Regression Analysis of Tourist Photographic Activity Using Geo-tagged Photos and GPS Trajectory

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\textbf{ABSTRACT}

Nowadays, many photos are posted on social photo sharing web sites (e.g. Flickr, Instagram). The number of the shared geo-tag photos in a certain attraction does not correlate to the number of visitors because the photographic activity is influenced by multiple factors. The estimation of the number of tourists in a certain attraction from the geo-tagged photos is useful for marketing and tourism policy making. In this paper, from the viewpoint of tourism information, we propose a photographic activity model to estimate the number of tourists in the attraction and examine the model by using the regression analysis. We analyze the dataset consists of GPS trajectory and the photographic history of foreign tourists who traveled in Kyoto area in Japan. As the results, we show that the proposed photographic activity model indicates high goodness-of-fit and correlation to the dataset.

\textbf{KEYWORDS}

GPS, tourism informatics, photo, smartphone, social photo sharing, regression analysis, correlation

\section{INTRODUCTION}

Nowadays, many photos are posted on social photo sharing web sites (e.g. Flickr [1], Instagram [2]). The shared photo has a photo ID, a photographer ID and a geo-tag that indicates the shooting location (latitude and longitude) as metadata. Shared geo-tagged photos can be assumed as a sequence of the photographer’s trajectory, and they are used for various researches. For examples in the tourism informatics field, travel route recommendation [3-5], tourist interest map [6-10], analysis of travel pattern of tourists [11-12], forecasting tourists’ characteristics [13], and attraction mining [14-18] are proposed.

The estimation of the number of tourists in a certain attraction from the geo-tagged photos is socially useful. For examples, tourists industry wants to estimate the number of tourists for marketing. The local governments use the estimation for their tourism policy making in the area. However, the number of shared geo-tag photos does not correlate to the number of visited tourists in the attraction because the photographic activity is influenced by multiple factors. In a photogenic attraction with beautiful scenery (e.g. Kinkaku-Ji Temple), tourists may take more photo than those in the other attractions. Some tourists tend to take more photos than the other tourists even if they visit the same attraction. Furthermore, tourists do not always post their photos in social photo sharing website. Thus, we investigate the photographic activity for estimating the number of visited tourists in a certain attraction.

In this paper, we propose a new photographic activity model to estimate the number of tourists and examine the model by using regression analysis with other GPS photography dataset. As the dataset, we use foreign tourists’ GPS trajectory and geo-tagged photos that are collected with GPS smartphones in our field experiments.

In section 2, as the related works, we introduce researches about visualization of photographer’s...
interest and GPS data mining. In section 3, we describe the proposed photographic activity model and the overview of the GPS dataset, and introduce the process of computing the regression analysis and the correlation of the proposed model. In section 4, we show the result of the experiments. In section 5, we discuss the photogenic factor of the proposed model. In section 6, we conclude the paper.

2 Related Works

2.1 Visualization of interest

The geo-tagged photos show location where photographers have been interested. Some researchers try to visualize photographers’ interest. Some methods [7-10] focus on selecting representative photos for the locations where the photographers are interested by using the features of the photos and geospatially clustering. The other method tries to map density of the geo-tagged photos by using kernel density estimation [6]. Some researchers investigate travel route recommendations using the interests extracted from the geo-tagged photos [3-5].

These papers focus on the interest. They equate the number of the geo-tagged photos with the number of tourists or do not analyze the number of tourists. Our research shows that the rank correlation between the number of photos and the number of tourists is not high.

2.2 GPS data mining

We mine the tourist activity data from GPS trajectory data and the geo-tagged photos. Some researchers study the data mining of the tourism attractions from GPS data where many people visit [14-18]. Clustering (e.g. mean shift [19], k-means) is a popular method for detecting the attractions from the GPS data. In our research, we determine the number of tourists by point-to-polygon spatial matching [20] with the geo-tagged photos and positional information of attractions. We use the address of the attractions in survey area as the positional information.

The other researcher studies determining tourist’s transportation modes from the GPS trajectories [21]. We refer the mode determination methods for an error correction of the dataset. Some researchers investigate tourists’ travel pattern [11-12] and tourists’ characteristics [13]. In these papers, they focus on mining the transitions among the attractions and they do not deal with the photographic activity.

3 PHOTOGRAPHIC ACTIVITY MODEL

3.1 Definition of Photographic Activity

The number of photos at a certain attraction depends on each tourist’s photographic characteristic and degree of photogenic of each attraction. For example, tourist A takes 100 photos in a day at 5 attractions, and tourist B takes 10 photos in a day at the same attractions. In this case, the number of photos in the attraction is more influenced by tourist A than tourist B (Tourist factor). The total number of photos is influenced by the difference of the photographic characteristics. At a photogenic attraction (e.g. Mt. Fuji), the number of photos may be more than that of the other non-photogenic attractions (Photogenic factor). Based on these assumptions, we describe the relation between the number of photos and the number of visited tourists in the attraction as following equation (1).

\[ V_i = tgP_i + c \]

\[ P : \text{Number of photos in } i \]
\[ V : \text{Number of visited tourists in } i \]
\[ t : \text{Tourist factor} \]
\[ g : \text{Photogenic factor} \]
\[ i : \text{Attractions index} \]
\[ c : \text{Constant} \]

The number of photos and the number of visited tourists who take photos can be known by using the shared geo-tagged photos. However, the total number of visited tourists cannot be known by the shared geo-tagged photos. In our research, we analyze the tourist factor and the photogenic factor through the other GPS dataset collected in our field experiments. We compute the regression analysis of the GPS dataset.
3.2 Overview of ‘Foreigner 2008’ Dataset

In this section, we describe the overview of dataset.

We use a dataset that is collected in the experimental project in Kyoto area in 2008. The dataset is called ‘Foreigner 2008.’ The ‘Foreigner 2008’ dataset contains the tourists GPS trajectories and the photography history.

Respondents of the ‘Foreigner 2008’ dataset are foreign tourists who stayed over 1 night in Kyoto city in 2008. The respondent carry a smartphone with GPS sensor and a camera, and the smartphone records the GPS trajectories and the geo-tagged photography history all the day. The interval of GPS data recording is 2 minutes. In case of group travel, only 1 smartphone is carried by group leader. The number of the effective respondents is 507. Nationalities of the respondents are shown in Table 1. The number of visited tourists does not equal to the number of tourists take photos because all tourists do not take a photo in the visited attraction.

The respondents visit the attractions around the Kyoto area, including Kyoto, Osaka, Nara, Shiga, and Hyogo prefectures. Kyoto is one of the largest tourism destinations in Japan, and approximately 50 million tourists visit in a year. Among the tourists, 1 million are from foreign countries. GPS trajectories are plotted in figure 1. Green circles mean the points of trajectory and orange circles mean the points of photography. Kyoto/Shiga is located in the northern part of the figure. Nara is located in the southern east part, and Osaka/Hyogo is located in the southern west part. 200 famous attractions located in Kyoto area are selected as subjects of the analysis. As the attraction, temples (e.g. Golden Pavillon (Kinkaku-Ji), Ginkaku-Ji), shrines (e.g. Fushimi-Inari Shrine), palaces (e.g. Kyoto-Gosho Palace), parks, museums, shopping centers and central stations (e.g. Kyoto station, Osaka Station) are selected. The attraction is defined as the polygon on the geospatial space as purple area depicted in figure 2 that shows the central area in Kyoto City.

For the proposed method, we use tourists’ GPS trajectory and photography history all the day during their trip in a destination area. GPS trajectory should include time, latitude and

<table>
<thead>
<tr>
<th>Nationality</th>
<th>Population</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australia</td>
<td>111</td>
<td>22%</td>
</tr>
<tr>
<td>USA</td>
<td>101</td>
<td>20%</td>
</tr>
<tr>
<td>German</td>
<td>31</td>
<td>6%</td>
</tr>
<tr>
<td>UK</td>
<td>30</td>
<td>6%</td>
</tr>
<tr>
<td>Singapore</td>
<td>30</td>
<td>6%</td>
</tr>
<tr>
<td>China (incl. Taiwan)</td>
<td>28</td>
<td>6%</td>
</tr>
<tr>
<td>Canada</td>
<td>26</td>
<td>5%</td>
</tr>
<tr>
<td>Other</td>
<td>150</td>
<td>30%</td>
</tr>
<tr>
<td><strong>Sum</strong></td>
<td><strong>507</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

Table 1. Nationality of Respondents

Figure 1. Survey Area of Dataset 'Foreigner 2008'

Figure 2. Trajectory and Photographic Points in Kyoto City Central Area.
longitude. Photography history should include photo, shooting time, latitude and longitude. Recent multifunctional smartphones (e.g. iPhone) equip a camera and a GPS. We use the functions for collecting data. The number of photos and the number of visited tourists are extracted from the dataset by matching with attractions’ spatial information and tourists’ GPS trajectories, or the photography history. ‘Foreigner 2008’ dataset is suitable to our purpose.

3.3 Data Extraction from Dataset

In this section, we describe the way of data extraction from the dataset ‘Foreigner 2008.’ Framework of the data extraction is depicted in figure 3.

1) Data Extraction

We focus on visiting order of the tourism attractions in this research. We apply point-in-polygon spatial matching method [20] that uses published positional information of attractions.

By using the spatial analysis function of GIS application, we extract the points of photography within the range of any attraction polygons, and count the number of photos in each attraction. In a similar way, we count the number of visited tourists by the spatial matching with the GPS trajectory and the attractions. As the GIS application, we use ArcGIS 10.1. ArcGIS is one of the most popular GIS applications.

2) Error Correction

GPS data include noises caused by propagation delay and other factors [22]. GPS devices equipped in the smartphones provide low accuracy GPS data. The error correction process is necessary for GPS position estimation. Position estimation methods using stochastic process (e.g. Kalman filter [23], particle filter [24]) are popularly used. In this paper, we do not use these methods because the data recording interval of the dataset is too long to use them. Instead of these filters, we correct the data by two filtering methods, one uses the speed constraint that the speed of tourists’ transportation devices are limited, and the other uses the time constraint that the tourists spend a block of time for sightseeing at each attraction.

As the speed filtering, if the speed of the tourist is estimated too high in an attraction, the data is filtered. In the attractions, most of tourists travel on foot. Therefore, the threshold can be decided based on the speed of transportation devices [21]. As the time filtering, when the period of the staying time at each attraction is too short, the data is considered as ‘moving’. Threshold of duration can be decided based on the shortest periods of standard time for the attraction sightseeing. In the experiment, we adopt 10 minutes as the threshold by referring to some commercial guidebooks and websites for the tourists who visit Kyoto area.

3.4 Correlation and Regression Analysis

Based on the extracted data, we calculate the linear regression analysis and the correlation coefficient for evaluating the proposed model.

Firstly, we describe the linear regression. The number of visited tourists ($V$) is chosen as a dependent variable, and the number of photos ($P$) is chosen as an explanatory variable. As described in equation (1), the coefficient $tg$ of explanatory variable $P$ is product of tourist factor $t$ and photogenic factor $g$. Tourist factor $t$ is defined as the ratio of the total number of photos taken in the attraction $i$ to the number of photos that each tourist takes. Therefore, equation (1) can be replaced to the equation (3) by normalized $P'$.
described in equation (2). \( P_{ij} \) means the number of photos that the tourist \( j \) takes at the attraction \( i \). As photogenic factor \( g \), we assume that this is the inverse of \( A_{\nu} \). \( A_{\nu} \) means the average number of photos per visited tourists. Therefore the equation (3) is replaced to equation (4). We call this VNPA model.

\[
P'_i = \sum_j \left( \frac{P_{ij}}{\sum_i P_{ij}} \right)
\]

(2)

\( i \): Attraction Index \((i = 1, \ldots, T)\)
\( j \): Tourist Index \((j = 1, \ldots, K)\)
\( K \): The number of all attractions
\( T \): The number of all tourists

\[
V_i = gP'_i + c
\]

(3)

\[
V_i = \frac{1}{A_{\nu}} P'_i + c
\]

(4)

Secondly, as the correlation coefficient \( \tau \), we use Kendall tau rank correlation coefficient [25]. \( \tau \) is described as the division of the difference of the number of concordant pairs \( R \) and the number of discordant pairs of the two variables by the number of combination of all item of the variables. A concordant pair is formed in a joint distribution that is ranked in the same order on both variables. In this case, the variables are the number of the visited tourists \( V \) and the number of photos \( P \) or normalized \( P' \). If \( V_a > V_b \) and \( P_a > P_b \), the pair \((a, b)\) is concordant. If \( V_a > V_b \) and \( P_a < P_b \), the pair \((a, b)\) is discordant. From the definition of the concordant pair, the number of the discordant pair is the difference of the number of all combination and the number of concordant pairs. \( \tau \) is described in equation (5).

\[
\tau = \frac{R - \left( \frac{1}{2} n(n-1) - R \right)}{\frac{1}{2} n(n-1)}
\]

(5)

\( R \): Number of concordant pairs
\( n \): Number of items the dataset includes

(in this case, number of attractions \( j \))
4 RESULTS OF EXPERIMENTS

We examine the proposed photographic activity model by using regression analysis with the dataset 'Foreigner 2008.' For statistical computing, we use the R that is a free environment for statistical computing.

The relation between the number of visited tourists $V$ and the number of photos $P$, and the result of the regression analysis are depicted in figure 4. We call this VP model. The coefficient of determination (adjusted R squared) is 0.7244, and the correlation coefficient $\tau$ is 0.6291. In case of the relation between $V$ and normalized $P$ ($P'$) as depicted in Figure 5, the p-value is $2.2 \times 10^{-16}$, and is less than 0.01. There is a significant relationship. We call this VNP model. The adjusted R squared is 0.9231, and the correlation coefficient $\tau$ is 0.7006. In case of the VNPA model, the p-value is $2.2 \times 10^{-16}$, and is less than 0.01. There is a significant relationship. The adjusted R squared is 0.8797. The data point fits the VNPA model better than the VP model, but fits worse than the VNP model.

As the results, the VNPA model indicates higher goodness-of-fit in the dataset and the correlation coefficient than that of the VP model. Although the goodness-of-fit of VNPA model is worse than that of the VNP model, the goodness-of-fit of the VNPA model is sufficiently high. Therefore, we demonstrate that we can estimate the number of visited tourists in the attraction by using the VNPA model.

5 PHOTOGENIC FACTOR

In this section, we discuss the element of photographic factor $g$.

For comparison, the ranking of the data is described in Table 2. Table 2 show top 10 attractions from the most number of total visited tourists $V$, total number of photos $P$ and the normalized total number of photos $P'$, and $P'/Av$. Italic-font item means that the attraction is not included in top-10 of $V$.

In $P$, 6 attractions of top 10 are included in top 10 attractions of $V$. For $P'$, 8 attractions is the same. For $P'/Av$, all attractions are the same as those of $V$. The different attractions between $P$ and $V$ are ‘Todai-Ji Temple (in Nara City),’ ‘Tofuku-Ji Temple,’ ‘Fushimi-Inari Shrine,’ ‘Heian-Jingu Shrine.’ Since the tourist factor $t$ is removed from $P$ in equation (3) by normalization, only ‘Fushimi-Inari Shrine’ and ‘Todai-Ji Temple’ are different between $P'$ and $V$.

For understanding the photogenic factor, we show some examples of the photos that are taken in ‘Fushimi-Inari Shrine’ and ‘Todai-Ji Temple’. ‘Todai-Ji Temple’ is famous for the Great Buddha statue, and many deer are roaming about in the park. The tourists take many photos of deer (Figure 7). ‘Fushimi-Inari Shrine’ is famous for many Shinto vermeil gateways, called Torii, and

<table>
<thead>
<tr>
<th>Visited Tourists ($V$)</th>
<th>Total Photo ($P$)</th>
<th>Normalized P ($P'$)</th>
<th>Normalized P ($P'/Av$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Kyoto Station</td>
<td>Kyoto-Gosho Palace</td>
<td>Kyoto Station</td>
<td>Kyoto Station</td>
</tr>
<tr>
<td>2 Kinkaku-Ji Temple</td>
<td>Kinkaku-Ji Temple</td>
<td>Kiyomizu-Dera Temple</td>
<td>Kinkaku-Ji Temple le</td>
</tr>
<tr>
<td>3 Kiyomizu-Dera Temple</td>
<td>Kiyomizu-Dera Temple</td>
<td>Kinkaku-Ji Temple</td>
<td>Kiyomizu-Dera Temp</td>
</tr>
<tr>
<td>4 Kyoto-Gosho Palace</td>
<td>Nijo-Jo Castle</td>
<td>Kyoto-Gosho Palace</td>
<td>Kyoto-Gosho Palace</td>
</tr>
<tr>
<td>5 Nijo-Jo Castle</td>
<td>Kyoto Station</td>
<td>Nijo-Jo Castle</td>
<td>Shin Kyogoku Street</td>
</tr>
<tr>
<td>6 ShinKyogoku Street</td>
<td>Todai-Ji Temple</td>
<td>Ryuan-Ji Temple</td>
<td>Tenryu-Ji Temple</td>
</tr>
<tr>
<td>7 Ryuan-Ji Temple</td>
<td>Tofuku-Ji Temple</td>
<td>Fushimi-Inari Shrine</td>
<td>Togetsu-Kyo Bridge</td>
</tr>
<tr>
<td>8 Togetsu-Kyo Bridge</td>
<td>Fushimi-Inari Shrine</td>
<td>Tenryu-Ji Temple</td>
<td>Ryuan-Ji Temple</td>
</tr>
<tr>
<td>9 Tenryu-Ji Temple</td>
<td>Ryuan-Ji Temple</td>
<td>Togetsu-Kyo Bridge</td>
<td>Sanjusangendo Temple</td>
</tr>
<tr>
<td>10 Sanjusangendo Temple</td>
<td>Heian-Jingu Shrine</td>
<td>Todai-Ji Temple</td>
<td>Nijo-Jo Castle</td>
</tr>
</tbody>
</table>

Table 2. Top 10 attractions
the scenery is very popular among foreign tourists who visit to Kyoto. Most of tourists who visit there take these vermeil gateways (Figure 8). We estimate that these objects are ones of the elements of photogenic factor.

Figure 7. Photos Taken in Todai-Ji Temple

Figure 8. Photos Taken in Fushimi-Inari

6 CONCLUSIONS

In this paper, we propose a new photographic activity model and examine the model by using regression analysis. We can estimate the number of visited tourists in a certain attraction by using the proposed model. We use tourists’ photographic histories in the destination area in this model, and social photo sharing web sites permit using the photographic history of the share photos. If we get the ratio of photo sharing, we can estimate the number of tourists in the attraction from the photographic history of the shared photos. Policy maker or tourism marketers utilize the estimation for their purpose.

As further research, we will analyze the element of photogenic factor by image analysis of photos to identify what the shooting objects are. As the element of the photographic factor, the point of interest (POI) inside the attraction (e.g. garden, statue, buildings) influences the number of photos in the attraction.

The research described in this paper was supported by JSPS KAKENHI Grant Number 24650055. We would like to express our thanks to the tourists who took part in our field experiments during their memorable trips to Kyoto.

7 REFERENCES


