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Empirical Research Article

Tourist Transition Model among Tourist Attractions based on GPS Trajectory

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Abstract

Before COVID-19, tourist destinations have experienced problems with congestion of both famous tourist attractions and public transportation. Over-tourism is not an issue at this time, but it is likely to rekindle after the COVID-19 pandemic ends. One method of mitigating over-tourism is to estimate tourist behavior using a tourist transition model and consequently adjust public transportation operations. In this study, we propose a construction method for a model of tourist transitions among tourist attractions based on tourist GPS trajectory data. We construct tourist transition models using actual trajectory data for tourists staying in the vicinity of Kyoto City. The results verify the model performance.

Keywords

GPS; tourism informatics; tourist behavior modelling; over tourism; smart tourism

1. Introduction

Before COVID-19, over-tourism, i.e., extreme concentrations of tourists at famous tourist attractions and associated congestion of public transportation, has become a significant problem for many tourist destinations. Because of the pandemic, there are very few tourists in any tourist destinations, but the over-tourism problem is expected to rekindle after the COVID-19 pandemic. One way to avoid over-tourism is to reduce the number of tourists to the destination itself. For example, restricting the number of visitors during peak seasons or limiting the number of hotel licenses. However, these methods reduce the number of tourists and thus have a negative impact on the performance of existing tourism industry. Therefore, instead of restricting the number of visitors to the destination area, a method to reduce congestion by dispersing tourists to some tourism attractions within the destination has been required. For example, a method to avoid congestion by simulating where and when many tourists are likely to gather and informing tourists about it (Yang, Na, Li, Li, & Zhong, 2018), a method to disperse tourists by recommending personalized routes (Konstan et al., 1997; Zach & Gretzel, 2011). In order to realize or improve the accuracy of the above methods, tourist transition models between sightseeing attractions are effective, but until now, not much research has been done on the transition model. Especially, there is little research on tourists who travel mainly on foot. This is where the research gap lies.

We also need to think about what information to use to build models. To construct a tourist transition model among tourist attractions, information on the attraction locations is necessary. Some existing methods use external data such as tourist guidebooks and Wikipedia to obtain the information required for model construction (Horvitz & Krumm, 2012; Ziebart, Maas, Dey, & Bagnell, 2008). However, there are two disadvantages of collecting location information of tourist attractions from an external data source. First, with that external source approach is applied, only known tourist attractions can be reflected in the behavior model. Furthermore, there are many tourist attractions that are not well known and that do not appear in tourist guidebooks and on Wikipedia (Ieiri, Nakajima, & Hishiyama, 2018). Secondly, the time and effort required to collect such external data from multiple information sources, format the data, and input it into the system is a burden for users. The burden is especially heavy for small-size Destination Management Organizations (DMOs), which have fewer staff. On the other hand, there is a method of extracting tourist spots and building a model using only movement trajectories without using external information. If we do not rely on external information, the above disadvantages will not occur. In addition, it is a highly versatile method that can be used in any region, which is a great advantage. Therefore, a model representing transitions between tourist attractions that is not dependent on external data but, instead, depends on actual data reflecting all visited tourist attractions (e.g., global positioning system (GPS) trajectories) is required. From the informatics view point, it is challenge to make tourist transition model only from tourist behavior data without any other external data. From the practical view point, it is useful for DMOs because they should not collect any external data but GPS data.

In this study, we use GPS trajectory data to construct a tourist transition model; these data are employed because they can be collected automatically (with advance permission for privacy data usage from users) by having tourists carry GPS equipment such as smartphones. To extract tourist attractions from GPS trajectories, we focus on the tourist movement speed, because tourists tend to move slowly when sightseeing. However,

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they also move slowly at stations or bus stops, when waiting for trains or buses. Thus, we first extract concentration points, which are points where tourists move slowly and include both tourist attractions and transit hubs. We then classify these points using the tourist speed distributions. Finally, we calculate the transition probability between tourist attractions. This is the proposed transition model.

The remainder of this paper is organized as follows. Section 2 discusses related works. Section 3 presents the proposed method, with subsections describing the extraction of tourist attraction data from GPS trajectories only and the construction of the tourist transition model. Section 4 reports construction of a tourist transition model based on actual data and its performance evaluation. Section 5 discusses and concludes this paper. This includes the scope, the limitation of our method, and outlines our future work.[1]

2. Related Work

In this section, we describe the position of our study in the past researches on solutions against over-, and furthermore, from the viewpoint of informatics, we describe the existing studies on the proposed method of tourist spot extraction and tourist behavior models.

2.1 Over-Tourism Management

BeforetheCOVID-19 pandemic, over-tourism appeared like a sudden disaster, sweeping famous tourist destinations around the world. The studies for definitions or analysis of its causes are outside the scope of this study and will not be dealt with in this paper. In this paper, we will discuss the solution of over-tourism. In order to solve the problem of over-tourism, research has been conducted in the fields of business administration, transportation engineering, economics and informatics (Dodds & Butler, 2019). Based on these studies, main strategies are classified as follows; taxation, advance booking systems, creation of alternative routes, virtual access, limited number of hotel beds, restricted access to tourist attractions, leveling of the congestion, etc. (Krizaj, Brodnik, & Bukovec, 2014).

The authors believe that the proposed method is a technology to realize the strategies of creation of alternative routes and leveling of the congestion. One of the technologies to realize the alternative routes strategy is the route recommendation technology, which creates and proposes an efficient route around multiple spots (Konstan et al., 1997; Zach & Gretzel, 2011). In the past, most of the research in this field has been aimed at finding the shortest route in terms of distance and time, but in recent years, research has also been conducted to find a route that takes into account tourists' preferences and time constraints (Kurata & Hara, 2013; Quercia, Schifanella, & Aiello, 2014). Route planning methods that predict and take into account congestion have been proposed, but they are for cars and not for tourists, who are mainly on foot (Kuriyama, Murata, Shibata, Yasumoto, & Ito, 2007).

2.2 Extraction of Tourist Attractions

One of the purposes of this study is to find tourist attractions from tourist behaviors. This research topic can be regarded as a branch of the well-explored research domain that seeks to identify characteristic places by considering human behavior (Crandall, Backstrom, Huttenlocher, & Kleinberg, 2009; Kurashima, Iwata, Irie, & Fujimura, 2010). Studies detecting commonly used routes and traffic flows are also included in this research domain (Gonzalez, Hidalgo, & Barabasi, 2008; Omer & Jiang, 2015).

As a large number of behavioral records are required to find characteristic places, research is widely conducted using information posted by users of social networking services (SNSs) such as Twitter, Foursquare, Flickr, and Facebook (Ajao, Hong, & Liu, 2015; Pat, Kanza, & Naaman, 2015). Ajao et al. (2015) have defined seven types of Twitter spatial indicators: location mentions in tweet texts, friend networks, location fields, IP addresses, geotags, URL links, and time zones. Text mining of location mentions is broadly used by existing methods that identify characteristic places (Cheng, Caverlee, & Lee, 2010; Ikawa, Enoki, & Tatsubori, 2012; Maeda, Tsubouchi, & Toriumi, 2017; Schulz, Hadjakos, Paulheim, Nachtwey, & Mühlhäuser, 2013). Among them, geotags attached to photographs (Crandall et al., 2009; Dang-Nguyen, Piras, Giacinto, Boato, & Natale, 2017; Kurashima et al., 2010) or text (Han, Ren, Du, & Gui, 2020; Peng & Huang, 2017; Zheng, Li, Zha, & Chua, 2011) are generally used for detection of tourist attractions. Other location detection methods involving GPS trajectories, which are collected via mobile devices such as smartphones, are also used (Lv, Qiao, Ansari, Liu, & Yang, 2016; Massimo & Ricci, 2019; Okada et al., 2008; Palma, Bogorny, Kuijpers, & Alvares, 2008; Suhara, Toda, Nishikawa, & Washizaki, 2013; Zheng, Zhang, Xie, & Ma, 2009).

Crandall et al. (2009) and Kurashima et al. (2010) have proposed methods of extracting tourist attractions from pictures geotagged on SNS. Those methods operate under the assumption that tourists take many pictures of attractions, and cluster geotagged pictures to identify those attractions. However, the methods proposed by Crandall et al. (2009) and Kurashima et al. (2010) fail to distinguish between tourist attractions and transit points if applied to GPS trajectories. Therefore, we must classify tourist attractions and transit hubs to construct a model involving only tourist attractions.

Finally, Okada et al. (2008) presented a method of extracting tourist attractions from GPS trajectories that uses rest points identified according to movement speed. Tourists tend to decrease their movement speeds in the vicinity of a tourist attraction as the observe the sights, take photographs, and talk with companions. However, tourists also exhibit decreased movement speeds at other locations. Therefore, this method fails to classify tourist attractions and other points such as transit hubs.

2.3 Transition Model Construction

There are two topics regarding tourist transition model constructing; how to represent the transition of tourists and the use of external data.

As how to represent the transition, existing studies on tourist-attraction transition models can be broadly divided into two categories, those considering grid models (Krumm & Horvitz, 2006; Takimoto et al., 2017; Xue et al., 2013, 2015) and those employing spot models (Ashbrook & Starner, 2003; Tamura, Kasahara, & Hibiki, 2014; Zheng et al., 2011). The former model accurately represents the geographical location, and the latter model abstractly represents the relationship between spots.

A grid model divides a geographical space of the target destination area into the same size cells. It is then assumed that the tourists move on those grids. Existing studies include those by Xue et al. (2013, 2015) and Krumm and Horvitz (2006). Since this model describes the transitions of tourists as a cell array, it can accurately represent the movement in geographic space. The problem with this model is that the size of the cells must be set relatively large in order to achieve sufficient accuracy. The transition probability is small when the cell size is small. In the approach developed by Xue et al. (2013, 2015), the destination prediction accuracy is highest when the cell side is 2 km. Krumm and Horvitz (2006) set the cell side to 1 km. However, for cell

[1] This paper is an extended version of the conference article "Tourist Transition Model based on Trajectory Data and Sightseeing Spot Detection" presented at the 26th Annual ENTER eTourism Conference in Nicosia, Cyprus.

sizes of 1 or 2 km, some tourist attractions may fall within the same cell. Additionally, in actual use, since it is necessary to adjust the optimum cell size for each tourist destination, there is a problem in practicality.

To establish a spot model, it is assumed that a tourist moves directly between tourist attractions. Related studies include those by Ashbook and Starner (2003), Zheng et al. (2011), and Tamura et al. (2014). In those methods, Markov models are employed and the geographical distance, transport networks, and data sparseness are neglected; however, it is difficult to determine the transition probability for a tourist attraction with few tourists.

Next, we describe the related works of the usage of external data for model constructing. In related works on tourist-attraction transition models, methods that try model improvement by using some external data have been used. Those methods employ GPS trajectories as well as external data such as polygon data on tourist attractions and route information. For example, Horvitz and Krumm (2012) predicted destinations using intersection location information, while Ziebart et al. (2008) used accident reports, road conditions, and driving habits. However, the external information used by those methods must often be renewed within a short period of time because of tourist attraction transitions. It is difficult to obtain all required information, such as tourist attraction changes, in advance.

3. Tourist Attractions Extraction and Model Construction

3.1 Method Overview

Here, we present an overview of the method proposed in this paper. Our method consists of two parts; extraction of tourist attractions and construction of tourist transition model.

As noted above, tourist movement speeds tend to be low at attractions, because the tourists observe the sights, take photographs, and talk with companions. In the method proposed in this study, we first extract points with low movement speed from the tourist trajectory dataset; we call those points “rest points.” We obtain the tourist concentration points by clustering the rest points. Next, we classify the tourist concentration points as either “tourist attractions” or “transit hubs,” which are defined as points targeted and not targeted by tourists, respectively.

The network including all tourist concentration points is called the “concentration point network.” We determine the transition probability between all concentration points from the concentration network. Using this probability, we build a tourist transition network consisting of tourist attractions only and obtain the tourist transition model.

3.2 Extraction of Tourist Attractions

This subsection describes the method used to remove the trajectory measurement error and to extract the tourist attractions from the trajectories. As noted above, tourist movement speeds tend to decrease around at our is attraction. However, as tourists may stop to wait for transportation (e.g., to take buses or trains), eat, and shop at locations other than tourist attractions, we must classify the concentration points into two categories. Tourists tend to move on foot around tourist attractions and to use other forms in transport in the vicinity of transit hubs. Therefore, those features were used to classify the concentration points into tourist attractions and transit hubs, as detailed in this subsection.

3.2.1 Trajectory Preprocessing

In this work, a trajectory is a sequence of points, each with latitude (*lat*), longitude (*lon*), time stamp (*t*), and ID (*id*), as recorded by GPS equipment. GPS trajectories are automatically collected by GPS equipment such as smartphones with advance permission of user’s privacy data usage.

However, we must remove the GPS measurement errors from the trajectories. A trajectory featuring large errors is expected to have sudden speed changes. That is, tourist speed depends on transportation, but measurement errors cause larger speed changes than any transportation. Therefore, we add the velocity v to trajectory points obtained from the corresponding latitude and longitude values and classify the points where v is larger than the threshold v_e as errors. These errors are then removed.

3.2.2 Concentration Point Extraction

This subsection describes the method used to extract the concentration points from preprocessed trajectories. The concentration points are the tourist attractions and transit hubs.

There are two patterns through which tourists decrease their speeds for long periods of time, i.e., for sightseeing and for transfer. We extract the former as rest points. Temporary resting is shorter than that for sightseeing and transfer. In this work, we define t_s as the longest time period of temporary resting and v_s as the maximum speed for sightseeing and transit. When v is continuously less than v_s for more than t_s, we extract the intermediary points as rest points. These thresholds are empirically determined in this study.

Next, we obtain the tourist concentration points by clustering the rest points using the mean-shift method. We define the tourist concentration points c as the centers of gravity of each cluster.

3.2.3 Concentration Point Classification

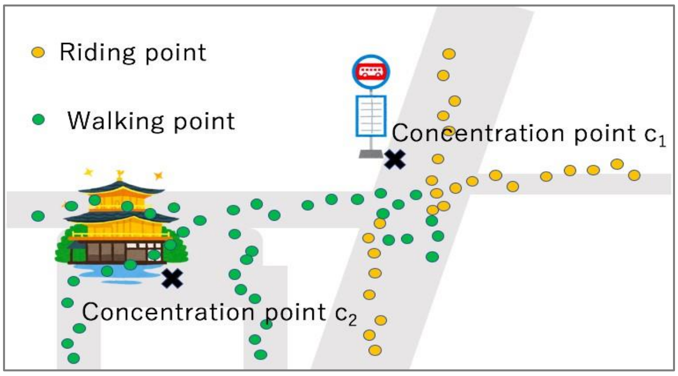
In this subsection, we describe the method used to classify concentration points into tourist attractions and transit hubs. Tourists tend to move on foot at tourist attractions and in vehicles around transit hubs because they transfer to buses or trains. We classify the concentration points using these features.

First, we define the concentration point area S as the area divided using Voronoi division. We define I_{walk} and I_{trans} as the areas in S a tourist can enter on foot and in a vehicle, respectively, with I_{all} being the union of I_{walk} and I_{trans} (Figure 1). We assume that the ratio of the area occupied by I_{trans} in I_{all} is small and large for a tourist attraction and transit hub, respectively. We classify the concentration points using this assumption.

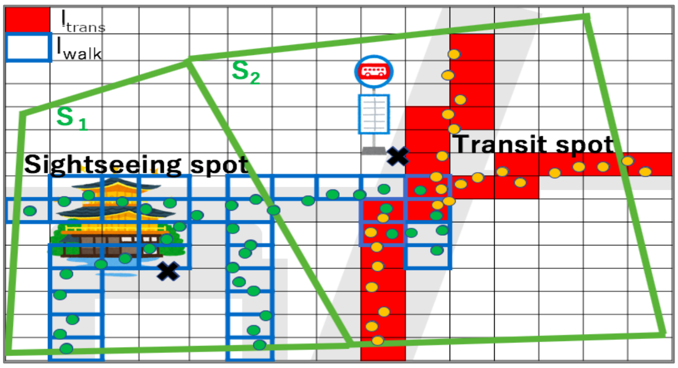
To obtain the area of I_{walk} and I_{trans}, we create images of them using tourist speed data. First, we assume that points in the trajectory are “walking” and “riding points” if the speeds are lower and higher than v_w, respectively. Next, we create heat map images of the walking and riding points, and binary image from the heat map images for every concentration point. We call these binary images I^c_{walk} and I^c_{trans} . Finally, we define the feature value R_c as

$$R_c = \frac{M(I^c_{trans})}{M(I^c_{all})}$$

where $M(I)$ is the number of pixels in I and I^c_{all} is the union of I^c_{walk} and I^c_{trans} . If R_c is smaller or larger than R_α, the concentration point is a tourist attraction or transit hub, respectively. In this study, R_α is empirically determined.



(a) Concentration points division from trajectories



(b) Walking points (I_{walk}) and vehicle riding points (I_{trans})

Fig. 1. Concentration points classification to walking points and riding points

3.3 Construction of Tourist Transition Model

In this subsection, we define the concentration point network and discuss construction of the tourist transition network and model.

First, we construct the concentration point network, which is a directed weighted network. It has concentration points as nodes. Edges exist if the transitions between the concentration points are along trajectories. The edge weight $p_{i,j}$ is the ratio of the transition from tourist concentration point i to tourist concentration point j. We define $p_{i,j}$ as the probability of direct transition from node i to node j.

Next, we construct the tourist transition network. Tourists do not use the shortest path only.

Therefore, we define the probability of transition from node i to node j, $p_{i\rightarrow j}$ as:

$$P_{i\rightarrow j} = \alpha \left(\sum_{r=d_{ij}}^{I_{ij}} M^r \right)_{ij}$$

where $M = (p_{i,j})$, $d_{i,j}$ is the number of nodes on the shortest path from node i to node j, and $l_{i,j}$ is the upper limit of the number of nodes that can be traversed from node i to node j. In this study, we define $l_{i,j}$ as

$$I_{i,j} = 2 \times d_{i,j}$$

Furthermore, α is a normalization term, with

$$\alpha = \frac{1}{\sum_{c\in K} p_{i\rightarrow c}}$$

Here, K is the set of tourist attractions. We define the tourist transition network as a network that has tourist attractions as nodes and directed weighted edges as $p_{i\rightarrow j}$. In this work, we construct the tourist transition model using a Markov chain; that is, tourists' subsequent destinations depend only on their current points.

4. Experiment

4.1 Preprocessing

Here, we report an experiment on a school trip excursion trajectory dataset for 579 students collected by Kasahara, Mori, Mukunoki, and Minoh (2015).

The trajectories were obtained by an application installed in a GPS unit, and were recorded in one-second intervals over a single day in December 2015. The experiment area was set to latitude 34.80 degrees or more, 35.15 degrees or less, longitude 135.65 degrees or more, 135.85 degrees or less. This area was selected to span Kyoto City, which was visited by a large number of students for a school excursion. The threshold value to eliminate outliers v_e was set to 180 (km/h). As points measured using Assisted GPS and Wi-Fi have low accuracy, they were eliminated. The experiment dataset included 9,530,489 observation points, which was reduced to 5,108,676 observation points upon outlier deletion.

4.2 Concentration Point Classification

In this experiment, we used v_s = 3.6 (km/h) and t_s = 200 (s) for rest-point extraction. We also set the Gaussian kernel of the mean-shift method to 0.0010.

Using our method, we extracted 354 concentration points. Then, to evaluate the method performance, we classified them by hand, obtaining 170, 171, and 13 tourist attractions, transit hubs, and erroneous extractions, respectively. Figures 2 and 3 show the R_c distribution of the proposed method and the receiver operating characteristic (ROC) curve, respectively. From Figure 2, the tourist attraction R_c values are mostly smaller than 0.4187, whereas those of the transit hubs are mostly larger than 0.4187. Therefore, we used 0.4187 as the threshold R_α in the model construction. The correct answer rate was found to be 76.6%.

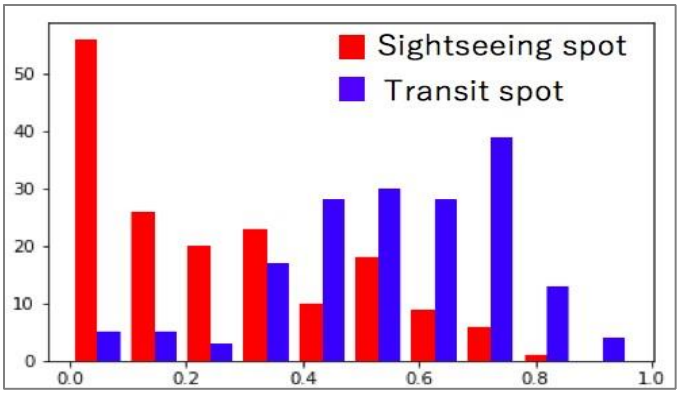


Fig. 2. Distribution of threshold R_c

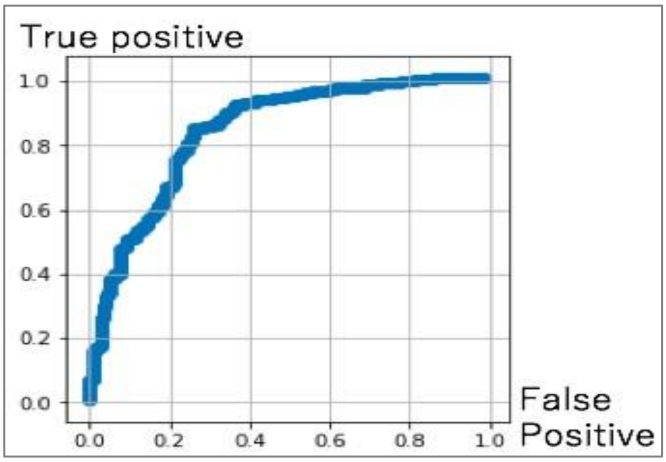
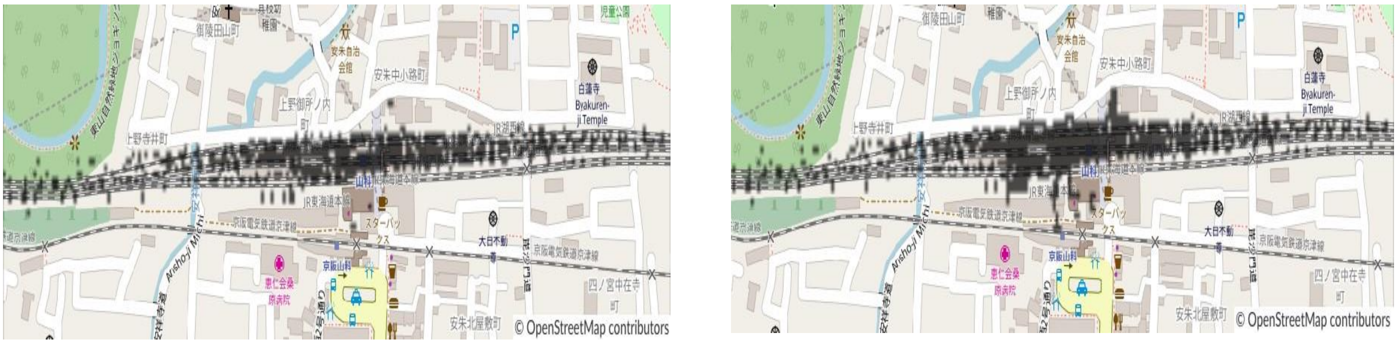


Fig. 3. ROC curve

Concentration points

Roads in Ginkaku-ji, I_{all}

Fig. 4. Correct classification (Ginkaku-ji Temple), R_c = 0.040



I_{trans}

I_{all}

Fig. 5. Correct classification (Yamashina Station), R_c = 0.855

Examples of correct classification by the proposed method are shown in Figures 4 and 5. Figure 4 shows binary images created at the Ginkakuji tourist attraction, which is a famous temple in Japan. The R_c of this tourist attraction is very small, at 0.040. The figure shows that the roads inside Ginkakuji were extracted as I_{all}. Furthermore, it is apparent from the I_{trans} result on the left of the figure that the area has almost no car access. However, car access is indicated for small areas; this result was obtained because the speeds for the indicated points could not be measured correctly because of GPS measurement errors.

Figure 5 shows binary images created at the Yamashina Station transit hub. The R_c of this transit hub is very large, at 0.855. In the figure on the left (I_{trans}), the tracks were extracted as an area accessible by train. Furthermore, the I_{all} result (right) almost covers that for I_{trans}.

An example of incorrect classification by the proposed method is shown in Figure 6, which presents binary images created for the Tofukuji Temple tourist attraction. There is a road oriented in a western direction from Tofukuji Temple; therefore, the R_c of this tourist attraction is very large, at 0.626. If a tourist attraction does not have another concentration point like this, the divided area can be so large that it contains additional features unrelated to the tourist attraction, as for the road and track visible in this case. Therefore, the R_c of this tourist attraction is large and misclassified.

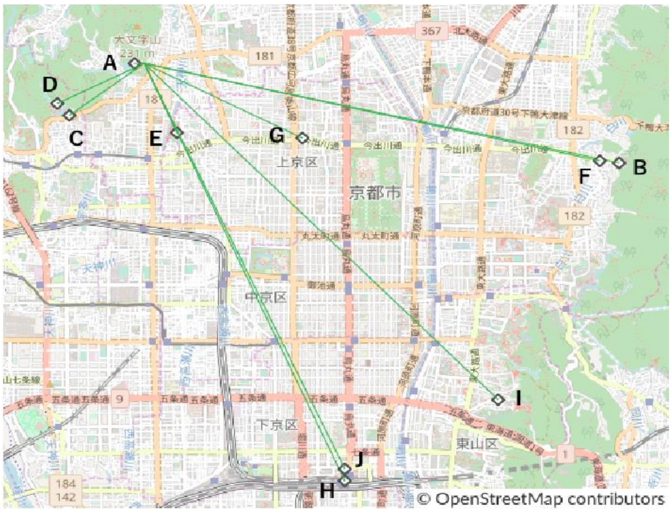
I_{trans}

I_{all}

Fig. 6. Incorrect classification (Tofukuji Temple), R_c = 0.626

4.3 Construction of Tourist Transition Model

To evaluate our model construction method, we constructed a tourist transition model for the experiment dataset. As an example, Figure 7 is a map showing Kinkakuji, which is a famous Japanese temple, and 10 tourist attractions and transit hubs with high transition probability from Kinkakuji. To evaluate the whole model, we assigned the tourist attractions to several areas and obtained the transition probability between each area. The results are listed in table on Figure 7. From table on Figure 7, the highest transition probability is from Kinkakuji to Kinkakuji Shariden, i.e., the same area. This is followed by high transition probabilities to Kiyomizu Temple or Kyoto Station. In addition, transition probabilities tend to be high between geographically adjacent areas. These results show that tourists may transition to popular points such as Kyoto Station and Kiyomizu Temple regardless of distance, or move to neighboring tourist attractions.



	Destination	Probability
A	Kinkakuji Shariden	0.136
B	Ginkakuji Temple	0.072
C	Souvenir shops in front of Ryuanji Temple	0.064
D	Ryuanji Temple	0.045
E	Kitano Tenman-gu Shrine	0.045
F	Souvenir shops in front of Ginkakuji Temple	0.045
G	Shiromine Shrine	0.037
H	Kyoto Station	0.031
I	Souvenir shops in front of Kiyomizu Temple	0.030
J	Kyoto Station bus terminal	0.023

Fig. 7. Potential attractions from Kinkakuji Temple and transition-probability table

5. Discussion and Conclusion

In this study, we extracted tourist concentration points from trajectories only and classified them into tourist attractions and transit hubs. Furthermore, we proposed a method for modeling the transitions between tourist attractions. Using this method, it is possible to construct a network considering the presence of transit hubs.

This method was developed as a versatile method that can construct a transition model based only on the trajectories of tourists, with one of our aims being to deal with over-tourism. It fulfills the existing research gap that Over-tourism is a complex problem, and the scope of this paper is to reduce the concentration of tourists in specific attractions within a destination, and to level out the situation as a whole. Specifically, it is assumed to be incorporated into technologies for predicting congestion, recommending tourist attractions to visit next, and recommending routes to avoid congestion. Therefore, it cannot be applied to methods for limiting the number of tourists in a destination as a whole. In addition, the data used in this study is the behavioral history of students on school excursions, and the means of transportation used by the students were mainly walking and public transportation (buses, subways, trains, and cabs), not electric scooters, which have been increasingly used in recent years. (In Japan, the use of electric scooters on public roads is prohibited by law as of 2021.) However, other researchers have developed methods for estimating the means of transportation, and by using such methods, it is possible to include other means of transportation.

Future improvements are planned, such as development of a method for automatically determining the feature value threshold(R_α), the bandwidth of the mean-shift method, and the routes tourists may choose on the concentration point network.

Declaration of competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Ajao, O., Hong, J., & Liu, W. (2015). A survey of location inference techniques on twitter. *Journal of Information Science*, *41*(6), 855–864.

Ashbrook, D., & Starner, T. (2003). Using GPS to learn significant locations and predict movement across multiple users. *Personal and Ubiquitous Computing*, *7*(5), 275–286. https://doi.org/10.1007/s00779-003-0240-0

Cheng, Z., Caverlee, J., & Lee, K. (2010). *You are where you tweet: A content-based approach to geolocating twitter users*. Proceedings of the 19th ACM International Conference on Information and Knowledge Management, Canada, 759–768.

Crandall, D. J., Backstrom, L., Huttenlocher, D., & Kleinberg, J. (2009). *Mapping the world's photos*. Proceedings of the 18th International Conference on World Wide Web, Spain, 761–770.

Dang-Nguyen, D. T., Piras, L., Giacinto, G., Boato, G., & Natale, F. G. D. (2017). Multimodal retrieval with diversification and relevance feedback for tourist attraction images. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, *13*(4), 1–24.

Dodds, R., & Butler, R. (2019). *Overtourism: Issues, realities and solutions* (Vol. 1). Berlin: Walter de Gruyter GmbH & Co KG.

Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *Nature*, *453*(7196), 779–782.

Han, S., Ren, F., Du, Q., & Gui, D. (2020). Extracting representative images of tourist attractions from flickr by combing an improved cluster method and multiple deep learning models. *ISPRS International Journal of Geo-Information*, *9*(2), 81.

Horvitz, E., & Krumm, J. (2012). *Some help on the way: Opportunistic routing under uncertainty*. Proceedings of the 2012 ACM Conference on Ubiquitous Computing, USA, 371–380.

Ieiri, Y., Nakajima, Y., & Hishiyama, R. (2018). Construction of the method to discovery potential sightseeing spot based on information integration process. *The IEICE Transaction D*, *101*(9), 1325–1333.

Ikawa, Y., Enoki, M., & Tatsubori, M. (2012). *Location inference using microblog messages*. Proceedings of the 21st International Conference on World Wide Web, France, 687–690.

Kasahara, H., Mori, M., Mukunoki, M., & Minoh, M. (2015). *Tourist status* *estimation from GPS trajectory using environmental constraints*. Proceedings of the Annual Conference of JSAI, Japan, Vol. 29.

Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R., & Riedl, J. (1997). Grouplens: Applying collaborative filtering to usenet news. *Communications of the ACM*, *40*(3), 77–87.

Krizaj, D., Brodnik, A., & Bukovec, B. (2014). A tool for measurement of innovation newness and adoption in tourism firms. *International Journal of Tourism Research*, *16*(2), 113–125.

Krumm, J., & Horvitz, E. (2006). *Predestination: Inferring destinations from partial trajectories*. International Conference on Ubiquitous Computing, USA, 243–260.

Kurashima, T., Iwata, T., Irie, G., & Fujimura, K. (2010). *Travel route recommendation using geotags in photo sharing sites*. Proceedings of the 19th ACM International Conference on Information and Knowledge Management, Canada, 579–588.

Kurata, Y., & Hara, T. (2013). Ct-planner4: Toward a more user-friendly interactive day-tour planner. In *Information and communication technologies in tourism 2014* (pp. 73–86). Cham: Springer.

Kuriyama, H., Murata, Y., Shibata, N., Yasumoto, K., & Ito, M. (2007). *Congestion alleviation scheduling technique for car drivers based on prediction of future congestion on roads and spots*. 2007 IEEE Intelligent Transportation Systems Conference, USA, 910–915.

Lv, Q., Qiao, Y., Ansari, N., Liu, J., & Yang, J. (2016). Big data driven hidden Markov model based individual mobility prediction at points of interest. *IEEE Transactions on Vehicular Technology*, *66*(6), 5204–5216.

Maeda, T. N., Tsubouchi, K., & Toriumi, F. (2017). *Next place prediction in unfamiliar places considering contextual factors*. Proceedings of the 25th ACM Sigspatial International Conference on Advances in Geographic Information Systems, USA, 1–4.

Massimo, D., & Ricci, F. (2019). Clustering users' pois visit trajectories for next-poi recommendation. In *Information and communication technologies in tourism 2019* (pp. 3–14). Cham: Springer.

Okada, K., Yokoyama, T., Okuda, T., Kashihara, S., Kadibayashi, Y., & Yamaguchi, S. (2008). *Proposal of a method for extracting points of interest from user's trajectory*. Multi Media Communication and Dispersion Treatment (DPS)) Research Report of Information Processing Society of Japan, 89–94.

Omer, I., & Jiang, B. (2015). Can cognitive inferences be made from aggregate traffic flow data? *Computers, Environment and Urban Systems*, *54*, 219–229.

Palma, A. T., Bogorny, V., Kuijpers, B., & Alvares, L. O. (2008). *A clustering-based approach for discovering interesting places in trajectories*. Proceedings of the 2008 ACM Symposium on Applied Computing, Brazil, 863–868.

Pat, B., Kanza, Y., & Naaman, M. (2015). *Geosocial search: Finding places based on geotagged social-media posts*. Proceedings of the 24th International Conference on World Wide Web, Italy, 231–234.

Peng, X., & Huang, Z. (2017). A novel popular tourist attraction discovering approach based on geo-tagged social media big data. *ISPRS International Journal of Geo-Information*, *6*(7), 216.

Quercia, D., Schifanella, R., & Aiello, L. M. (2014). *The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city*. Proceedings of the 25th ACM Conference on Hypertext and Social Media, Chile, 116–125.

Schulz, A., Hadjakos, A., Paulheim, H., Nachtwey, J., & Mühlhäuser, M. (2013, Jun.). *A multi-indicator approach for geolocalization of tweets*. Proceedings of the International AAAI Conference on Web and Social Media, 7(1). https://ojs.aaai.org/index.php/ICWSM/article/view/14396

Suhara, Y., Toda, H., Nishikawa, J., & Washizaki, S. (2013). Simultaneous estimation of dwell points and visit pois from GPS logs using integer programming. *IPSJ SIG Technical Report (DBS)*, *2013*(24), 1–8.

Takimoto, Y., Nishida, K., Endo, Y., Toda, H., Sawada, H., & Ishikawa, H. (2017). Personalized destination prediction with consideration of time zone. *IEICE Transactions D*, *100*(4), 472– 484.

Tamura, K., Kasahara, S., & Hibiki, M. (2014). Modeling tourist activity via probe-car data and stop area similarity. *Society for Tourism Informatics*, *10*(1), 101–112.

Xue, A. Y., Qi, J., Xie, X., Zhang, R., Huang, J., & Li, Y. (2015). Solving the data sparsity problem in destination prediction. *The VLDB Journal*, *24*(2), 219–243.

Xue, A. Y., Zhang, R., Zheng, Y., Xie, X., Huang, J., & Xu, Z. (2013). *Destination prediction by sub-trajectory synthesis and privacy protection against such prediction*. 2013 IEEE 29th International Conference on Data Engineering (ICDE), Australia, 254–265.

Yang, C., Na, J., Li, G., Li, Y., & Zhong, J. (2018). *Neural network for complex systems: Theory and applications.* London: Hindawi.

Zach, F., & Gretzel, U. (2011). Tourist-activated networks: Implications for dynamic bundling and en route recommendations. *Information Technology & Tourism*, *13*(3), 229–238.

Zheng, Y., Zhang, L., Xie, X., & Ma, W. Y. (2009). *Mining interesting locations and travel sequences from GPS trajectories*. Proceedings of the 18th International Conference on World Wide Web, Spain, 791–800.

Zheng, Y. T., Li, Y., Zha, Z. J., & Chua, T. S. (2011). *Mining travel patterns from GPS-tagged photos*. International Conference on Multimedia Modeling, Taiwan, 262–272.

Ziebart, B. D., Maas, A. L., Dey, A. K., & Bagnell, J. A. (2008). *Navigate like a cabbie: Probabilistic reasoning from observed context-aware behavior*. Proceedings of the 10th International Conference on Ubiquitous Computing, Korea, 322–331.

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