Event Detection from Flickr Data through Wavelet-based Spatial Analysis

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ABSTRACT

Detecting events from web resources has attracted increasing research interests in recent years. Our focus in this paper is to detect events from photos on Flickr, an Internet image community website. The results can be used to facilitate user searching and browsing photos by events. The problem is challenging considering: (1) Flickr data is noisy, because there are photos unrelated to real-world events; (2) It is not easy to capture the content of photos. This paper presents our effort in detecting events from Flickr photos by exploiting the *tags* supplied by users to annotate photos. In particular, the temporal and locational distributions of tag usage are analyzed in the first place, where a wavelet transform is employed to suppress noise. Then, we identify tags related with events, and further distinguish between tags of aperiodic events and those of periodic events. Afterwards, event-related tags are clustered such that each cluster, representing an event, consists of tags with similar temporal and locational distribution patterns as well as with similar associated photos. Finally, for each tag cluster, photos corresponding to the represented event are extracted. We evaluate the performance of our approach using a set of real data collected from Flickr. The experimental results demonstrate that our approach is effective in detecting events from the Flickr photo collection.

Categories and Subject Descriptors

H.3.3 [**Information Systems**]: Information Storage and Retrieval—*Information Search and retrieval*

General Terms

Algorithms, Experimentation, Measurement

Keywords

event detection, flickr tag, wavelet transform

1. INTRODUCTION

Due to the rapid advancement of digital technology in the last two decades, there has been an increasingly large amount of image files available on the web. With the recent spreading of web 2.0, more and more individual users began to upload photos taken by themselves to image community web sites, such as Flickr[1], Picasa[2], and Webshots[3]. The enormous —and continuously growing— volume of online image data necessitates the development of efficient and effective web image retrieval systems. Many approaches have been proposed in the literature, including text-based image retrieval as well as content-based image retrieval (CBIR). Orthogonal to improving technologies to help image retrieval, vertical search, in contrast to broad-based search, appeared to facilitate searching images in specific domains. For example, Webshots[3] allows users to search images in a list of prespecified categories and subcategories, including "events". Obviously, automatically detecting events from image collection will be beneficial for focused searching/browsing of images related to events. Other applications of detecting events from images range from reducing semantic gap between low-level and high-level features of images [23], to recommending event tags for photos based on location and time of capture, and extracting event semantics from image tags [20].

In this paper, we aim to detect events from Flickr photos, although our approach can be applied to any other image collection with similar metadata. This is a challenging problem considering that Flickr data is noisy. Different from a data set of news stories, where each story is related with a certain event, not every Flickr photo represents some event in the real world. Consequently, most of the existing approaches [24, 18, 10, 14] which detect events from news stories cannot be employed directly. The situation is exacerbated as the content of photos cannot be captured as easily as documents. A fundamental task of image analysis is yet largely an unsolved problem [15]. Existing web image search engines mainly rely on the text on the pages in which images are embedded. Compared with normal web pages with images, pages on Flickr contain much less text. However, similar to many other popular social networking websites, Flickr provides users the service to annotate photos with textual labels called "tags". Studies on tag data [12, 11] have demonstrated that tags resulting from collaborative tagging systems represent a stable, emergent consensus of system users. Consequently, in our work, we capture the content of Flickr photos by exploiting user-supplied tags.

Existing algorithms of retrospective event detection can be generally classified into two categories: *document-pivot*

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[1]http://www.flickr.com
[2]http://picasa.google.com
[3]http://www.webshots.com

approaches and *feature-pivot approaches*. The former detects events by clustering documents (e.g., news stories) based on semantics and timestamps [24, 18], while the latter studies the temporal and document distributions of words and discovers events of words [10, 14]. Considering that not every Flickr photo is related to some real-world event, adopting a document-pivot approach and directly clustering photos based on content and timestamps may lead to non-optimal results involving photos irrelevant with events. Therefore, we follow the fashion of feature-pivot approaches by detecting *event-related tags* before detecting photos of events.

Our approach can be briefly described as follows. Given a set of Flickr photos, with both user-supplied tags and other metadata, including time and location (consisting of latitude-longitude coordinates), the objective is to discover a set of photo groups, where each group corresponds to an event. Associated through photos, each tag usage occurrence can be attached with temporal and locational encodings. We simultaneously analyze the temporal and locational distributions of tag usage occurrences to discover event-related tags with significant distribution patterns (e.g. "bursts") in both dimensions. We further examine the characteristics of distribution patterns to distinguish between tags of two categories: *aperiodic*-event-related and *periodic*-event-related. Next, tags of the same event category are clustered based on their temporal and locational distributions as well as photo distributions. Finally, for each tag cluster, photos representing the particular event are extracted.

To summarize, this paper has the following three main contributions: (1) We map each tag usage occurrence to a point in 3D space where dimensions represent latitude, longitude and time respectively. To the best of our knowledge, our approach is the first effort, among feature-pivot event detection approaches, which simultaneously considers the temporal and locational distributions of features (tags). (2) The robustness of our approach is strengthened by employing wavelet transform, which not only suppresses noise but also provides multi-resolution analysis of tag distributions. (3) We implemented our Flickr event detection approach and conducted experiments to evaluate the effectiveness of our approach using a set of real data collected from Flickr.

The rest of this paper is organized as follows. In Section 2, related studies of event detection as well as collaborative tagging data are reviewed. Section 3 defines the research problem investigated in this paper. In Section 4, we firstly describe the main steps of the event detection approach. The details of each step is then illustrated respectively. Section 5 presents the performance evaluation of our approach. Finally, some conclusive remarks are given in Section 6.

2. RELATED WORK

The problem of *event detection* is part of a broader initiative called *Topic Detection and Tracking* (TDT) [3]. The objective of event detection is to discover new or previously unidentified events, where each event refers to a specific thing that happens at a specific time and place [2]. In particular, event detection can be divided into two categories: *retrospective detection* and *on-line detection* [24]. The former refers to the detection of previously unidentified events from accumulated historical collection, while the latter entails the discovery of the onset of new events from live feeds in real-time. Since our focus in this paper is retrospective event detection, we here concentrate on representative retrospective event detection approaches. As one of the very first several efforts of event detection, in [24] a simple agglomerative clustering algorithm, called augmented Group Average Clustering, is used to discover events from the corpus. A probabilistic approach which models both content and time information of documents explicitly is given in [18]. Recently, there has been another research direction which detects events from text streams using *feature-pivot* approaches. This line of research is inspired by Kleinberg's seminal work that describes extracting bursty features using an infinite automaton model [17]. Fung et al. [10] proposed to identify bursty features by using binomial distribution to model the occurrences of features, and cluster features based on document distributions to generate bursty events. The work presented by He et al. [14] also detects events by examining features first. They analyzed every feature using Discrete Fourier Transformation (DFT) and classified features to different categories (e.g., important and unimportant events, periodic and aperiodic events). Most of the existing approaches focus on detecting events from news stories. In contrast, our dataset is much more noisy for event detection. Not every Flickr photo is related to some event. Consequently, directly applying a document-pivot approach may generate events (i.e., photo groups) containing photos irrelevant to events. Due to the similar reason, existing feature-pivot approaches which mainly rely on analyzing the temporal distributions of features may not be robust enough. The work [25] described an interesting effort of detecting events from web click-through data. Although click-through data contain queries irrelevant to events, the proposed approach directly clustered query-page pairs without addressing the issue of noise. Recently, Chen et al. [5] proposed to detect events from the click-through data by transforming data to a 2D polar space, where the angle and radius of each point respectively reflects the semantics and the time of a query session. However, it may not be intuitive and sufficient to represent the semantics of data in one dimension. In our work, we analyze data in the 3D space where dimensions reflect the time and the location of data points directly.

Lately, known social networking websites like Del.icio.us[4], Flickr and Last.fm[5] have appeared which offer users the opportunity to tag web resources (bookmarks, images, audio tracks, among others) by supplying textual labels. This service has attracted not only individual users to contribute tags but also researchers to investigate the structure, dynamics, and applications of collaborative tagging data. In [11], the dynamics of this collaborative system was examined using the tag data at the bookmarking site Del.icio.us. The results demonstrate that tag distributions tend to stabilize over time. Halpin et al. confirmed these results in [12] and showed additionally that tags follow a power law distribution. The wide usage of this emerging metadata has been explored by various applications such as navigation [8], enterprise search [7] and web search [4]. One recent work, which is most related to this paper, attempts to extract semantics from Flickr tags [20]. Specifically, the work aimed to detect two types of tags, place-related and event-related. Although detecting event-related tags is one of the steps of our approach, we could not apply their method directly be-

[4]http://del.icio.us
[5]http://www.last.fm

cause of the reasons given in Section 4.1. Furthermore, our perspectives on tags and our ultimate research objectives are different. They determined a tag as either event-related or not. Considering the ambiguity and polysemy issues of tag data, it is very likely that some of the usage occurrences of a tag is irrelevant to the event, even if it is an "event-related" tag. Only the occurrences of a tag which corresponds to the event are interesting to us to finally discover photos of events. There is also some research on Flickr data which focuses on finding images of scenes and landmark [22, 16]. Such works usually rely on not only the user-supplied tags, but also the content of images.

3. PRELIMINARIES

This section begins with a description of data representation, followed by a discussion of problem definition.

3.1 Data Representation

Let $\mathcal{P}$ denote a set of geo-referenced Flickr photos. Each photo p_i is associated with a location, $(la(p_i), lo(p_i))$, consisting of latitude and longitude coordinates. The location generally refers to the location where the photo was taken, while sometimes marks the location of the photographed object. Each photo is also associated with a timestamp, $t(p_i)$, which usually refers to the time when the photo was taken, although occasionally refers to the time when the photo was uploaded to Flickr.

Let $\mathcal{Q}$ denotes a set of Flickr tags. Each photo $p_i \in \mathcal{P}$ is associated with a subset of tags $Q(p_i) = \{q_1, q_2, \cdots, q_m\} \subseteq \mathcal{Q}$. Associated through a photo p_i, a tag $q_j \in Q(p_i)$ can be attached with the location and time of p_i. A tag $q_j \in \mathcal{Q}$ can be used to annotate more than one photo in $\mathcal{P}$. We use $P(q_j)$ to denote the set of photos annotated by q_j, *s.t.* $P(q_j) = \{p_1, p_2, \cdots, p_n\} \subseteq \mathcal{P}$. Accordingly, the tag q_j can be attached with a sequence of locations $\mathcal{L}(q_j) = \{(la(p_1), lo(p_1)), (la(p_2), lo(p_2)), \cdots, (la(p_n), lo(p_n))\}$ and a sequence of points in time $\mathcal{T}(q_j) = \{t(p_1), t(p_2), \cdots, t(p_n)\}$.

3.2 Problem Definition

As defined in [2], an event refers to a specific thing that happens at a specific time and place. Hence, given a set of photos, if it represents an event, it should at least satisfy the following three constraints: (1) The group of photos represents a specific thing. That is, the content of the photos should be semantically consistent. Since we represent a photo as a set of tags, this constraint regulates the tags of the group of photos to be semantically similar. (2) The group of photos should be taken within a certain time segment. (3) The group of photos should be taken around a similar location.

Note that the event definition given in [2] mainly addresses an *aperiodic event*. That is, the event happens only once within some given time period. We are also interested in discovering periodic events, which occurs regularly with certain fixed periodicity. Thus, the second constraint on the time should be extended for periodic events. That is, the group of photos should be taken at a sequence of time points with equal intervals.

Therefore, given a set of Flickr photos $\mathcal{P}$, the problem we address in this paper is to find subsets from $\mathcal{P}$ such that each subset $\mathcal{P}_k \subseteq \mathcal{P}$ is a set of photos satisfying either the constraints of aperiodic events or the constraints of periodic events.

4. EVENT DETECTION

In this section, we first describe the main steps of our Flickr event detection approach. The details of each step are then explained sequentially.

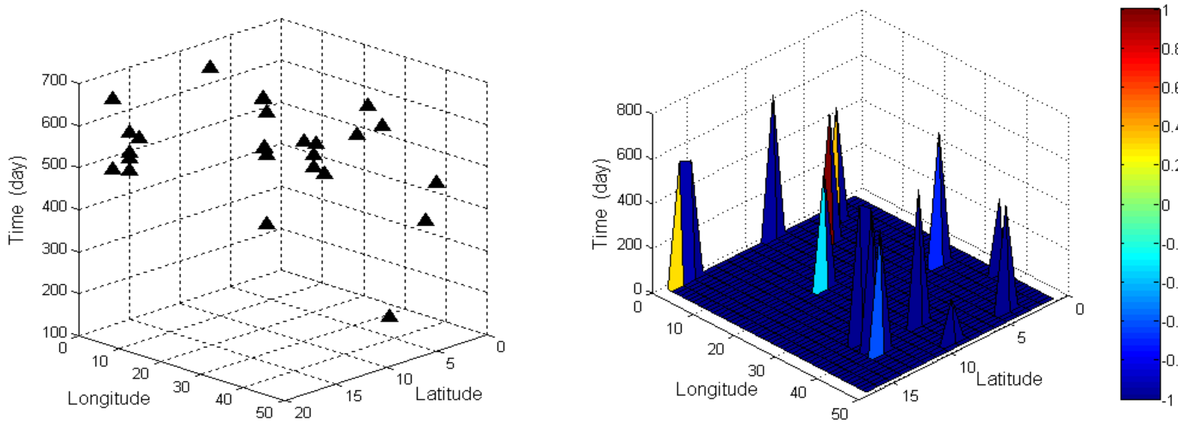
As mentioned before, considering not every Flickr photo corresponds to some event, we follow the fashion of *feature-pivot* approaches to detect event-related tags before detecting events of photos. Then, the main steps of our event detection approach are as follows.

1. `Event Tag Detection`. The objective of this step is to analyze tags and discover those related with events. As described above, each tag is associated with a sequence of locations and a sequence of timestamps. We aim to discover event-related tags based on their temporal and locational distributions.
2. `Event Generation`. After detecting event-related tags, we further distinguish between tags which are related with periodic events and tags related with aperiodic events. Then, tags representing the same events are clustered. The clustering criteria should consider the three constraints of an aperiodic or periodic event.
3. `Event Photo Identification`. Finally, for each tag cluster which represents an event, the set of photos corresponding to the event are retrieved.

4.1 Event Tag Detection

The objective of this step is similar to the existing work [20] which extracts event semantics from tags. We briefly describe their approach, called *Scale-structure Identification* (SI), before highlighting the limitations of this work. As stated in [20], the number of usage occurrences for an *event tag* should be much higher in a small segment of time than the number of usage occurrences of that tag outside the segment. Therefore, SI analyzes the usage distributions of tags along the time dimension. In particular, for each tag q, a graph is constructed for the sequence of its associated time points $\mathcal{T}(q) = \{t(p_1), \cdots, t(p_n)\}$ where edges between points exist if the points are closer together than some scale variable r. Let $\mathcal{S}_r$ be the set of connected subcomponents of the graph. An entropy measure, $E_r = \sum_{S \in \mathcal{S}_r} (|S|/|\mathcal{T}(q)|) \log_2(|\mathcal{T}(q)|/|S|)$, is computed to evaluate how similar the data is to a single cluster. If the entropy value is low, the usage occurrences of the tag distribute closely and the tag is possibly event-related.

Although the method SI works well on a small dataset used in [20], it is limited for a large set of data. It is known that entropy measure is sensitive to noise, while tag data is quite noisy considering the frequently cited ambiguity and polysemy problems. For example, the tag bodybuilder was used to annotate not only photos of the annual event "Muscle Beach International Classic" but also photos of well muscled persons. Thus, the entropy measure of this tag may not be low enough so that the tag can be correctly identified as event-related. Furthermore, SI considers the tag usage occurrences along the time dimension only. According to the definition of events, the usage occurrences in the location dimension can be exploited as well. For example, the number of usage occurrences for an *event tag* should be much higher in a small region of location than the number of usage occurrences of that tag outside the region. Therefore, in our work, we consider both the temporal and the locational distributions of tag occurrences. In particular, we consider



(a) usage occurrences in the original 3D space

(b) surface plot in the original 3D space

Figure 1: Spatial distribution of usage occurrences of the example tag bodybuilder.

the two dimensions simultaneously by mapping each usage occurrence of a tag to a point in the 3D coordinates.

Suppose a tag q is associated with a sequence of locations $\mathcal{L}(q) = \{(la(p_1), lo(p_1)), (la(p_2), lo(p_2)), \cdots, (la(p_n), lo(p_n))\}$ and a sequence of times $\mathcal{T}(q) = \{t(p_1), t(p_2), \cdots, t(p_n)\}$. Each usage occurrence $p_i \in P(q)$ will be mapped to the point (x, y, z) such that $x = la(p_i) - MIN_{la}$, $y = lo(p_i) - MIN_{lo}$, and $z = t(p_i) - MIN_t$, where MIN_{la}, MIN_{lo} and MIN_t are respectively the minimum latitude, minimum longitude, and minimum time point of a given data set.

For example, Figure 1 (a) shows the usage occurrences of the tag bodybuilder, assigned to photos with locations in the United States and time points during the period from Jan 01, 2006 to Dec 31, 2007, in the 3D space. Note that, to show the distribution clearly, we normalized the location and time with respect to the minimum values of all occurrences of this particular tag in the figure. This tag was assigned to 1090 photos, where multiple usage occurrences can be mapped to the same point in space (e.g. users annotate a bunch of photos taken at the same location and same time with the same tag). The minimum and maximum latitudes associated with this tag are 30.273521 and 47.61552 respectively. The minimum and maximum longitude of this tag are -123.278885 and -74.187935 respectively. The minimum and maximum time associated with this tag are 2006-07-11 12:34:36 and 2007-11-03 12:51:07.

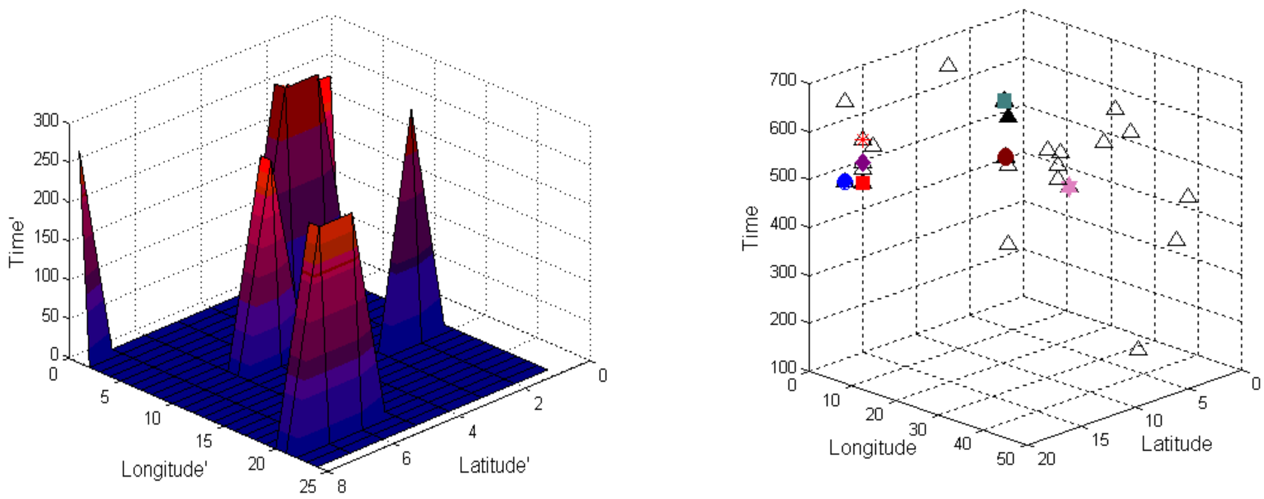
After mapping the usage occurrences of a tag to points in 3D space, the goal is to examine whether the distribution exhibits "dense spatial regions". Note that, by considering the time and location dimensions simultaneously, some false positive dense segments discovered by SI can be avoided. For example, we observe that 65 usage occurrences of the tag bodybuilder are mapped to a spatial region $([15, 16], [0, 1], [545, 546])$, and 60 usage occurrences of this tag are mapped to the region $([12, 13], [40, 41], [545, 546])$. Since SI takes into account the time dimension (Z axis) only, the two sets of occurrences will be merged and the time segment $[545, 546]$ will probably be discovered as a dense one. However, the usages actually occur at different locations. If considered separately, each region may not be dense enough.

Although considering time and location dimensions simultaneously can improve the robustness of dense region detection to certain degree, there is still other noise hindering the accurate discovery of dense regions in space. For example, Figure 1 (b) is the surface plot of the usage occurrences of the tag bodybuilder, where the significance of each point (i.e., the number of usage occurrences corresponding to the point) is normalized, with respect to the total number of occurrences of the tag, and mapped to some color in the attached color bar. The higher the color locates in the bar, the more significant the point is. It can be observed that many points represent very weak information. To further suppress noise, a wavelet transform is used to detect dense regions in a transformed space.

The employment of wavelet transform is motivated by the observations in [21] as follows. Firstly, wavelet functions emphasize regions where points cluster, and simultaneously suppress weak information in their boundary. Consequently, the dense regions in the original space become more salient in the transformed space. Secondly, wavelet transform removes noise in the original space, resulting in more accurate dense region detection. Thirdly, wavelet transform provides multiresolution analysis of signals. As mentioned in [20], the selection of scale value is an important issues in examining the distribution of occurrences. Thus, the multiresolution property of wavelet transform can help detect dense regions at different scales from fine to coarse. Finally, wavelet transform can be computed efficiently.

Given a 1D input signal s_0, Discrete Wavelet Transform (DWT) convolves it with a low-pass filter (scaling function) and a high-pass filter (wavelet function). The former generates an approximate signal s_1 by downsampling the signal by 2, while the latter extracts the difference between s_0 and s_1. The process is iterated downward on the approximate signal generated by the low-pass filter. To apply wavelet transform to our three dimensional data, we perform 1D wavelet transform for each individual dimension, X, Y and Z sequentially. That is, the process is iterated on the resulting approximate data generated by convolving the low-pass filter to each dimension.

Considering the data sparsity, we quantize the data in the original 3D space before performing wavelet transform.



(a) surface plot of the distribution in the transformed space

(b) significant subcomponents discovered in the original space

Figure 2: Wavelet transform and detected subcomponents of the example tag bodybuilder.

Specifically, we segment the 3D space into cells by dividing each dimension into intervals of equal size. For the latitude and longitude dimensions (X and Y axes), we set the interval size as 1. For the time dimension (Z axes), each interval represents one day. We use $C_{i,j,l}$ to denote a cell which occupies the ith interval of the X axis, the jth interval of the Y axis, and the lth interval of the Z axis ($i, j, l \geq 1$). For each cell, we consider the number of points inside the cell. The total number of usage occurrences mapping to points in this cell is denoted as $V(C_{i,j,l})$.

The wavelet we used is Daubencies-4 [6], with its low-pass and high-pass filters H and G as

$$\begin{aligned} H[0] &= -G[3] = (1+\sqrt{3})/(4*\sqrt{2}), \\ H[1] &= G[2] = (3+\sqrt{3})/(4*\sqrt{2}), \\ H[2] &= -G[1] = (3-\sqrt{3})/(4*\sqrt{2}), \\ H[3] &= G[0] = (1-\sqrt{3})/(4*\sqrt{2}) \end{aligned}$$

After performing a wavelet transform along each dimension, the cells with weak wavelet coefficients in the transformed space should be removed. In our work, we remove a cell if its wavelet coefficient if less than the average coefficient over non-empty cells. That is, we set the coefficient of a cell as zero if $V^{'}(C_{i,j,l}) < \frac{\sum V^{'}(C_{i,j,l})}{|\{C_{i,j,l}|V'(C_{i,j,l})\neq 0)\}|}$, where $V^{'}(C_{i,j,l})$ is the wavelet coefficient of the cell $C_{i,j,l}$. Otherwise, $V^{'}(C_{i,j,l})$ is reserved for subsequent transforms or set to 1 if no further transform is performed. For example, Figure 2 (a) presents the surface plot of the usage occurrences of the tag bodybuilder in the transformed space. Compared with Figure 1 (b), fewer dense regions are observed because weak information are removed by wavelet transform. Note that, since we assign, in this example, value 1 to cells with coefficient values greater than the threshold in the figure, the color of the peaks does not reflect the significance of cells anymore.

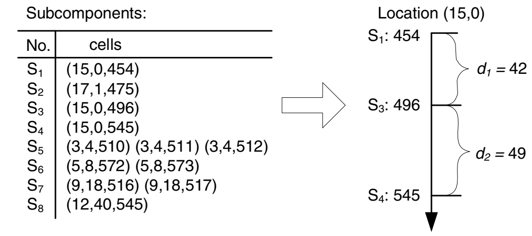
We then detect dense regions from the transformed space. In particular, we construct a graph where each nonempty cell, $V^{'}(C_{i,j,l}) \neq 0$, is modelled as a vertex. Edges between two vertexes exist if the two vertexes representing adjacent cells in space (i.e., two cells are adjacent if they locate in the same $2 \times 2 \times 2$ cube). Then, we detect dense spatial regions by finding connected subcomponents from the graph. We discover connected subcomponents by scanning all cells in the transformed space twice, extending the algorithm for labelling connected components in a binary image [13].

Finally, we need to label back each subcomponent from the transformed space to the original space. That is, cells in the original space belonging to the same subcomponent should be identified. Note that, since we use the Daubencies-4 wavelet, each cell in the original space is involved in at most $2 \times 2 \times 2$ cells in the transformed space. As we define cells as neighbors if they are located in the same $2 \times 2 \times 2$ cube, it can be proved that each cell in the original space is assigned to at most one subcomponent in the transformed space. In Figure 2 (b), the discovered subcomponents of tag bodybuilder in the original space are depicted by colored markers, while the hollow triangles denote the removed insignificant occurrences. Compared with Figure 1 (b), it can be observed that significant regions, with colors in the upper part of the color bar, are correctly identified as significant subcomponents.

Tags without any significant subcomponents are removed as they are unlikely to be related with events. For the rest of the tags, we further compute the mean and standard deviation for each significant subcomponent of each tag. That is, each tag is associated with a set of significant subcomponents $\{S_1, S_2, \cdots, S_m\}$, where each subcomponent S_i is associated with three pairs of values $[(M_x(S_i), SD_x(S_i)),$ $(M_y(S_i), SD_y(S_i)), (M_z(S_i), SD_z(S_i))]$ representing respectively the means and standard deviations of the subcomponent along the three dimensions. These values will be used in the next step of tag clustering.

4.2 Event Generation

The objective of this step is to cluster event-related tags, detected by the first step, such that tags representing the same event are grouped together. Since we are interested in detecting not only aperiodic but also periodic events, there



$$sd(d) = \sqrt{\frac{1}{2}(42-45.5)^2 + (49-45.5)^2} = 3.5 < (20\% \times 45.5) = 9.1$$

Figure 3: Examining periodicity of tag bodybuilder.

are basically the two following options. One is to cluster tags and then examine the generated clusters to distinguish between aperiodic and periodic events; the other is to classify tags as being related to either aperiodic or periodic events and then cluster tags belonging to the same class. With the focus on computation efficiency, we adopt the second solution as the clustering can be performed more efficiently with reduced tag sets for periodic event generation, and reduced tag subcomponents for aperiodic event generation. Consequently, we start with a description of periodic-event-related tag identification before presenting the tag clustering.

Given the set of tags generated by the first step, we identify tags related with periodic events using the following criteria. In the first place, only tags with at least two subcomponents are taken into account. Then, for each tag, suppose it has a set of subcomponents $\mathcal{S} = \{S_1, S_2, \cdots, S_n\}$. Starting from the first subcomponent S_1, we create a *timeline array* initialized with the first entry of the value $M_z(S_1)$, which is the mean time when the first subcomponent occurs. For every other subcomponent $S_i \in \mathcal{S}$, if its corresponding location and that of S_1 overlap each other, we register its corresponding time in the array. That is, if $[M_x(S_1)-SD_x(S_1), M_x(S_1)+SD_x(S_1)] \cap [M_x(S_i)-SD_x(S_i), M_x(S_i)+SD_x(S_i)] \neq \emptyset$ and $[M_y(S_1)-SD_y(S_1), M_y(S_1)+SD_y(S_1)] \cap [M_y(S_i)-SD_y(S_i), M_y(S_i)+SD_y(s_i)] \neq \emptyset$, we add $M_z(S_i)$ into the timeline array and remove S_i from $\mathcal{S}$.

For each timeline array with more than one entry, we check the time distance between entries. Particularly, considering our two years' worth of data crawled from Flickr, if there are only two entries in the array, we examine whether the distance between the two entries is between $[350, 380]$. If it is, the tag is probably related with an annual event. If the array has more than two entries (supposing that entries are ordered by time), we calculate the standard deviation of the distances between every two adjacent entries. If the standard deviation is small (e.g., less than 20% of the average distance between every two adjacent entries), the subcomponents occur almost regularly in time. We then predict that the tag is probably related with periodic events. For example, Figure 3 shows the set of 8 significant subcomponents of the tag bodybuilder detected by the first step. It can be observed that only one timeline array, associated with the location ($x = 15, y = 0$), can be created with more than one entry. As shown in the figure, subcomponents S_1, S_3, and S_4 are involved in the timeline array, with means of time as 454, 496 and 545 respectively. Since the standard deviation of the two distances (e.g., 3.5) is less than the 20% of the average distance (e.g., 9.1), bodybuilder is identified as a tag related with periodic events.

Once a tag is identified as being related with periodic events, the subcomponents, which correspond to the entries in the timeline array and pass the regularity checking, are used to generate periodic events. The rest subcomponents of the tag are preserved for the generation of aperiodic events. We perform clustering on tags of each category to generate events. In particular, we cluster tags based on the three constraints specified by the event definition. Considering the first constraint, each tag cluster, representing an event, should be semantically consistent. Similar to the existing works [10, 14], we measure the semantic similarity between tags based on their associated photos. Given two tags q_i, q_j, the semantic similarity between them, denoted as $SemSim(q_i, q_j)$, is defined as

$$SemSim(q_i, q_j) = \frac{|P(q_i) \cap P(q_j)|}{\min\{|P(q_i)|, |P(q_j)|\}} \quad (1)$$

where $P(q_i)$, $P(q_j)$ are the sets of photos annotated by q_i and q_j respectively. The more photos annotated by both q_i and q_j, the more semantically similar are the two tags.

Considering the second and the third constraints of the event definition, the usage occurrences of tags of a cluster representing an aperiodic (or periodic) event should manifest one (or more than one) dense region around similar time and similar location. Namely, if two tags are related to the same event, their associated subcomponents should distribute along the time dimension and location dimensions similarly. Thus, we define the spatial distance between two tags q_i and q_j, denoted as $SpaDist(q_i, q_j)$, based on the KL-divergence of Normal densities. Given two Normal densities with mean and standard deviation as (m_i, sd_i) and (m_j, sd_j), the KL-divergence between the two densities is [19]

$$KL^N(m_i, sd_i; m_j, sd_j) = \frac{1}{2}(\log(\frac{sd_j^2}{sd_i^2}) + \frac{sd_i^2}{sd_j^2} + \frac{(m_i - m_j)^2}{sd_j^2} - 1) \quad (2)$$

Given two subcomponents of two tags S_{q_i} and S_{q_j}, we use KL-divergence to measure their distance in three dimensions. That is,

$$\begin{aligned} KL(S_{q_i}|S_{q_j}) = & KL^N(M_x(S_{q_i}), SD_x(S_{q_i}); M_x(S_{q_j}), SD_x(S_{q_j})) \\ & + KL^N(M_y(S_{q_i}), SD_y(S_{q_i}); M_y(S_{q_j}), SD_y(S_{q_j})) \\ & + KL^N(M_z(S_{q_i}), SD_z(S_{q_i}); M_z(S_{q_j}), SD_z(S_{q_j})) \quad (3) \end{aligned}$$

Since KL-divergence is asymmetric, we define the distance between two subcomponents as $D(S_{q_i}, S_{q_j}) = \max\{KL(S_{q_i}|S_{q_j}), KL(S_{q_j}|S_{q_i})\}$.

Suppose tag q_i is associated with subcomponents $\{S_1, S_2, \cdots, S_n\}$, and tag q_j is associated with subcomponents $\{V_1, V_2, \cdots, V_m\}$, where $1 \leq n \leq m$. Then, the spatial distance between tags q_i and q_j is defined as

$$SpaDist(q_i, q_j) = \sum_{k=1}^{n} D(S_k, V_l) \quad (4)$$

where $V_l = \arg\min_{1 \leq l \leq m} D(S_k, V_l)$. That is, for each subcomponent of tag q_i, we search for the most similar subcomponent of tag q_j. The value of spatial distance is non-negative.

Combining the semantic similarity and the spatial distance between two tags, we define the similarity between two tags q_i and q_j as

$$S(q_i, q_j) = \frac{SemSim(q_i, q_j)}{1 + SpaDist(q_i, q_j)} \quad (5)$$

The value of $S(q_i, q_j)$ ranges in $[0, 1]$. We employ the simple and effective density-based clustering method, DBSCAN [9], to cluster tags, where the required distance metric is supplied with $1 - S(q_i, q_j)$.

For each generated tag cluster $E = \{q_1, q_2, \cdots, q_n\}$, we compute a measure $Pr(E)$ to evaluate how likely the cluster represents a real event. In our work, we define $Pr(E)$ as the average pair-wise tag similarity in the cluster.

$$Pr(E) = \frac{2\sum_{q_i, q_j \in E, q_i \neq q_j} S(q_i, q_j)}{|E|(|E| - 1)} \quad (6)$$

The higher the value of $Pr(E)$, the more similar the tags in a cluster. The more does the cluster satisfy the constraints of the event definition, the more likely it is related to some real event.

4.3 Event Photo Identification

The last step of our approach is to find photos representing the detected events. Note that, directly retrieving photos annotated by tags of a generated tag cluster may lead to suboptimal results considering that not every usage occurrence of an event related tag is related to some event. Therefore, we aim to decide the time and the location of each event represented by a tag cluster. Afterwards, only photos associated with both event related tags as well as event related time and location will be returned.

For an aperiodic event, by aligning the subcomponents of tags of a tag cluster, there may exist more than one spatial region covered by overlapped subcomponents of at least two tags. We decide the time and location of the event by selecting the most significant spatial region. The *significance* of a spatial region is defined as follows. Let $\mathcal{G}$ be a spatial region covered by overlapped subcomponents of tags $\{q_1, \cdots, q_m\}$ belonging to a tag cluster $E = \{q_1, \cdots, q_n\}$. Let $La(\mathcal{G})$, $Lo(\mathcal{G})$ and $T(\mathcal{G})$ respectively represent the latitude, longitude and time range covered by $\mathcal{G}$. Then, the significance of $\mathcal{G}$ is

$$W(\mathcal{G}) = \frac{m}{n} \times \frac{\sum_{j=1}^{m} |P'(q_j)|}{\sum_{j=1}^{n} |P(q_j)|} \quad (7)$$

where $P'(q_j) = \{p_i | p_i \in P(q_j), la(p_i) \in La(\mathcal{G}), lo(p_i) \in Lo(\mathcal{G}), t(p_i) \in T(\mathcal{G})\}$. That is, the significance of the region is decided by not only the percentage of tags whose subcomponents are covered by the region, but also the percentage of photos occurring in the region.

For a periodic event, we align the subcomponents of tags similarly. Recall that, after identifying tags related with periodic events, only subcomponents with regular time intervals are preserved. Therefore, we simply align subcomponents of tags so that similar subcomponents, in terms of their means in three dimensions, are grouped to represent the periodic occurrences of the event.

After determining the time and location of each event, we retrieve photos whose time and location match with the event's attributes. Furthermore, photos should be annotated by at least one tag of the corresponding cluster.

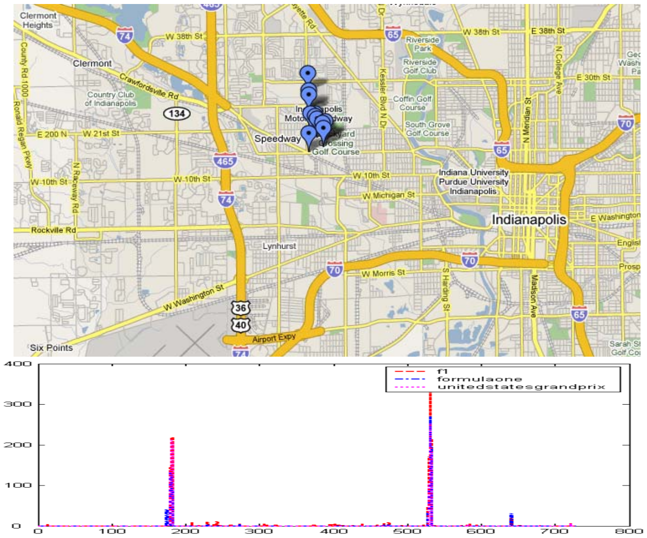


Figure 4: Periodic Event Example with tags f1, formulaone, and unitedstatesgrandprix.

5. EVALUATION

In this section we evaluate the performance of our approach for detecting events of Flickr photos. We start with the description of the data set used in the experiments, followed by an analysis of an exemplary event. Next, we examine the quality of detected events with respect to associated tags and associated photos. We also compare the performance of our approach with SI, the existing work which detects event semantics from Flickr tags [20].

5.1 Data set

We crawled geo-tagged photos from the Flickr site using the available Flickr API. Specifically, we collected photos from the two-year-period starting at Jan 01, 2006, until Dec 31, 2007. We also limited ourselves to photos taken in the United States. For each photo, we extracted its user-supplied English tags. A total 7,405,135 photos were collected, where 2,680,640 photos belong to the year 2006 and 4,724,495 photos were taken in 2007. These photos cover a temporal range of 730 days. The average number of photos per day is 10,144, with a minimum of 1,571 and a maximum of 40,238. The locational area covered by the photos has the minimum latitude 18.91113 and maximum latitude 71.38854, and minimum longitude -177.8916 and maximum longitude -66.95. These photos are annotated with 44,139,261 tags. Among this set, 907,197 tags are unique. On average, each photo is annotated with 5.96 tags, with a minimum of 1 and a maximum of 226. Each tag is used to annotate 48.65 photos on average and at most 507,051 photos (i.e., the tag 2007).

5.2 Example of a Detected Event

To demonstrate the results generated by our approach, we show a detected event by plotting its associated locations in Google map and its associated occurring time. Figure 4 presents one detected periodic event represented by three tags: f1, formulaone and unitedstatesgrandprix. The upper part of the figure shows the detected locations of the event, while the lower part indicates the occurring time of

Periodic Event Tags	housewarming, bigbear, skysinger, indigogirls, deathvalleynationalpark, legionofdoom, westtexas, californiaadventure, ames, samantha, dealsgap, **grandam**, bymiketravis, detourart, adamhubenig, chincoteague, **nights**, paragliding, leavenworth, thebigapple
Aperiodic Event Tags	bourbonstreet, nueva, theindigogirls, portage, mountdesertisland, tueam, threatdottv, shores, sams, ska, sebastian, boone, dnalounge, greatscott, worldinferno, dawnanddrew, delraybeach, doorcounty, ig, southpadreisland

Table 2: Top 20 event tags detected by SI, where tags in bold are true positives. Tag grandam refers to the car racing event. Tag nights is related to the event of Hollywood nights.

Periodic Events					
Rank	1 - 10	11 - 20	21 - 30	31 - 40	41 - 58
No. of events	7	10	10	10	15
Aperiodic Events					
Rank	1 - 10	11 - 20	21 - 30	31 - 40	41 - 50
No. of events	7	6	7	7	4

Table 1: Distributions of periodic and aperiodic event tag clusters.

the event by drawing the temporal distributions of the three tags. It can be observed from the figure that this event occurs around the Indianapolis Motor Speedway. It happened twice in the time period we studied, days 180-183 and days 530-534, which respectively correspond to July 2006 and June 2007. Clearly, the detected tags, location and time comply with the real event "The United States Grand Prix".

5.3 Tag-based Results

We firstly evaluated the results of tag clusters. For this, we processed tags with at least 100 usage occurrences. A total 493 periodic tags are detected. We performed clustering on periodic tags by setting the two DBSCAN parameters *Eps* and *MinPts* to 0.8 and 2 respectively. The results contain 58 clusters. Since no ground truth data is available, we manually checked each of the clusters. Out of the 58 clusters, we found only 6 clusters are unrelated to events. (Interested users are referred to our online interface [1] to browse all of the detected events.) Thus, the precision of our approach for periodic event detection is approximately 89.66%. We concentrate on precision here rather than recall because it is usually infeasible to manually label all events in a huge image collection. As pointed out in [22], the sheer volume of content associated with each tag makes it hard to browse all relevant content.

We further ranked tag clusters according to Equation 6, and presented the distribution of true positive event clusters in the upper part of Table 1. We noticed that in the top 10 tag clusters, 3 of them are irrelevant to events. By checking associated photos, we found that these non-event clusters mainly contained albums of photos regularly uploaded by some photographer and annotated with same tags such as the different abbreviations of the photographer's name (e.g., danielhartwig, danielwaynehartwig, and danielwhartwig). Consequently, such tags have similar temporal and locational distributions as well as similar associated photos, which leads our approach to detect them as events by error and mistakenly ranked them high. The upper part of Table 3 lists the detected top 12 periodic events. It can be observed from Table 3 that our approach is rather accurate in detecting the location of events as well as the periodicity of events. A notable cluster is the event E_7. Although the event E_7 is a periodic event indeed, it actually starts from 2007. However, our approach detected that it started from 2006 because some user mistakenly specified the year as 2006 when uploading photos of this event. Note that, we still consider this cluster as a true positive when evaluating the precision of our approach, because the error is caused by the input data instead of the algorithm itself.

A total $22,974$ aperiodic tags are involved in the generation of aperiodic events. For aperiodic tags, we performed clustering with *Eps* and *MinPts* as 0.9 and 3 respectively. We manually examined the top 50 clusters and listed the distribution of true positives in the lower part of Table 1. Not surprisingly, the performance is worse than that of periodic event detection, because periodic event detection has extra constraints on the temporal regularity of tag usage occurrences. Note that, the results given in the lower part of Table 1 is obtained by considering public events only. The precision of our approach is even better if personal events, such as wedding ceremonies and birthday parties, are considered as true positive as well. Table 3 presents the top 12 tag clusters representing aperiodic events in the bottom.

We also implemented the existing method SI [20] which identifies event-related Flickr tags and assigns confidence scores to tags. Table 2 respectively lists the top 20 (from left to right) periodic event related tags and aperiodic event related tags returned by SI. Unfortunately, only two tags, within the top 20 periodic tags, are related with periodic events. (Note that, SI is able to identify more event-related tags. However, according to the confidence scores assigned by the SI method, these event-related tags are ranked lower than many tags which are irrelevant with events.) As we analyzed before, the main reason that SI can't handle large dataset well is that tags are noisy, while the SI method based on entropy measure and temporal analysis solely is sensitive to noise.

5.4 Photo-based Results

In order to evaluate the detected event photos, we attempt to conduct a user study to evaluate photos returned for top 10 periodic events and top 10 aperiodic events. For each event, we aim to diversify the results by retrieving photos satisfying the requirements of time and location of the event and annotated with at least one tag of the cluster. However, we observed that: (1) For each of the top 10 aperiodic events, all photos are uploaded by the same user for the same event, even if we retrieve photos by requesting that the photo needs to be annotated by only one tag of the cluster. This indicates that there exists no false positive photos which accidently satisfy the requirements of tags, time and location of these events. (2) For top 10 periodic events, only the events E_3, E_4, E_7, E_8 and E_{10} have photos uploaded by different users when fewer number of tags of a cluster is required. By taking a closer look at the photos uploaded by different users, we found they are all relevant with the events. Both observations indicate that our approach rarely returns false positive photos. Furthermore, our approach is able to retrieve all true positive photos as long as photos are associated with correct metadata. We still involved twenty users to evaluate photo-based precision through the online system [1]. Although all photos are related with corresponding events, users sometimes think differently. For example, some users assessed a photo of the audience of a football match as being unrelated with the event. According to users, the average precision of periodic events and aperiodic events are 88% and 91% respectively.

6. CONCLUSIONS

Detecting events from image collection is not only an interesting problem but also an advantageous task which facilitates a number of applications in image retrieval systems. In this paper, we address this problem by exploiting multiple sources of metadata associated with photos on an image community website Flickr. Specifically, we make use of the available user-contributed social tags to capture the content of photos. We rely on the metadata of time and location to analyze the distribution of photos through tags. The fact that not every photo is related to some real event poses challenges in handling noise. Our approach attempts to overcome this problem by taking a few measures, including simultaneously considering time and location dimensions and performing wavelet transform. A timeline array is employed to efficiently classify tags as either periodic or aperiodic event related. Tags of each category are then clustered based on the constraints specified by the event definition. Event photos are then determined by event tag clusters, as well as the time and location attributes of events. Evaluated on a set of real Flickr data, our approach exhibits high accuracy in detecting periodic events. Although our approach is a bit less accurate in detecting aperiodic events, it is still much more effective than the existing approach. Furthermore, our approach retrieves photos related to discovered events precisely.

7. ACKNOWLEDGEMENT

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8. REFERENCES

[1] Flickr event detection, http://www.l3s.de/~lchen/FlickrEvent.

[2] J. Allan, J. G. Carbonell, G. Doddington, J. Yamron, and Y. Yang. Topic detection and tracking pilot study: Final report. In *DARPA Broadcast News Transcription and Understanding Workshop*, 1998.

[3] J. Allan, R. Papka, and V. Lavrenko. On-line new event detection and tracking. In *SIGIR*, 1998.

[4] S. Bao, G.-R. Xue, X. Wu, Y. Yu, B. Fei, and Z. Su. Optimizing web search using social annotations. In *WWW*, pages 501–510, 2007.

[5] L. Chen, Y. Hu, and W. Nejdl. Deck: Detecting events from web click-through data. In *ICDM*, pages 123–132, 2008.

[6] I. Daubencies. Orthonormal bases of compactly support wavelets. *Comm. Pure Applied Mathematics*, 41(909-996), 1988.

[7] P. A. Dmitriev, N. Eiron, M. Fontoura, and E. J. Shekita. Using annotations in enterprise search. In *WWW*, pages 811–817, 2006.

[8] M. Dubinko, R. Kumar, J. Magnani, J. Novak, P. Raghavan, and A. Tomkins. Visualizing tags over time. In *WWW*, pages 193–202, 2006.

[9] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In *KDD*, pages 226–231, 1996.

[10] G. P. C. Fung, J. X. Yu, P. S. Yu, and H. Lu. Parameter free bursty events detection in text streams. In *VLDB*, pages 181–192, 2005.

[11] S. A. Golder and B. A. Huberman. The structure of collaborative tagging systems. *CoRR*, abs/cs/0508082, 2005.

[12] H. Halpin, V. Robu, and H. Shepherd. The complex dynamics of collaborative tagging. In *WWW*, pages 211–220, 2007.

[13] R. M. Haralick and L. G. Shapiro. *Computer and Robot Vision*. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, USA, 1992.

[14] Q. He, K. Chang, and E.-P. Lim. Analyzing feature trajectories for event detection. In *SIGIR*, pages 207–214, 2007.

[15] Y. Jing and S. Baluja. Pagerank for product image search. In *WWW*, pages 307–316, 2008.

[16] L. S. Kennedy and M. Naaman. Generating diverse and representative image search results for landmarks. In *WWW*, pages 297–306, 2008.

[17] J. M. Kleinberg. Bursty and hierarchical structure in streams. *Data Min. Knowl. Discov.*, 7(4):373–397, 2003.

[18] Z. Li, B. Wang, M. Li, and W.-Y. Ma. A probabilistic model for retrospective news event detection. In *SIGIR*, 2005.

[19] W. D. Penny. Kullback-liebler divergences of normal, gamma, dirichlet and wishart densitites, 2001. Technical report.

[20] T. Rattenbury, N. Good, and M. Naaman. Towards automatic extraction of event and place semantics from flickr tags. In *SIGIR*, pages 103–110, 2007.

[21] G. Sheikholeslami, S. Chatterjee, and A. Zhang. Wavecluster: A wavelet based clustering approach for spatial data in very large databases. *VLDB J.*, 8(3-4):289–304, 2000.

[22] I. Simon, N. Snavely, and S. M. Seitz. Scene summarization for online image collections. In *ICCV*, 2007.

[23] C. Wang, L. Zhang, and H.-J. Zhang. Learning to reduce the semantic gap in web image retrieval and annotation. In *SIGIR*, pages 355–362, 2008.

[24] Y. Yang, T. Pierce, and J. G. Carbonell. A study of retrospective and on-line event detection. In *SIGIR*, pages 28–36, 1998.

[25] Q. Zhao, T.-Y. Liu, S. S. Bhowmick, and W.-Y. Ma. Event detection from evolution of click-through data. In *KDD*, pages 484–493, 2006.

No.	Event Tags	Time	Location (la, lo)	Event Description
E_1	partnershipwalk akf agakhanfoundation	10/29/2006, 11/10/2007	(29.71, -95.37)	Partnership Walk is an initiative of Aga Khan Foundation USA to raise funds and awareness to help communities in Africa and Asia. It is held annually at Atlanta, Chicago, Dallas, Houston, Los Angeles.
E_2	southoaklandcountysoccer socs storm95	09/15/2007, 09/22/2007, 09/29/2007, 10/07/2007	(42.49, -83.21)	Weekly games of team SOCS Storm95 in south oakland country soccer club in 2007.
E_3	crosswalkamerica crosswalk scottgriessel creatista griessel	07/02/2006, 08/01/2006, 08/20/2006, 09/01/2006, 07/02/2007, 08/06/2007, 08/23/2007, 09/01/2007	(33.99, -110.08)	Crosswalk is a journey made by a couple of progressive Christians who trekked across the country from April to September. Griessel is the photographer of this walk.
E_4	f1 formulaone unitedstatesgrandprix	07/02/2006, 06/17/2007	(39.69, -86.24)	The United States Grand Prix was a Formula One race held on July 2, 2006, and June 15-17, 2007, at the Indianapolis Motor Speedway.
E_5	asl northpark deaf gpccd	04/22/2006, 04/14/2007	(34.24, -116.90)	The annual ASL fundraising picnic party at Pittsburgh North Park hosted by GPCCD in April.
E_6	beachjam amusementrides moreyspiers wildwoodbeachjam amusements beachcamping	05/20/2006, 05/20/2007	(38.99, -74.81)	The Beach Jam is an annual camping event on the Wildwood, NJ, beach at Morey's Piers that includes amusement rides. There is a 3-day Spring Beach Jam before Memorial Day.
E_7	tei tei07 tei2007	02/06/2006, 02/16/2007	(30.41, -91.19)	The first international conference on Tangible and Embedded Interaction was held Feb 15-17, 2007 in Baton Rouge, Louisiana.
E_8	greeksing fraternities sororities	03/25/2006, 03/24/2007	(40.45, -79.96)	Greek Sing is an annual tradition among the Greek community of Carnegie Mellon University. Each year in March, fraternities and sororities take the stage to perform in a musical variety show.
E_9	naia nationaltournament universityofillinoisatspringfield uofispringfield uis prairiestars	03/17/2006, 03/16/2007	(39.10, -94.59)	The Prairie Stars of University of Illinois at Springfield engaged in the national tournament.
E_{10}	emmylouharris hardlystrictlybluegrassfestival	10/07/2006, 10/06/2007	(37.77, -122.49)	Hardly strictly bluegrass festival is an annual free show in October in Golden Gate Park.
E_{11}	fatima ironworks gilmanton needs ec	08/15/2006, 08/15/2007	(43.40, -71.30)	Camp Fatima, located in Gilmaton Iron Works, offers two separate camps for children with disabilities: Special Needs and Exceptional Citizens
E_{12}	camporee encampment danielboone patriotdays danielboonehomestead douglassville patriotdaysencampment	06/11/2006, 06/10/2007	(40.30, -75.80)	Patriot Days Encampment is an annual event where youth groups gather in June in Pennsylvania to share a unique camping experience.
E_1	epiphanymagazine epiphanycoffeehouse evangeluniversity	09/28/2007	(37.22, -93.26)	Epiphany coffeehouse is the event held in the Evangel University to enrich the social and academic life of the campus.
E_2	photoemagery mikekelly adagerd michaelkelly	06/23/2007	(38.88, -77.17)	A perform given by a nervy collection of all-out performing talent, held in Hillwood, Falls Church.
E_3	youthaids equalitycenter globalindiafund	11/17/2007	(38.91, -77.04)	On November 17, 2007 the Global India Fund official launch took place at the Human Rights Campaign Equality Center in Washington, DC.
E_4	tdttailgating tailgating2007 towerdrivetigerfanz fluidvapor	09/08/2007	(30.41, -91.18)	The official unveiling of the Tower Drive Tigerfanz logo and shirts of LSU tiger team.
E_5	schoolsports spirts wideouts delawarestate delawarefootball udee	09/14/2007	(39.66, -75.75)	NCAA American football match between Delaware Blue Hens and Rhode Island in 2007.
E_6	fragmentsofeternity bayofblood magegame	06/09/2007	(28.06, -82.41)	This event is about a role-playing game, Mage: The Awakening.
E_7	skippack brucecastor uppermerion montgomerycountysheriff	10/25/2007	(40.23, -75.40)	Pennsylvania State Police Memorial.
E_8	poomse palgwe taeguk	10/13/2007	(26.70, -80.24)	Florida Martial Arts Tournaments for the Competitive Martial Artist.
E_9	cornitems shellers cornitemcollectors	10/19/2007	(38.54, -90.17)	Seed Corn Collectibles Auction, Illinions
E_{10}	starguitar burstgenerator goldenpath chems galvanize heyboyheygirl doitagain	09/25/2007	(41.97, -87.66)	Chemical Brothers Live Show in Chicago, Sep. 2007.
E_{11}	putnamcountyflorida bluecrabfestival palatkaflorida	09/28/2007	(29.65, -81.63)	Blue Crab Festival in Palatka, FL, for Memorial Day Weekend.
E_{12}	paulbuentello alistairovereem bobbysouthworth cungle	11/16/2007	(37.33, -121.90)	Strikeforce is an American professional kickboxing and mixed martial arts promotion based in San Jose, California.

Table 3: Top 12 periodic event tags and top 12 aperiodic event tags. Columns respectively show tags, means of time and location values of the detected events, and brief descriptions of the real events.