify points of interest (POIs), which are spots that might be interesting to tourists. In this research, hotspots were identified by clustering the spatial distribution of geotagged photos. Hotspots were defined as areas where many tourists take photos and where the POIs of each user clustered. To find hotspots, some research has applied DBSCAN, which can discover arbitrarily shaped clusters and outliers for clustering geotagged photos. The DBSCAN proceeds as follows. First, the number of points within a distance of ε from an arbitrary point p is counted. If this exceeds *minPts*, the point p is regarded as the core and the other points are reachable points. Second, the same procedure is conducted for all reachable points, and if true, the point becomes a new core of the cluster with core p. Third, the same procedure is repeated until all points are marked as certain clusters or noise. However, if all the photos in a cluster are taken by a single tourist, the cluster should not be a hotspot.

P-DBSCAN (Kisilevich et al., 2010) is a variation of DBSCAN developed for analyzing geotagged photos. P-DBSCAN has three parameters: neighborhood radius (*eps*), minimum number of owners (*MinOwners*), and adaptive density threshold (*Addt*). The *eps* was the same as that of DBSCAN. *MinOwners* is similar to *minPts* in DBSCAN. If the number of photo-owning neighbors of the core photo is less than that of *MinOwners*, neighboring photos are not considered as being included in the core of the cluster. *Addt* refers to adaptive density, which is a novel concept of P-DBSCAN. Adaptive density is useful for fast convergence toward high-density areas. Density is defined as the number of owners who take neighboring photos, and the density ratio is defined as the ratio of the density of a photo point p to the previous photo point. The neighbors of the photo are not considered as clusters if the density ratio is less than *Addt*.

3.2 Photo classification

3.2.1. Labeling photos: For each photo, a maximum of 20 labels were assigned by the Google Cloud Vision API, and 5,686 types of label were detected (Table 2 shows frequent labels). Frequent labels show the general features of the photos. There were 1,551 labels that appeared only once, and 4,336 labels appeared less than 21 times. Most of these had low reliability scores and specialized words (such as scientific names of animals or plants and names of foods). These were removed, and the remaining 1,350 labels were used.

A label-appearance table was generated for the analysis. The row represents each photo and the column represents the labels. For each photo, a reliability score was applied for the labels appearing in the above analysis, and 0 was applied for labels that did not appear. This label-appearance table is difficult to analyze because it is a sparse matrix. Therefore, it is essential to reduce the number of variables. In this research, classification of photos was performed using two methods: ClustOfVar and hierarchical clustering comprised one method, and the other was a topic model based on LDA.

Table 2: Top 7 frequent labels

	Architecture	Building	Tree	Plant	Temple	Tourism	Sky
Number of photos	20,994	19,218	18,753	16,586	14,724	14,228	11,533

3.2.2 ClustOfVar: ClustOfVar (Chavent et al., 2012) is an R package for arranging variables into clusters hierarchically, in which the variables are strongly related to each other. In this method, variables are classified into clusters so that the sum of the correlation ratios of any set of two variables in the cluster is maximized. This enables the clustering of labels with similar meanings (Table 3). Labels were classified into 150 clusters, which were determined by the aggregation levels of hierarchical clustering. The points of each cluster were calculated as the linear sum of the squared loading and reliability scores of the labels.

On the basis of the scores of the variable clusters, hierarchical clustering using Ward's method with cosine similarity was conducted. The number of clusters was 32, determined using the Jain-Dubes method. The Jain-Dubes method is used to determine the number of clusters for hierarchical clustering.

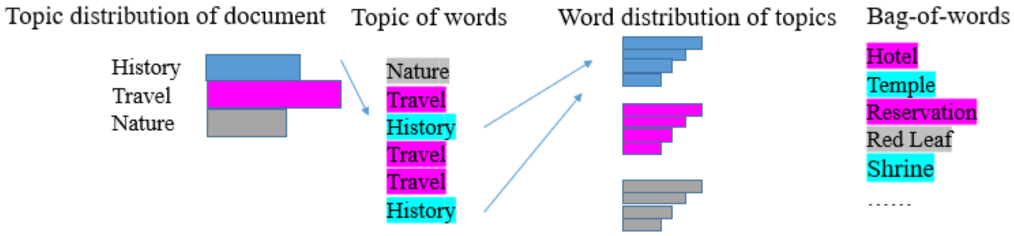
Table 3: Part of the result of clustering labels

Label	Squared loading	Correlation
Place of worship	0.803	-0.896
Japanese architecture	0.755	-0.869
Chinese architecture	0.750	-0.866
Shrine	0.748	-0.865

3.2.3 Topic model: The topic model is a method of unsupervised classification, which is often used in text mining. This model is supported by the following two basic concepts: Every document is a mixture of topics, and each topic is a mixture of words (Figure 5). Under these assumptions, the features of documents are estimated from the combinations of topics that are obtained from the combinations of words. LDA (Blei et al., 2003) is one of the most common algorithms for topic models. LDA assumes that the probabilistic distribution of topics and words follows a Dirichlet distribution. The topic distribution for each document (topic mixing ratio) was calculated by estimating the parameters of the Dirichlet distribution.

In this research, documents are considered as photos, words are considered as labels, and frequencies of words are considered as reliability scores to apply the topic model. The topic mixing ratio was calculated for each photo, and photos were classified by the topic with the largest mixing ratio. The number of topics was determined to be 21 according to "perplexity," which is an index for estimating the optimal number of topics.

Figure 5: An illustration of topic model



3.2.4 Verification of the contents of the cluster: To check the contents of the cluster, tf-idf is calculated for each label in the cluster. This is an index used to extract feature words from a document. Tf-idf is the product of tf (term frequency) and idf (inverse document frequency). The value of label *i* in cluster *j* is defined as follows.

$$tf_{ij} = \frac{\text{summation of reliability score of label } t_i \text{ in cluster } d_j}{\text{number of labels in cluster } d_j} \quad (1)$$

$$idf_i = \log \frac{\text{number of clusters}}{\text{number of clusters that include the label } t_i} \quad (2)$$

$$tf\text{-}idf_{ij} = tf_{ij} \cdot idf_i \quad (3)$$

where, d_i: cluster i in the set of clusters d

t_j: label j in the set of labels t

The greater the value of tf-idf, the more representative the label describing the contents of the cluster, because the label appears in the cluster and appears less in other clusters. In this research, clusters are described by checking some labels with the largest tf-idf and checking some photos by sight.

3.3 Classification of hotspots

The hotspots were classified on the basis of the results of the photo classification. Different procedures were applied to calculate the photo cluster table. In the ClustOfVar method, photos belong to a single cluster. The composition ratio of the photos was calculated and clustered for each hotspot.

In the topic model method, The mixing ratio is used for classification because photos comprise to multiple topics. The sum of the composition ratio of each topic for photos in a hotspot was calculated and used as the photo cluster table. Hotspot classification was performed using the k-means method. The number of clusters was established at nine using the elbow method.

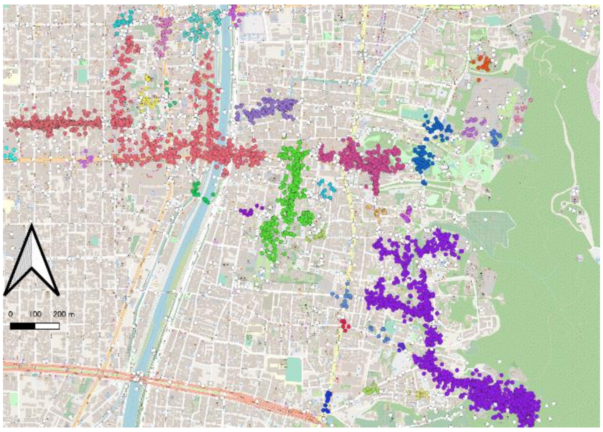
3.4 Classification of tourists

On the basis of the hotspot classification, tourists were classified using the k-means method. The composition ratio of the POI type was calculated for each tourist. The number of clusters was established at seven using the elbow method.

4. RESULT

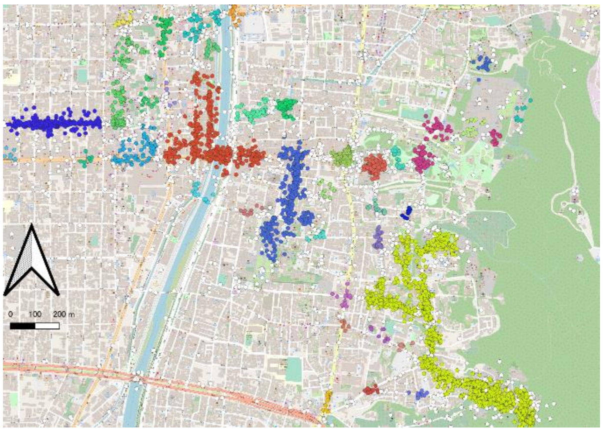
4.1 Extracting hotspots

Figure 6 shows the results of the P-DBSCAN with parameters in the Higashiyama-Kawaramachi area, Kyoto. "The number of photos clustered" means that photos not classified are the noise. It is shown that the smaller the *eps* and the larger the *Addt*, the fewer the number of photos and the greater the number of hotspots. In Figure 5 (c), most photos in this area belong to a single cluster because the *eps* was so large. By contrast, Figure 5 (a) and (b) contain multiple hotspots. Hotspots that are too large prevent identification of tourist spots and in hotspots that are too small, the noise becomes excessively large, so the size of the hotspot needs to be set properly. That is, the number of clustered photos needs to be as large as possible, and the number of hotspots needs to be as large as possible. In this study, the parameters in Figure 5 (a) were used for the analysis.



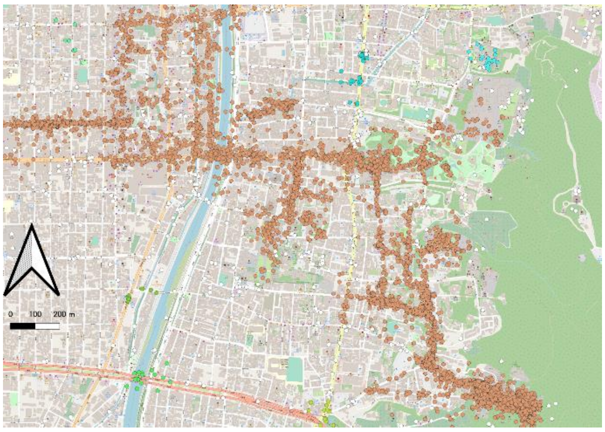
(a)

eps	0.0005
Addt	0.1
Number of hotspots	276
Number of photos clustered	24,774
Number of photos per hotspot	89.8



(b)

eps	0.0005
Addt	0.3
Number of hotspots	293
Number of photos clustered	23,725
Number of photos per hotspot	81.0



(c)

eps	0.001
Addt	0.1
Number of hotspots	165
Number of photos clustered	30,583
Number of photos per hotspot	185.4

Figure 6: Classification of hotspots with different parameters around the Higashiyama-Kawaramachi area, Kyoto

4.2 Photo classification

Table 4 shows the number of photos and brief descriptions of the clusters based on the contents of the photos and tf-idf by ClustOfVar. The name of each cluster was determined using the labels with the largest tf-idf (Table 5). For example, there was the cluster containing the labels "ingredient" and "dish" with the largest tf-idf, and the meanings of these labels were related to food. Moreover, checking the photos by sight indicated that the main contents of the photos were food. Therefore, the cluster was named "food." Photos in "history" cluster accounted for 12% of the photos, which shows the importance of historical heritage in the area. In addition, the cluster "flower", "cherry", and "red leaf" implies the importance of natural spots, they sometimes combine to historical spots. However, there were clusters in which the contents of photos could not be described using feature labels.

Table 6 presents the descriptions of the topics of photos using the topic model. The number of topics is smaller than the number of clusters using the ClustOfVar method because the contents of the photos are represented as a combination of topics. The table indicates the topic with the largest topic mixing ratio for each photo. Note that this photo classification is insufficient if there are topics with a close topic mixing ratio. This is because this table does not consider photos with a combination of topics.

Table 4: Description of clusters by ClustOfVar

Name	Number of photos	%	Name	Number of photos	%	Name	Number of photos	%
History	5,433	12.3	Night	1,056	2.4	Statue	757	1.7
Food	2,194	5.0	Animal	973	2.2	Advertisement	715	1.6
Water	2,004	4.5	Railway	965	2.2	Room	687	1.6
Face	1,983	4.5	Boat	920	2.1	Mountain	667	1.5
Flower	1,621	3.7	Furniture	915	2.1	Shoes	654	1.5
Downtown	1,527	3.5	House	910	2.1	Kimono	559	1.3
Cherry	1,419	3.2	Text	899	2.0	Vehicle	510	1.2
Other	1,379	3.1	Castle	883	2.0	Trail	453	1.0
Metropolitan	1,357	3.1	Crowd	801	1.8	Snow	323	0.7
Red leaf	1,336	3.0	Yard	787	1.8	Other	7,475	16.9
Plant	1,249	2.8	Market	780	1.8			

Table 5: Part of cluster names and labels with largest tf-idf by ClustOfVar

Name	Label with largest tf-idf	Label with second largest tf-idf
History	Chinese architecture	Pagoda
Food	Ingredient	Dish
Water	Water resources	Body of water
Face	Face	Selfie
Flower	Flowering plant	Field
Downtown	Human settlement	Pedestrian crossing
Cherry	Prunus	Flowering plant

Table 6: Description of topics by topic model

Name	Number of photos	%	Name	Number of photos	%	Name	Number of photos	%
History	6,970	15.77	Plant	2,287	5.18	Others	1,182	2.67
Flower	4,578	10.36	House	2,127	4.81	City, Road	1,140	2.58
Road	2,772	6.27	Metropolitan	2,118	4.79	Night	1,031	2.33
Crowd	2,726	6.17	Transportation	2,018	4.57	Mountain	941	2.13
Food	2,516	5.69	Water	1,941	4.39	Tree	719	1.63
Room	2,383	5.39	Art	1,673	3.79	Sky	628	1.42
Person	2,352	5.32	Animal	1,658	3.75	Stone	431	0.98

4.3 Classification of hotspots

Table 7 shows the results of hotspot classification based on the two methods of photo classification. The description of hotspots was determined by the composition ratio of the photo classification. Clusters such as "history," "water," and "flower" were found in both methods. These are resources popular with tourists in the Kansai area. In addition, there are clusters defined as "balanced," "history_mixed," and "others" for both methods, the characteristics of which are difficult to identify. They contain a large number of photos, as shown in the number of photos per hotspot. This implies that they are popular tourist spots and that they contain various kinds of photos. These hotspots seemed to be classified properly in both methods.

On the other hand, there are clusters that exist in one method but not in the other, such as the clusters "character" and "city" in ClustOfVar, and the cluster "transportation" and "nature" in the topic model. In ClustOfVar, the cluster "character" is found mainly at Universal Studios Japan and the Kyoto Railway Museum, and the cluster "city" is a cityscape mainly around Osaka and Kyoto stations. In the topic model, the cluster "transportation" is mainly in the Kyoto Railway Museum and Shin-Osaka station, and the cluster "nature" is mainly around Arashiyama and Ginkakuji Temple. Comparatively, the method using the topic model has a better classification because the contents of hotspots seem to be clear in the photos in this method.

Table 7: Description of hotspot classifications by ClustOfVar (left) and topic model (right)

Name	Number of hotspots	Number of photos	number of photos per hotspot	Name	Number of hotspots	Number of photos	Number of photos per hotspot
Others	73	6,091	83.4	Balanced	72	5,728	79.6
Balanced	54	8,956	165.9	Food	41	2,590	63.2
Character	35	1,635	46.7	History_mixed	39	8,998	230.7
History	32	3,856	120.5	Flower	26	918	35.3
Food	25	1,088	43.5	Transportation	24	607	25.3
Water	24	1,527	63.6	History	22	2,449	111.3
City	16	729	45.6	Water	22	636	28.9
Animal	10	553	55.3	Nature	19	1,911	100.6
Flower	7	339	48.4	Animal	11	937	85.2

4.4 Classification of tourists

Table 8 shows the results of tourist classification using ClustOfVar. A detailed description is shown below, which is estimated by plotting photos on the map. Tourists of Cluster 1 take photos at various spots, regardless of whether the spot is popular or not or historical or modern. Tourists of Cluster 2 take photos mainly at popular spots, such as Kiyomizu Temple, Fushimi-Inari Shrine in Kyoto, and Dōtonbori in Osaka. These spots are representative of the research area, so they emphasize photos being taken at popular spots. Tourists of Cluster 4 take photos mainly at Kitano Shrine and Ginkakuji Temple, which are famous for their beautiful gardens. Tourists in Cluster 6 took photos mainly at Universal Studios Japan, the Namba area, and Fushimi-Inari Shrine. Cluster 7 shows similar trends to Cluster 2, but spots where photos were taken were limited because the number of photos was small. On the basis of the results, three types of tourist can be identified: (a) tourists who mainly take photos at various types of spot regardless of their popularity (Clusters 1 and 5); (b) tourists who take photos mainly at popular spots (Clusters 2, 3, and 7); and (c) tourists who take photos mainly at less popular spots (Clusters 4 and 6).

Table 8: Tourist classification by ClustOfVar

No.	Number of owners	Number of photos	Characteristics of distribution
1	149	18,546	Taken in various spots
2	119	13,142	Mainly in popular, historical spots
3	87	5,019	Mainly in popular spots
4	57	2,403	Mainly taken in Osaka
5	53	1,124	Similar to Cluster 1
6	42	3,456	Mainly taken in Osaka
7	35	501	Similar to Cluster 2, mainly at Fushimi-Inari Shrine

Table 9: Tourist classification by the topic model

No.	Number of owners	Number of photos	Characteristics of distribution
1	167	25,510	Taken in various spots
2	132	8,598	Mainly popular spots in Kyoto
3	66	2,359	Mainly at natural spots
4	57	3,648	Mainly at Universal Studios Japan
5	56	1,310	Mainly at Fushimi-Inari Shrine
6	50	2,174	Mainly at Namba
7	14	592	Mainly at Kaiyūkan (Aquarium)

Different trends were observed using the topic model (Table 9). There is a cluster of tourists who take photos at various spots similar to Cluster 1 by ClustOfVar, but the other clusters show different trends. The model suggests tourists who visit a certain area, such as Universal Studios Japan, Namba, or Fushimi-Inari.

5. DISCUSSION

Hotspots were identified from photos using P-DBSCAN. The parameters were adjusted for separate each spot, but some hotspots were too large and there were too many photos clustered as noise. Further improvements can be expected by adjusting the parameters more precisely.

Photos were classified using two methods: one method used ClustOfVar and hierarchical clustering, and the other used a topic model based on LDA. The characteristics of the research area can be clarified: historical spots are the most important, and natural spots were composed of locations featuring cherry blossom and red leaves. The results of the classification were different for each method in terms of the number of photos and names of clusters, due to the method of determining the topics in the topic model.

For hotspot classification, the topic model method was better than ClustOfVar. This was because the topic model approach showed the composition ratio of the topics, whereas hierarchical clustering gave unique clusters for each photo. The topic model approach is considered to have a low information loss rate. Popular spots were indicated as a result of the classification method, and historical spots or modern spots were classified, two important outcomes.

Seven clusters were found for tourist classification. Tourists can be divided into three groups: (a) tourists who visit both popular tourist spots and less popular tourist spots; (b) tourists who mainly visit popular tourist spots; and (c) tourists who mainly visit less popular tourist spots. However, it is believed that the number of clusters is not sufficient in the topic model because different trends can be observed from the ClustOfVar method.

Different approaches for each type of tourist are important for tourist dispersal. For type (a) tourists, recommending alternative tourism spots might be effective for dispersal, because they will be interested in a wide range of spots. Tourists of type (b) seem to have an interest in popular spots, so temporal dispersal will be effective. It does not seem to be necessary to promote dispersal for tourists of type (c) since they do not visit popular areas.

6. CONCLUSION

In this study, tourist behavior and interest were researched using geotagged photos in the Kansai area. Photos were classified into clusters, and the characteristics of tourist spots (historical spots, natural spots, popular spots, etc.) were clarified only by the contents and positional information of photos. Tourists were classified into three main groups, and it was possible to suggest appropriate dispersal measures, such as temporal and spatial dispersal.

By comparing the two methods, the method by topic model showed better results in photo and hotspot classification than in tourist classification. The topic model method should be used for further analysis, but it is necessary to improve the method of classification.

The results will be used for future analysis, applying the model to new users and analyzing their interests. Recommendation will be made for new users on the basis of their interest estimated by their photos with considering dispersion of tourism spots.

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