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A Big Data Framework to Identify Tourist Interests Based on Geotagged Travel Photos

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ABSTRACT Understanding the interests of tourists is a key skill for attraction managers to prepare plans and make strategic decisions in tourism marketing. The rapid growth and spread of social media websites provide an information-rich channel from which tourism researchers and managers can collect a large amount of text-based reviews or comments and photos relating to the past travel experiences of users. The travel photos with geographic information are especially helpful in identifying the geographical location of the destinations. By analyzing these big data in various formats can help to understand the interests of tourists at destinations. In this paper, a framework is proposed to identify the interests of tourists by integrating information carried by the geotagged photos shared on social media websites. Such an approach is expected to provide sustainable tracking on popular places of interest (POIs) updated by tourists and pick the best representative photos taken by them. The performance of this model is evaluated by conducting a case study using the geotagged photos taken in Hong Kong. A case study proved this proposed framework could make a thriving tourism industry more efficient.

INDEX TERMS representative photo, geotagged photo, tourist interest, tourist activity.

I. INTRODUCTION

Hong Kong has been a popular tourist destination for decades. Given its geographical location, Hong Kong has become a successful airport hub in Asia that acts as a gateway to China since the 1980s and 1990s. Following the introduction of the Individual Visit Scheme for Mainland Chinese [1], the number of Chinese tourists in Hong Kong has increased dramatically since 2003, with many of these tourists going on repeated visits to Hong Kong with an average stay length of 3.3 days reported by Hong Kong Tourism Board (HKTB) [2]. However, this length is shorter compared with that recorded in the past decade [3], which indicates that the tourism activities in Hong Kong cannot effectively encourage tourists to stay for longer periods, especially those repeat tourists who actively seek new tourist spots or activities.

HKTB actively promotes the outdoor and heritage tourism of Hong Kong to extend the stay length of tourists. Approximately 87% of tourists visit Hong Kong to shop, while less than 8% of these tourists participate in heritage- and

ecology-related tourism activities [4]. Although these tourists still maintain the "traditional" image of Hong Kong in their minds, their length of stay has not changed significantly. Destination Management Offices (DMOs) attract the expanding tourist market by promoting various tourism activities that suit different market needs and guarantee a quality travel experience for visitors [5]. Given that marketing focus can significantly affect the destination image and target tourists, DMOs must carefully inspect the interests of tourists. Mehmetoglu [6] suggested that DMOs should balance the expectations, preferences, and attitudes of individuals toward the environment with the resource management of a nature-based experience. No previous study has thoroughly addressed the following questions: What attracts the tourists when they visit a destination? What are their special interests and activities at the destination? What are their experiences in each of their visited POIs? How do the interests and experiences of these tourists differ across groups? Therefore, DMO managers are required to develop an effective destination management

plan to suit the interests of tourists at different places of interest (POIs). Such analysis requires a large amount of data relating to the interests, activities, preferences, and satisfaction of tourists. The Internet, particularly travel-related social media websites, offers an information-rich channel from which DMOs can obtain these data.

In previous studies on the activities at tourist destinations, researchers and DMO managers usually compile a list of pre-determined tourist interests. Only a limited number of interests and activities are included in this list, while small or emerging interests are often neglected. These studies are not efficient in capturing the interests of tourists comprehensively. Major tourism destinations have diverse POIs, and tourists are attracted by many things in the locations that they visit. Nevertheless, only a few studies have constructed tourist profiles based on POIs where they have visited. The information in text-based online reviews and comments is the primary source of data analyzed in the current research work. An increasing number of social media users also upload their travel photos online with limited or without textual descriptions. Travel photos offer an important source of information that captures the interests and travel experiences of tourists. Compared with text, images can quickly impart the feelings of the uploader to his/her readers.

Some studies have used travel photos to explore how tourists perceive their destination [7,8] or to identify tourist behaviors, but these studies have mostly analyzed a small number of collected photos manually [9-13]. However, such a manual approach is time-consuming, ineffective, and unable to utilize the values of the massive volume of travel photos available on the Internet entirely. Computer scientists have proposed advanced image processing techniques that can help identify tourist interests based on travel photos. As an emerging technique, image representation has been used in the automatic selection of a small set of images that best answers a search query relating to specific tourist interest. DMOs can use this technique to obtain comprehensive information regarding the perspective of tourists toward a particular destination, which in turn, they can use to improve their marketing strategies continuously. However, only a few studies have explored the activities and preferences of tourists based on the photos they take and share.

This study aims to fill such a technical gap by obtaining comprehensive travelling behavior from both text-based posts and the photos that tourists upload on social media websites. Some tasks of this work are accomplished to achieve the goal:
- Introduce a framework that is capable of processing textual, geotagged and visual data collected from the posts with travel photos that tourists have shared on social media websites;
- Construct a profile of the top interests and locations of these interests (POIs) by applying the proposed framework;
- Identify the representative photos of major tourism POIs in Hong Kong;

- Provide a big data method for DOM to continuously monitor the tourists' interests at POIs.

The rest of the paper is organized as follows: Section 2 reviews the existing research work on tourist interests and their activities at the destinations followed by the image processing techniques applied on travel photo analysis; Section 3 introduces the proposed framework that integrates textual, geographical, and visual processes for tourist interest study; the results are reported and explained in Section 4; Section 5 is used to discuss the findings obtained from this work; and finally, Section 6 concludes the entire paper with current limitations and possible future work.

II. RELATED WORK
This section reviews the literature on tourist interests, travel activities, and destination image, and then introduces state-of-the-art image representation techniques. The research gaps and the objectives of this study are also defined.

A. TOURISTS INTERESTS AND TRAVEL ACTIVITIES
Tourist destinations are incredibly complex products with tangible and intangible elements [14,15]. Given their limited resources, DMOs must identify critical areas for improving the overall perception of tourists toward specific destinations. Mehmetoglu [6] classified 17 major tourist activities in Norway into four categories, including historical/cultural events relaxing nature-based activities, pleasure-based activities, and challenging nature-based activities. According to Zbuchea [16], cultural events include visiting parks, heritage sites, museums, and theatres for shows, plays, or opera. Traditional food and cuisine may also be considered an exceptional tourist POIs because food consumption can be regarded as an activity for both entertainment and cultural exploration [17]. Shopping is another popular tourist activity apart from sightseeing and visiting tourist attractions [18]. Shopping not only takes place during trips but may also be performed while tourists visit duty-free stores at airports before heading home [19].

Travel photos contain information relating to the interests and activities of tourists during their trips. "The art of much tourist photography is to place one's 'loved ones' within an 'attraction' in such a way that both are represented aesthetically" [20] (p. 179). Travel photos can reflect the feelings of the tourist and record the travel experience of the photographer [21]. Stepchenkova, Kim, and Kirilenko [22] studied the activities and interests of Korean tourists based on the photos they took in Russia and found that their travel activities included leisure activities (i.e., shopping, dining, and watching performances) and outdoor sports (i.e., skiing, hiking, kayaking, and tennis), while their interests included local lifestyle (i.e., everyday activities of local residents in markets or schools), transportation and infrastructure (i.e., buildings, transportation systems, and highways), nature (i.e., trees, rivers, and mountains), heritage sites, weather and sceneries (i.e., greenery and climate), and tourist

accommodations (i.e., hotels, beaches, and restaurants). Another study related the photographic representation of Jeju Island to the availability of natural, cultivated, heritage, cultural, and touristic spaces in this area. By examining such photos, DMOs can identify "benchmarking" tourist activities and interests and subsequently improve their promotion strategies. Tourists share photos on social media, and analyzing geotagged photos can help DMOs identify the travel patterns [23], travel behavior [24], and activities that tourists perform in each POI [25,26].

B. DESTINATION IMAGE AND PHOTOS

Martineau [27] proposed that human behavior, such as visiting a tourist destination, was based upon perceptions toward an image instead of objective reality. Destination image refers to the aggregate sum of beliefs, impressions, and expectations of a tourist about a destination—including their beliefs and impressions on the information being advertised by such destination [28]—that can greatly affect their decision-making process [29]. DMOs dedicate much of their efforts to marketing to create a proper destination image that can attract more tourists. Destination advertising has become increasingly competitive worldwide [30]. New information technologies allow public and private travel organizations to deliver destination information regardless of geographical boundaries [31]. As a contemporary communication tool, the Internet offers many advantages over traditional media. Specifically, the Internet is an interactive, fast, and flexible channel from which DMOs can collect and review the preferences and/or satisfaction of tourists with the provided products or services [32]. Apart from projecting a destination image, DMO websites offer information and important functions, such as maps, sample travel routes, and dining and lodging locations [31]. Effectively managing the perceptions and experiences of tourists can maintain the value of a destination [33]. Destinations compete with one another for increased visitation, thereby increasing their need to create a unique identity and differentiate themselves from their competitors [34,35]. Law and Cheung (2010) examined the destination images of Hong Kong from online blogs and identified 24 tourist spots. However, they did not examine the tourist activities of these bloggers in Hong Kong. Previous studies have examined the destination images from user-generated content via content analysis [36,37] but merely focused on text-based materials from DMO websites [38,7]. Prebensen [39] used pictures, words, and free associations to explore the relationship between travel information and destination image among French, German, and Swedish tourists visiting Norway. He concluded that various methods should be employed to understand fully the vast array of knowledge and images that people hold of destinations.

Travel is a unique visual experience, and vacation photos are important components of travels. The "slideshows and photographs are a common way to communicate personal trip experiences and perceived destination images" [40] (p. 245).

Travel photos may provide evidence of having a vacation, and vacations may feel incomplete without taking any photo [41]. Stepchenkova and Zhan [11] found that DMOs in Peru tend to present a well-rounded image by giving a "voice" to all regions and focus on the natural beauty, archaeological heritage, customs, traditions, and art of the country. Another study examined the content and destination images reflected in travel photos [13]. However, they manually analyzed 500 photos from 162 blogs. The professional photos taken by DMOs are crucial in creating a destination image, while the photos from tourists can alter a destination image via "public channels" [42,20].

C. IMAGE PROCESSING AND REPRESENTATION

Image processing and representation are popular topics in computer science and data mining for many years that have attracted demand in many application areas. Tourism managers gain insights into the experiences of tourists by choosing the most representative photos from a collection of photos relevant to specific tourist interest. Representative photos refer to those photos which contents appear most frequently in a photo collection. Unlike previous studies that use manual content analysis approaches [9,11,12], this work analyzes automatically and identifies the representative photos. Given that computers cannot directly recognize objects and understand the photo content, the photo must be processed and represented in an appropriate format before further analysis.

The local regions in a photo offer powerful cues in automatic natural scene recognition [43]. Local areas are also more robust to occlusions and spatial variations compared with traditional global features, such as frequency distribution, edge orientations, and color histogram [44-46]. This work represents photo content using the Speeded-Up Robust Features (SURF) descriptor [47], an advanced feature descriptor for local areas that has proven its effectiveness in object recognition tasks [48,49]. This descriptor identifies the local areas in each photo based on the interest points detectors or a random sampling of photo patches [50-52]. The SURF descriptor is a histogram of Haar wavelet responses that are accumulated at different spatial bins of the local region.

III. MATERIALS AND METHODS

To achieve the above objectives, this section proposes a framework for identifying tourism interests based on geotagged photos that are shared on social media websites. This framework involves the following major steps, as shown in Figure 1: (1) textual metadata processing, (2) geographical data clustering, and (3) visual content processing. After inputting the collected geotagged photos, a list of tourist interest candidates can be automatically obtained with their corresponding spatial extents on the global map. The actual activities of tourists at certain locations, as shown in the representative photos, can provide insights into their interests and preferences.
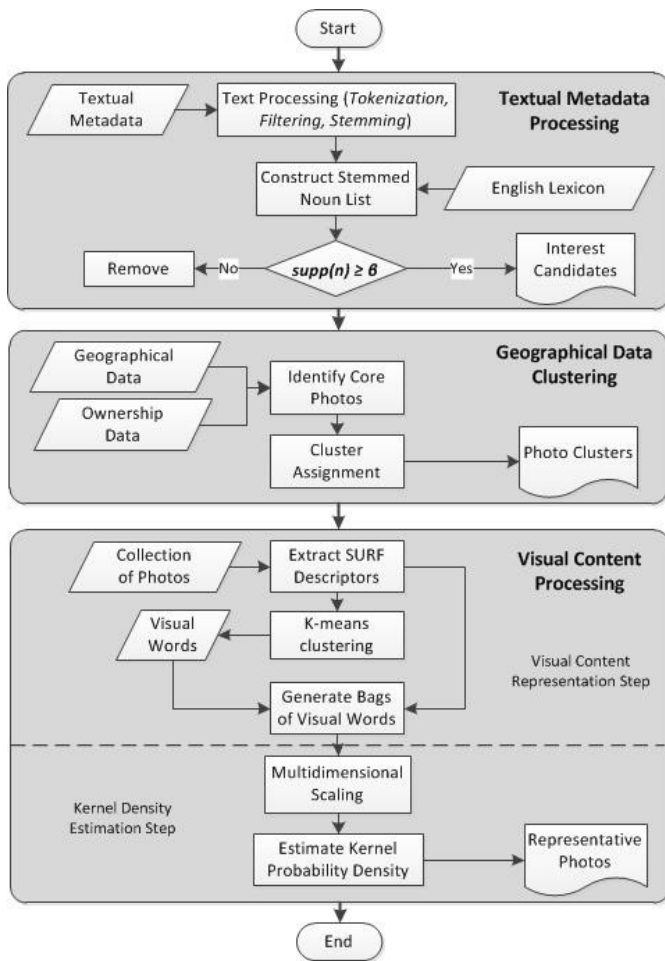
FIGURE 1. Tourist Interest and Representative Photos Identification Framework

A. TEXTUAL METADATA PROCESSING

The textual metadata attached to the uploaded photos contains textual tags, photo titles, and content descriptions, which often reflect the motivation behind taking the photo. Text processing techniques are applied to these metadata to discover the interests of tourists and infer the activities in which they want to participate. The textual metadata of a photo often contains specific keywords that reflect certain things or objects that are of interest to the tourists when they are taking photos. Such textual data are normally unstructured and cannot be easily analyzed directly. The General Architecture for Text Engineering (GATE)[1], a text processing tool, is adopted to extract the keywords from textual metadata automatically. Several applications in tourism have been built based on GATE, such as the cultural-tourist information system [53] tourism recommender system [54], and tourism web services [55].

GATE provides several language databases, including an English lexicon that contains a comprehensive list of vocabulary terms to describe tourist interests. Suppose p_i is

a travel photo in the collected photo dataset P, while its metadata $t^{(p_i)}$ contains user-defined tags, photo titles, and descriptions. First, the metadata $t^{(p_i)}$ is loaded into a text tokenistic algorithm, wherein the text stream is broken into a set of "tokens" that can be words, phrases, symbols, or other meaningful elements. Second, a token filter is applied to normalize all letters to lower case and to remove special symbols and numbers. The remaining tokens are then inputted into a stemming process to reduce the inflected words to their stem, base, or root form. Given that the photos in this work are collected from Flickr, only the English vocabulary of noun type is considered to represent the entities of interest (i.e., street, building, and tree). The type of words, such as nouns, verbs, or adjectives, can be determined based on a set of tags associated with each word in the English lexicon. A list of stemmed nouns appearing in the dataset is then constructed and denoted as $N = \{n_1, n_2, \ldots, n_m\}$. A binary vector $v^{(u_i)} = \{v_1^{(u_i)}, v_2^{(u_i)}, \ldots, v_m^{(u_i)}\}$ is constructed for each user, where each $v_j^{(u_i)}$ takes the value of 1 if a certain noun n_j appears at least once in the textual metadata of the photo collection for user u_i, or 0 if this noun is not found.

	u_1	u_2	...	u_i	...			u_1	u_2	...	u_i	...
n_1	$v_1^{(u_1)}$	$v_1^{(u_2)}$	...	$v_1^{(u_i)}$	...		n_1	1	1	...	1	...
n_2	$v_2^{(u_1)}$	$v_2^{(u_2)}$	...	$v_2^{(u_i)}$	...	$\rightarrow$	n_2	0	1	...	0	...
⋮	⋮	⋮	⋮	⋮	⋮		⋮	⋮	⋮	⋮	⋮	⋮
n_m	$v_m^{(u_1)}$	$v_m^{(u_2)}$	...	$v_m^{(u_i)}$	...		n_m	1	1	...	0	...

Let $|U|$ denote the total number of users in the dataset, and $sum(\boldsymbol{v}_j)$ denote the sum of all values in $\boldsymbol{v}_j$. The occurrence frequency of each noun n_j is calculated as follows:

$$supp(n_j) = \frac{sum(\boldsymbol{v}_j)}{|U|}, \qquad (1)$$

The interest of users (tourists) to a specific object or activity is measured by the occurrence frequency of the corresponding noun. A support threshold β is predefined to measure the significance of the nouns in the dataset. If a noun n_j satisfies $supp(n_j) \geq \beta$, then this noun is added as a candidate to a list of tourist interests; otherwise, this noun is discarded without warning. A list of tourist interest candidates is automatically constructed from the textual metadata.

B. GEOGRAPHICAL DATA CLUSTERING

The tourist interests obtained from the first step are only considered candidates because they are identified by the frequency of their occurrence in the photo tags, titles, and descriptions. Despite being mentioned several times, some keywords may denote various meanings or represent a common object instead of a tourist interest. For example, "apple" frequently appears on the candidate list, but the

[1]http://gate.ac.uk

corresponding photos show the tourists either eating an apple or visiting the "Apple store" in Hong Kong Island. Moreover, most of these photos were captured using Apple devices, such as iPhones or iPads. Therefore, to ensure that the identified locations have actually been visited by many tourists in pursuit of particular interest, the numbers of photos and users (tourists) must achieve a certain density. After identifying the interests and relevant photos, a clustering technique for geographical data is applied to identify the popular locations for each interest. The P-DBSCAN clustering technique [56] is adopted to identify the popular areas of actual tourist interests, as reflected in the number of photos taken.

Suppose P' is a collection of photos in which textual metadata contain keywords that indicate a specific tourist interest. The geographical data of each photo p_i is referenced by the value pair $<x_{p_i}, y_{p_i}>$ for longitude and latitude, respectively. The distance between photos p_i and p_j is defined as $Dis(p_i, p_j)$. Let r be a neighbourhood radius. The neighbourhood photo $N_r(p_i)$ of photo p_i is defined as follows:

$$N_r(p_i) = (p_j \in P', Owner(p_j) \neq Owner(p_i) | Dis(p_i, p_j) \leq r) \quad (2)$$

where $Owner(\bullet)$ is an ownership function that specifies the owner of photo p_i. A photo p_j is the neighborhood of another photo p_i if this photo belongs to a different user and if its location is within a neighborhood radius r from photo p_i. Let $NeighborOwner(p_i)$ be the owner number of neighbour photos $N(p)$, and let δ be the owner number threshold. A photo p_i is considered a core photo if its neighbor photos belong to at least a minimum number of owners ($NeighborOwner(p) \geq \delta$). Let $NeighborOwner(p_i)$ be the owner number of the neighbor photo $N_r(p_i)$, and let δ be an owner number threshold. Photo p_i is considered a core photo if $NeighborOwner(p_i) \geq \delta$. All photos are marked as unprocessed at the beginning of the clustering process. If p_i is a core photo, then this photo is assigned to cluster c, and its neighbors are assigned to a queue to be processed next; otherwise, this photo is discarded. Each neighboring photo is then processed and assigned to the current cluster c until the queue is empty. The process is iterated for the rest of the photos in P' to form a set of clusters C. The geographical coordinates of the clusters are then examined to determine the location and spatial extent of tourist interests.

C. VISUAL CONTENT PROCESSING

Visual content processing identifies the representative photos for each interest at specific locations to generate insights into the experiences or interests of the tourists. This step aims to identify the most representative photos for specific interests taken at different locations. This process is performed automatically using relatively new techniques in computer vision for photo content representation and processing. Two main sub-processes are involved, namely, visual content representation and kernel density estimation (KDE).

1) VISUAL CONTENT REPRESENTATION

The photo content is often represented via local region descriptors by representing each image as a bag of visual words [51,57]. A bag of visual words features is generated as follows [58]. The SURF descriptors are initially extracted for a large set of local regions that are extracted from a set of random photos. K−means clustering is then applied to construct a visual word vocabulary. Visual words are defined as the centers of the clusters, and the value of k determines the number of available visual words. For a new photo p_i with several local regions, the SURF descriptors are extracted and then vector quantized into visual words for the vocabulary. Each photo is then represented as a bag of visual words denoted as $\boldsymbol{w}^{(p_i)} = \{w_1^{(p_i)}, w_2^{(p_i)}, ..., w_k^{(p_i)}\}$. The value of each element $w_j^{(p_i)}$ denotes the number of times that the visual word w_j appears in photo p_i. The values of w_j vary depending on the photo content to characterize the visual content of the photos.

2) KERNEL DENSITY ESTIMATION

KDE is a non-parametric method that estimates the probability density function of a random variable [59]. Let $\{\boldsymbol{x_1}, \boldsymbol{x_2}, ..., \boldsymbol{x_n}\}$ be a sample set of d-dimensional random vectors drawn from a common distribution described by density function $f(\bullet)$. The multivariate kernel density at each point $\boldsymbol{x}$ is estimated as follows:

$$\hat{f}_H(\boldsymbol{x}) = \frac{1}{n} K_H(\boldsymbol{x} - \boldsymbol{x}_i), \quad (3)$$

where $\boldsymbol{H}$ is a $d \times d$ symmetric and positive definite matrix that acts as a smoothing parameter, while $K_H(\boldsymbol{u}) = |\boldsymbol{H}|^{-\frac{1}{2}} K(|\boldsymbol{H}|^{-\frac{1}{2}} \boldsymbol{u})$, with $K(\bullet)$ as the kernel or a non-negative function that integrates to one and has a zero mean.

The choice of kernel function $K(\bullet)$ does not affect the accuracy of the kernel density estimators [60]. The standard multi-dimension normal kernel can be used as follows:

$$K(u) = (2\pi)^{-\frac{d}{2}} exp - \frac{1}{2} u^T u, \quad (4)$$

In practice, the multivariate kernel density estimators in more than three dimensions suffer from dimensionality [61]. A large dimensional space is sparsely populated by data points, with very few neighboring data points to any value x. Therefore, the dimension of the data points for the bag of visual words features must be reduced while preserving the similarity or distance between these data points. We apply the multidimensional scaling (MDS) technique [62] to the bag of words features. Let $\delta_{i,j} \approx ||w^{(p_i)} - w^{(p_j)}||$ denote the Euclidian distance between the bags of word features of photos p_i and p_j. MDS aims to find vectors $x^{p_1}, x^{p_2}, ... \in R^d$ such that $||x^{(p_i)} - x^{(p_j)}|| \approx \delta_{i,j}$, where d has a small chosen value (2 or 3). After employing MDS, each bag of word feature $w^{(p_i)} = \{w_1^{(p_i)}, w_2^{(p_i)}, ..., w_k^{(p_i)}\}$ with k-dimensions is transformed into a low-dimensional vector $x^{(p_i)} = \{x_1^{(p_i)}, x_2^{(p_i)}, ..., x_d^{(p_i)}\}$ with d dimensions.

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The MDS technique has been widely used in tourism [63,64]. Given the reduced dimensional features x, we then identify the probability density of each photo using Eq. 3.3. The top m photos with the highest probability densities are returned as representative photos. The general theme of the photo collection for each interest can be easily identified by examining the small number of representative photos.

D. CASE STUDY DATA COLLECTION

This study uses publicly available geotagged photos from Flickr, a photo-sharing website. These photos and their associated metadata are extracted using Flickr's application programming interface[2]. The region of photo data extraction can be defined by a bounding box that coordinates for minimum longitude, minimum latitude, maximum longitude, and maximum latitude are denoted as x_{min}, y_{min}, x_{max}, and y_{max}, respectively. Two time-related parameters, t_{start} for and t_{end} for, are used to set up the start and end dates of the period when the photos are taken. Only those photos taken within a defined region and time period are considered.

In this case study of Hong Kong, the collected dataset contains photos of three popular tourism regions identified in [24], namely, Lantau Island (hereafter Lantau), Kowloon, and Hong Kong Island (hereafter HK Island). A bounding box was designed to cover the selected regions. Table 1 shows the coordinates. The photo-taking time frame was set from 1st January 2013 to 30th June 2015. A total of 159,321 photos were collected from 5,861 tourist Flickr accounts. All photo metadata, including textual tags, titles, descriptions, geotags, and userIDs, were retrieved. The photos were downloaded in medium-size following Flickr's standards. This size clearly shows the contents of the photo and saves computing costs for visual content processing. Table 2 summarizes the collected dataset. Note that one tourist may have visited one or more regions during his/her trip. In the collected dataset, Kowloon and HK Island were visited by a nearly similar number of tourists (around 3,000), with each tourist taking an average of 20 photos. By contrast, only a few tourists visited Lantau, with each tourist taking an average of 6 photos.

TABLE 1. Extracted Parameters

Parameter	Value	Description
x_{min}	113.825103	Minimum longitude of the bounding box
y_{min}	22.202805	Minimum latitude of the bounding box
x_{max}	114.280349	Maximum longitude of the bounding box
y_{max}	22.359108	Maximum latitude of the bounding box
t_{start}	1/1/2013	Earliest date the photo was taken
t_{end}	30/6/2015	Latest date the photo was taken

TABLE 2. Photos Collected per Location

Location	Number of Tourists	Number of Photos	Photos per Tourist
Lantau	1,700	21,090	6.18
Kowloon	3,255	68,690	21.10
HK Island	3,411	69,541	20.38

IV. RESULTS

This section demonstrates the effectiveness of the proposed framework in using geotagged photos from Flickr to identify popular tourist interests, photo-taking locations, and representative photos of certain interests. The results were described and analyzed before presenting their practical implications.

A. CANDIDATE TOURIST INTERESTS

After preparing the dataset, the textual metadata of all collected photos was processed by following the first step of the proposed framework in Section 3.1. A pre-defined value for support threshold β was selected. Setting a small value would return a long list of tourist candidates that contains many irrelevant keywords and unnecessarily increases the computational cost in the subsequent processes. By contrast, setting a large value may generate a candidate list of only a few keywords and prevent the experiment from going any further. To obtain an objective result, the value of β was not pre-defined in the experiment. Instead, a set of 11 values [0, 0.01, 0.02… 0.09, 0.1] were examined on the collected dataset to identify an appropriate support threshold for this case study. The metadata from Lantau, Kowloon, and HK Island was examined separately to obtain an ideal result. Figure 2 presents the significant results of the examination. When $\beta = 0$, all existing tokens in the stemmed noun list were counted as candidates, which did not make any sense. However, the number of interest candidates dramatically decreased as β increased from 0 to 0.01, and then gradually decreased in a relatively stable range as β increased to 0.1. Accordingly, β was set to 0.01 for all three tourism regions to generate a reasonable amount of interest candidates for further processing.
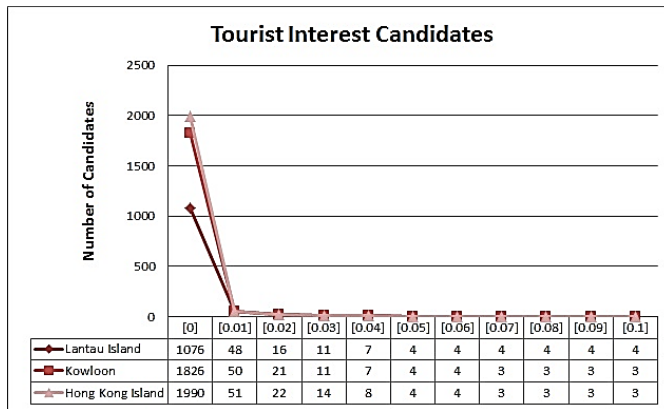
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[2]http://www.flickr.com/service/api

Tourist Interest Candidates

	[0]	[0.01]	[0.02]	[0.03]	[0.04]	[0.05]	[0.06]	[0.07]	[0.08]	[0.09]	[0.1]
Lantau Island	1076	48	16	11	7	4	4	4	4	4	4
Kowloon	1826	50	21	11	7	4	4	3	3	3	3
Hong Kong Island	1990	51	22	14	8	4	4	3	3	3	3

FIGURE 2. Interest Candidates for different β values

The general words in the candidate list, such as "Hong Kong," "China," "Asia," "time," and "place," were refined because they did not define tourist interests specifically. For synonymous words such as "plane," "airplane," and "aircraft," only the word with the highest support score was retained. Table 3 shows a refined list of tourist interest candidates in the three tourism regions. For straightforward interpretation, tourist interests were grouped into five categories, including attraction, cultural, natural, transportation, and infrastructure. The interest candidates were sorted based on their support scores within each category for easy reading. The candidate interests in the grey shadow were frequently mentioned in the metadata of the photos taken in two or all three tourism regions.

TABLE 3. Popular Tourist Interest Candidates

	Lantau		Kowloon		HK Island	
	Interest	Support	Interest	Support	Interest	Support
Tourist's Attractions	disneyland	0.032	light	0.030	light*	0.021
	food	0.011	star**	0.025	park	0.020
			market	0.018	people	0.016
			food	0.015	star**	0.011
			people	0.014	shop	0.011
			park	0.012		
			duck	0.010		
Cultural POIs	buddha	0.041	temple	0.014	film^	0.012
	monastery	0.011	film^	0.011	temple	0.010
Natural POIs	island	0.035	skyline	0.025	peak	0.043
	sunset	0.021	island	0.018	island	0.026
	sky	0.015	sunset	0.016	bay	0.023
			sky	0.013	skyline	0.018
			harbour	0.013	sky	0.013
					sunset	0.012
					landscape	0.012
Transportation POIs	flight	0.019	ferry	0.015	ferry	0.012
	plane	0.017				
	airline	0.015				
	car	0.011				
Infrastructure POIS	airport	0.102	street	0.047	street	0.043
			city	0.043	city	0.042
			hotel	0.016	skyscraper	0.020
			architecture	0.013	architecture	0.013
			skyscraper	0.012		

* Light show with Symphony
** Avenue of Stars
^ Film scene

The tourists in all three regions share some common candidate interests that mainly belong to the attraction, cultural, and natural categories. Those tourists who visited Kowloon and HK Island shared many common interests in all five categories because of their close geographic locations as well as the similarities in the transportation systems, infrastructures, and commercial environments of these areas. For cultural, the keyword "temple" appeared more frequently in Kowloon and HK Island than in Lantau because the two former regions featured three famous temples, such as Wong Tai Sin, Tin Hau, and Man Ho. At the same time, Lantau only had one temple, the Tian Tan Buddha Buddhist temple [25].

Some differences were also observed among these regions. As a young developed region, Lantau returned a much lower number of candidate interests than the other two regions yet still attract many tourists because of its unique landmarks. Hong Kong Disneyland, Tian Tan Buddha, and Hong Kong International Airport are three of the most frequently mentioned places from the collected dataset. More than 10% (support = 0.102 in Table 3) of the photos taken in Lantau were marked with the keyword "airport," followed by "buddha" (support = 0.041, over 4%) and "disneyland" (support = 0.032, over 3%).

For **attractions**, the tourists in Lantau were mostly interested in "disneyland" and "food," while those in Kowloon and HK Island were mostly interested in "light," "people," and "park." Kowloon offers unique tourist interests, such as "star" and "market," while HK Island offers "shop" or "shopping."

For **cultural POIs**, temples and monasteries were the main interests of those tourists who were seeking a cultural experience in Hong Kong. Therefore, "buddha," "monastery," "film," and "temples" were among the most popular tourist interests. The tourists in Lantau visited the Po Lin Monastery and the Giant Buddha, while those in Kowloon saw movie stars and took pictures of the Yellow Duck during its showcase in Hong Kong [65]. Although Yellow Duck had a relatively short exhibition period, many tourists took photos of this art piece, thereby listing "duck" as one of the most popular tourist interests.

For **natural POIs**, "island," "sunset," and "sky" were common candidate interests in all locations. "Victoria" and "skyline" were popular interests at Kowloon and HK Island,

while "peak," "bay," and "landscape" referred to specific natural scenes at HK Island.

For **transportation POIs**, "flight," "plane," "airline," and "car" were common interests in Lantau, while "ferry" was the most popular interest at Kowloon and HK Island.

For **infrastructure POIs**, tourists enjoy taking photos of various infrastructures in Hong Kong, such as "airport" at Lantau, and "street," "city," "architecture," and "skyscraper" at Kowloon and HK Island. "Hotel" was also among the popular interests at Kowloon.

These textual metadata highlight potential keywords yet cannot provide detailed information about tourist interests. The next section performs a further analysis using the geotags and the actual contents of photos to gather additional in-depth information.

B. LOCATIONS OF INTERESTS

The relevant photos for each candidate were extracted based on the tourist interest list in Table 3. Each photo collection was then inputted into the geographical data clustering process, as presented in Section 3.2. The neighborhood radius r was set to 0.002, which was equivalent to approximately 150 meters. The minimum owner δ was set to 0.1 or 10% of the total number of tourists in each photo collection. The resulting clusters were further inspected to determine the name of the locations. Figure 3 shows the clusters for the tourist interests in Lantau, Kowloon, and HK Island. These clusters were represented by colored dots on the satellite image. We identified all regions where at least one interest exists, and the cluster of interests was visualized using the same color.

Figure 3a shows four distinct locations for the tourist interests recorded at Lantau, including Hong Kong International Airport, Ngong Ping, Tung Chung, and Disneyland. Some distinct locations for the tourist interests in Kowloon included Sham ShuiPo, West Kowloon, Wong Tai Sin Temple, Flower Market, Mong Kok, and Temple Street (Figure 3b). The clusters around Tsim Sha Tsui were located near one another and covered a vast geographical region. These clusters were further investigated and named based on their characteristics. The segments included the spots inside Kowloon Park, the waterfront areas around the Clock Tower and Avenue of Stars, and the inner-city area of Tsim Sha Tsui. For HK Island in Figure 3c, the clusters at the city center included Man Mo Temple, Hong Kong Park, Central Ferry Pier, and the inner-city area of Hong Kong Central. Other distinct locations included Causeway Bay, Victoria Park, and Peak Tower. For Ocean Park, although the clustering result showed two distinct clusters, both of these clusters belonged to the same park. Therefore, both clusters were named under Ocean Park.

(a) Lantau

(b) Kowloon
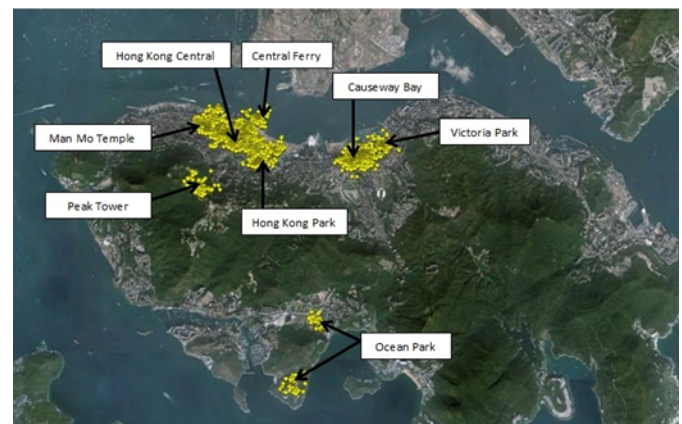
(c) HK Island

FIGURE 3. Clusters of Tourist Interests

A location profile for tourist interests was then constructed. The clusters were inspected on each interest separately to identify their locations. Table 4 summarizes the locations of each interest. The tick mark indicates that the tourists have a specific interest at that location. Some locations have multiple interests, such as the Hong Kong International Airport, Clock Tower, Avenue of Stars, Hong Kong Central, and Peak Tower,

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as reflected in their high values for overall interests. These interests corresponded to the most popular tourist attractions in Hong Kong. Some locations had unique interests, such as the cable car at Tung Chung, Wong Tai Sin Temple, Flower Market, Kowloon Park, Man Mo Temple, Hong Kong Park, and Ocean Park. Some locations also showed similar interests. Given the diversity of Hong Kong, those photos of the same interest that were taken at different locations might have different contents and reflect different tourist experiences. Accordingly, Section 4.4 further explores the contents of photos for each interest that were taken at different locations.

TABLE 4. Tourist Interest by Specific Locations

		Tourist Attractions								Cultural				Natural										Transportation					Infrastructure					Interest Count
		disneyland	food	light	star	market	people	park	ship	buddha	monastery	temple	film	duck	island	sunset	sky	harbor	peak	victoria	skyline	bay	landscape	flight	plane	airline	car	ferry	street	city	hotel	architecture	skyscraper	
Lantau Island	Hong Kong International Airport	✓														✓	✓							✓	✓	✓				✓				8
	Ngong Ping									✓	✓																			✓				
	Disneyland	✓																												✓				2
	Tung Chung																													✓				1
Kowloon	Clock Tower			✓	✓		✓					✓	✓	✓	✓	✓	✓		✓	✓					✓		✓	✓		✓	✓	16
	Avenue of Stars			✓	✓		✓						✓		✓	✓	✓		✓	✓								✓	✓	✓	12
	Mong Kok		✓			✓	✓					✓																✓				5
	Tsim Sha Tsui		✓				✓					✓															✓	✓			5
	West Kowloon												✓															✓	✓	✓	5
	Temple Street					✓																						✓				3
	Sham Shui Po					✓																						✓				1
	Wong Tai Sin Temple											✓																				1
	Flower Market					✓																										1
	Kowloon Park							✓																								1
Hong Kong Island	Peak Tower			✓										✓	✓	✓		✓	✓	✓		✓							✓	✓	✓	10
	Hong Kong Central						✓	✓					✓																✓	✓	✓	✓	7
	Causeway Bay						✓	✓					✓								✓								✓	✓			6
	Central Ferry				✓																✓							✓					2
	Victoria Park							✓													✓											2
	Man Mo Temple											✓																				1
	Hong Kong Park							✓																								1
	Ocean Park							✓																								1
	Locations Count	1	3	3	3	4	6	4	2	1	1	3	5	1	3	4	4	2	1	4	3	1	2	1	1	1	3	2	1	7	5	2	3	5

C. REPRESENTATIVE PHOTOS

To identify similarities in the interests of tourists, we identified the representative photos using the visual content processing approach described in Section 3.3. The photo visual content was extracted using maximally stable extremal regions detectors [66] and SURF descriptors, which default settings followed those of the MATLAB toolbox[3]. A visual word vocabulary was conducted by applying k-means clustering on approximately 200,000 SURF descriptors that were randomly selected from the photo collection. The vocabulary size was set to $k = 400$ words. A small number of visual words were proven sufficient for visual words construction [67], while a high number of visual words did not significantly influence the construction performance [68]. The SURF descriptor of each photo is then vector quantized into the visual words for the vocabulary. Each photo was presented as a bag of visual words. Those photos relevant to each interest at each location were grouped together as a photo set from which representative photos were identified. Multidimensional scaling was applied to each photo collection to reduce the dimensions of data points to $d = 3$, which is sufficient for KDE. The probability density for the photos was estimated using the normal kernel with default smoothing parameters, as suggested in Bowman & Azzalini [60]. The top 10 photos with the highest probability densities in each photo set were considered the representative photos.

1) COMMON TOURIST INTERESTS

Some tourist interests appeared in more than one location. This section identifies the differences among the representative photos by analyzing their contexts. Several photo collections, such as film, island, people, street, Victoria, star, sky, skyline, city, ferry, and architecture, appeared randomly and did not follow a specific theme. For example, given that the keyword "sky" refers to the view of any outdoor scene with the sky in the background, the sky photo collection does not have a theme. However, the photo collections for light, food, temple, park, sunset, and skyscraper showed the following interesting differences across locations:

- The "**light**" at Kowloon and HK Island captured the night scene of the Hong Kong downtown area from different viewing angles (Figure 4a and 4b). The photo with the horizontal view was taken at Kowloon near the front of Victoria Harbor, while the photo with the panoramic view was taken at HK Island from the Peak Tower.

- The "**skyscraper**" photos at HK Island had viewing angles and were taken during the daytime. These photos focused on a tall building from a far distance (Figure 4c and 4d). By contrast, the skyscrapers at Kowloon were taken at a closer distance.

- The "**food**" photos at Kowloon showed the actual food taken by tourists, while those at Lantau focused on restaurants (Figure 4e and 4f). Huge differences were also observed between Wong Tai Sin Temple and Man Mo Temple; specifically, the former focused on outdoor scenes, while the latter focused on indoor scenes (Figure 4g and 4h).

- The "**park**" photos showed the iconic features of four major parks in Hong Kong. The main themes included artefacts for Kowloon Park, bird for Hong Kong Park, flower for Victoria Park, and the marine world for Ocean Park (Figure 4i, 4j, 4k, and 4l).

- Distinct "**sunset**" themes were observed at different locations (Figure 4m, 4n, and 4o). The sunset photos at Lantau were usually taken at the airport and featured the sky and a plane, those at Kowloon featured the harbor view of Victoria Harbor, and those at HK Island featured the mountain view from the Peak Tower.

(a) Light at Kowloon (by Roberto Trombetta)

(b) Light at HK Island (by Nicolas Hoizey)

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[3]http://au.mathworks.com/help/vision/ref/extractfeatures.html

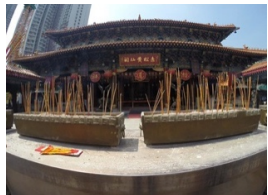**(c) Skyscraper at Kowloon (by Warren R.M. Stuart)**

(d) Skyscraper at HK Island (by Jacob Johan)

(e) Food at Kowloon (by ..zuzu..)

(f) Food at Lantau (by Can Pac Swire)

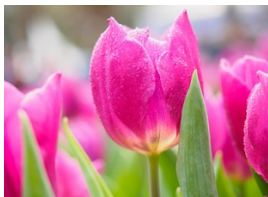**(g) Wong Tai Sin Temple (by shutterbugger I engr)**

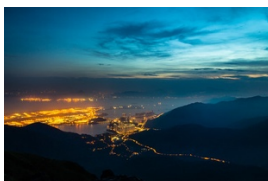**(h) Man Mo Temple (by Jonathan Ichikawa)**

(i) Kowloon Park (by Aaron G)
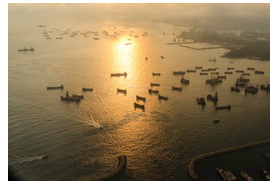

(j) Hong Kong Park (by Carlo Ghio)

(k)Victoria Park (by Jonathan Leung)

(l) Ocean Park (by YKevin1979)

(m) Sunset at Lantau (by Mario Madrona)

(n) Sunset at Kowloon (by Shinichiro Hamazaki)

(o) Sunset at HK Island (by november-13)

FIGURE 4. Representative Photos of Common Interests in Hong Kong (All the photos are permitted to be shared and adapted)

2) UNIQUE TOURIST INTERESTS

This section describes the representative photos for unique interests at Lantau, Kowloon, and HK Island. These representative photos were inspected to identify the themes of the photo collections. Figure 5, 6, and 7 show some representative photos for each interest.

- **Lantau:** The photo collections for the airport, flight, plane, and airline share a similar theme of flying aircraft at the Hong Kong International Airport (Figure 5a). Photos of the Buddha and monasteries mainly featured the Tian Tan Buddha at Ngong Ping. Although the Giant Buddha and Po Lin Monastery were in the same location, the photos taken within this location mostly focused on the former (Figure 5b). The photos at Disneyland focused on several major iconic scenes, such as the Cinderella castle and the Disney Paint the Night parade (Figure 5c). The "car" interest referred to either the mobile parade light shows at Disneyland or the cable cars at Tung Chung and Ngong Ping (Figure 5d and 5e).

- **Kowloon:** "Harbor" shows the scene at Victoria Harbor with vessels and buildings in the background (Figure 6a). Interestingly, the Yellow Duck was identified as a theme in the analysis (Figure 6b). Although the Yellow Duck was displayed in Hong Kong for only a short period in 2013, many tourists visited this exhibit at the Clock Tower area and uploaded their photos to Flickr. "Hotel" mainly shows the interior decoration of hotels at Tsim Sha Tsui (Figure 6c), while "market" mainly shows the general market scenery in Kowloon, including the Flower Market, Sham Shui Po Market, Ladies Street Market, and Temple Street Market (Figure 6d-6g). Most of the photos taken at the Flower Market focused on various types of flowers.

- **HK Island:** "Peak" shows a view of downtown Hong Kong from the Peak Tower (Figure 7a), while "landscape" shows the Peak Tower and its surrounding areas (Figure 7b). "Bay" and "shop" show random scenes taken at Causeway Bay and Hong Kong Central without a specific theme.

(a) Plane at Hong Kong International Airport (by Luke Lai)

(b) Buddha at Ngong Ping (by James Handlon)

(c) Mobile Parade Light Show at Disneyland (by Peter Cartledge)

(d) Disneyland (by quillshadwo)

(e) Cable Car at Tung Chung (by Kee Yip)

FIGURE 5.   Representative Photos of Unique Tourist Interests at Lantau (All the photos are permitted to be shared and adapted)
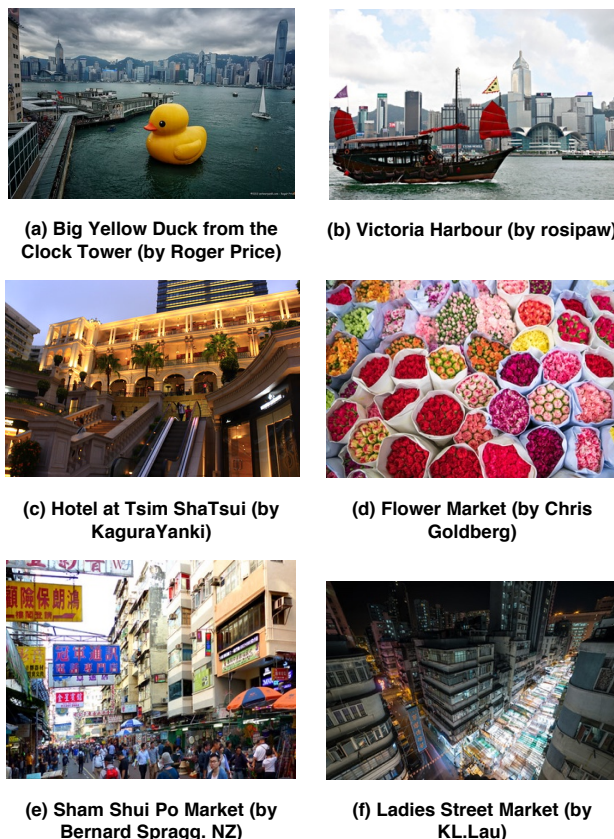

(a) Big Yellow Duck from the Clock Tower (by Roger Price)

(b) Victoria Harbour (by rosipaw)

(c) Hotel at Tsim ShaTsui (by KaguraYanki)

(d) Flower Market (by Chris Goldberg)

(e) Sham Shui Po Market (by Bernard Spragg. NZ)

(f) Ladies Street Market (by KL.Lau)

(g) Temple Street Market (by Terry Hassan)

FIGURE 6.   Representative Photos of Unique Tourist Interests at Kowloon (All the photos are permitted to be shared and adapted)

(a) Landscape at Peak Tower (by Bernard Spragg. NZ)

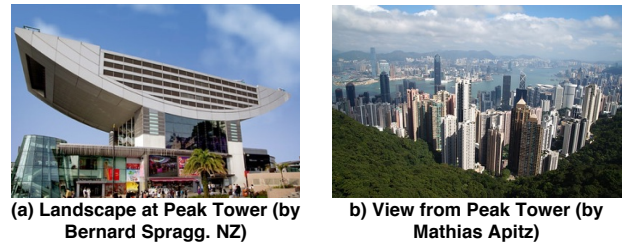**b) View from Peak Tower (by Mathias Apitz)**

FIGURE 7.   Representative Photos of Unique Tourist Interests at HK Island (All the photos are permitted to be shared and adapted)

C. CONTRAST ANALYSIS OF DOMESTIC AND INTERNATIONAL TOURISTS

This section contrasts the interests of domestic and international tourists. The location of the origin of Flickr users was identified based on their UserIDs. However, some users did not provide such information because the location of origin is not a mandatory field when registering for a Flickr account. Table 5 shows 2,080 Flickr users with country information, among whom 552 were Hong Kong residents and treated as domestic tourists, while 1,528 were from other countries and treated as international tourists. Domestic tourists upload more photos (around 60 photos per tourist) than international tourists (about 22 photos per tourist).

TABLE 5.   Data on Domestic and International Tourists

Group	Number of Tourists	Number of Photos	Photos per Tourist
Domestic	552	32,957	59.70
International	1,528	33,828	22.14
Overall	2,080	66,785	32.11

The proportional analysis was performed on both domestic and inbound tourist groups. A chi-squared statistical test [69] was applied to verify the differences between domestic and international tourists. Table 6 lists all interests that show statistical differences in the chi-squared test. The proportional values were based on the number of tourists than on the number of photos. Local tourists were particularly interested in "park", "sunset", and "duck", especially sunset with a proportion ratio of more than 1: 3.4. By contrast, international tourists were particularly interested in "hotel", "skyscraper", "Buddha", and "skyline". These differences were significant at $p < 0.05$. The photos taken by local residents and

international tourists also showed different contexts. International tourists enjoyed taking pictures of their hotels, the Big Buddha, and Hong Kong infrastructures. By contrast, local residents enjoyed taking photos of natural sceneries, such as flowers in parks, sunset views, and the Yellow Duck.

TABLE 6. Chi-Square Analysis of the Photo Distribution of Domestic and International Tourists

| Interest | Proportion (%) | | Ratio | χ^2 | p-value [*] |
	Domestic	International			
sunset	15.94	4.58	3.480	74.566	0.000
park	12.14	5.96	2.038	22.080	0.000
duck	6.16	2.62	2.353	14.824	0.000
skyline	2.90	7.98	−2.755	16.930	0.000
hotel	3.26	6.41	−1.967	7.654	0.006
skyscraper	2.36	6.22	−2.640	12.288	0.000
buddha	1.27	3.66	−2.890	7.931	0.005

[*] Significant at $p < 0.05$

D. COMPARISON WITH THE PROMOTION FOCUS OF HKTB

The tourists at Lantau take an average of six photos per person, while those at HK Island and Kowloon take more than 20 photos per person. Lantau has many popular tourist attractions, such as Disneyland, the Giant Buddha, and the Hong Kong International Airport. According to HKTB [3], Disneyland ranked the fourth most popular attraction for short-haul tourists, while the Giant Buddha ranked the seventh most popular attraction for long-haul tourists. However, Flickr had a much lower number of photos taken at Lantau than those taken at the other two locations. These findings indicate that some tourists visited Lantau only for fun and not for taking photos or that this region had a dull scenery that drove these tourists to upload one representative photo to summarize their trip.

The Hong Kong International Airport received the highest number of photos taken, with around 10% of the photos in our database being taken at this location. The airport also serves as the starting and ending point of the trip, which motivates many tourists to take photos at the boarding gate and include their flight details into their digital travel diaries. Tourists are also being encouraged to take selfies at the airport to participate in photo competitions [70,71]. The metropolitan city and street views of Hong Kong received the second-highest number of photos taken, followed by the island/peak/Victoria Harbor. These rankings indicated that tourists enjoy taking photos upon their arrival or before departing from the city, and then use the photos to keep a record of their visit. These tourists also enjoy seeing the Hong Kong city view, seeing that Hong Kong is one of the most densely populated metropolitan cities around the world. Many of these tourists were amazed by the skyscrapers and the Hong Kong skyline. The Hong Kong street market makes these tourists feel like local residents with its "east meets west" style, thereby driving many tourists to walk around this area and shop for items. The natural scenery at Victoria Harbor offers a mixture of modern (skyscrapers) and natural (harbor, sunset, and mountain) views in a single destination.

A total of 22 main attractions in Hong Kong were identified based on the photos uploaded by the tourists. Ten of these tourists were located in Kowloon, eight were located in HK Island, and four were located in Lantau. HKTB [72] published a list of top 10 recommended attractions and nine highlighted attractions for tourists, with six of these attractions located in HK Island, nine located in Kowloon, two located in Lantau, and three located in other areas. However, some discrepancies were observed between these recommendations and the results of this work, as shown in Table 7. Specifically, only half of the recommendations published in the HKTB website were actually popular among tourists. HKTB produced similar findings on the attractions in Kowloon and Lantau, but had different findings on the attractions in HK Island. The results of this study agreed with HKTB for only two attractions, namely, The Peak and Ocean Park. HKTB recommended artificial attractions, but tourists preferred to experience natural and cultural activities in parks and temples.

TABLE 7. Comparison of HKTB Promoted POIs and the Results Obtained from Experiments

	HK Island	Kowloon	Lantau
HKTB	Ocean Park	Ladies Market	Disney
	The Peak	Temple street	Ngong Ping
	Harbour cruises	Clock Tower	Noah's Ark
	Madame Tussaud's	TST Promenade	
	Lan Kwai Fong	Wong Tai Sin Temple	
	HK Observation Wheel	Avenue of stars	
	HK Convention & Exhibition Centre	Sky100	
		Light show Symphony of Lights	
This Study	Ocean Park	Mongkok	Disneyland
	The Peak	Temple Street	Ngong Ping
	Ferry	Clock Tower	Tung Chung
	Central	Tsim ShaTsui	Airport
	HK Park	Wong Tai Sin Temple	
	Victoria Park	Avenue of Stars	
	Causeway Bay	West Kowloon Flower Market	
	Man Mo Temple	Kowloon Park	
		Sham Shui Po	

Note: Items in grey background indicate the common POIs

Each location offers specific tourist attractions. For instance, Lantau has the Big Buddha, Kowloon has the harbor view and the street markets, and HK Island has many shops and offers the best sightseeing spots at The Peak. However, the HKTB did not list the Big Buddha as a top attraction; this tourist spot was only listed under cultural and heritage–Chinese Temples [73], which was not a highlighted attraction for tourists.

Regardless of their location, all tourists were interested in the local cuisine, parks, sunset views, and daytime or night-time views of Hong Kong. As a famous food paradise, Hong Kong offers an excellent food selection to its tourists who enjoy sharing food photos with their friends. Although Hong Kong is a metropolitan city, tourists still enjoy a natural, peaceful feeling when staying in its parks. Many tourists enjoy taking pictures in these parks, including Kowloon Park, Hong Kong Park, and Victoria Park. The keyword "lights" may refer to either the Symphony of the Lights event organized by the HKTB and the spectacular view of lights from skyscraper windows. Famous for its night views, nearly all tourists in Hong Kong take photos of the night view at The Peak or at the harbor front. The combinations of sunset and the natural scenery of Hong Kong (i.e., mountains, parks, skylines, and harbors) generated many beautiful pictures that motivate many tourists to upload their photos and share their experiences with their friends.

V. DISCUSSION

Tourist interest analysis is one of the key topics in destination image study. The existing work is limited due to either the small number of data samples collected through survey/questionnaires or analysis techniques that can mainly deal with textual data. This study takes advantage of rich data resources from the Internet and social media. A large data set of over 159,000 photos of Hong Kong from the Flickr accounts of 5,861 tourists have been collected for analysis. The collected big data set contain data samples in various formats, including text, geotagged numbers, and photos posted by tourists to record their experiences in past travels. The proposed framework is specially designed to handle such big data with various data sources and structures. To our understanding, this is the first work to integrate data mining techniques for text processing, clustering, and image processing together for tourist interest analysis. This study provides technical instructions for a new means to academic researchers in the tourism management area to work with big data available on social media sites. The findings obtained from the experiments also bring attraction managers at DMO or organizations like HKTB to understand tourists' interests at destinations and track their movements to monitor and update their plans, offers at tourist nominated POIs sustainably.

The case study took Hong Kong as a popular destination and successful airport hub in Asia. Three geographical locations: Lantau, Kowloon, and HK Island, are drawn to be the main focused areas based on the extracted geotags. The geotagged information can provide accurate locations where the photos were taken. In other words, the geotagged data give strong evidence where the tourists have been exactly. The keywords mentioned in the textual metadata show single locations in most of the cases, but by combining with the visual content, extra location information can be obtained. For example, the long harbor front promenade in Kowloon allows tourists to enjoy the view of the harbor, then the keyword "harbor" appears frequently in the POI recommendation descriptions of Kowloon only. However, the photos of Victoria Harbor can be taken from hotel rooms at Kowloon as well as The Peak and skyline at Hong Kong Island. Multiple POIs can be identified for the same tourist interests in this work. In addition, the representative photos shown in the results could provide tourists more options for locations to enjoy the landscape from different angles.

By comparing the obtained tourism POIs with the official ones listed by HKTB, only half of the official recommended POIs were popular in tourists' past experiences. The official list does not frequently change, in which 8 POIs are still listed in the current top 10 attractions [74]. The two new ones are Ngong Ping and Stanley. Ngong Ping is identified as popular by tourists in this work. The official list could be updated in a more frequent manner using the results obtained by the framework and techniques introduced in this work. The frequency can be determined by the tourism organizations according to their business strategies and plans as the data can be collected easily from social media. This provides a sustainable way for tourism organizations to grasp the information regarding tourist interests and movement all the time.

From the results, not only the tourist nominated popular POIs but also the unique tourist interests at each POI from the analysis of the visual content carried by the photos. For example, at Disneyland, more tourists took photos for the light show; at Tung Chung, the cable car attracted a lot of tourists than the other activities; at Tsim Sha Tsui, many photos were taken in the hotel lobbies and rooms. The metadata carried by the geotagged photos can also tell the popular time for tourists to visit these POIs. Many photos were taken at sunset from The Peak, skyline and harbor are a representative example. The work also captured the special events at destinations. For example, the Big Yellow Duck attracted a large group of tourists to visit Victoria Harbor in May 2013. These findings tell the attraction managers more on what the tourists are doing when they visit those POIs at a particular period.

The contrast analysis implemented between location and international tourists returns the different interests of these two groups. Domestic tourists enjoyed the natural scenery of Hong Kong, while international tourists enjoyed taking photos of the skyscraper, the Hong Kong skyline, and the Buddha. Interestingly, the latter group of tourists also enjoyed sharing pictures of their hotel rooms with their friends. This finding reminds the attraction managers to consider the differences between these two groups of tourists when preparing plans or making strategic decisions.

VI. CONCLUSION

This work aims to help tourism organizations like HKTB to find out what tourists enjoy doing at destinations and what they expect from their trips based on the photos they see on the Internet. The framework proposed in this work provides a sustainable approach for attraction manager to understand the special interests shared by the tourists on social media sites and prepare better strategic plans for the future. The Internet and social media sites provide the best data resources, and the framework is particularly designed to handle big data with various data structures and formats.

The results reported in this work focus on tourist nominated POIs and their interests at each POI. The tourist interests and popular POIs obtained from geotagged photos exist a big difference to the ones published on the official HKTB website. The geotagged photos provide richer information than text-based content in the metadata only. Contrast experiments on domestic and international tourist groups indicate different interest focuses. These results and findings could support attraction managers to prepare plans and make strategic decisions in tourism marketing.

Like the other studies, this work also has several limitations. First, Flickr is a Yahoo!-owned website based in North America. Therefore, Flickr only has a limited number of Asian users. Second, around 75% of the tourists visiting Hong Kong were Mainland Chinese. Given that Flickr does not mainly target this tourist group, the results may not represent all tourists visiting Hong Kong. Third, although the photos uploaded on Flickr are accessible to the public, some tourists may only upload a selected subset of their photos from their trips. Therefore, the photos they upload on Flickr may not completely reflect their actual activities in Hong Kong. To gain a more detailed and comprehensive understanding of these tourists, future studies must separately investigate tourists from different countries to compare the behavior of Chinese tourists with that of international tourists.

As the data is collected directly from the social media sites on the Internet, this framework provides tourism researchers and industry organizations a sustainable means to analysis tourist interests and monitor the changes in popular POIs and interests. To use this framework to do analysis, once the input data is updated, for example, new data is collected, the same processes can be implemented to obtain the new results, including the popular POIs, the unique tourist interests, and representative images for each POI at any time. The tourism organization could update their business strategy or plan based on the new results obtained whenever they need.

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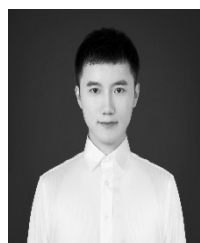
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