Crowdsensing based Multi-Modal Storytelling of Urban Emergency Events using Social Media

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ABSTRACT
With the development of Web 2.0, ubiquitous computing, and corresponding technologies, social media has the ability to provide the concepts of information contribution, diffusion, and exchange. Different from the permitting the general public to issue the user-generated information, social media has enabled them to avoid the need to use centralized, authoritative agencies. One of the important functions of Weibo is to monitor real time urban emergency events, such as fire, explosion, traffic jam, etc. Weibo user can be seen as social sensors and Weibo can be seen as the sensor platform. In this paper, the proposed method focuses on the step for storytelling of urban emergency events: given the Weibo posts related to a detected urban emergency event, the proposed method targets at mining the multi-modal information (e.g., images, videos, and texts), as well as storytelling the event precisely and concisely. To sum up, we propose a novel urban emergency event storytelling method to generate multi-modal summary from Weibo. Specifically, the proposed method consists of three stages: irrelevant Weibo post filtering, mining multi-modal information and storytelling generation. We conduct extensive case studies on real-world microblog datasets to demonstrate the superiority of the proposed framework.

CCS Concepts
•H.2.8 [**Database Management**]: Database Application – Data Mining; H.3.1 [**Information Systems**]: Content Analysis and Index

Keywords
Crowdsensing; emergency events; Multimedia Storytelling; Social Media

1. INTRODUCTION
With the development of Web 2.0, ubiquitous computing, and corresponding technologies, social media has the ability to provide the concepts of information contribution, diffusion, and exchange. Different from the permitting the general public to issue the user-generated information, social media has enabled them to avoid the need to use centralized, authoritative agencies. In other words, this makes virtually the real person to a potential information contributor or disseminator. The ability of social media to spread information of urban emergency events has been demonstrated effectively and efficiently during the last few years. For instance, Sina Weibo [1], one of the largest microblogging platforms on the Web, has more than 500 million registered users, and the average number of daily active users has reached 46 million by the end of 2012. The contents of microblogs are becoming more multimedia with close to 37% of Weibo microblogs containing images [1]. With efficient usage of information sources, quick information spread and ease of use, Weibo has quickly become one of the most important medium for sharing, connecting and producing real-time contents and topics.

With recent advancements in mobile ubiquitous sensing and communication technologies, especially the explosion of smart phones, we are rapidly meeting the era of the Internet of Things (IoT), which aims at sensing and communicating some real world objects and their environment in the realistic world more convenient and on a larger scale [2, 3]. Moreover, recent advancements in mobile pervasive sensing and communication technologies research in leveraging mobile devices (e.g., smartphones, wearable devices) or vehicle based sensors (e.g., GPS, OBD-II) to manage phenomena which cannot easily be computed by an individual user. This sensing method is popularly called crowdsensing [4, 5] or participant sensing [6]. This novel sensing paradigm has enabled numerous applications such as urban emergency events management, traffic monitoring, urban environment monitoring etc.

One of the important functions of Weibo is to monitor real time urban emergency events, such as fire, explosion, traffic jam, etc. Weibo user can be seen as social sensors and Weibo can be seen as the sensor platform [7]. Recently, social media provides the list of real time social events. For example, Twitter [2] provides the *Trends* service, and Weibo provides the *Hot Topics* service. However, these services only provide cues of the existence of social events such as breaking news. The listed social event is given together with the many unprocessed posts, which usually offer too many details and without logistics to browse. Especially, urban emergency events have the unique spatial and temporal feature. Without effective description method, the users are often faced with incomplete, irrelevant and duplicate information. Thus,

[1] www.weibo.com

[2] www.twitter.com

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it is needed that if an effective method can be provided for summarizing the real time urban emergency events.

In this paper, the proposed method focuses on the step for storytelling of urban emergency events: given the Weibo posts related to a detected urban emergency event, the proposed method targets at mining the multi-modal information (e.g., images, videos, and texts), as well as storytelling the event precisely and concisely. To sum up, we propose a novel urban emergency event storytelling method to generate multi-modal summary from Weibo. Specifically, the proposed method consists of three stages: irrelevant Weibo post filtering, mining multi-modal information and storytelling generation. We conduct extensive case studies on real-world microblog datasets to demonstrate the superiority of the proposed framework.

The rest of the paper is organized as follows. Related works are briefly summarized and discussed in Section II. Section III introduces the proposed method. Experimental results are reported and discussed in Section IV, followed by the conclusion in Section V.

2. RELATED WORK

In this section, two aspects including social media based events processing and crowdsensing are given.

2.1 Crowdsensing

Crowdsensing is a new mechanism which takes advantage of pervasive mobile devices to efficiently collect data, enabling numerous large scale applications. Human involvement is one of the most important features, and human mobility offers unprecedented opportunities for both sensing coverage and data transmission [8]. Mobile crowd sensing is a new sensing paradigm that empowers ordinary people to contribute data gathered or generated from their mobile devices [9]. It further aggregates heterogeneous crowdsourced data in the cloud to extract hidden intelligence [10]. From the AI perspective, crowdsensing is based on a distributed data-driven model where social sensors are engaged in complex problem solving steps through open calls [11]. There have been many crowdsensing related applications, such as environment monitoring [12, 13], traffic planning [14, 15], social context sensing [16], public safety [17], social event replay [18], etc. With the recent trend of sensor-rich (e.g., accelerometer, GPS, camera, etc.) smart phones and the usage of GPS-equipped cars, taxis, and buses, crowdsensing has also become an emerging paradigm for large-scale, real-world sensing and information gathering.

Xie et al. [31] investigate the phenomenon of visual memes, i.e., video segments that are often repurposed on sites like YouTube and that emerge as a trend when world-events unfold. Chen et al. [32] address the problem of generating personalized travel recommendations by exploiting large-scale photo sites like Flickr. Their recommendation approach combines individual demographic attributes extracted from user-generated geo-tagged images along with social link information. Zhang et al. [33] propose a four-stage process to characterize the crowdsensing life cycle. The life cycle is represented as task creation, task assignment, individual task execution, and crowd data integration. Pankratius et al. [34] describes a revolutionary architecture that uses mobile devices to form a monitoring network for Earth's near space environment. Many observed phenomena have large signatures in the ionosphere, and affect communications, navigation, and power systems. Mahali exploits existing GPS signals traveling through the ionosphere to acquire a vast set of ionosphere total electron content projections. Rosen et al. [35] presents a system for efficiently and effectively monitoring enterprise WiFi networks through crowdsensing. Using unmodified consumer mobile devices to passively collect measurements, MCNet produces an aggregate map of performance problems that directly reflects the performance experienced by users. Periodic sampling and leveraging mobile sensor information to intelligently schedule measurements allows meaningful WLAN performance problems to be detected while keeping battery consumption low.

2.2 Social Media based Events Processing

Twitter, as one of the most important social sensors platform, has attracted a large number of works for topic discovery [23], event detection [24], and content analysis 25]. Also, Twitter users are regarded as social sensors [26] for detecting and tracking earthquakes, typhoons or traffic jams. TwitterStand [27] is built to capture and investigate latest breaking news. Similarly, a framework consists of feature extraction, event clustering, and classification steps have been given to distinguish real-world event [28]. Walther et al. [29] presented a situation awareness algorithm to detect geospatial events in a given monitored geographic area, which offers good summary of events. Twitris [30] uses spatio-temporal-thematic features in processing large scale social data, and integrates semantic context from multiple web resources, which facilitates social sensing in a broad variety of application fields. Recently, Crooks et al. [19] thought Twitter as a distributed sensor system. They analyzed the spatial and temporal features of the Twitter feed activity responding to a 5.8 magnitude earthquake. Their experimental results argued that the Twitter users represent a hybrid form of a sensor system that allows for the identification and localization of the impact area of the event. Longueville et al. [20] used Twitter as a source of spatial-temporal information. By focusing on a real-life case of forest fire, they aimed to demonstrate its possible role to support emergency planning, risk and damage assessment activities. Besides the emergency events management, other researchers use the spatial and temporal information from social networks to support location based services. Liu et al. [21] presented MoboQ, the location-based real-time question answering service that is built on top of microblogging platform. Qu and Zhang [22] used Twitter user generated mobile location data for trade area analysis. Their model includes three key processes: identifying the activity center of a user, profiling users based on their location history, and modeling users' preference probability.

In our previous work, in order to detect and describe the real time urban emergency event, the 5W (What, Where, When, Who, and Why) model is proposed by Xu [36, 40-42]. Xuan [37] proposed a framework to identify the different underlying levels of semantic uncertainty in terms of Web events, and then utilize these for Webpage recommendations. The basic idea is to consider a Web event as a system composed of different keywords, and the uncertainty of this keyword system is related to the uncertainty of the particular Web event. Liu [38] explored a Markov random field based method for discovering the core semantics of event. The method makes semantics collaborative computation for learning association relation distribution and makes information gradient computation for discovering k redundancy-free texts as the core semantics of event. A crowdsourcing based burst computation algorithm of an urban emergency event is developed in order to convey information about the event clearly and to help particular social groups or governments to process events effectively [39].

Figure 1. The illustration Weibo post (The fire is heavy and the fireman is coming. Hope all safe.).

3. THE PROPOSED STORYTELLING METHOD

In this section, the proposed storytelling method is given. Specifically, the proposed method consists of three stages: irrelevant Weibo post filtering, mining multi-modal information and storytelling generation. Firstly, the irrelevant post is filtered by four rules. Secondly, multi-modal information including keywords, sentences, location, and multimedia is mined. Thirdly, the storytelling method of a given urban emergency event is given.

3.1 Filtering Irrelevant Weibo Post

Relevant post is the set of messages posted by Weibo users, which mentions the real time happening urban emergency event. The relevant post can be used to mine the basic elements of the storytelling of an urban emergency event. For example, the message "A fire is happened at Qipu[3] Road (Fig. 1)." can be seen as a relevant post of a fire event. Based on common sense and our observations on real data, we have four rules to filter irrelevant post from Weibo.

Rule 1: The relevant post should contain the seed words of an urban emergency event.

The seed words reflect the basic sematic of an urban emergency event. For example, for a fire event, the similarity words of fire can be the seed word. The post in Fig. 1 contains the seed word fire and can be seen as a relevant post.

Rule 2: The relevant post should contain the location information of an urban emergency event.

The location information is an important aspect of an urban emergency event. The relevant post can provide the location information sensing by Weibo users. The post in Fig. 1 contains the location information (Qipu Road) and can be seen as a relevant post.

Rule 3: The relevant post should contain the multimedia information (e.g., image, videos) of an urban emergency event.

The multimedia information can reflect the real situation of an urban emergency event. Moreover, the image or video information is an important evidence to prove the presence of a Weibo user. A Weibo user is prone to be a witness if she/he uploads the scene image of videos of an urban emergency event. Thus, the location information is prone to be accuracy since the user is a witness of the emergency event.

Rule 4: The relevant post should be the original post.

The original post means the Weibo user is the witness of an urban emergency event. If a post follows all four rules, it can be seen as a perfect post. The perfect post provides the location, real situation multimedia, the semantic information of an urban emergency event.

3.2 Keywords Ranking

For an appropriate storytelling of an urban emergency event, keywords are an important element. Keywords can reflect the semantic aspect of an urban emergency event. Keywords ranking step aims at finding useful semantic information from relevant post to obtain valuable description or knowledge. The part-of-speech tool[4] is used for extracting noun words and removing stop words. Noun words have real and clear meaning, which can reflect the real semantic information of an urban emergency event. The weight of each keyword is computed for giving a ranking. In the proposed method, the post frequency of each keyword is computed to rank keywords. The post frequency is computed by the frequency of each keyword in posts. For example, if a keyword appears 5 times from 50 posts, the post frequency is 0.1. For example, in Fig. 1 the word "fireman" is a keyword.

3.3 Location Mining

The location information is mined from the post. For example, in Fig. 1, the posted location information "Qipu Road" can be mined. The location detection method is based on the OpenStreetMap[5]. The location word is queried by OpenStreetMap to detect whether it is a location word or not.

Different from the location word from the post, the check-in information can reflect the real location of the user. The check-in information is the location of the user other than the urban emergency event. The check-in information can be mined from the element of HTML page. For example, in Fig. 1, the GIS information of the user is "geo=121.47, 31.24".

3.4 Multimedia Text Correlation

Besides the text information, the multimedia information such as image or videos is usually uploaded with the post. For example, in Fig. 1, the user uploads three images about a happening fire event. The user is near the fire place and the image can reflect the real time situation of the fire.

Different from the text processing, it is still difficult to extract the useful information from image. For example, in Fig. 1, some figures contain the fire truck. Users also mention the fireman in the Weibo post. The image is correlated to the keywords in the post. The multimedia information is tagged with the keywords along with the post.

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[3] A road in Shanghai, China

[4] http://ictclas.org/

[5] https://www.openstreetmap.org/

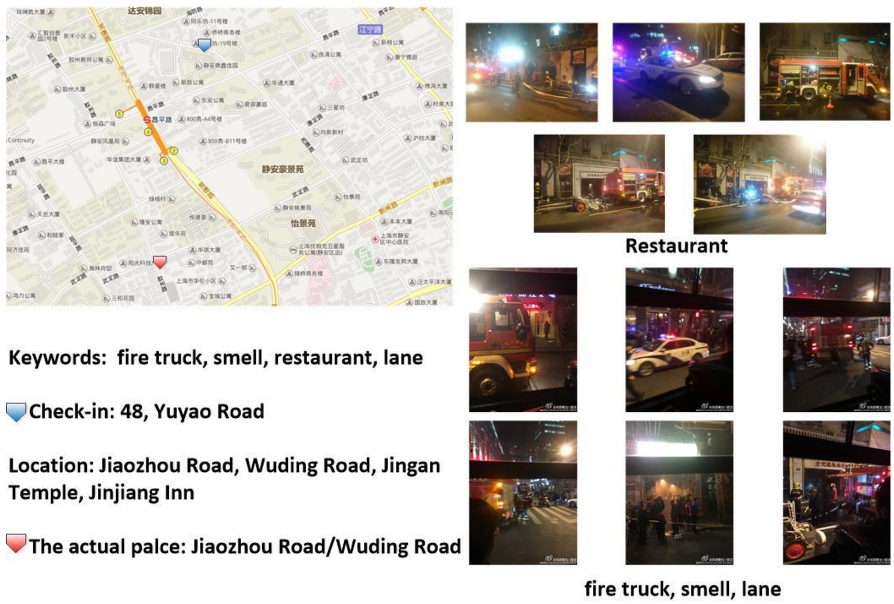

Figure 2. The illustration Weibo post (The fire is heavy and the fireman is coming. Hope all safe.).

3.5 Storytelling Generation

The storytelling of an urban emergency event consists of three parts including keywords, location map, and tagged image. Keywords can be obtained by the step given in section 3.2. Also all keywords are ranked by the post frequency. The high rank keywords will give in the top of the storytelling. The check-in information of users is illustrated in the map. The location map gives a visual part of an urban emergency event. Besides the check-in information, the spatial information extracted from the Weibo post is also listed by their post frequency. The tagged image is listed by their uploaded time. The upload time is the post time.

4. CASE STUDIES

The "fire" is a major emergency event to the city. For example, in Shanghai[6], there are about 4600 times "fire" alarms from in 2015. In the case study section, we select a real fire event to show the storytelling result.

We select a "fire" event happened in 18:00 at "Jiaozhou Road/Wuding Road" on February 2 in Shanghai. Three seed words about the "fire" are used to search in Weibo Totally, 22 posts are returned. According to 4 rules, 5 posts are relevant. The storytelling result is shown in Fig. 2. The check-in information is annotated in the blue point in the map. The real place is annotated in the red point in the map. The check-in information is close to the real place, which means the post provided by user is reliable. The keywords are "fire truck, smell, restaurant, and lane". These four keywords show two aspects of the "fire". "Fire truck" and "smell" is related to the situation of the fire. "Restaurant" and "lane" is related to the place of the fire. The location information is "Jiaozhou Road, Wuding Road, Jingan Temple, and Jinjiang Inn". The tagged image is also illustrated in the right of the strorytelling.

The case study can show the effective and efficient of the proposed storytelling method. The map information can show the place of the story. The keywords can show the main semantic of the story. The image gives the visual information of the story.

[6] The biggest city with about 23 million people in China

5. CONCLUSIONS

With recent advancements in mobile ubiquitous sensing and communication technologies, especially the explosion of smart phones, we are rapidly meeting the era of the Internet of Things (IoT), which aims at sensing and communicating some real world objects and their environment in the realistic world more convenient and on a larger scale. One of the important functions of Weibo is to monitor real time urban emergency events, such as fire, explosion, traffic jam, etc. Weibo user can be seen as social sensors and Weibo can be seen as the sensor platform. Recently, social media provides the list of real time social events. In this paper, the proposed method focuses on the step for storytelling of urban emergency events: given the Weibo posts related to a detected urban emergency event, the proposed method targets at mining the multi-modal information (e.g., images, videos, and texts), as well as storytelling the event precisely and concisely. To sum up, we have proposed a novel urban emergency event storytelling method to generate multi-modal summary from Weibo. The case study can show the effective and efficient of the proposed storytelling method. The map information can show the place of the story. The keywords can show the main semantic of the story. The image gives the visual information of the story.

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