SIMILAR SEASONAL-GEO-REGION MINING BASED ON VISUAL CONCEPTS IN SOCIAL MEDIA PHOTOS

Yasutomo Kawanishi†, *Ichiro Ide*†, *Lu Chen*†,∗, *Takatsugu Hirayama*‡,
Keisuke Doman††,†, *Daisuke Deguchi*‡†,†, *and Hiroshi Murase*†

† Graduate School of Informatics, Nagoya University, Nagoya, Aichi, JAPAN
{kawanishi,ide,murase}@i.nagoya-u.ac.jp
‡ Institutes of Innovation for Future Society, Nagoya University, Nagoya, Aichi, JAPAN
†† School of Engineering, Chukyo University, Toyota, Aichi, JAPAN
‡† Information Strategy Office, Nagoya University, Nagoya, Aichi, JAPAN
∗ Currently at Hitachi, Ltd.

ABSTRACT

In this paper, we propose a method for similar geo-region mining focusing on the seasonality. We define "seasonal-geo-region" as a geographically and temporally continuous area where many travelers share common targets of interest. In order to extract such targets of interest, we consider that observing people's interests through the contents of social media photographs is an effective way. We first introduce a clustering method to decide seasonal-geo-region boundaries based on the geo-tag and shooting time accompanying a photo. Next, we introduce the proposed method that compares the similarity of a given pair of seasonal-geo-regions based on the likelihood distribution of Visual Concepts that appear in photographs belonging to each seasonal-geo-region. In the end, we introduce results of the seasonal-geo-region mining experiment and report an evaluation on the part of the results through a subjective experiment. The results showed the effectiveness of the proposed method.

***Index Terms*—** Seasonal-geo-region, social media photographs, clustering, Visual Concepts

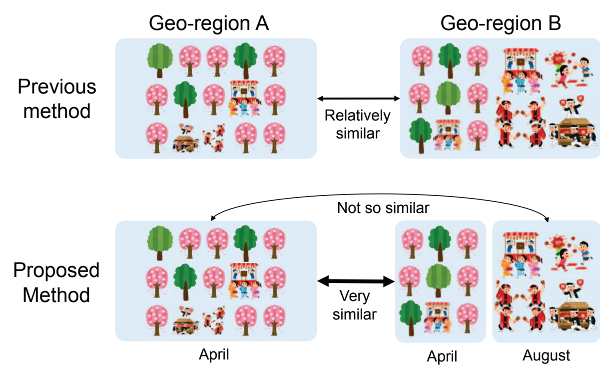

Fig. 1: Comparison of the similar geo-region search by our previous method and the proposed method. In this example, by the previous method, geo-regions A and B are judged as relatively similar. Actually, parts of the seemingly related contents come from different seasons in geo-region B, so the proposed method judges only in April the two geo-regions are very similar, but not for other seasons.

1. INTRODUCTION

Travelling is one of the top activities during vacations. Now that we have access to immense amount of information on the Web, more and more people plan their travel destinations on their own rather than joining a prefixed group tour. Since most of these Web-sites are, in general, text-oriented, we would need to be able to explicitly express our interests in text to search for destinations that match them. However, this is not always the case when we do not have a concrete image or knowledge of the destination in our mind; In the first place, we would not know what to search for.

As one solution for this, we have proposed a method that allows us to search for a geo-region that is similar to that we already know, in a query-by-example style [1]. This method calculates the degree of similarity between a pair of geo-regions by referring to the contents of photographs taken inside each geo-region and posted on social media. In this method, we intended to support travellers to search for a destination that has a similar atmosphere to a geo-region that he/she is familiar with (e.g. past travel destinations with good memories, well-known destinations with good reputations, etc.), and prefers to visit as a travel destination. Since such atmospheres may not necessarily be able to be described explicitly in text, they are represented as a set of Visual Concepts [2] that appear in people's photographs.

However, since this method does not take into account the seasonal information, it cannot handle seasonal events that

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take place at certain timings in a year, as shown in Fig. 1. We consider that this is insufficient to support travelers who will most likely visit the destination for only a short period of time. Therefore, in this paper, we define the concept of "seasonal-geo-region" which represents a geo-region in a specific season (The season can be defined as an arbitrary period of time). A pair of seasonal-geo-regions is compared in the same framework as in our previous method, which allows us to search for a geo-region in a certain season that is similar to that we already know.

This paper is organized as follows: First, Section 3 describes the proposed method. To analyze the mining results, we created an interactive visual interface of the mining results. The interface is introduced in Section 4. Next, Section 5 introduces the application of the proposed method to actual data collected from the YFCC100M [3] dataset, where examples of extracted similar seasonal-geo-regions are introduced. Then, Section 6 reports the results of subjective evaluations on part of the extracted similar seasonal-geo-regions. Finally, Section 7 concludes the paper.

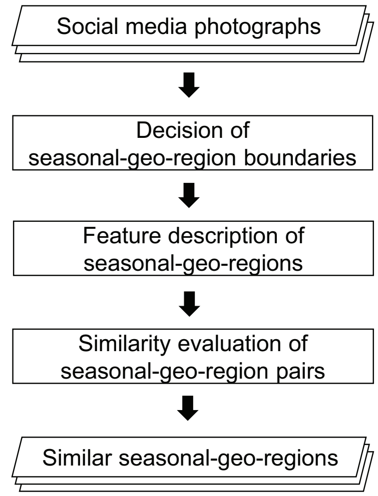


Fig. 2: Process flow of the proposed method.

2. RELATED WORK

Supporting travel based on social media contents has recently been interests of many research groups. Here, we will introduce a few pieces of work on supporting the decision of travel destinations by extracting their functions / atmospheres.

First, Kitayama et al. proposed a method to extract functions of touristic spots based on the distribution of terms in user-posted reviews [4]. Although reviews are surely an informative source, we consider that they do not include implicit information that is difficult to verbalize, whereas in photographs, such information is implicitly included.

Next, Yuan et al. proposed a method that discovers geo-regions with different functions in a city by analyzing both human mobility between regions obtained from GPS-log data of taxis, and Points of Interests (POIs) located in a geo-region obtained from map data [5]. Although this is an interesting approach that could possibly extract implicit information, it does not directly observe people's interests, so we will need to infer them manually.

Finally, Zhang et al. proposed a method that learns the correlation between clothing and locations from social media photographs and leverage it for location-oriented clothing recommendations [6]. Although clothing is an important aspect that composes part of the atmosphere, we consider that it alone is insufficient to represent a touristic destination.

In contrast to these attempts, we consider that observing people's interests through the contents of social media photographs is an effective way to infer the atmosphere of a geo-region.

As similar work along this line, Honjo et al. proposed a method for extracting Visual Concepts which are strongly related to specific location and time from geo-tagged photographs accompanied with textual tags [7]. This work is the closest work related to our research, but it does not consider the relation between locations.

3. SIMILAR SEASONAL-GEO-REGION MINING

3.1. Mining of similar geo-regions considering their seasonalities

The proposed method finds seasonal-geo-region pairs whose atmospheres are similar to each other in specific seasons based on meta-data (time and location) corresponding to photographs posted on social media and contents in the photographs taken in each seasonal-geo-region.

The similarity is calculated by the following process. First, seasonal-geo-region boundaries are determined based on spatio-temporal clustering of social media photographs. Then, the feature of each seasonal-geo-region is calculated based on Visual Concepts detected from photographs taken in the seasonal-geo-region as same as in our previous work [1]. Finally, the similarity between a pair of seasonal-geo-regions is calculated, and those with high similarity are output as similar seasonal-geo-regions. The process flow is shown in Figure 2.

3.2. Decision of seasonal-geo-region boundaries

In general, a geo-region is defined as a geographic area segmented from surrounding areas according to certain criteria. For travel support, we have previously defined "geo-region" based on the interests of the crowd [1]. It was defined as a geographically continuous area where many travelers share common targets of interest.

However, even in the same geo-region, the atmosphere changes from time to time. Thus, we expand the definition of

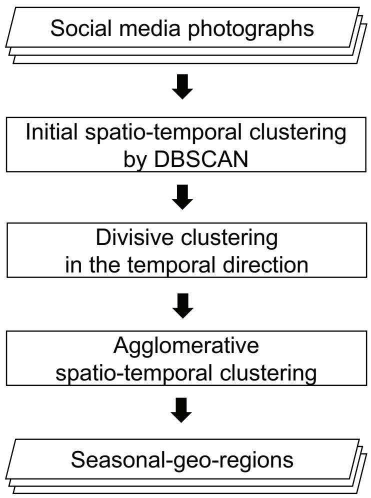


Fig. 3: Detailed process flow of the decision of seasonal-geo-region boundaries.

geo-region along the temporal axis, and define the "seasonal-geo-region" as a geographically and temporally continuous area where many travelers share common targets of interest.

In the previous method, we decided the boundary of a geo-region by clustering geo-tagged photographs posted on social media since we considered that they reflect people's interests directly. For the decision of seasonal-geo-region boundaries, we make use of social media photographs not only accompanied with geo-tags, but also with shooting time, and then cluster them both geographically and temporally.

The overview of the proposed clustering procedure is shown in Figure 3. First, given a set of social media photographs $\{(I_i, g_i, t_i)\}$, they are initially clustered by DBSCAN [8] based on the geo-tags and shooting time, where I_i, g_i, t_i represents the photograph itself, the geo-tag accompanying it, and the shooting time, respectively. DBSCAN is known as a clustering method which does not require the number of clusters to be given as a parameter. It detects a set of data points as a cluster whose data points are densely-connected, and removes sparsely distributed data points as noise. Concretely, if two data points share more than $P_{\min}$ samples within their vicinity defined by the radius ε, they will be members of the same cluster. By applying DBSCAN, we obtain a set of initial clusters $\{\widehat{C}_c \,|\, c = 1, 2, \ldots\}$.

In order to focus on the seasonal characteristics of the geo-regions, divisive hierarchical clustering is applied to each initial seasonal-geo-region which is distributed widely towards the temporal axis. By this process, the initial seasonal-geo-regions are recursively divided into smaller seasonal-geo-regions $\{\widetilde{C}_c \,|\, c = 1, 2, \ldots\}$ until the span of the shooting time of all the photographs in the cluster becomes smaller than a threshold T [days]. Here, DBSCAN is recursively applied to the clusters by increasing the parameter $P_{\min}$.

Next, geographically overlapping and temporally adjacent clusters with similar features are merged by agglomerative clustering. Here, the features are calculated from the contents of photographs represented by Visual Concepts which will be described in Section 3.3, and the measurement of their similarity will be described in Section 3.4.

Finally, after removing small clusters since few people are interested in them, we obtain clusters $\{C_c \,|\, c = 1, 2, \ldots\}$ which correspond to the proposed seasonal-geo-regions.

The overall clustering process is illustrated in Figure 4.

3.3. Feature representation of a seasonal-geo-region

As mentioned above, social media photographs reflect the interests of the people who shot them. Therefore, a huge number of photographs collected in a seasonal-geo-region should reflect the interests of the crowd, thus can be considered to reflect the atmosphere of the geo-region at a specific season. Here, we recognize the contents of each photograph and describe the atmosphere of a seasonal-geo-region based on the likelihood distribution of the contents of all the photographs that compose it.

Recently, Visual Concepts [2] are often used to describe the contents in a photograph. It can describe various concepts not only limited to concrete objects but also more visually abstract concepts such as *cherry blossom* and *mountain*. We use a Visual Concept detector f to recognize N^V Visual Concepts in a photograph I_i as $\mathbf{v}_i = f(I_i)$ Here, in order to focus on the likelihood distribution of the recognized top-ten Visual Concepts in each photograph, the Visual Concept detector suppresses the likelihood values other than the top-ten to 0. Then, the top-ten likelihood vector $\mathbf{v}_i$ extracted from each photograph belonging to a seasonal-geo-region C_c is merged as

$$\mathbf{V}_c = \sum_i \mathbf{v}_i. \tag{1}$$

To emphasize the characteristics of each seasonal-geo-region, each likelihood value is re-weighted by a TF-IDF [9]-like method. The original TF-IDF method is a term weighting method for document analysis and retrieval. In this research, we consider each Visual Concept as a term and each seasonal-geo-region as a document. By the TF-IDF-like method, the likelihood values of Visual Concepts commonly detected in many seasonal-geo-regions are suppressed, while those of Visual Concepts that are detected in only a limited number of seasonal-geo-regions are raised. After this process, re-weighted feature vectors $\widehat{\mathbf{V}}_c (c = 1, 2, \ldots)$ are obtained.

3.4. Mining similar seasonal-geo-regions

For the similar seasonal-geo-region mining, we calculate the similarity of all pairs of the obtained seasonal-geo-regions and select the pairs whose similarities are higher than a threshold τ, as same as in our previous method. As the similarity measure, we use the Normalized Cross-Correlation

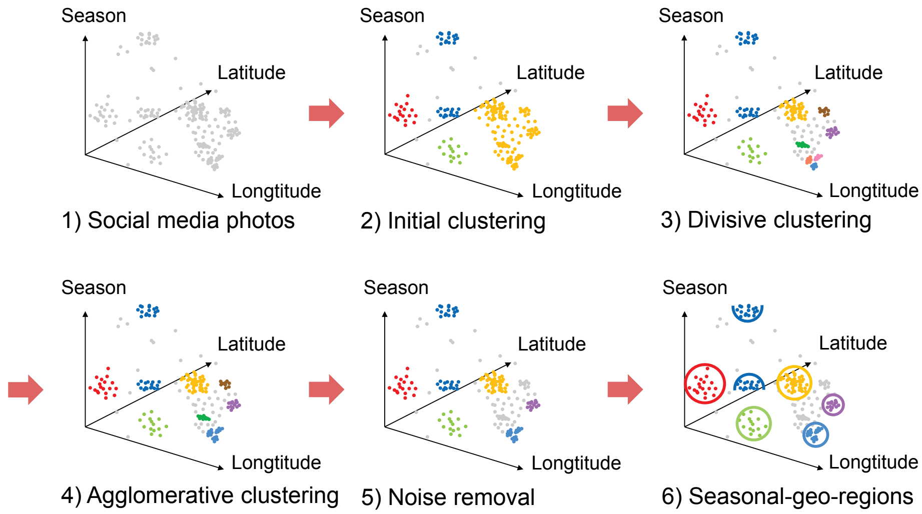
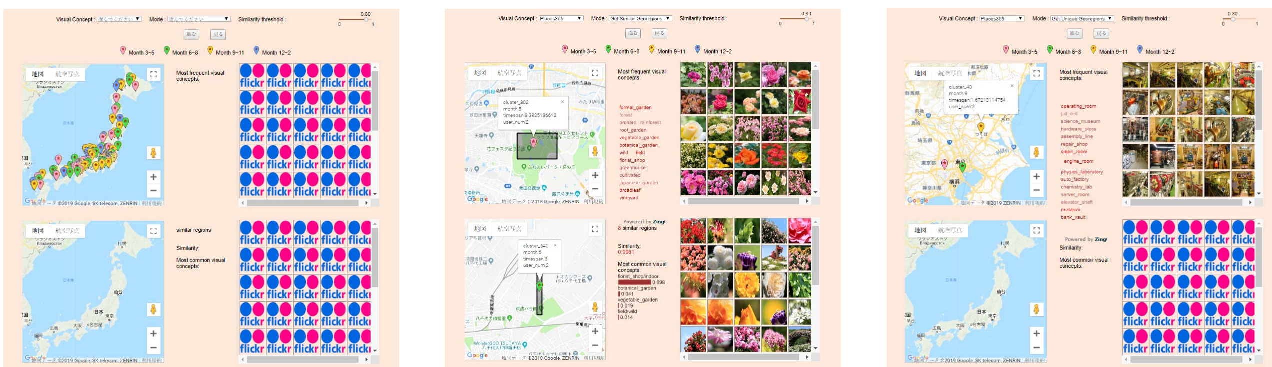


Fig. 4: Clustering process. Since the season repeats every year, the season axis circulates.



(a) Initial view (b) Similar seasonal-geo-region pair view (c) Unique seasonal-geo-regions view

Fig. 5: Interactive visual interface.

(NCC). Given seasonal-geo-regions r_a and r_b corresponding to clusters C_a and C_b, respectively, NCC S_{r_a,r_b} is calculated by using their feature vectors $\widehat{\mathbf{V}}_a$ and $\widehat{\mathbf{V}}_b$, respectively as

$$S_{r_a,r_b} = \frac{\sum_{n=1}^{N}(\widehat{V}_a(n) - \overline{\widehat{\mathbf{V}}_a})(\widehat{V}_b(n) - \overline{\widehat{\mathbf{V}}_b})}{\sqrt{\left(\sum_{n=1}^{N}(\widehat{V}_a(n) - \overline{\widehat{\mathbf{V}}_a})^2\right)\left(\sum_{n=1}^{N}(\widehat{V}_b(n) - \overline{\widehat{\mathbf{V}}_b})^2\right)}}, \tag{2}$$

$$\overline{\widehat{\mathbf{V}}_c} = \frac{1}{N}\sum_{n=1}^{N}\widehat{V}_c(n), \tag{3}$$

where N denotes the dimension of the feature vectors, $\widehat{V}_a(n)$ and $\widehat{V}_b(n)$ denote the n-th elements of the feature vectors, respectively.

4. VISUALIZATION OF THE MINING RESULTS

To analyze the mining results, we created an interactive visual interface of the mining results. In addition to similar seasonal-geo-regions, this interface can also show "unique seasonal-geo-regions", which stands for isolated seasonal-geo-regions which do not have any similar seasonal-geo-region. This will support users to find destinations where they can expect to experience a unique atmosphere that cannot found anywhere else.

Figure 5 shows several views of the interface. At the top of the screen, we can select the Visual Concept detector to be used (Only Places365 [2] was used for the experiments in this paper), type of mining results (similar or unique seasonal-geo-regions), and the threshold of the similarity defined in Eq. 2.

In the case of similar seasonal-geo-regions, seasonal-geo-regions which are similar to the query seasonal-geo-region selected by a user are plotted on the map.

The interface has several views. In the initial view, all seasonal-geo-regions are plotted on the map as shown in Figure 5a. The color of each pin represents the corresponding season of the seasonal-geo-region (Pink: Spring (March to May), Green: Summer (June to August), Yellow: Autumn (September to November), Blue: Winter (December to February)).

In order to set a query seasonal-geo-region, a user needs to click the corresponding pin on the upper map in Figure 5a. By clicking the "proceed" button, the number of the similar seasonal-geo-regions are displayed at the middle bottom, and similar seasonal-geo-regions are also plotted on the lower map.

If the user clicks one of the similar seasonal-geo-regions, the view changes and the detailed information on the seasonal-geo-region pair is presented, as shown in Figure 5b. As for the detailed information, photographs and the detected Visual Concepts that belong to each of the seasonal-geo-regions are presented. In addition, the similarity of the pairs and also Visual Concepts which contributed to the similarity are shown at the middle bottom of the screen. Note that the contribution $w_k(a,b)$ of a Visual Concept k while calculating the similarity between seasonal-geo-regions r_a and r_b is calculated as

$$w_k(a,b) = \frac{(\widehat{V}_a(k) - \overline{\widehat{\mathbf{V}}_a})(\widehat{V}_b(k) - \overline{\widehat{\mathbf{V}}_b})}{\sqrt{\left(\sum_{n=1}^{N}(\widehat{V}_a(n) - \overline{\widehat{\mathbf{V}}_a})^2\right)\left(\sum_{n=1}^{N}(\widehat{V}_b(n) - \overline{\widehat{\mathbf{V}}_b})^2\right)}}. \tag{4}$$

Here, when the contribution $w_k(a,b)$ of a Visual Concept is greater than 0.01, the Visual Concept is considered as contributed to the similarity of the seasonal-geo-regions. Finally, such Visual Concepts are displayed at the middle of the screen.

On the other hand, in the case of unique seasonal-geo-regions, the candidates are plotted on the map as shown in Figure 5c from the beginning without any querying. As same as in the similar seasonal-geo-region view mode, when the user selects one of the unique seasonal-geo-region, detailed information is presented.

5. EXPERIMENT ON SIMILAR SEASONAL-GEO-REGION MINING

In this section, we report the results from the similar seasonal-geo-region mining by applying the proposed method to actual social media photographs.

5.1. Dataset

As a source of actual social media photographs, We used the YFCC100M dataset [3]. This dataset is composed of approximately 100 million photographs and video clips taken around the world collected from the photo-sharing service Flickr[1]. In this experiment, since we need to locate when and where the photographs were taken, and also to facilitate the subjective evaluation in the next section, we work on a subset of approximately 91 thousand photographs with spatio-temporal information taken within the geographic boundaries of Japan.

5.2. Experimental settings

The clustering parameters for the decision of seasonal-geo-region boundaries were set as follows:

- Initial spatio-temporal clustering by DBSCAN
  - Minimum common data points: $P_{\min} = 100$
  - Maximum radius: $\varepsilon = 0.01$
    (Equivalent to 1 km in the spatial direction and 4 days in the temporal direction)
- Divisive clustering in the temporal direction
  - Increment $P_{\min}$ by 100 points in case of a cluster which is widely distributed in the temporal direction.
- Agglomerative spatio-temporal clustering
  - Concatenate clusters with a seasonality of less than one month and a similarity higher than 0.70.

As for the Visual Concept detector, we made use of a CNN-based model named Places 365 [10] which specializes in scenes and outputs the likelihood for each of the 365 scene classes of an input photograph.

5.3. Results

The distribution of similarities for the ${}_{633}\mathrm{C}_2 = 200,028$ pairs of all the 633 seasonal-geo-regions detected in the dataset by the proposed method based on the above parameters, is shown in Fig. 6. For the subjective evaluation in the next section, we set the threshold of the similarity defined in Eq. 2 to 0.80. This yielded 5,031 seasonal-geo-region pairs. Examples of some of the pairs are shown in Figures 7, 8, and 9. We can see that with the proposed method, we can detect similar seasonal-geo-regions based on natural phenomena (floral blooming), social events (military base festival), and human activities (diving) that take place only during certain seasons throughout the year.

6. EVALUATION

In the experiment of the previous section, we confirmed the feasibility of mining similar seasonal-geo-regions based on

[1]Flickr: `https://www.flickr.com/`

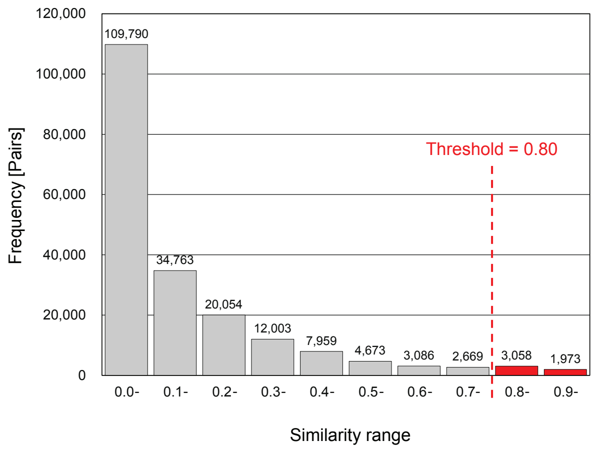


Fig. 6: Distribution of the similarities of seasonal-geo-regions.

the attention of the crowd. In this section, the proposed similarity measurement is evaluated through a subjective experiment on part of the mined results, and then the effectiveness of considering the seasonality of a geo-region is demonstrated through comparison with the results when it is not considered.

6.1. Evaluation of the proposed similarity measurement

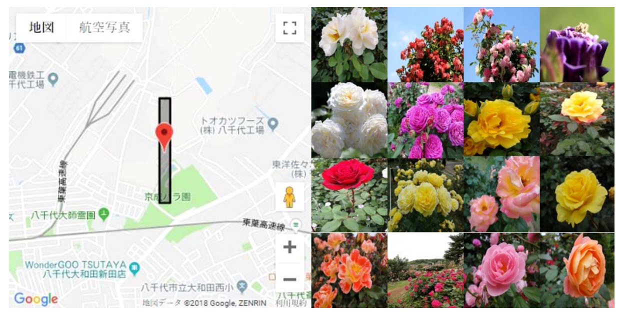
This section evaluates the validity of the similarity values measured by the proposed method by comparing them with the similarity judged in a subjective experiment.

6.1.1. Subjective experiment

A subjective experiment was carried out with the cooperation of 19 participants in both sex within the age group of teens to 30s. The participants were asked which of two seasonal-geo-regions A or B is more similar to a reference region X. Here, 53 sets of regions X, A, and B (Noted as task set (X, A, B) in the following) were prepared for the experiment. In order to make the task neither too simple nor too difficult, for each task set (X, A, B), X and A were selected from geo-region pairs with similarities higher than a threshold of 0.80; similar geo-regions, while X and B were selected from those higher than 0.50 but lower than 0.75; not similar geo-regions. Note that when selecting geo-region pairs as above, those located in the vicinity were excluded, and also we tried to keep the variety of relations (i.e. common contents between the pair) as diverse as possible. The order of A and B were changed at random when being presented to the participants.

The participants were shown a map with all the locations X, A, and B plotted on it. They were asked to click on each of them to view detailed geographic information, seasonal information, and an excerpt of photos taken in the corresponding geo-region. The participants were then, asked to choose from

(a) Flower Fiesta Park (Kani, Gifu) in May.



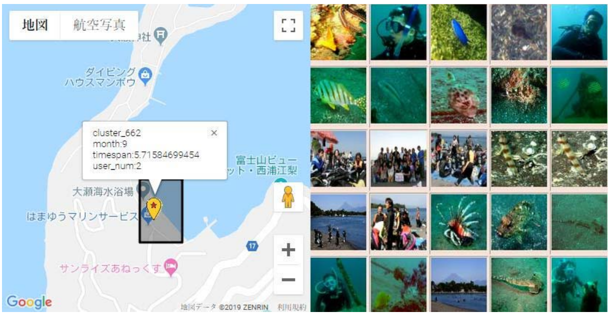
(b) Keisei Rose Garden (Yachiyo, Chiba) in June.

Fig. 7: Example of a detected similar seasonal-geo-region pair (Similarity: 0.9958) related to natural phonomena.

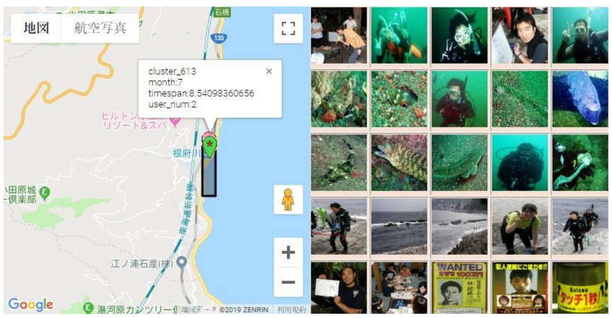
(a) JASDF Iruma Base (Sayama, Saitama) in November.

(b) USAF Yokota Base (Fussa, Tokyo) in September.

Fig. 8: Example of a detected similar seasonal-geo-region pair (Similarity: 0.9593) related to social events.



(a) Ose beach (Numazu, Shizuoka) in September.



(b) Nebugawa diving center (Odawara, Kanagawa) in July.

Fig. 9: Example of a detected similar seasonal-geo-region pair (Similarity: 0.8887) related to human activities.

A or B, the region which they consider was more similar to the reference region. Note that they were allowed to choose "Cannot decide (Please explain the reason)" if they cannot select between A or B. In addition, they were also asked to report all geo-regions that they had visited in the past so that we could consider them during the analysis if needed.

6.1.2. *Results and discussion*

Figure 10 shows the distribution of concordance ratios for all 53 task sets. Here, the concordance ratio is defined as the ratio that participants judged in concordance to the similar geo-region judged by the proposed method. Note that when a participant could not decide, it was omitted from the calculation of the concordance ratio of the corresponding task set.

We considered that for task sets with concordance rates higher than 0.5 were successfully judged by the proposed method. Note that we ignored the task set whose concordance rate was exactly 0.5, since we could not judge the majority of judgments. As a result, $46/52 = 89\%$ task sets were considered as successful judgments by the proposed method.

6.2. Effectiveness of considering the seasonality

In this section, we evaluate the validity of considering the seasonality of geo-regions through comparing the seasonal-geo-

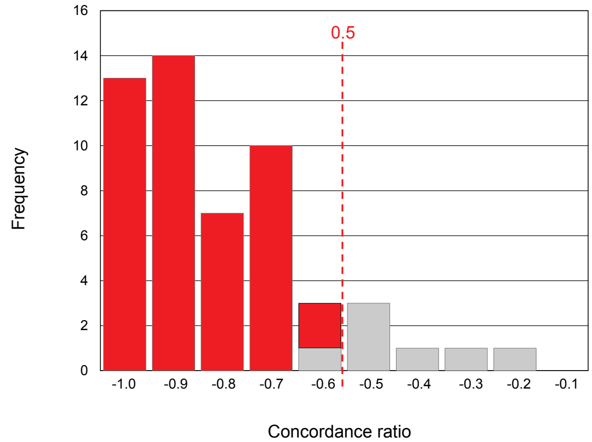


Fig. 10: Distribution of concordance ratios.

regions with geo-regions that do not consider the seasonality.

6.2.1. *Experimental settings*

For geo-regions that do not consider the seasonality, all photographs shot throughout the year within the geographic boundary as the seasonal-geo-region to-be-compared-with, were accumulated. The similarity between a pair of these geo-regions that do not consider the seasonality was evaluated the same as the seasonal-geo-regions using Eq. 2. The similarity threshold was also set to 0.80.

6.2.2. *Results and analysis*

We compared all the 5,031 pairs of seasonal geo-regions mined in Section 3.4 with geo-regions.

As a result, 3,156 of the geo-regions that do not consider the seasonality were not detected under the same criteria, which tended to be geo-regions in big cities. We consider that this trend can be explained from the fact that a wide-range of events take place in big cities, thus considering seasonality is important to characterize the geo-region at a certain season.

An example that illustrates this discussion is shown in Fig. 11. This example is taken from a geo-region in the center of Sapporo, Hokkaido (Figure 11a). Since snow, food, festivals, etc. are mixed in the no seasonality photographs shown in Fig. 11b, it is difficult to characterize the geo-region. By considering the seasonality of the geo-region, we could characterize the seasonal-geo-region with festival in summer (Fig. 11e), and snow in winter (Fig. 11c). Meanwhile, spring was characterized with food (Fig. 11d), which could be the base function of this geo-region.

(a) Location (b) No seasonality

(c) Jan. and Feb. (d) April and May (e) June

Fig. 11: Examples of different seasonalities through the year.

7. CONCLUSION

In this paper, we proposed a method for mining similar seasonal-geo-regions by using spatio-temporal information accompanying photographs posted on social media and their image contents represented by Visual Concepts.

A similar seasonal-geo-region mining experiment was performed by applying the proposed method to photographs posted on a social photo-sharing platform; Flickr within the geographic boundaries of Japan. As a result, we could retrieve similar geo-regions that included seasonal events such as natural phenomena, social events, and human activities that took place only in certain seasons throughout the year.

Through a subjective experiment, the proposed similarity measurement was proved to be effective with high concordance rates with human judgments. In addition, the effectiveness of considering the seasonality of a geo-region was demonstrated through comparison with the results when the seasonality was not considered.

We will consider incorporating activities of users, and latent semantic analysis of the detected Visual Concepts for each seasonal-geo-region in the future.

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8. REFERENCES

[1] Hiroki Takimoto, Magali Philippe, Yasutomo Kawanishi, Ichiro Ide, Takatsugu Hirayama, Keisuke Doman, Daisuke Deguchi, and Hiroshi Murase, "Detection of similar geo-regions based on visual concepts in social photos," in *Advances in Multimedia Information Processing —PCM 2017, 18th Pacific-Rim Conf. on Multimedia, Harbin, China, Sept. 28–29, 2017, Revised Selected Papers Part I*, May 2018, vol. 10735 of *Lecture Notes in Computer Science*, pp. 497–504.

[2] Thomas Deselaers and Allan Hanbury, "The visual concept detection task in ImageCLEF 2008," in *Evaluating Systems for Multilingual and Multimodal Information Access —9th Workshop of the Cross-Language Evaluation Forum, CLEF 2008, Aarhus, Denmark, Sept. 17–19, 2008, Revised Selected Papers*, Jan 2009, vol. 5706 of *Lecture Notes in Computer Science*, pp. 531–538.

[3] Bart Thomee, David A. Shamma, Gerald Friedland, Benjamin Elizalde, Karl Ni, Douglas Poland, Damian Borth, and Li Li-Jia, "YFCC100M: The new data in multimedia research," *Communications of the ACM*, vol. 59, no. 2, pp. 64–73, Jan. 2016.

[4] Daisuke Kitayama, Tomofumi Yoshida, Shinsuke Nakajima, and Kazutoshi Sumiya, "A tourist spot search system based on paragraph vector model of location and category tags using user reviews," in *Trans. Engineering Technologies: IMECS2017*, Feb. 2018, pp. 211–225.

[5] Jing Yuan, Yu Zheng, and Xing Xie, "Discovering regions of different functions in a city using human mobility and pois," in *Proc. 21st ACM Int. Conf. on Knowledge Discovery and Data Mining*, Aug. 2012, pp. 186–194.

[6] Xishan Zhang, Jia Jia, Ke Gao, Yongdong Zhang, Dongming Zhang, Jintao Li, and Qi Tian, "Trip outfits advisor: Location-oriented clothing recommendation," *IEEE Trans. Multimedia*, vol. 19, no. 11, pp. 2533–2544, Nov. 2017.

[7] Hiroshi Honjo, Naoko Nitta, Kazuaki Nakamura, and Noboru Babaguchi, "Constructing geospatio-temporal concept graphs from tagged images," in *Proc. 3rd IEEE Int. Conf. on Multimedia Big Data*, Apr. 2017, pp. 169–176.

[8] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," in *Proc. 2nd AAAI Int. Conf. on Knowledge Discovery and Data Mining*, Aug. 1996, pp. 226–231.

[9] Gerard Salton and Michael J.McGill, *Introduction to Modern Information Retrieval*, McGraw-Hill, 1986.

[10] Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba, "Places: A 10 million image database for scene recognition," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 40, no. 6, pp. 1452–1464, July 2017.