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Information retrieval of a disaster event from cross-platform social media

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Abstract
Purpose – The purpose of this study is to propose a method to retrieve data on an event based on a preliminary collection of event-specific hashtags.
Design/methodology/approach – Extra knowledge, or a list of events with recorded features that can be used to characterize an event and separate it from other simultaneously occurring social phenomena, is employed. The first step involves the estimation and use of the impact area to retrieve messages from Twitter. This is followed by an extraction of hashtags from these messages. After that, the noisy hashtags would be filtered out by some heuristic rules. Finally, hashtags are used to collect relevant messages from not only Twitter but also other social media platforms.
Findings – The proposed method has high selectivity and is able to collect distinct sets of hashtags even for similar simultaneous events. In addition, spatial and temporal features are sufficient to improve collecting information of disaster events.
Originality/value – This work discusses a method of information retrieval of an event from cross-platform social media. The proposed method can be applied to other studies of geographically related events.

Keywords Information retrieval, SVM, Typhoon Haiyan, Cross-media, Event-related, Hashtags

Paper type Research paper

1. Introduction

Social media is a computer-mediated tool that allows people and companies to exchange news, information, ideas, pictures and videos in virtual communities. Social media provides information on a wide range of social activity and contains inter-agent connections that are characterized by fast response from a local to a user event. Therefore, social media is often used to analyze human behavior in dangerous situations. For example, Lu and Brelsford (2014) use a complex network to investigate the digital human behavior change in the 2011 Japanese Earthquake and Tsunami, and Olteanu *et al.* (2015) found that emergency managers and official emergency response agencies are increasingly using social media as part of their information gathering processes. In such kind of studies, the first task is to find proper information in social big data.

Historically, most of the studies on information extraction of disaster events were conducted on Twitter, as it provides open (but limited) access to its data (Regalado *et al.*, 2015; Grasso and Crisci, 2016; Lachlan *et al.*, 2015; Salfinger *et al.*, 2016). The common practice is to use keywords to retrieve messages and then classify them to filter the noisy records out to increase the relevance of data.

The correct choice of the keywords is a crucial part, as social media is a big data source and limits the amount of records to be downloaded and processed in the following procedure. The keywords are usually chosen manually. Indeed, Olteanu *et al.* (2014) proposed a method to build event-specific lexicons to simplify data-retrieval process. First, awareness systems used manual classification, and then modern systems combined crowdsourcing and machine-learning methods for classification (Ashktorab *et al.*, 2014; Chowdhury *et al.*, 2013; Imran *et al.*, 2014).

A similar approach can be used to retrieve data in other social media platforms (Facebook, Instagram, Pinterest, etc.), but it should be adapted for every case individually (Benkhelifa and Laallam, 2016; Kagaya and Aizawa, 2015; Yang *et al.*, 2015). These platforms use different programming interfaces and data formats and contain different types of

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information, such as text, image and video. As a consequence, every data set of an event from different platforms is unique. Hence, the existing classification methods are that the model must be trained separately for every platform based on its own data set. For example, the AIDR project uses approximately 200 messages of manually collected information to train a classifier and to use this model to filter real-time streaming data (Imran *et al.*, 2014). That is why most of the existing research about an event is usually limited to only one social platform. However, the presented approach in this paper is suitable for a wide variety of social media platforms. It can be used without modification to analyze a series of disasters.

Additionally, the previous studies of information retrieval of disaster events from social media neglect the extra geographic information of disasters and the problem of similar simultaneous events (Olteanu *et al.* 2014; Ashktorab *et al.*, 2014; Chowdhury *et al.*, 2013; Imran *et al.*, 2014). But the work of Albuquerque *et al.* (2015), which combined geographic data and social media to identify useful information of an event, shows that the geographic data can serve as a basis to improve the identification of messages that contain useful information for managing disasters. Hence, to improve the selectivity and collect distinct data sets of classification models, spatial and temporal features are used to exclude non-relevant messages from the initial collected messages.

This work proposes a method based on hashtags, which is another specific element of social media. This method improves the relevance of data and simplifies cross-media retrieval significantly. Section 2 describes hashtags and their role in social media. Section 3 explains the steps of the method. Although this work focuses on disaster management, the method can be modified to be used in social and humanity sciences. For illustration, the base list of events in the experiment comprises disaster accidents. Any other geo-referenced databases (e.g. riots, news media, art exhibitions) can be used to collect appropriate hashtags and create a link between the real and virtual worlds. Section 4 offers certain experiments to show the discrimination ability of the method. Section 5 provides a discussion and a conclusion.

2. Hashtag: a cross-platform reference structure

Hashtags, which are special words in social media, are used to connect several messages of similar topic. The simple rules to create a hashtag are as follows:

- it should be a single word or a phrase without spaces, and begin with a hash character "#"; and
- users are free to reuse existing hashtags or create a new one.

Hashtags became popular as an effective way to categorize, find and join conversations. For example, searching Twitter for #rio2016 returns many tweets about the 2016 Olympic Games in Rio de Janeiro, Brazil from individuals around the world. Hashtags can be used to collect public opinion on events and ideas at the local, corporate or world level.

Hashtags are a popular instrument to mark and connect messages of similar topics. They are used in many social media platforms and web sharing services (e.g. Twitter, Facebook, Instagram and others). The percentage of messages with hashtags is different on different platforms. For example, Twitter is more than 25 per cent, Flickr is 8.1 per cent and YouTube is 4.7 per cent (Gao *et al.* 2017). Users of different platforms often use the same hashtags to describe the same event, and thus, hashtags can be treated as a cross-platform reference structure. Consequently, hashtags collected from Twitter can be used to retrieve messages from several sources on a single occasion. Aside from textual information, photo and video content can be found using hashtags. In such a way, hashtag approach leads to a significant expanse of information awareness of an event.

There are two categories of studies about disasters or emergencies report using hashtags to retrieve a large amount of social media data. One is to collect hashtags by men and use tags to retrieve social media data for analysis (Fung *et al.*, 2017; Graham *et al.*, 2015;Olteanu *et al.*, 2015; Saleem *et al.*, 2014; Stiegler *et al.*, 2011; Takahashi *et al.*, 2015). The other is to detect hashtags by algorithms (Wang *et al.*, 2014). However, this study only used the content of messages and ignored extra information of an event, such as spatial and temporal information of a disaster event. But this paper combined the content and extra information to improve the relevance of hashtags.

3. Method on hashtags collection process

This work proposes a method to automatize collecting hashtags. This method enables the selection of hashtags to be more objective and unbiased by combining with extra temporal and geographic information of a disaster event. This paper also applied a significantly simplified algorithm to estimate the impact area of disasters and to enable the processing to be fully automatic.

To accurately compare our method with previous studies, the Twitter was chosen to identify hashtags first. The reasons for choosing Twitter are as follows:

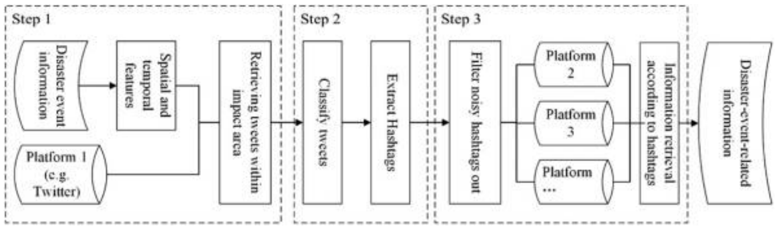
- Twitter is a major platform for public communication between volunteers, governments, relief organizations and affected people; and
- as Twitter provides open (but limited) access to its data, most of the studies on information extraction of disaster events were conducted on it (Graham *et al.*, 2015; Olteanu *et al.*, 2015).

Hashtags are used to overcome various cross-platform compatibility challenges. The key of the presented method is that extracting disaster events hashtags from a social media platform (e.g. Twitter). The proposed method is separated into three steps (Figure 1). First of all, the messages on Twitter, within the impact area, during the time period of a disaster event are retrieved. And then a classifier is used to classify these messages and extract hashtags. Finally, the noisy hashtags are filtered out manually. Afterward, these hashtags are employed for retrieving disaster-event-related information from cross social media platforms.

3.1 Estimate the impact area of a certain event and then retrieve messages from Twitter

The goal of the first step is to estimate the impact area of a certain event and then retrieve messages from Twitter according to the cities named in the impact area. Taking a disaster event as an example, the affected area should be the

Figure 1 The diagram of main steps for disaster-event-related information retrieval



damaged region. Several rules for every kind of hazard process should be developed (Huang and Xiao, 2015).

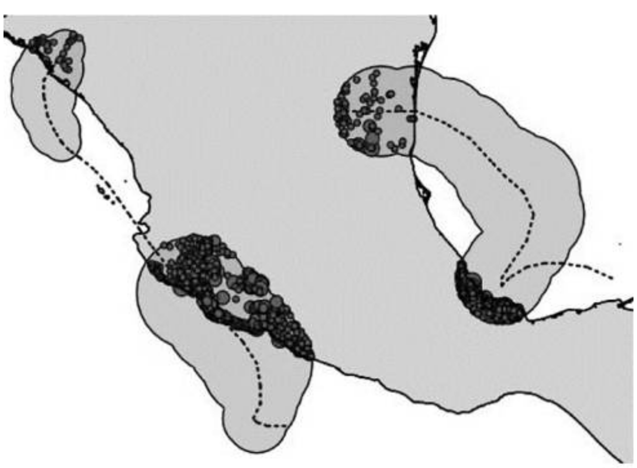
For example, a tropical cyclone is characterized by its track and wind speed levels. Such information is used to find the period of cyclone activity and determine its affected area and the distance of the damage from its center. Names of populated places (e.g. cities, villages) within the estimated area are used as keywords to retrieve messages from Twitter (Figure 2).

3.2 Classify tweets and extract hashtags

In the second step, the messages retrieved using the list of populated places should be classified to remove non-disaster messages. Frequently, only a small part of the messages contains geographic names; thus, classification models can be applied directly without worrying about computational cost.

A training data set (72,244 records) was combined with English language disaster data sets: CrisisLexT6 (Olteanu *et al.*, 2014), CrisisLexT26 (Olteanu *et al.*, 2015) and AIDR2015Q2 (Imran *et al.*, 2014). Several machine learning methods were used to build binary classification model to separate feature space into two classes: disaster and non-disaster. The best accuracy was archived using radial basis kernel Support Vector Machine (SVM). In the training set $(\mathbf{x_i}, y_i)$, $i = 1, 2, \dots, n$, $\mathbf{x_i} \in \mathbf{R}^d$, where $\mathbf{x_i}$ is the training data vector of d-dimensions, $y_i \in \{-1, +1\}$ is the corresponding classes and n is the size of the training set. The original data are projected through nonlinear mapping $\Phi(x)$_onto a new space. In general, the decision function is:

Figure 2 Emergency zone



Source: Cyclones Manuel and Ingrid in 2013

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i \langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \rangle + b \quad (1)$$

where α_i is the Lagrange multiplier. The inner product $\langle \Phi(\mathbf{x}_i), \Phi(x) \rangle$ in formula 1 is the kernel function of SVM. In this study, Radial basis function which is chosen as the kernel function is:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\|\mathbf{x}_i, \mathbf{x}_j\|^2}{2\sigma^2}\right), \sigma > 0 \quad (2)$$

where σ is a parameter to control the range of the kernel function. The result of radial basis kernel SVM models is precision, 89.3 per cent; recall, 85.4 per cent; and area under the receiver operating characteristic curve, 0.937. The model is not needed to be modified for every analyzed event, as it was built to fit a wide variety of disaster processes. Similar models can be trained for big classes of events, such as riots, festivals and exhibitions. Subsequently, the candidate hashtags are extracted from those messages identified as disaster-related.

3.3 Filter noisy hashtags out

The third part of the method is intended to filter noisy hashtags out. Although the set of the hashtags contains event-specific hashtags, it also includes a number of noisy hashtags related to certain background processes rather than the current event. An exemplary list of hashtags collected in the previous step is shown below (related to a flood in Texas, USA 2013):

- #voteaustinmahone;
- #votearianagrande;
- #texas;
- #atfloods;
- #atx;
- #txwx;
- #temple;
- #photo;
- #jobs;
- #tx;
- #redgage;
- #atxtrafflc;
- flooding;
- #update;
- #lfc
- #pjnet;
- #atxjobs;
- #georgetown;
- #dallas;
- #proudskwater;

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- #syria;
- #sanantonio;
- #remodelingkilleen;
- #realestate;
- #flood;
- #srilanka;
- #keyewx;
- #keyetv;
- #txflood;
- #work;
- #smokerstourafterparty;
- #wendydavis;
- #motd;
- #breakoutartist;
- #dogs;
- #startups; and
- #yelllikehell. . .

On the basis of this study's experiments, several heuristics (filters) are proposed to clean up this set of hashtags.

- *Filter 1*. Remove those hashtags that occur before the start time of the event. Single underlined hashtags in the list above are related to daily life and background processes, which existed before the analyzed event; hence, they are not event-related and can be dismissed. According to this study's experience, this filter removed about 60 per cent of noisy hashtags.
- *Filter 2*. Remove those hashtags in which the ratio of event-related messages is less than 50 per cent of the total number. The number of messages collected in the first step is relatively small because city names are not often mentioned in the text. Such small corpus is sensitive to classification errors. Moreover, disaster topics can be mentioned in messages that are not strongly related to the event (e.g. political speech, see double underlined hashtags in the list above). Consequently, up to 200 additional messages were retrieved for every hashtag. These data sets are classified again using a 50 per cent threshold. This heuristic typically enables the elimination of another 30 per cent of false-positive hashtags.

4. Experiments

To prove high selectivity of the proposed method, two groups of simultaneous disasters were selected: cyclones Nari (Philippines) and Phailin (India) in October 2013; cyclone Haiyan (Philippines) and flood in Texas (USA) in November 2013. All these disasters had the same impact, including rainfall and river flood. Hence, similar lexicon should be used in their descriptions, and existing keyword-based methods are not able to disambiguate events.

For instance, a keyword "typhoon" was used to retrieve messages from Twitter. The time period was limited from October 5, 2013 to October 14, 2013. When Nari hit Vietnam and the Philippines, Phailin landed in India at the same time. The geographic scopes of Nari and Phailin were used to filter out tweets from outside scopes of these typhoons.

The results of the proposed method are distinct sets of hashtags:

- *Nari*. #walangpasok, #santiph, #sjworldtour2013;
- *Phailin*. #phailin, #cyclonephailin, #cyclone;
- *Flood in Texas*. #atxfloods, #txflood, #remodelingkilleen; and
- *Haiyan*. #yolandaph, #haiyan, #tacloban, #yolanda, #tracingph, #reliefph, #ormoc, #rescueph, #typhoonhaiyan, #typhoonyolanda, #yolandaupdates, #prayfortheph, #ukgdos.

Compared with the results of Graham *et al.* (2015), most of the hashtags found by our method were strongly related to Typhoon Haiyan (Table I). The proposed method effectively filtered out some weakly related hashtags, such as #Philippines, #news, #vietnam and #typhoon. However, Graham *et al.* (2015) took these hashtags as important tags. Meanwhile, our result still contained all strongly related hashtags, such as #haiyan, #yolanda and #yolandaph. Certainly, these tags are also in Graham's result. In addition, our method detected some strongly related hashtags, such as #tacloban and #ormoc. However, these hashtags cannot be identified by Graham.

To verify the effectiveness of the hashtags identified by the proposed method cross different social media platforms, the hashtags #yolandaph, #reliefph, #tacloban and #ormoc are applied. Figure 3 shows typical messages related to Typhoon Haiyan. Figure 3(a)–(d) shows messages from Facebook that contains the hashtags #yolandaph, #reliefph or #ormoc in the text. Not only the situation of Typhoon Haiyan was posted at that time, but also the recovery after the natural disaster can be shown through social media. Figure 3(c), which is retrieved from the Instagram, indicates the rebuilt areas that was attacked by the typhoon three years ago.

5. Discussion

The article presents a method for retrieving natural disaster event information from cross-media. The aim of this method is to apply hashtags for cross-platforms retrieval. Besides, the other goal of the method is to investigate if the geographic data are valuable to extract distinct messages of social media. Although Grasso and Crisci (2016) extracted hashtags from Twitter for weather forecasting, the application of hashtag for cross-platform retrieval gets little attention. The experiment of the proposed method shows that hangtags are valuable to extract disaster-related information from different social media platforms for improving the situation awareness of emergency management.

In this study, the rate of tweets with hashtags is up to 24 per cent. Although the rates of the message with hashtags from Facebook or Instagram are unclear, the messages with hashtags will prompt users to use hashtags on various social platforms due to their high engagement. In addition, when a

Table I Comparison of extracted hashtags about Haiyan typhoon

Type	Graham *et al.* (2015)	This paper
Hashtags	#haiyan, #yolandaph #typhoonhaiyan, #yolanda, #rescueph, #typhoon, #filipinas, #news, #vietnam, #philippines,	#yolandaph, #haiyan, #tacloban, #yolanda, #tracingph, #reliefph, #ormoc, #rescueph, #typhoonhaiyan, #typhoonyolanda, #yolandaupdates, #prayfortheph, #ukgdos

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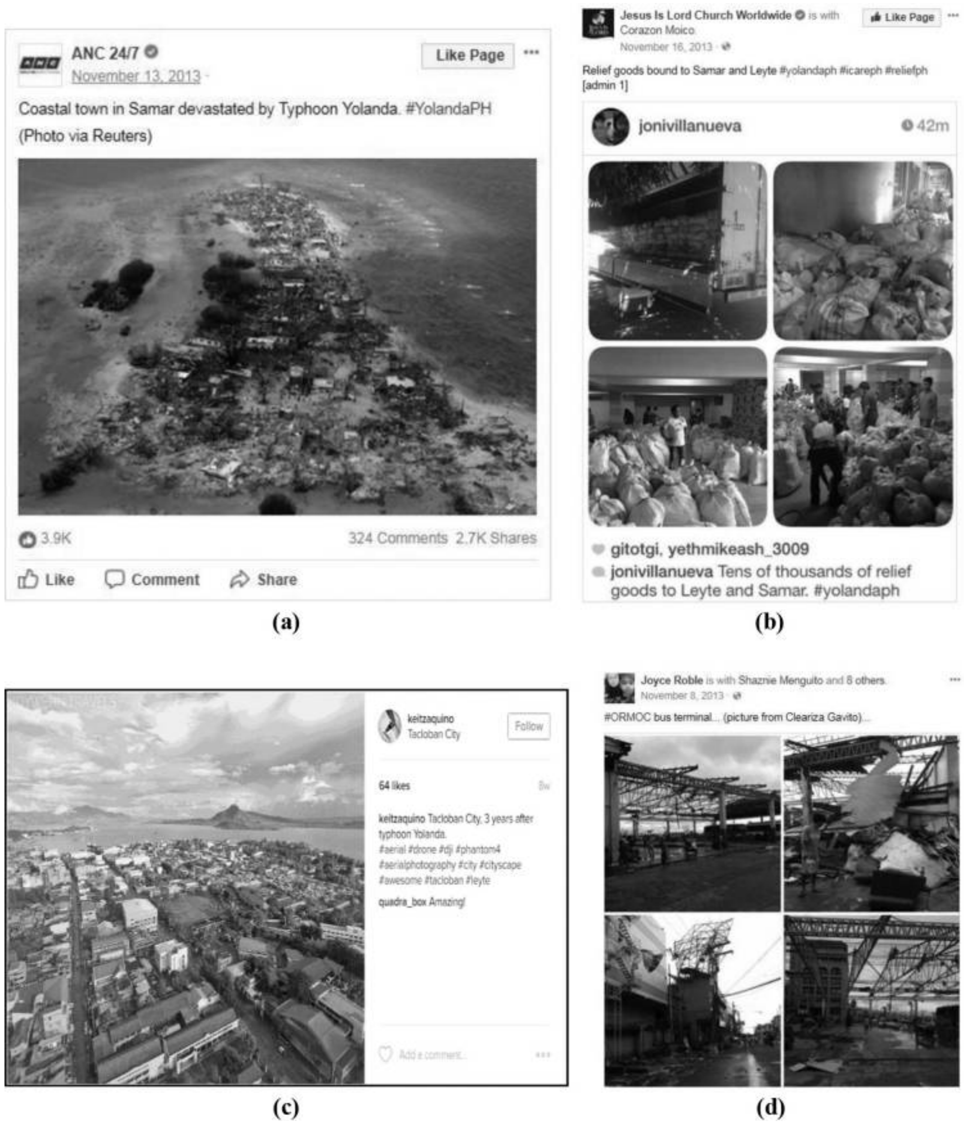
Figure 3 Typical results of hashtags related to Typhoon Haiyan from Facebook and Instagram: (a) a message containing #yolandaph from Facebook indicates a devastated coastal town; (b) a picture including #yolandaph and #reliefph from Facebook shows relief goods; (c) a post with #tacloban from Instagram describes the recovery of Tacloban City; (d) a post with #ormoc shows damaged buildings



disaster occurs, it is recommended to use hashtags to post disaster-related messages.

Extra-spatial and temporal features of disaster events are not taken full advantage in previous studies. In contrast, by relying upon the geographic information of natural disasters, this method increases the relevancy of train data set, reduce the amount of non-relevance messages and improve the training efficiency of models. The results of two groups of simultaneous disasters show distinct data sets of hashtags. And the precision and recall of radial basis SVM model of Typhoon Haiyan increase to 89.3 and 85.4 per cent. This work thereby offers a contribution to extending and improving existing research studies (Olteanu *et al.*, 2014; Imran *et al.*, 2014; Graham *et al.* (2015)).

However, the weakness of the proposed method is occasional to obtain robot-generated hashtags. For instance, #sjworldtour2013 and #remodelingkilleen are two robot-generated hashtags of Nair typhoon and Texas flood. This weakness can be explained by the fact that these noisy hashtags and real related hashtags appear together in messages which are generated by robot programs. This phenomenon will be studied in our future works.

6. Conclusion

The proposed method was tested on disaster databases and disaster media. Experiments show that the proposed method has high selectivity and is able to collect distinct sets of hashtags even for similar simultaneous events. The experiments also show that time and space features from an extra data source are enough to collect hashtags in social media, and this method can be expanded to any social and humanitarian study of geographically related events.

Many social media platforms use the same hashtags; hence, hashtags mined from Twitter can be used to connect with several other platforms. The proposed method can be used to process several events automatically, and thus opens a way to build a dictionary of hashtags and analyze social media on an aggregated level.

Additional processing can be applied to hashtags depending on the field of application. For example, disasters share certain common hashtags (e.g. #flood, #relief, #update) that can be separated into a special group. More investigations are required to study phenomena of hashtags and their distribution in social media.

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