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# Discover "Anaba" Sightseeing Spots Using Social Images

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***Abstract:*** Discovering diverse sightseeing resources is addressed more attentions to meet the increasing demand from personalized tour. "Anaba" spot is one of them which is less well-known but still worth visiting. In this paper, we propose a novel method of using social geo-tagged images to discover "Anaba" spots. We first select possible candidates according to the visiting frequency asymmetry of photographers. Then, we evaluate the sightseeing score of each candidate by considering both social support and content quality of images shot around there. We will demonstrate the effectiveness of proposed approach on a collection of 3293 Flickr images.

***Keywords:*** Sightseeing, "Anaba" spots, SNS, cross-media analysis

## 1. Introduction

Travel, as an important part of the service sector, plays an indelible role in people's lives. Since traditional tourism has become more and more mature, personalized tour now is becoming popular. Instead of the most popular sightseeing spots, personalized tour demands more diverse sightseeing resources. By taking Sakura as an example in Figure 1, for someone's first visiting to Kyoto, the most popular places(e.g. Kiyomizu-dera in Fig.1) are always the best choices. However, there are so many people visiting these famous places during Sakura's short follower season. For a visitor who wishes an in-depth travel in Kyoto(e.g. he/she has been to these famous places), diverse sightseeing spots might be a better choice(e.g. "Anaba" spots in Fig.1). In contrast to popular sightseeing places, an "Anaba" spot is a place where is less well-known but still worth visiting.

Powered by SNS(Social Network Site) and mobile devices, modern technologies have provided us rich ways to share personal travelling experience[13]. Compared with the traditional text-based travel logs, modern forms of travel trails can record more information such as locations, time, content of sceneries, and so on. Geo-tagged images is one form of such trails. Social image hosting websites(e.g. Flickr.com, and Panoramio.com) have recently become very popular. On these sites, users can upload and tag their images for sharing his/her own travel experience. The underlying information it contains provides researchers with excellent opportunities to mine users' travelling patterns[3, 5, 6], and to discover popular significant sightseeing places in the world[1, 7]. However, to the best of our knowledge, how to discover an "Anaba" spot has not been well investigated in previous work.

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**Fig. 1** Diverse sightseeing resources

In order to discover an "Anaba" spot, a candidate spot should meet two requirements: 1) not well-known; and 2) high sightseeing value. Even though there is less information about "Anaba" spots on the web, fortunately we find that geo-tagged images have four key information dimensions, 1) temporal; 2) spatio; 3) people; and 4)image content, to help us to do the detection. Especially for landscape:

(1) temporal dimension contains the season sensitive information of a scenery;
(2) from the spatio dimension, certainly we can retrieve the location information;
(3) people information can tell us whether a spot is a not well-known place;
(4) according to the image content, we can evaluate the sightseeing value of a spot.

Consequently, in this paper we propose a novel approach to discover "Anaba" spots by using social geo-tagged images. In our approach, a series of methods are raised to discover and rank each spot. To summarize, the contributions of this paper are as follows:

- Based on the review of related work in Section 2, we investigate whether social geo-tagged images can be used for discovering "Anaba" spots. A novel approach is proposed successfully to discover the spots in Section 3.
- We introduce two criteria, *secret score* and *sightseeing score*, to do the discovery. Correspondingly, a visiting frequency

based method is proposed in Section 4 to discover less well-known spots. Following is a novel ranking method by considering both social support and content quality of images to rank these less well-known spots with high sightseeing value as the standard in Section 5.
- We verify the effectiveness of our approach on a collection of 3293 Flickr images in Section 6.

## 2. Related Work

A survey given in [2] shows us that collections of geo-multimedia are widely used in landmark recognitions, visualizations, and trip recommendations. For instance, a tourism recommendation system is developed using geo-tagged images collected from Flickr[3]. Based on the similarity to a user's query, the system returns representative images of the corresponding scenery. In [4], a visualization application is developed for automatically generating tourist maps. By utilizing geo-tags and user tags of images, landmarks with icons can be displayed on tourist maps. Except for the geo-tagged images, there are also other kinds of geo-multimedia that can been utilized to discover popular locations. [1] proposes a joint authority analysis framework to discover areas of interest with geo-tagged images and check-ins. Since in check-ins locations are already associated with their names and travelers, both location-location transitions and user-location relations are considered in their framework. GPS trajectories is another form of geo-multimedia which can represent people's location histories. By mining multiple users' GPS traces, Yu Zhang et al. [5] aimed to detect interesting locations and typical travel sequences in a given geo-spatial region. [6] then further develops a recommender system which can perform two types of travel recommendations: 1) recommend top interesting locations; and 2) recommend personalized locations matching someone's travel preferences. Semantic locations(e.g. shopping malls and restaurants) can also be mined form user's GPS trajectories[7].

However, a traveler's interest should not be limited to the popular locations. Although in [6], by incorporating correlation between locations into personalized recommendation the system can predict a user's interests in an unvisited location, it still cannot solve the problem that instead of the popular locations someone may prefer an "Anaba" location. What's more, in the previous work only subjective user experience has been used to discover popular locations. In other words, the sightseeing value of locations is evaluated only by social support(e.g. rank-by-count or rank-by-frequency). The reality is that not all the sightseeing locations can be effectively evaluated only by social support. For example, everyday Shugaku-in Imperial Villa in Kyoto allows limited visitors to enjoy the beautiful sceneries during a fixed time period. Therefore, besides social support, we should introduce a objective standard to evaluate the sightseeing value. We find that the image itself could provide valuable information for us to evaluate the corresponding location. Researchers have already proposed some methods to rank attractiveness of images[8], and to assess quality of image's content[9] from a visual perspective. Nonetheless, the relationship between image content quality and a spot's sightseeing value has not been established.

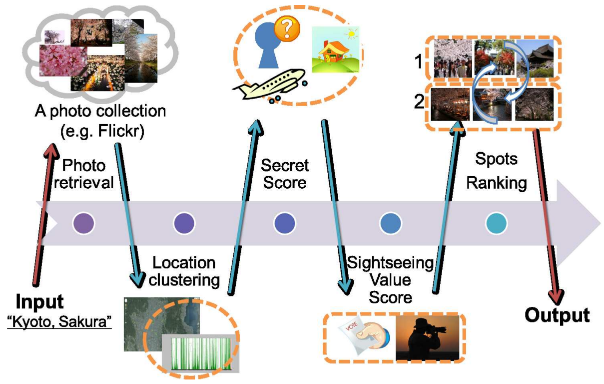



**Fig. 2** Approach overview

## 3. Approach Overview

In this paper, we define an "Anaba" sightseeing spot as a place which is less well-known but still worth visiting. Our problem is defined as below:

***Problem***:
- *Input: a set of key words (e.g. "Kyoto, Sakura") that represents a sightseeing topic.*
- *Output: a list of ranked "Anaba" sightseeing spots.*

Hereafter, we use term *spot* to represent a sightseeing place. A spot is a set of pairs of GPS coordinates, i.e., `<latitude, longitude>`.

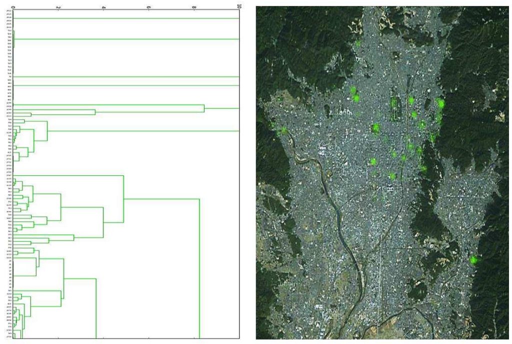
Figure 2 summarizes our approach for discovering "Anaba" sightseeing spots. Based on the inputted keywords, we first retrieve related geo-tagged images from Web 2.0 photo sharing systems(e.g. Flickr). Then by utilizing images' geo-information, we perform location clustering to detect each candidate sightseeing spot. We filter and rank these spots based on the two criteria, *secret score* and *sightseeing score*. Therefore, there are two major tasks in our approach:

(1) *discovering spots*: we use hierarchical clustering to detect spots. Then by considering visiting frequency asymmetry of different photographers, we calculate the secret score of each spot. Currently, for a target city(e.g. Kyoto) we classify photographers into "familiar group" and "unfamiliar group". A photographer is familiar with a city if and only if he/she is a resident or he/she has a higher *familiar score* which is used to measure a photographer's familiarity of a target place.

(2) *ranking spots*: we assume that there is weak relationship between a spot's secret score and sightseeing score. For this reason, according to the secret score we first do filter to get all the less well-known spots, and then rank them due to the sightseeing score. Both social support and content quality of images are considered to calculate the score.

## 4. Discovering spots

By analysis of input keywords, we first retrieve the related geo-tagged images from on-line photo sharing systems. For instance, Flickr[10] provides us APIs to collect public images. Then we use both image's geo-information and photographer information for the discovering of less well-known spots.



(a) Hierarchical cluster (b) Heat map

**Fig. 3** Hierarchical clustering

### 4.1 Distance-based Clustering

Since in advance we don't know how many clusters and how big a spot should be, we want to detect spots on a flexible way. On the other hand, the geo-information itself originally has a hierarchical structure. Therefore, unlike DBSCAN in [11] which focuses on the discovery of clusters with arbitrary shapes, we use hierarchical clustering to detect each spot. In our case, the input of the clustering is a set of geo-points(i.e. `<latitude, longitude>`). We define the distance as the length of arc between two points. Then We iterate the clustering algorithm to find a suitable distance value($d$) to reach convergence. Fig.3(a) shows one of the clustering results. In this diagram, y-axis represents the No. of clusters and x-axis means the distance(in "*km*") between different clusters. Fig.3(b) shows the distribution of discovered spots($d = 5km$) on google map.

### 4.2 Photographer Classification

After clustering, a candidate sightseeing spot is composed of a set of geo-tagged images related to it. In order to detect whether a spot is a less well-known place or not, we utilize the information asymmetry of different photographers. By utilizing the visiting frequency asymmetry between photographers who are familiar or unfamiliar with a spot, we calculate the secret score. First we introduce the concept of "Familiar". In this paper, we set the *target place* as a particular city.

*DEFINITION 1 (Familiar). A photographer is familiar with a spot if and only if he/she meets one of the following conditions:*
*(1) For the target place, he/she is a resident;*
*(2) He/She has a higher familiar score. We propose the score to measure a photographer's familiarity of a target place.*

#### 4.2.1 Identifying residents

In general, corresponding to a particular spot we can detect whether a photographer belongs to a resident group by his/her public profile on the Web. For example, we can retrieve a photographer's home town information in his/her public profile. However, there are also some special cases in which we cannot find out the home town information directly. On these occasions, we need extra information to help us to mine the information. We propose a notion of probability of being a resident $P_r(u_i)$ for the judgement.

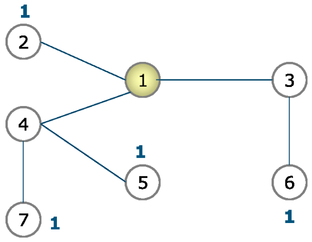



**Fig. 4** A two-level community

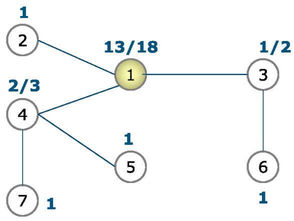



**Fig. 5** Probability splitting

By utilizing a photographer's friend-information on SNS, we first set up a friend-relationship network. Then we cluster the network to find a community of the photographer. Figure 4 shows a two-level community including a photographer's friends and friends of friends. We set $P_r(u_i) = 1$ if we can detect that a user, $u_i$, is a resident according to his/her profile. At last, in order to calculate the target photographer's $P_r(u_i)$ (i.e. $u_1$ in Fig.4), we use a bottom-up probability splitting algorithm to get the value. From the penultimate layer (i.e. $[u_2, u_3, u_4]$ in Figure 5) to the top (i.e. $u_1$), for the uncertain users we successively calculate the probability by following formula. $u_j$ indicates all the friends of $u_i$ and $n$ is the number of $u_i$'s friends.

$$P_r(u_i) = \frac{1}{n}\left(\sum_{j=1}^{n} P_r(u_j)\right)$$

Similarly, we can retrieve a $n$-level ($n > 2$) community graph to get a more precise result. However, this method cannot cover the situation when a photographer is unwilling to disclose his/her friend-information. Therefore, in the next section, we will introduce another classification method to solve this problem.

#### 4.2.2 Familiar score

Based on images' taken-time information of a photographer $u_i$, we introduce a notion of *familiar score* to confirm whether he/she is familiar with the target place. By utilizing images' geo-information and taken-time information in past $t$ years, firstly we establish a mapping relationship between places where $u_i$ has been to and numbers of days spent in corresponding places as a $t \times s$ matrix. $N_{mn}$ indicates the number of days spent in $n$th place during $m$th year. As an example, $[Kyoto : 20\ days]$ means that among a photographer's images taken in Kyoto there are 20 different dates detected from images' taken time.

$$M_{mapping}(u_i) = \begin{pmatrix} N_{11} & N_{12} & N_{13} & \cdots & N_{1s} \\ N_{21} & N_{22} & N_{23} & \cdots & N_{2s} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ N_{t1} & N_{t2} & N_{t3} & \cdots & N_{ts} \end{pmatrix}_{t \times s}$$

Next, for the target place $k$,

$$TP(u_i, k) = (N_{1k}, N_{2k}, \cdots, N_{tk})$$

we take two factors into consideration: 1) for each year, the proportion of number of days the target place accounts for; and 2) throughout the $t$ years, the reproducibility of the target place. Therefore, we first calculate the proportion in each year $\alpha$.

$$\delta_\alpha(u_i, k) = \frac{N_{\alpha k}}{\sum_{\beta=1}^{s} N_{\alpha\beta}}$$

Then, we integrate the reproducibility by a weighted sum to calculate the *familiar score*. $\omega_\alpha$ is a weight which indicates that higher reproducibility and newer user information has a greater contribution, since we assume that stale information has less value for our classification

$$FamiliarScore(u_i, k) = \sum_{\alpha=1}^{t} \omega_\alpha \delta_\alpha(u_i),\ \omega_\alpha = 1 + \frac{\alpha}{t}$$

### 4.3 Secret Score Calculation

We calculate the secret score based on the following hypothesis: a spot with a low frequency of unfamiliar ones is a less well-known spot. Based on the numbers of photographers in familiar group and unfamiliar group, for a particular $spot_i$ now we can define two vectors to represent the visiting frequency during the past $\lambda$ years. For each year, through the photographer classification we calculate the percentage of familiar group and unfamiliar group. Similarly, we use the weight $\omega_\alpha$ in section 4.2.2 to distinguish the importance of information produced in different years.

$$VF_f(spot_i) = (\omega_1 Pct_f(1), \omega_2 Pct_f(2), \cdots, \omega_\lambda Pct_f(\lambda))$$

$$VF_{unf}(spot_i) = (\omega_1 Pct_{unf}(1), \omega_2 Pct_{unf}(2), \cdots, \omega_\lambda Pct_{unf}(\lambda))$$

$Pct_f(x)$ and $Pct_{unf}(x)$ respectively stands for the percentage of photographers from familiar and unfamiliar groups for the $x$th year. Since not all the photographers can be classified into familiar group or unfamiliar group, obviously $Pct_f(x) + Pct_{unf}(x) \leqslant 1$. Finally, we can define the secret score of each spot as below. We compare these two visiting frequency vectors by calculating the norm of vector.

$$SecretScore(spot_i) = \left|VF_f(spot_i)\right| - \left|VF_{unf}(spot_i)\right|$$

Even if there is only one photographer who submitted images about a spot, according to our hypothesis we would identify the spot as a less well-known spot as long as we find that the photographer belongs to the familiar group. However, up to now we cannot know whether it is a good place for sightseeing. In the next section, we will rank these less well-known spots according to the sightseeing score.

## 5. Ranking spots

In our datasets, a spot is represented by geo-tagged images which have been submitted to SNS by different photographers. Because of our goal which is to discover the less well-known spots, the number of images is no longer an important indicator for ranking spots. In other words, the classical authority analysis, which is always used to discover popular spots, is not suitable in our cases. On the contrary, the sightseeing value of a spot itself is the most essential criterion to rank these less well-known spots. However, the problem is how to evaluate a spot's sightseeing value by the images taken there. For this purpose, we define the sightseeing score as follows.

*DEFINITION 2 (Sightseeing Score). Given a $spot_i$, its sightseeing value score, denoted as $SightseeingScore(spot_i)$, is calculated as:*

$$SightseeingScore(spot_i) = \sum_{j=1}^{m} (w_o(O_j) \times ObjectScore(spot_i, O_j))$$

*where $O_j$ is one kind of scenery objects(e.g."Sakura"), $w_o(O_j)$ is the corresponding weighted value, and $ObjectScore(spot_i, O_j)$ calculate different scenery objects' sightseeing value in $spot_i$.*

Therefore, the key point of ranking spots is to compute each scenery object's sightseeing value. In this paper, since we retrieved all the images by keyword-based search, we assume that the mapping relationship between images and different scenery objects has already been established. Therefore, we define $I_j$ as a image set in which images are all related to scenery object $O_j$. In the next, we will introduce a method to calculate $ObjectScore(spot_i, O_j)$ by considering both social supports and content qualities of images in $I_j$.

### 5.1 Image's Social Support

Here we use an intuitional value, numbers of "I like it", to evaluate a image's social support. "I like it" is a common function on SNS for friends or visitors to mark on a message or an image. However, obviously an absolute number cannot be used to do the evaluation.

Therefore, for a particular image $\eta$ in $I_j$, we should retrieve enough relevant images to get a relative social support score. "Relevant images" contains two kinds of social images: 1) content similar images $S_\eta$; and 2) image $\eta$'s context $C_\eta$. By taking "Kyoto, Sakura" as an example, we first collect as many as possible images taken in Kyoto during the Sakura season by SNS public APIs(e.g. Flickr APIs [10]). Then we utilize a content-based image search method[12] to find content similar images which also contain Sakura objects. By constructing an image-tag relationship graph with images and their tags as vertices, we calculate content similarity by both visual similarity and social tag similarity. For image $\eta$'s context $C_\eta$, we retrieve all the corresponding photographer's images published on SNS.

After we retrieved the two relevant image sets, we use $A_i$ to represent each image's absolute score:

$$A_i = \frac{Num_i^{vote}}{Num_i^{view}}$$

$A_i$ is calculated by the ratio between number of "I like it" (i.e. $Num_i^{vote}$) and the image's view count (i.e. $Num_i^{view}$). Second, we calculate two average values for content similar image set $S_\eta$ and context image set $C_\eta$:

$$\bar{A}(S_\eta) = \frac{1}{\left|S_\eta\right|} \sum_{i=1}^{|S_\eta|} A_i,\ \bar{A}(C_\eta) = \frac{1}{\left|C_\eta\right|} \sum_{i=1}^{|C_\eta|} A_i$$

Then, for image $\eta$ we define its social support score as following equation:

$$SocialSupport(\eta) = w_s \frac{A_\eta - \bar{A}(S_\eta)}{\sigma_s} + w_c \frac{A_\eta - \bar{A}(C_\eta)}{\sigma_c}$$

For the raw score $A_\eta$, two standard scores are calculated based on the two average values of content similar image set $S_\eta$ and context image set $C_\eta$. $\sigma_s$ and $\sigma_c$ are the standard deviations of $S_\eta$ and $C_\eta$, while $w_s$ and $w_c$ are two corresponding weights. Finally, we can calculate a $spot_i$'s social support score by the sum of social


**Fig. 6** Images with high social support

support value of all the images taken there.

$$SocialSupport(spot_i) = \sum_{\eta \in spot_i} SocialSupport(\eta)$$

Nonetheless, in some cases a high social support score cannot be regarded as a high sightseeing value. By taking the two professional Sakura images in Figure 6 as an example, there is a high probability that viewers clicked the "I like it" button just because of photographer's professional shooting skills. Therefore, we need an additional criterion to support our estimation. In the next part, we will evaluate a spot's sightseeing value from a heuristic perspective.

### 5.2 Image's Content Quality

To evaluate a spot's sightseeing value, we propose a heuristic method to do the evaluation. We assume that a spot which has a high sightseeing value should not only have a beauty of group, but also need a delicate beauty of detail. Fig.6(A) shows us the Sakura with a beauty of group, at the same time in Fig.6(B) we can see the beautiful flowers through a close view. By classifying images into "distance view" and "close-up view", we find that they are exactly corresponding to those two kinds of beauty. Consequently, we assume that if a spot's ratio of distance view images or close-up view images is within a range $R$, it would have a higher sightseeing value. Through investigations on images taken by photographers in famous sightseeing spots, we first collect the sample data. Then by normal distribution fit we detect the range $R$ within which a spot would have a higher sightseeing value. Finally, for each candidate spot we apply the distribution obtained to compute image's content quality. The value of $R$ is different based on different scenery object.

According to our hypothesis, the most important task is how to classify images into distance view image set and close-up view image set. We apply machine learning methods to do the classification. In our learning method, we use two image features to generate the training model: "`<edge, blur>`". Compared with the distance view image, the close-up view image has clearer object edges in Fig.6(B). By applying Laplacian filter to images, we can easily compare the clarity of object edges. On the other hand, we find that close-up view images have a relatively blurred background. In other words, an close-up view image would have a higher contrast in the part where photographer's camera focused. On the contrary, a distance view image would have a gentle contrast throughout the whole image. Based on these two features, we do the image classification.

When we get the numbers of both distance view images and close-up view images, two ratios can be calculated. Since the sum of two ratios is equals to 1, without loss of generality here we use the ratio of distance view images as $r_i$. We assume that the ratio $r_i$ is distributed normally with mean $\mu$ and variance $\sigma^2$.

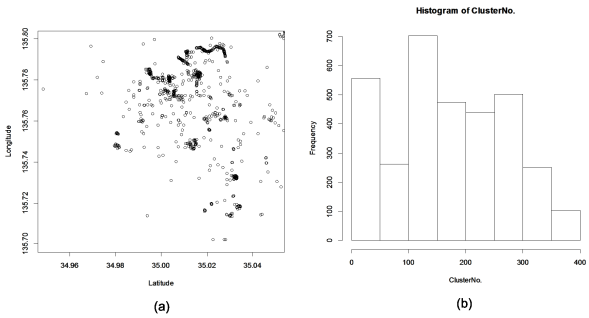



**Fig. 7** Data information

$$r_i \sim \mathcal{N}(\mu, \sigma^2)$$

Mean $\mu$ and variance $\sigma^2$ are decided by our sample data collected from investigations. For a particular scenery(e.g. Sakura), we use normal distribution fit to detect a normal distribution with mean $\mu_s$ and variance $\sigma_s^2$. Since all the sample data are collected from famous sightseeing spots, we can find a range R(e.g. $2\sigma_s$) which represents a greater likelihood about having a high sightseeing value. Therefore, for ratio $r_i$, we calculate the content quality by the probability density function.

$$ContentQuality(spot_i) = \frac{1}{\sigma_s \sqrt{2\pi}} e^{-\frac{(r_i-\mu_s)^2}{2\sigma_s^2}}$$

## 6. Preliminary Experiments

As mentioned in Section 5.2, different scenery objects have different content quality definitions(i.e. different values of $R$). Up to now, we only use "Sakura in Kyoto" as the study object(i.e. $O_j = sakura$). As Kyoto is a famous tourism city, we are wondering whether we can find out some "Anaba" spots there. We collect 7 years' geo-tagged images taken in Kyoto by using Flickr APIs. In our experiment, we selected 3293 Sakura images which are all taken in the past 3 years. Fig.7(a) shows the images' geo-distribution by "`<latitude, longitude>`". Because we have removed several noise data, in this graph all the points are located within Kyoto. Fig.7(b) shows the result of hierarchical clustering. We totally obtain 368 potential spots. For each spot, there is at least one image related with it. We calculate the $SecretScore(spot_i)$ and $SightseeingScore(spot_i)$. Since there is only one scenery object in our experiment, $SightseeingScore(spot_i) = ObjectScore(spot_i, sakura)$). And also because of the ongoing experiment, we haven't evaluated the content quality of images. For these reasons, the two scores in following cases respectively represent $SecretScore(spot_i)$ and $SocialSupport(spot_i)$.

**Case 1** Fig.8 gives an example with a high secret score and a relatively high social support score(i.e. $SecretScore(No.237) = 0.4106$; $SocialSupport(No.237) = 3.3066$). Because we cannot automatically calculate images' content quality, a manual evaluation of images has been done to detect whether there has a beautiful Sakura scenery. According to

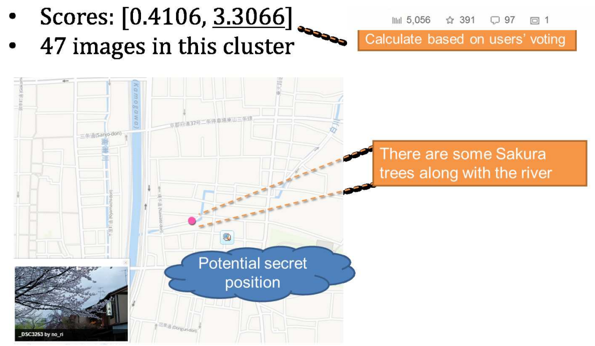



**Fig. 8** Case 1: Cluster No. 237

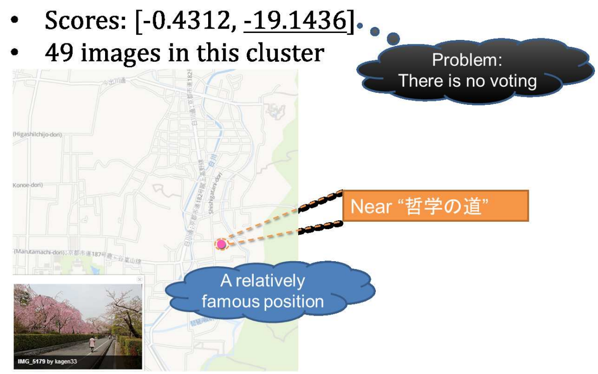



**Fig. 9** Case 2: Cluster No. 123

the map information, we find that this is a potential secret spot with some Sakura trees along with a river.

**Case 2** Fig.9 shows exactly the opposite situation. In this spot, according to the secret score there are more photographers form unfamiliar group who submitted their images to Flickr. On the map, we find that it is very close to ”Tetsugaku-no-michi” which is a famous place in Kyoto. However, in this case for the 49 images there are few user voting which results in $SocialSupport(No.123) = -19.1436$.

## 7. Discussion

In this paper, we introduce an original approach about how to discover “Anaba” spots. Although we have tested our approach on a image collection from Flickr, there are also some exceptions and improvements for our methods.

In the secret score calculation, because of the lack of image data in a single year we have to take images from past $t$ years into consideration to classify photographers and to get the secret score. However, if $t$ becomes a larger and larger number, calculating a ratio of days is not a suitable way to detect the overall trend of data. Therefore, in the future work we will use PCA to find the principal components. By PCA, we try to analysis the proportion and reproducibility of patterns in our data.

For image’s social support score, by utilizing similar images and context images we calculate a relative results. However, up to now we haven’t verified the effectiveness of “I like it”. In some particular cases, a user clicks the ”I like it” button just because we are friends. Although based on the analysis of a large enough dataset we can reduce the influence of this situation, in the next work we are considering whether it is necessary to take photographer’s friends into our analysis scope. Because in a sense the number of friends has a strong relationship with the view count. For a photographer, more friends means a higher exposure probability of his images on the Internet.

At last we use the ratio of distance view images to calculate the content quality. There is also an exception when the content of images are about indoor sceneries. For the indoor images, the ratio will be totally different from the outdoor images. We try to filter the indoor images by using Flickr APIs, but the effect is not as good as expected. Therefore, a more comprehensive classification is needed to do with this exception.

## 8. Conclusion

We presented an approach for discovering “Anaba” spots by using social geo-tagged images. First, according to the images’ geo-information and visiting frequency of photographers we select the not well-known spots. Then, we evaluated the sightseeing value of each spot by considering both social support and content quality of images. Using a image set collected from Flickr, we demonstrated the effectiveness of our approach by different cases.

Up to now, our work is not meant to provide a full solution, but rather it aims to inspire more interests in how to find diverse sightseeing resources based on the user experience shared on the web. For future work, we will improve our approach based on a more diverse and complex image set crawled from the web.

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### References

[1] J. Liu, Z. Huang, L. Chen, H. Shen, Z. Yan: Discovering areas of interest with geo-tagged images and check-ins. ACM Multimedia 2012:589-598.

[2] J. Luo, D. Joshi, J. Yu, A. C. Gallagher: Geotagging in multimedia and computer vision - a survey. Multimedia Tools Appl. (MTA) 51(1):187-211 (2011).

[3] L. Cao, J. Luo, A. C. Gallagher, X. Jin, J. Han, T. S. Huang: A worldwide tourism recommendation system based on geotaggedweb photos. ICASSP 2010:2274-2277.

[4] W. Chen, A. Battestini, N. Gelfand, V. Setlur: Visual summaries of popular landmarks from community photo collections. ACM Multimedia 2009:789-792.

[5] Y. Zheng, L. Zhang, X. Xie, W. Ma: Mining interesting locations and travel sequences from GPS trajectories. WWW 2009:791-800.

[6] Y. Zheng, X. Xie: Learning travel recommendations from user-generated GPS traces. ACM TIST (TIST) 2(1):2 (2011).

[7] X. Cao, G. Cong, C. S. Jensen: Mining Significant Semantic Locations From GPS Data. PVLDB 3(1):1009-1020 (2010).

[8] J. S. Pedro, S. Siersdorfer: Ranking and classifying attractiveness of photos in folksonomies. WWW 2009:771-780.

[9] Y. Ke, X. Tang, F. Jing: The Design of High-Level Features for Photo Quality Assessment. CVPR 2006:419-426.

[10] Flickr APIs. http://www.flickr.com/services/api/.

[11] M. Ester, H. Kriegel, J. Sander, X. Xu: A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. KDD 1996:226-231.

[12] J. Li, Q. Ma, Y. Asano, M. Yoshikawa: Ranking Content-Based Social Images Search Results with Social Tags. AIRS 2011:147-156.

[13] K. Hasegawa, Q. Ma, M. Yoshikawa: Trip Tweets Search by Considering Spatio-temporal Continuity of User Behavior. DEXA (2) 2012: 141-155.