

Event-Radar: Real-time Local Event Detection System for Geo-Tagged Tweet Streams

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ABSTRACT

The local event detection is to use people's posting messages with geotags on social networks to reveal the related ongoing events and their locations [1]. Recent studies have demonstrated that the geo-tagged tweet stream serves as an unprecedentedly valuable source for local event detection. Nevertheless, how to effectively extract local events from large geo-tagged tweet streams in real time remains challenging. A robust and efficient cloud-based real-time local event detection software system would benefit various aspects in the real-life society, from shopping recommendation for customer service providers to disaster alarming for emergency departments.

We use the preliminary research GeoBurst [1] as a starting point, which proposed a novel method to detect local events. GeoBurst+ [2] leverages a novel cross-modal authority measure to identify several pivots in the query window. Such pivots reveal different geo-topical activities and naturally attract related tweets to form candidate events. It further summarises the continuous stream and compares the candidates against the historical summaries to pinpoint truly interesting local events. We mainly implement a website demonstration system Event-Radar with an improved algorithm to show the real-time local events online for public interests. Better still, as the query window shifts, our method can update the event list with little time cost, thus achieving continuous monitoring of the stream.

KEYWORDS

Event detection, Local event, Location-based service, data stream, Data mining, Web mining

1 INTRODUCTION

With over 500 million tweets written by users every day and there are more than 100 million users, Twitter has been one of the most popular online news and social networking service. This means that a large amount of data is frequently generated. Users post and interact with tweets, which restricted to 140 characters. Beyond Twitter, we have online social media sites like Facebook, Youtube and Instagram, which have transformed the method we connect with individuals, groups, and communities and altered everyday practices [5]. Numerous recent workshops, such as Semantic Analysis in Social Media [6], are increasingly focusing on the influence of social media on our daily lives. Unlike other media sources, Twitter messages offer timely and fine-grained information about any

event, reflecting personal perspectives, social information, emotional reactions, and local event.

A local event is an unusual activity burst in a local area and within specified duration while engaging a considerable number of participants. Empirical studies [7] show that the online social networking service Twitter is often the first medium to break significant natural events such as earthquakes often in a matter of seconds after they occur. Twitter is "what's-happening-right-now" tool [8] and given the nature of its tweets are a real-time flow of text messages coming from very different sources covering various kinds of subjects in distinct languages and locations. The Twitter free stream is an interesting source of data for "real time" event detection based on text mining techniques. Noticing that here "real time" means that events need to be discovered as early as possible after they start unravelling in the online social networking service stream. Such information about emerging events can be hugely valuable if it is visible in real time.

Studying those data can provide us with useful information. "What is happening right now?" is a fascinating question that many people ask every day. People are interested in those events happens locally [9]. Corporations are interested in sponsoring their product to favourable customers [10]. Event detection can answer this question. Besides that, nature disasters might be detected by Twitter and warn people even faster than other media [11]. Some predictions can also be completed from Twitter data, such as the crime prediction [12]. Typical examples include the bomb blasts in Mumbai in November 2008, the flooding of the Red River Valley in the United States and Canada in March and April 2009, and the "Arab Spring" in the Middle East and North Africa region [13]. Several studies have analysed Twitter's user intentions. For example, user intentions can be categorised on Twitter into daily chatter, conversations, allocation information, and journalism news. They also identified Twitter users as information sources, friends, and information hunters.

Considerable research efforts have been made in detecting real-time events. However, most of them lack the accuracy when dealing with local events or the capability for real-time events. For example, Abdelhaq's EvenTweet [3], using spatial entropy, clustering, and feature ranking to extract and rank local events, cannot deal with the real-time environment.

Nevertheless, there are also trials of event detection in Twitter rivaling to event detection in traditional media. Twitter messages are usually not well organised. Twitter streams cover huge amounts of meaningless messages, which negatively affect the detection performance. Furthermore, conventional text mining techniques are not appropriate, since the short length of tweets, a significant number of spelling and grammatical mistakes, and the chronic

use of straightforward and mixed language. Since spelling and grammar errors, mixed languages, colloquial expressions and shortened words are very common in tweets, we are very hard to understand their semantic meanings. Similarly, while a significant amount of data, it is tough to find a well-organized way to select valuable tweets in Twitter. While the real-time detection of local events was nearly incredible years ago due to the lack of reliable data sources, the explosive growth of geo-tagged tweet data brings new opportunities to it. With the ubiquitous connectivity of wireless networks and the vast proliferation of mobile devices, more than 10 million geo-tagged tweets are created in the Twitter every day. Numerous real-world examples have exposed the effectiveness and the timely information reported by Twitter during disasters and social movements. For example, when the Tohoku Earthquake hit Japan on March 2011 and when the Baltimore Riot took place in April 2015, many people posted geotagged tweets to broadcast it right there. Its sheer size, multi-faceted information, and real-time nature make the geo-tagged tweet stream an unprecedentedly valuable source for detecting local events [2].

Tweets are about contents from daily life things to newest local and worldwide events. Twitter streams contain significant amounts of meaningless messages (pointless babbles) and rumours [13]. These are important to help to understand people’s reactions to events. Nevertheless, they undesirably affect event detection performance.

A major test facing event detection from Twitter streams is to separate the dull and polluted information from exciting real-life events. In practice, highly scalable and efficient approaches are required for handling and processing the increasingly significant quantity of Twitter data especially for real-time event detection. Other challenges are intrinsic to Twitter’s natural. These are due to the short length of tweet messages, the frequent use of simple words, the enormous quantity of spelling and grammatical errors. Such data sparseness, lack of context, and diversity of vocabulary make the traditional text analysis techniques less appropriate for tweets [14]. Also, different events may enjoy different popularity among users and can differ significantly in content, the number of messages and participants, periods, internal structure, and causal relationships [15].

Thus, the challenges are in below three aspects:

1. Integrating diverse types of data. The geo-tagged tweet stream involves three different data types: location, time, and text. Considering the entirely different representations of those data types and the complex cross-modal interactions among them, how to effectively integrate them for local event detection is challenging.

2. Capturing the semantics of short text. Since every tweet is limited to 140 characters, the semantics of the user’s activity is expressed through short and sparse text messages. Compared with traditional documents (e.g., news), it is much harder to capture the semantics of short tweet messages and extract high-quality local events.

3. On-line and real-time detection. When a local event outbreaks, it is key to report the event instantly to allow for timely actions. As massive geo-tagged tweets stream in, the detector should work in an on-line and real-time manner instead of a batch-wise and inefficient one. Such a requirement is the third challenge of our problem [2].

2 RELATED WORK

The Topic Detection and Tracking program by Jonathan G. Fiscus and George R. Doddington [16] gave the following definitions of the event:

Event is “something that happens at some specific time and place along with all necessary preconditions and unavoidable consequences”;

Sakaki et al. [17] defines an event as an arbitrary classification of space/time region that might have actively participating agents, passive factors, products, and a location in space/time like is being defined in the event ontology by Raimond and Abdallah [18]. The target events in this work are significant events that are visible through messages, posts, or status updates of active users in Twitter online social network service. These events have several properties: (i) they are of large scale because many users experience the event, (ii) they particularly influence people’s daily life, being that the main reason why users are induced to mention it, and (iii) they have both spatial and temporal regions. The importance of an event is connected with the distance users have between themselves and the event, and with the spent time since the occurrence.

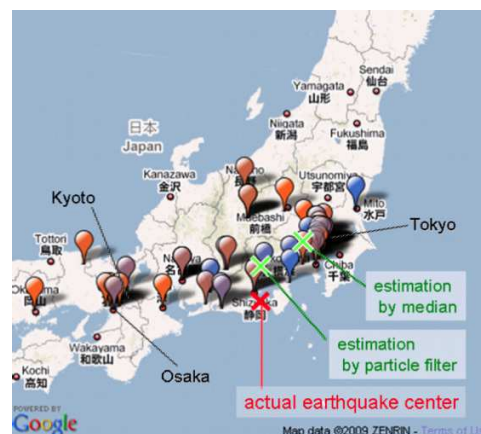


Figure 1: Earthquake location estimation based on tweets. Balloons show the tweets on the earthquake. The cross shows the earthquake centre. Red represents new tweets; blue represents later tweets [17].

2.1 Detection Task

Events are evaluated using a decision based on whether a document reports a new topic that has not been reported previously, or if should be merged with an existent event [22]. Differing on how data is treated, two groups of Event Detection systems were identified [23].

Online New Event Detection (NED).

Online New Event Detection denotes to the task of classifying events from live streams of tweets in real-time. Most new and retrospective event detection methods rely on the use of well-known clustering-based algorithms [24]. Usually, new event detection contains the continuous monitoring of tweet feeds for discovering

Published	Location	Title	Screen_name	URL
2009-08-11 05:05:57	Saitama, Japan	地震だ！わー	todot	http://twitte
2009-08-11 05:05:56	unknown	地震。 Lots of earthquakes	tracy	http://twitte
2009-08-11 05:05:53	iPhone 35309506.13915001	揺れたわ	Hakari	http://twitte
2009-08-11 05:05:53	Mie Prefecture	すごい地震だ (sai)	randu001 masu	http://twitte
2009-08-11 05:05:52	Kanagawa city	地震だ！！	Yasutakama	http://twitte
2009-08-11 05:05:52	unknown	地震こわいぞうさん	ette	http://twitte
2009-08-11 05:05:52	Kanazawa	地震だ！ My goshi	haruys	http://twitte
2009-08-11 05:05:52	Sakado, Saitama, Japan	あら、地震？	mechys	http://twitte
2009-08-11 05:05:51	unknown	震が来た！	down	http://twitte
2009-08-11 05:05:51	unknown	また地震 震	tsukid	http://twitte
2009-08-11 05:05:51	JP	地震だ。 Earthquake again. This is a long one	Earthquake now	http://twitte

Figure 2: Screenshot of Trotter, an earthquake reporting system [17].

events in near real time, which could do event detection of real-world events like breaking news, natural disasters or football game.

Retrospective Event Detection (RED).

Retrospective Event Detection denotes to the process of classifying unidentified events previously from gathered past data that have arrived in the past. In Retrospective Event Detection, most methods are founded on the retrieval of event relevant documents by performing queries over a collection of records. Both techniques assume that event relevant documents contain the query terms. A disparity of the previous approach is the use of query growth techniques, meaning that some messages related to a specific event do not contain specific event related information, but with the use of improved queries, messages related to the event can be recovered.

2.2 Type of Event

Event detection could be classified into specified or unspecified event detection techniques [25]. By using specific pre-known information and features about an event, traditional information retrieval and extraction techniques can be modified to perform specified event detection. Most traditional information retrieval and extraction methods are useless when no previous information is available about the event. Unspecified event detection methods address the issue on the basis that temporal signals constructed via document analysis can detect real work events. Monitoring trends in text streams, alliance topographies with same viewpoints, and categorising events into different categories are among those tasks to perform unspecified event detection.

2.3 Event Detection Overview

Event detection has been deeply studied in the past few years, and various methods have been proposed to address the problem. Frequently used feature representations are also presented and discussed. This survey does not provide an exhaustive review of existing approaches but rather techniques which related to the area that would focus on our most important research directions.

The event detection problem is not a new research topic, Yang et al. [26] in 1998, is a study on retrospective and on-line event detection which examined the usage and postponement of text retrieval and clustering techniques. The main task was to detect new events

from a well-organized stream of news stories repeatedly. The system performed quite well and showed that basic techniques such as document clustering could be highly effective to perform event detection. Depending on the type of events, these methods are classified into unspecified and specified event detection.

Unspecified Event Detection: This kind of events is mainly about emerging events, breaking news, and general topics that attract a considerable number of users' attentions. We are interested in using Twitter tweets to find ongoing local events. Thus, the general events will be of our interests [34]. Typically, such events often come with a significant temporary boost of the use of keywords. The trends in tweets can be clustered according to the frequent-occur feature. Whereas, there is a non-toxic event which is viewed as noise when conducting event detection [27]. Therefore, the major challenge to be dealt with in unspecified event detections is to distinguish significant trends event from those trivial non-events. Several techniques have been proposed to tackle this challenge by applying a range of machine learning, data mining, and text mining techniques.

TwitterStand: News in tweets [35] showed a novel system which deals with the problem of capturing proper tweets trends related to breaking news, TwitterStand. Two techniques were used, a naïve Bayes classifier and online clustering algorithms. Naïve Bayes classifier was applied to distinguish breaking news from irrelevant non-events in tweet streaming. Whereas, the online cluster which employs term frequency-inverse document frequency and cos similarity measures were used to from newsgroups. The paper used tweets' hashtag and timestamps as an additional method to reduce the clustering errors of online cluster algorithms.

Breaking news detection and tracking on Twitter [36] proposed a technique to capture breaking news from Twitter, with the additional functions of following and ranking. The tweets were extracted through pre-defined queries of Twitter API and indexed before similarity grouping. Grouping was based on the of-if similarity measure between messages. All tweets were sorted in ascending weight with authors, proper nouns, and hashtags. Stanford Named Entity Recognizer (NER) was used to identify proper nouns with the number of sponsors' followers and some shares of the tweets taken into consideration. In the paper, the author factor was introduced for the reliance and soundness of the tweets, which improved the accuracy. They also developed an application called Hot-streams to validate the algorithms.

Streaming first story detection with application to Twitter [37] focused on predicting new events which never occurred in previous tweets. The approach was mainly about improving the efficiency of conducting cosine similarity measurement within documents. The paper developed the locality sensitive hashing methods, which applied the search operations to a small number of records and optimised the complexity within a constant time and space. Whereas, the replies, the number of shares, and hashtags were not taken into consideration in the paper. The experiment results indicated two remarkable facts which are 1. User based prevails when compared with tweet-based ranking. 2. The entropy of information leads to less message spam.

Real-world event identification on Twitter [38] used an online clustering technique to associate tweets with the real-world event. It keeps clustering related tweets and then classifies the

clusters into two categories, real events or trivial nonevents. A significant difference between actual events and nonevents is that there are Twitter-centric topics within nonevents. Naaman pointed out that such topic is trending but do not reflect or represent any real-world events. All tweets were present as an of-if weight vector based on their contents. The paper used cosine similarity to calculate the distance between a tweet and cluster centroids. The weight of hashtag was doubled as it was hypothesized that it brings a strong connection between text and tweet topic. All standard methods of pre-processing, such as stem and stop word list were also used. The cluster was computed with a combination of term-frequency-based temporal features, twitter-operation-based social functions, local features, and Twitter-centric features. Term frequency-based features based on the number of the appearance in the message set with a cluster. The twitter operations include comments, replies, share, etc, and the feature contains the percentage of those operations in the cluster content. This paper assumes that the proposed cluster obtained the intention to revolve around a certain meaningful topic but the non-event clusters have the trends of revolving around some irrelevant terms such as “dinner”, “sleep”, or “right”. The twitter-centric. Upon all these work, an SVM is developed to classify the clusters and tweets associated with the clusters into real-world labelled portion or non-even labelled portion.

Towards effective event detection, tracking and summarization on microblog data [39] proposed a technique to assign some topic-word-based features to the microblog data to train a cluster. Topic words are those words which share more popularity when compared with others in an event. These words are computed from an extraction of daily messages in microblog data based on the frequency of the phrase, incidence of hashtag associated with the phrase, and entropy. A co-occurrence graph was generated by adding edges to messages and topical words where a hierarchical cluster was used upon to transfer the set of topical words into event clusters. The paper claims that the hierarchical cluster over forms traditional K-means algorithms.

Real-time event detection for online behavioural analysis of big social data, [40] employed a 5-stage method in real-time event detection. It collected tweets with search conditions and converted them into JSON format. The terms are then extracted from the tweets by adopting named entity recognition. It constructs the signals by tracking both occurrences of terms extracted from extraction phase and diffusion of the information. After this, a weighted graph of which nodes are tweets is computed. The edges are measured by the complement of the similarity degree. Clustering is a final stage which includes adjacent points that are close measured by timestamp and occurrences. Each cluster is viewed as a potential candidate for grouping events to whether they are real-world events or non-events.

Specified Event Detection: A specified event can be public or pre-planned social meetings such as a concert. It should contain the metadata such as venue, time, attendees, and musicians. The work introduced here attempt to exploit Twitter textual content or metadata information or both.

Popescu and Pennacchiotti [41] focused on identifying controversial events that provoke public discussions with opposing opinions on Twitter, such as controversies involving superstars. Their detection outline is based on the idea of a Twitter snapshot, a trio

consisting of a target entity, a given period, and a set of tweets about the entity from the target period. Assumed a set of Twitter snapshots, an event detection module first distinguishes between the event and non-event snaps using a supervised gradient boosted decision trees [42], trained on the manually labelled data set. To rank these event snaps, a controversy model allocates higher scores to controversial event snapshots, by a reversion algorithm applied to a large number of features. The employed features are based on Twitter-specific characteristics including linguistic, structural, buzziness, nine sentiment, and controversy features, and on external features for example news buzz. These external features require time alignment of entities in news media and Twitter sources, to capture entities that are trending in both sources because they are more likely to mention real-world events. The authors have also planned to merge the two stages into a single-stage system by including the event detection score as an extra feature into the controversy model. This produced an improved performance. Feature analysis of the single-stage system exposed that the event score is the most relevant feature because it discriminates event from nonevent snapshots. Hashtags are originated to be important semantic topographies for tweets in the meantime they help classify the topic of a tweet and approximation the topical cohesiveness of a set of tweets. External features based on news and the Web are also originated usefully; hereafter, association with traditional media helps authenticate and explain social media reactions. Also, the linguistic, structural, and sentiment features also deliver significant effects. The authors determined that a rich, diverse set of features be crucial for controversy detection.

Benson et al. [43] present a novel approach to identify Twitter messages for concert events using a factor graph model, which simultaneously examines individual messages, clusters them according to the event type, and induces a correct value for each event property. The motivation is to infer a comprehensive list of musical events from Twitter (based on artist-venue pairs) to whole an existing list (e.g., city event calendar table) by discovering new musical events mentioned by Twitter users that are difficult to find in other media sources. At the message level, this approach relies on a conditional random field (CRF) to excerpt the artist name and position of the event. The contribution features to CRF model include word form; a set of even expressions for mutual emoticons, time references, and venue types; a large number of words for artist names removed from an external source; and a bag of words for city place names. Clustering is directed by term popularity, which is an arrangement score among the message term labels and some candidate worth. To imprisonment the huge text difference in Twitter messages, this score is founded on a weighted combination of term similarity measures. This including complete string matching, and adjacency and equality indicators scaled by the inverse document frequency. Also, a uniqueness factor is working during clustering to expose rare event messages that are dominated by the general ones and to discourage various messages from the same facts to cluster into multiple incidents. Alternatively, a consistent indicator is employed to discourage messages from multiple events to form a single cluster. The factor graph model is then used to capture the interaction between all components and provide the final choice. The production of the model consists of an event-based

clustering of messages, where each cluster is characterised by an artist-venue pairs.

Lee and Sumiya [44] present a geosocial local event detection system based on modelling and monitoring crowd behaviours via Twitter, to identify local festivals. They rely on geographical regularities deduced from the usual behaviour patterns of crowds using geotags. First, Twitter geotagged data are collected and preprocessed over an extended period for a specific region [45]. The area is then alienated into several regions of interest (ROI) using the k-means algorithm, applied to the geographical coordinates (longitudes/latitudes) of the collected data. Geographical regularities of the crowd within each ROI are then predictable from historical data based on three main features: some tweets, users, and moving users within an ROI. Statistics for these functions are then accumulated over historical data using 6-hour time interval to form the estimated behaviour of the crowd within each ROI. Finally, unusual events in the monitored geographical area can be detected by comparing statistics from new tweets with those of the estimated behaviour. The authors found that an augmented user combined with an increased number of tweets provides a strong indicator of local festivals.

2.4 Local Event Detection

Abdelhaq [31] presents a method of EVENTTWEET which extracts hashtags and Twitter keywords based on temporal burst and spatial location. Then it employs a cluster on these keywords to compute events depending on location distribution.

Krumm, John [30] introduced a method, Eyewitness, to find local events from a large-scale stream of Twitter textures. The paper considers the location statistics of tweets and classifies the location data to train a classifier for locating meaningful tweets. Then it envisions the classifier being harnessed in a user-interaction system to identify and monitor the events based on users' locations. Eyewitness adopts a regression model to predict the number of geotagged tweets in a certain amount of time. If the real number of tweets is larger than the predicted number, the event is defined as a local event. It also employs a text summarization algorithm to extract the tweets belongs to the event.

Chao [1] proposed another approach, GEOBURST for local event detection. The paper assumed that a significant local event results in the scene of many geotagged texts around one certain place. Moreover, a method was built based on this assumption which firstly looks for all geo-clustered topics and secondly ranks those topics based on spatiotemporal business to get the significant local events. There is an ad-hoc streaming process embedded in the methods to implement the function of processing and updating continuous real-time tweets.

3 PRELIMINARIES

In this section, we describe the application of Local Event Detection algorithm, which consisted of Candidate Generator, Candidate Generator Classification, Online Updater.

3.1 Candidate Generator

Given a query window Q and the set D_Q of tweets falling in Q , the candidate generator is to divide D_Q into several geo-topical clusters, such that the tweets in each group are geographically close and semantically coherent. The Clustering of D_Q , however, poses several challenges: how to combine the geographical and semantic similarities in a reasonable way? How to capture the correlations between different keywords? Moreover, how to generate quality clusters without knowing the suitable number of clusters in advance? To address these challenges, we perform a novel pivot seeking process to identify the centres of geo-topical clusters. Our key insight is that: the spot where the event occurs acts as a pivot that produces relevant tweets around it; the closer we are to the pivot, the more likely we observe relevant tweets. Therefore, we define a geo-topical authority score for each tweet, where a kernel function captures the geographical influence among tweets, and the semantic influenced by random walk on a keyword co-occurrence graph. With this authority measure, we develop an authority ascent procedure to retrieve authority maxima as pivots; and each pivot naturally attracts similar tweets to form a quality geo-topical cluster. Below, we first introduce our geo-topical authority measure to define pivot tweets and then develop an authority ascent procedure for pivot seeking.

3.1.1 Pivot Tweet. Pivot Tweet is an amount of $G(d_0 \rightarrow d_1)$ energy is distributed from d_0 to d through random walk on the graph, $G(d_0 \rightarrow d_1) S(d_0!d)$ is the amount that successfully reaches d ; and d_0 authority is the total sum of energy that d receives from its neighbors [38]. The authority score is analogous to kernel density in the task of nonparametric kernel density estimation [7]. In kernel density estimation, the density of any point x in the Euclidean space is contributed mainly by the observed points that are close enough to x . As such, the density maxima can be defined in a nonparametric manner. Analogously, in our problem, the geo-topic authority of any tweet d is contributed by the observed tweets that are similar to d both geographically and semantically. As a result, the salient tweets for different activities can be selected in the geo-topical space.

3.1.2 Authority Ascent for Detecting Geo-Topical Clusters. Now our task is to find all pivots in D_Q and assign each tweet to its corresponding pivot. We develop an authority ascent procedure for this purpose. As shown in Figure 3, starting from a tweet d_1 as the initial center, we perform step-by-step center shifting. Assuming the center at step t is tweet dt , we find dt neighborhood $N(dt)$, and the local pivot $l(dt)$? the tweet having the largest authority in $N(dt)$. Then we regard $l(dt)$ as our new center, i.e., $dt + 1 = l(dt)$. As we continue such an authority ascent process, the center is guaranteed to converge to an authority maximum. It is because every shift operation increases the authority of the current

3.2 Candidate Generator Classification

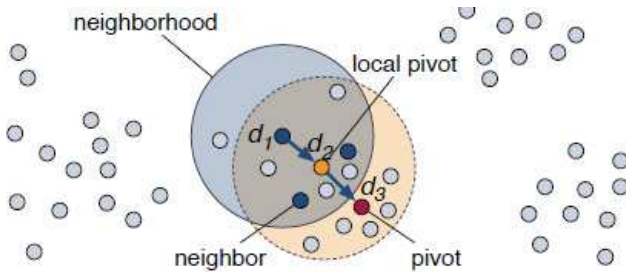
Up to now, we have obtained a set of geo-topical clusters in the query window as candidate events. Nevertheless, as aforementioned, not necessarily does every candidate correspond to a local event. In this section, we describe the module for candidate event classification. The foundation of our classification is the summarization

Algorithm 1: Pivot seeking.

Input: The tweet set D_Q , the kernel bandwidth h , the semantic threshold δ .
Output: The pivot for each tweet in D_Q .
 // Neighborhood computation.
foreach $d \in D_Q$ **do**
 $N(d) \leftarrow \{d' | d' \in D_Q, G(d' \rightarrow d) > 0, S(d' \rightarrow d) > \delta\}$;
 // Authority computation.
foreach $d \in D_Q$ **do**
 $A(d) \leftarrow d$'s authorith score computed from $N(d)$;
 // Find local pivot for each tweet.
for $d \in D_Q$ **do**
 $l(d) \leftarrow \arg \max_{d' \in N(d)} A(d')$;
 // Authority ascent.
foreach $d \in D_Q$ **do**
 Perform authority ascent to find the pivot for d ;

Algorithm 2: Approximate RWR score computation.

Input: The keyword co-occurrence graph G , a keyword q , the restart probability α , an error bound ϵ .
Output: q 's vicinity V_q .
 // $p(u)$ is the score of node u that needs to be propagated.
 $s(q) \leftarrow \alpha, p(q) \leftarrow \alpha, V_q \leftarrow \phi$;
 $Q \leftarrow$ a priority queue that keeps $p(u)$ for the keywords in G ;
while $Q.peak() \geq \alpha\phi$ **do**
 $u \leftarrow Q.pop()$;
 for $v \in I(u)$ **do**
 $\Delta s(v) = (1 - \alpha)p_{vu}p(u)$;
 $s(v) \leftarrow s(v) + \Delta s(v)$;
 $V_q[v] \leftarrow s(v)$;
 $Q.update(v, p(v) + \Delta s(v))$;
 $p(u) \leftarrow 0$;
return V_q ;

**Figure 3:** An illustration of the authority ascent process.

module, which learns word embedding to capture the semantics of short tweet messages and meanwhile constructs the activity timeline to reveal routine regional activities. In what follows, we describe embedding learning and activity timeline construction and then present the classier.

3.2.1 Learning Embeddings from the Stream. The embedding learner aims at capturing the semantics of short text by jointly mapping the tweet messages and keywords into the same low-dimensional space. If two tweets (keywords) are semantically similar, they are forced to have close embedding vectors in the latent space. The learner continuously consumes a massive amount of tweets from the input stream and learns to preserve their intrinsic semantics. As such, it can generate red-length vectors for any text pieces (e.g., the candidate event and the background activity), which serve as high-quality features to discriminate whether a candidate event is indeed a local event or not. Relying on the tweet caching strategy and the SGD optimisation procedure, the embedding learner continuously consumes the geo-tagged tweet stream and keeps updating the embeddings for different keywords and tweets. With the learnt keyword embeddings, the embedding of any ad-hoc text piece can be easily derived with SGD. As we will illustrate shortly, such a property enables us to quantify the spatiotemporal unusualness of each candidate event and extract highly discriminative features to pinpoint true local events.

3.2.2 Activity Timeline Construction. The activity timeline aims at unveiling the normal activities in different regions during different time periods. For this purpose, we design a structure called tweet cluster (TC) and extend the CluStream algorithm [2]. The TC essentially provides a concise where-when-what summary for S : (1) where: with n , ml , and 2 , one can easily compute the location mean and variance for S ; (2) when: with n , mt , and Mt 2, one can compute the average time and temporal variance for S ; and (3) what: me keeps the number of occurrences for each keyword. These fields in a TC-S enable us to estimate the number of keyword occurrences at any location. First, the quantities n , ml , and ml 2 allow us to compute the center location of the TC S . Second, theme tracks the number of occurrences for different keywords around the centered location of S . With either spatial interpolation or kernel density estimation, one can estimate the occurrences of keyword k at any ad-hoc location based on the distance to the center location of S . Moreover, TC satisfies the additive property, i.e., the fields can be easily incremented if a new tweet is absorbed. Based on this property, we adapt CluStream to continuously clusters the stream into a set of TCs. When a new tweet d arrives, it ends the TCM that is geographically closest to d . If d is within M 's boundary (computed from n , ml , and 2 , see [2] for details), it absorbs d into and updates its fields; otherwise, it creates a new TC for d . Meanwhile, we employ two strategies to limit the maximum number of TCs: (1) deleting the TCs that are too old and contain few tweets; Moreover, (2) merging closest TC pairs until the number of remaining TCs is small enough. We cluster the continuous stream and store the clustering snapshots at different timestamps. Since storing the snapshot of every timestamp is unrealistic, we use the pyramid time frame (PTF) structure [2] to achieve both excellent space efficiency and high coverage of the stream history.

3.2.3 The Classifier. We use logistic regression to train a binary classifier and judge whether each candidate is indeed a local event. We choose logistic regression because of its robustness when there is only a limited amount of training data. While we have also tried using other classifiers like Random Forest and SVM, we find that the logistic regression classifier produces the best result in our experiments. The labelled instances for the classifier are collected through a large-scale experiment on a popular crowdsourcing platform. We will shortly detail the annotation process in Section 6.

We analyse the complexity of the candidate classification step as follows. As the prediction time of logistic regression is linear in the number of features and has $O(1)$ complexity, the time cost is dominated by the feature extraction process. Let NC be the maximum number of tweets in each candidate, and M be the keyword vocabulary size, D be the latent embedding dimension, and N_Q is the number of tweets in the query window. We need to extract the features for all the candidates in the query window. The time costs for extracting different features for each candidate event are analyzed as follows: (1) For the temporal unusualness measure, its time complexity is $O(M + NA + D)$ where NA is the maximum number of TCs in one snapshot of the activity timeline; (2) For the spatial unusualness measure, its time complexity is $O(M + NQ + D)$; (3) For the temporal ACM Transactions burstiness measure, its time complexity is $O(MNA)$; (4) For the spatial burstiness measure, its time complexity is $O(MNC)$; (5) For the static features, the total time complexity is $O(NC)$.

3.3 The Online Updater

In this section, we present the online updater of GeoBurst+. Consider a query window Q , let Q_0 be the new query window after Q shifts. Instead of finding the local events in Q_0 from scratch, the online update leverages the results in Q and updates the event list with little cost. If one runs the batch detection algorithm in the updated window Q_0 , the candidate generation step will dominate the total time cost in the two-step detection process, while the candidate classification step is very efficient. Hence, our focus on supporting efficient online detection is to develop algorithms that can fast update the geo-topical clustering results when the query window shifts from Q to Q_0 . To guarantee to generate the correct clustering results in Q_0 , the key is to find the new pivots in The new window Q_0 based on the previous results in Q . Let D_Q be the tweets falling in Q and D_{0Q} be the tweets in Q_0 . We denote by RQ the tweets removed from D_Q , i.e., $RQ = D_Q \setminus D_{0Q}$; and by I_Q the tweets inserted into D_Q , i.e., $I_Q = D_{0Q} \setminus D_Q$. In the sequel, we design a strategy that finds pivots in D_{0Q} by just processing RQ and I_Q . Recall that, the pivot seeking process first computes the local pivot for each tweet and then performs authority ascent via a path of local pivots. So long as the local pivot information is correctly maintained for each tweet, the authority ascent can be fast completed. The major idea for avoiding ending pivots from scratch is that, as D_Q is changed to D_{0Q} , only some tweets have their local pivots changed. We call them mutated tweets, defined as follows.

Definition (Mutated Tweet). A tweet d_2 in D_{0Q} is a mutated tweet if d_1 local pivot in D_{0Q} is different from its local pivot in D_Q .

Now the questions are, how do we fast identify the mutated tweets by analysing the influence of RQ and I_Q ? Our observation

is that, for any tweet, it can become a mutated tweet only if at least one of its neighbours has authority change. Therefore, we take a reverse search strategy to find mutated tweets: (1) First, we identify in D_{0Q} all the tweets whose authorities have changed. (2) Second, for each authority-changed tweet t , we retrieve the tweets that regard t as its neighbor and update their local pivots.

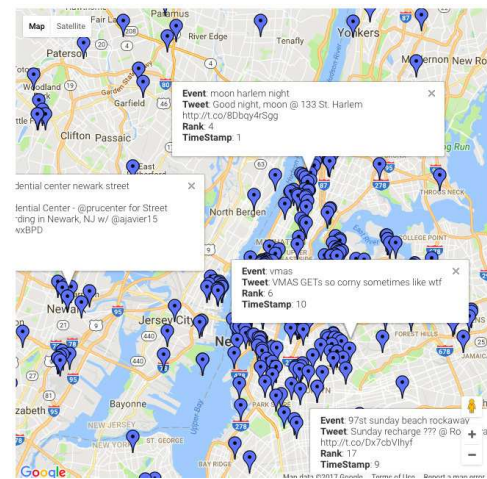
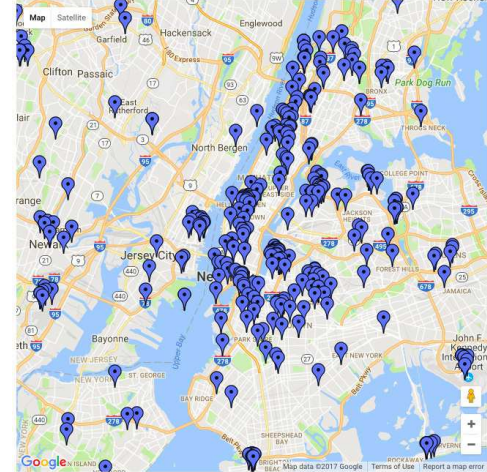
4 EXPERIMENTS

An Event Radar was implemented to test and simulate our approach as an experiment. The setting is a Mac OS laptop with a 1.6GHZ processor and 8GB RAM. Event Radar was implemented in MEAN Stack with MongoDB as database and Express.js as a server.

4.1 Events Visualisation

Event Radar can visualise all inputs from MongoDB on Google Map and enable users to view the events' tag, original tweets, timestamp and the rank score of the event.

The Geo-Burst MEAN MapApp



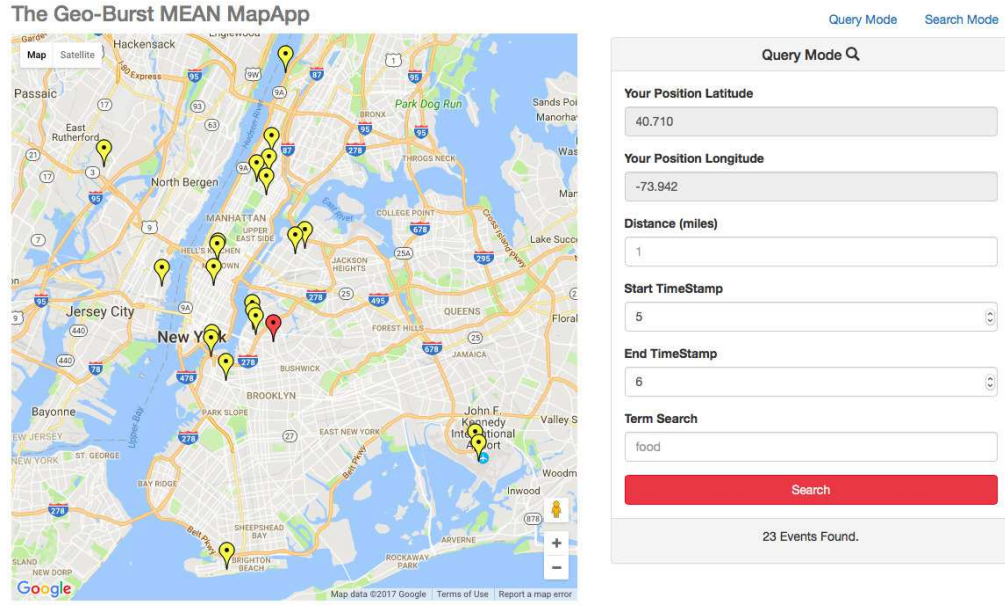


Figure 4: Query of finding the events with a timestamp from 5 to 6. The system returns 23 events.

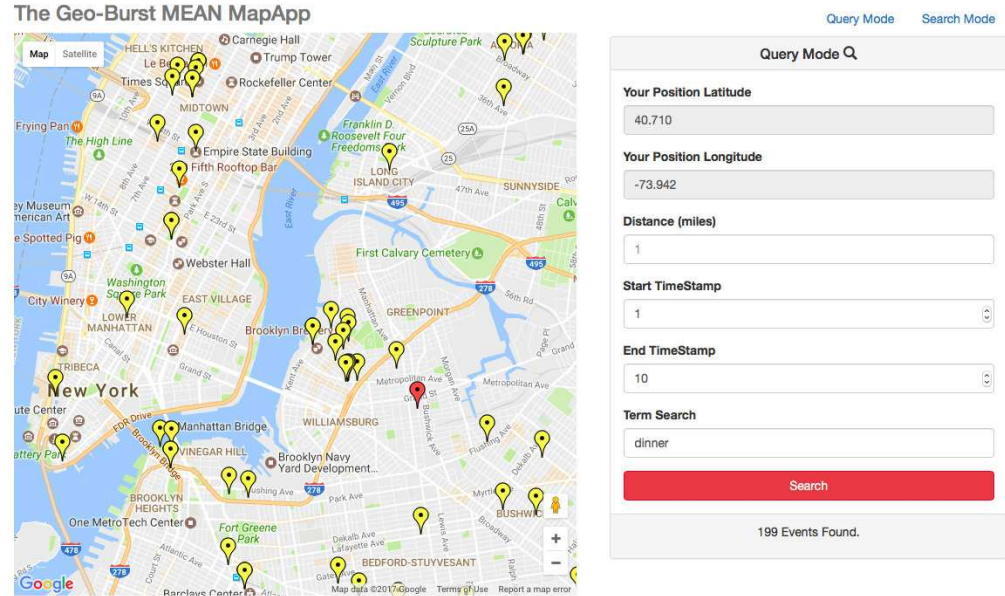


Figure 5: Query to obtain events with a timestamp from 1 to 10, and keyword dinner. The system returns 199 events.

4.2 Query Mode

The system also provides a query mode for users to send queries to the server to select the desired events, by providing the conditions of event tweets' terms, the geospatial distance between the users and events' locations, and the timestamp's query windows.

In summary, Event Radar is a novel approach to providing a web-based application for users to view the local events in a given area. Additionally, the system contains the query mode for users

to search the events of their interest. Therefore, such system has a promising perspective to be developed as a system for local security authority or press due to the reason that it can detect the local events, and update them in the dynamic time stream.

5 CONCLUSION

We studied the problem of real-time local event detection in geo-tagged tweet streams. Event detection aims at finding real-world

occurrences that unfold over space and time. We mainly implement a website demonstration system with an improved algorithm to show the real-time local events online for public interests. Our system Event-Radar is not limited to Twitter. Rather, any geo-textual social media stream (e.g., Instagram photo tags, Facebook posts) can use to extract interesting local events as well. For future work, it is interesting to extend Event-Radar for handling the tweets that mention geo-entities but do not include exact GPS coordinates.

We built a demonstration system to visualise the local event detection result dynamically. This system consisted of two servers, connected to the mongo database. One server is in charge of loading Twitter data from Twitter API, constructing of co-occurrence keyword graph, running batch mode to generate local event candidates based on geographic impact and semantic impact. It ranks the candidate by making vertical comparison across time frame and horizontal comparison across all clusters, finally outputting the local event results into Database. Meanwhile, we optimised the original project by saving the co-occurrence keyword graph into the database, so that when the system restarts, it reloads the graph from the database to save sufficient time. Another server deals with the front end request and excellent local event results from the database, sending results to the front end to be visualised.

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REFERENCES

- [1] Zhang, Chao et al. "GeoBurst: Real-Time Local Event Detection in Geo-Tagged Tweet Streams." *Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval*. ACM, 2016.
- [2] Chao Zhang, Dongming Lei, Quan Yuan, Honglei Zhuang, Lance Kaplan, Shaowen Wang, and Jiawei Han. 2017. GeoBurst+: Effective and Real-Time Local Event Detection in Geo-Tagged Tweet Streams. *ACM Trans. Intell. Syst. Technol.* 1, 1, Article 1 (March 2017), 23 pages.
- [3] Abdelhaq, Hamed, Christian Sengstock, and Michael Gertz. "Eventweet: Online localized event detection from twitter." *Proceedings of the VLDB Endowment* 6.12 (2013): 1326-1329.
- [4] Zhang, Chao, et al. "Fast inbound top-k query for random walk with restart." *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*. Springer International Publishing, 2015.
- [5] Ellison, Nicole B. "Social network sites: Definition, history, and scholarship." *Journal of Computer-Mediated Communication* 13.1 (2007): 210-230.
- [6] FARZINDAR, A., and D. INKPEN. 2012. *Proceedings of the Workshop on Semantic Analysis in Social Media*. Association for Computational Linguistics, Avignon, France 50.
- [7] Kwak, H., Lee, C., Park, H., Moon, S.: What is Twitter, a social network or a news media? Categories and subject descriptors. *Most* 112(2), 591-600 (2010).
- [8] Schonfeld, E.: Techcrunch: mining the thought stream (2009). Accessed 9 July 2013
- [9] Q. Yuan, G. Cong, Z. Ma, A. Sun, and N. M. Thalmann, "Who, where, when and what: discover spatio-temporal topics for twitter users," in *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2013, pp. 605-613.
- [10] A. Farzindar, "Industrial perspectives on social networks," in *EACL 2012-Workshop on Semantic Analysis in Social Media*, vol. 2, 2012.
- [11] A. Java, X. Song, T. Finin, and B. Tseng, "Why we twitter: understanding microblogging usage and communities," in *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis*. ACM, 2007, pp. 56-65.
- [12] X. Wang, M. S. Gerber, and D. E. Brown, "Automatic crime prediction using events extracted from twitter posts," in *Social Computing, Behavioral-Cultural Modeling and Prediction*. Springer, 2012, pp. 231-238.
- [13] Atefeh, Farzindar, and Wael Khreich. "A survey of techniques for event detection in twitter." *Computational Intelligence* 31.1 (2015): 132-164
- [14] METZLER, D., S. DUMAIS, and C. MEEK. 2007. Similarity measures for short segments of text. In *Proceedings of the 29th European Conference on IR Research, ECIR'07*. Springer-Verlag: Berlin, Heidelberg, pp. 16-27.
- [15] NALLAPATI, R., A. FENG, F. PENG, and J. ALLAN. 2004. Event threading within news topics. In *Proceedings of the Thirteenth ACM International Conference on Information and Knowledge Management, CIKM'04*, ACM, New York, NY, pp. 446-453.
- [16] Fiscus, J.G., Doddington, G.R.: Topic detection and tracking evaluation overview. In: *Topic Detection and Tracking*, pp. 17-31 (2002). 88
- [17] Sakaki, T., Okazaki, M., Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors. In: *Proceedings of the 19th International Conference on World Wide Web*, pp. 851-860. ACM (2010).
- [18] Raimond, Y., Abdallah, S.: The event ontology (2007).
- [19] Linguistic Data Consortium: TDT 2004: Annotation Manual - version 1.2, 4 August 2004.
- [20] Strassel, S.: *Topic Detection & Tracking (TDT-5)* (2004).
- [21] Cordeiro, Mário, and João Gama. "Online social networks event detection: a survey." *Solving Large Scale Learning Tasks. Challenges and Algorithms*. Springer International Publishing, 2016. 1-41.
- [22] Yang, C.C., Shi, X., Wei, C.P.: Discovering event evolution graphs from news corpora. *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.* 39, 850-863 (2009)
- [23] Allan, J., Papka, R., Lavrenko, V.: On-line new event detection and tracking. In: *Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval - SIGIR 1998*, New York, USA, pp. 37-45 (1998).
- [24] Aggarwal, C.C., Zhai, C.: A survey of text clustering algorithms. In: Aggarwal, C.C., Zhai, C. (eds.) *Mining Text Data*, pp. 77-128. Springer, New York (2012)
- [25] Farzindar, A.: Social network integration in document summarization. In: Fiori, A. (ed.) *Innovative Document Summarization Techniques: Revolutionizing Knowledge Understanding*. IGI-Global, Hershey (2014) Boettcher, Alexander, and Dongman Lee. "Eventradar: A real-time local event detection scheme using twitter stream." *Green Computing and Communications (GreenCom), 2012 IEEE International Conference on*. IEEE, 2012. 9 105.
- [26] Yang, Y., Pierce, T.T., Carbonell, J.G.: A study of retrospective and on-line event detection. In: *SIGIR 1998: Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, Melbourne, Australia, 24-28 August 1998, pp. 28-36. ACM, New York (1998).
- [27] NAAMAN, M., H. BECKER, and GRAVANO. L. 2011. Hip and trendy: characterizing emerging trends on Twitter. *Journal of the American Society of Information Science and Technology*, 62(5): 902-918.
- [28] Walther, Maximilian, and Michael Kaisser. "Geo-spatial event detection in the twitter stream." *European Conference on Information Retrieval*. Springer Berlin Heidelberg, 2013.
- [29] Girju, Roxana, and Dan I. Moldovan. "Text mining for causal relations." *FLAIRS Conference*. 2002.
- [30] Krumm, John, and Eric Horvitz. "Eyewitness: Identifying local events via space-time signals in twitter feeds." *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems*. ACM, 2015.
- [31] H. Abdelhaq, C. Sengstock, and M. Gertz. Eventweet: Online localized event detection from twitter. *PVLDB*, 6(12):1326-1329, 2013.
- [32] Q. He, K. Chang, and E.-P. Lim. Analyzing feature trajectories for event detection. In *SIGIR*, pages 207-214, 2007.
- [33] C. C. Aggarwal and K. Subbian. Event detection in social streams. In *SDM*, pages 624-635, 2012.
- [34] MATHIOUDAKIS, M., and N. KOUDAS. 2010. TwitterMonitor: Trend detection over the Twitter stream. In *SIGMOD Conference*, Indianapolis, IN, pp. 1155-1158.
- [35] SANKARANARAYANAN, J., H. SAMET, B. E. TEITLER, M. D. LIEBERMAN, and J. SPERLING. 2009. TwitterStand: News in tweets. In *Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems, GIS'09*, ACM, New York, NY, pp. 42-51.
- [36] PHUVIPADAWAT, S., and T. MURATA. 2010. Breaking news detection and tracking in Twitter. In *IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, Vol. 3, Toronto, ON, pp. 120-123.
- [37] PETROVIC, S., M. OSBORNE, and V. LAVRENKO. 2010. Streaming first story detection with application to Twitter. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, HLT'10*, pp. 181-189.
- [38] BECKER, H., M. NAAMAN, and L. GRAVANO. 2011a. Beyond trending topics: Real-world event identification on Twitter. In *ICWSM*, Barcelona, Spain.
- [39] LONG, R., H.WANG, Y. CHEN, O. JIN, and Y. YU. 2011. Towards effective event detection, tracking and summarization on microblog data. In *Web-Age Information Management*, Vol. 6897 of *Lecture Notes in Computer Science*. Edited by WANG, H., S. LI, S. OYAMA, X. HU, and T. QIAN. Springer: Berlin/Heidelberg, pp. 652-663.
- [40] Nguyen, Duc T., and Jai E. Jung. "Real-time event detection for online behavioral analysis of big social data." *Future Generation Computer Systems* 66 (2017): 137-145.

- [41] POPESCU, A. M., and M. PENNACCHIOTTI. 2010. Detecting controversial events from Twitter. In Proceedings of the 19th ACM International Conference on Information and Knowledge Management, CIKM '10, ACM, New York, NY, pp. 1873–1876.
- [42] FRIEDMAN, J. H. 2001. Greedy function approximation: a gradient boosting machine. *Annals of Statistics*, 29:1189–1232.
- [43] BENSON, E., A. HAGHIGHI, and R. BARZILAY. 2011. Event discovery in social media feeds. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Volume 1 of HLT'11, Association for Computational Linguistics, Stroudsburg, PA, pp. 389–398.
- [44] LEE, R., and K. SUMIYA. 2010. Measuring geographical regularities of crowd behaviors for Twitter-based geosocial event detection. In Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks, LBSN'10, ACM, New York, NY, pp. 1–10.
- [45] FUJISAKA, T., R. LEE, and K. SUMIYA. 2010. Discovery of user behavior patterns from geo-tagged microblogs. In Proceedings of the 4th International Conference on Ubiquitous Information Management and Communication, ICUIMC'10, ACM, New York, NY, pp. 36:1–36:10.
- [46] LEE, R., and K. SUMIYA. 2010. Measuring geographical regularities of crowd behaviors for Twitter-based geosocial event detection. In Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Location Based Social Networks, LBSN'10, ACM, New York, NY, pp. 1–10.