Sub-Event Detection Of Natural Hazards Using Social Network Data

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Abstract: - Social networking sites such as Flickr, YouTube, Facebook, etc. contain huge amount of user-contributed data for a variety of real-world events. These events can be some natural calamities such as earthquakes, floods, forest fires, etc. or some man-made hazards like riots. This work focuses on getting better knowledge about a natural hazard event using the data available from social networking sites. Rescue and relief activities in emergency situations can be enhanced by identifying sub-events of a particular event. Traditional topic discovery techniques used for event identification in news data cannot be used for social media data because social network data may be unstructured. To address this problem the features or metadata associated with social media data can be exploited. These features can be user-provided annotations (e.g., title, description) and automatically generated information (e.g., content creation time). Considerable improvement in performance is observed by using multiple features of social media data for sub-event detection rather than using individual feature. Proposed here is a two-step process. In the first step, clusters are formed from social network data using relevant features individually. Based on the significance of features weights are assigned to them. And in the second step all the clustering solutions formed in first step are combined in a principal weighted manner to give the final clustering solution. Each cluster represents a sub-event for a particular natural hazard.

Keywords: - Sub-event detection; emergency-situation awareness; social-network; natural-hazards; social-media data

1. Introduction

For the people looking for sharing their personal news and information, the social networking sites like Flickr, YouTube, Facebook, etc. has emerged as a popular destination. Due to this reason these sites holds a large amount of user contributed data for a wide variety of events ranging from popular, widely known organized events (e.g., a concert by a popular music band) to various natural hazards(e.g., earthquakes, hurricanes, wildfires, etc.). This work focuses on the natural hazards (e.g., earthquakes, floods, etc.).

During the emergency situation events it is important to acquire as much information about the event as possible. This can be helpful for the aid-team to carry out the rescue and relief activity management during such events. It can also be helpful for the people to remain updated about the ongoing situation. But it is not feasible for the command center or the news agency to have their correspondents cover the entire affected area for gathering information about the ongoing event for the entire period of time.

In this case they can rely on the data shared by the people on the social networking sites for getting updates about the event. Extracting information about the latest trends in the people using the social networking sites is one of the latest topics under research. Various researchers have studied and proposed various approaches for extracting useful information from the social networking sites. For example, social media data can be used for predicting election results, getting reviews about some product, etc.

Similarly, using social media data for situation awareness during emergency situations is also one of the latest topics for research. For any major event occurring there are many sub-events associated with it. For example during a natural hazard like earthquake, there might be sub-events like a bridge getting damaged at one location and some famous building getting damaged at some other location. During flood, crest observed in flood at different areas/cities can also be considered as sub-events. The problem discussed in this paper is to identify such sub-events in a particular natural hazard event using the data provided by the users on social networking site.

Identifying sub-events and their associated documents over social media sites is a challenging problem as the information provided by the social media users is inherently noisy and heterogeneous. We can say that the problem is much similar to the topic discovery task like the one used for news event identification in a continuous stream of news data. But for social networking site data, same approach as the one used for traditional news articles cannot be used. Because news articles have structured text while social networking sites may have unstructured data.

Even though the data obtained from social networking sites presents the challenges, they also provide opportunities for using the metadata or features associated with them like title, description, location, upload or creation time, etc. Sub-event detection using individual feature can prove to be unreliable and noisy. Hence here more than one feature is taken into consideration. However the features which are not of interest e.g., picture/video ID have been excluded. Based on the type of feature, variety in similarity measure can be observed. Clusters are formed considering each feature individually in the first step. Weights are assigned to features based on their significance. Then the clusters formed in the first step are combined in a weighted manner to form combined clusters in second step. Each of these combined clusters now corresponds to the sub-event in the particular event.

In the next section we discuss the related works done in the field of using social media data for emergency situations and sub-event detection. Section 3 discusses the overview of the framework for social media data exploration. Section 4 discusses sub-event detection using the method for obtaining the clusters taking features of the social media data into consideration. Section 5 and 6 discusses the experiment and results obtained.

2. Problem definition and related work

Social networking in emergency cases is getting increasingly important, comparable to its intense utilization in private and commercial areas to communicate different situational, news and contextual information. Extensive research has been done on social media in disasters by studying the Twitter microblogs[1]. The study identifies the types of emergency messages related to emergency situations (Red River Floods 2009 and Oklahoma grassfires 2009). References [2] discuss about how earthquake in Japan affected the twitter users and presents an approach for earthquake detection using twitter. [4] presents the study of use of a chinese micro blogging system, Sina-Weibo immediately after a major disaster – the 2010 Yushu earthquake. Besides using textual messages, visual information is also of great importance, especially in emergencies. Flickr, for example is a valuable source of information to detect events, as the work of Rattenbury et al. [6] shows. [7] describes the role of photo sharing during emergency situations.

Problem definition: From the data related to a particular natural hazard posted on various social networking sites, the goal is to find sub-events associated with the natural hazard.

The problem is similar to topic discovery and tracking of news events. The topic discovery and tracking found notable importance for discovering and organizing the news events in a continuous stream. However they are not suitable for social media data. This is because social network data might be unstructured. Becker et al. [8] discusses the use of features of Flickr photographs for event detection. For sub-event detection in social media Pohl et al. [5] presented an approach of using self-organizing maps for clustering of Flickr photos into cluster representing sub-events. Using self-organizing maps for large amount of data is computationally very expensive. Also the approach in [5] does not consider location and date/time information.

To find the similarity between social network documents, each textual feature (e.g.: title, description, tags, etc.) can be represented as *tf-idf* weight vector and the cosine similarity metric is used as the feature similarity metric [11]. Also while generating *tf-idf* weight vector, stop words are excluded and all the stems and synonyms of the word are considered same.

Dates are represented as values which are the number of days elapsed since the Unix epoch (i.e., since January 1st, 1970) and the similarity of two date values (say $d1$ and $d2$) is computed as, if $d1$ and $d2$ are more than a year apart then similarity is taken as 0, else similarity is given by,

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$$1 - \frac{|d_1 - d_2|}{y} \qquad (1)$$

where y is number of days in a year [10].

For location, another important feature in social media documents, values are represented as both the textual representation and geographical coordinates (i.e., latitude-longitude pairs). For textual representation of location name of each location is used as a token or element and the Jaccard similarity metric is used as the feature similarity metric.

$$sim_{Jaccard} = \frac{N_{11}}{N_{10} + N_{01} + N_{11}} \qquad (2)$$

where N_{11} is the number of elements common for both the documents, N_{10} is the number of elements that occur for first document but not for second and N_{01} is the number of elements that occur for second document but not for the first.

To compute the proximity of two locations as geographic coordinates, $L1 = (lat1,long1)$ and $L2 = (lat2,long2)$ as $1\text{-}H(L1,L2)$, where $H(.)$ is the Haversine distance, a widely accepted metric for geographical distance [9].

$$X1 = \left(sin\left(\frac{lat2 - lat1}{2}\right)\right)^2 \qquad (3)$$

$$X2 = \cos(lat1)\cos(lat2)sin\left(\frac{long2 - long1}{2}\right)^2 \qquad (4)$$

$$d = H(L1, L2) = 2rarcsin(\sqrt{X1 + X2}) \qquad (5)$$

3. Framework for social media data exploration

During emergency situation getting information from different perspectives is necessary. Identifying sub-events helps in assessing the situation. Information provided by the users on social network can be used for situation awareness in emergency situation. However manually identifying the sub-events is a cumbersome or often impossible for person under pressure. Fig. 1 shows a framework which allows automatically analyzing data from different social networking sites in case of large-scale emergency situation [5]. The analysis is conducted using the metadata (e.g., tags and title) associated with the content found on social media platforms like YouTube, Flickr, Twitter, etc. An interface collects the streaming data from the social media sites.

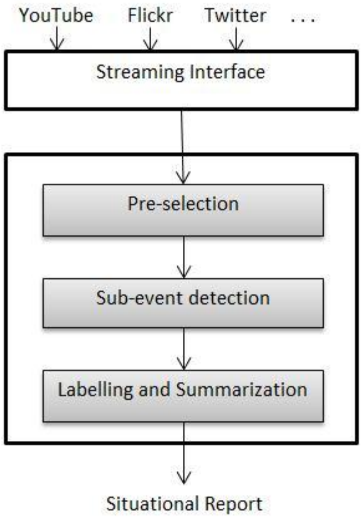

Fig. 1 Social media data exploration framework

First module of the framework performs a pre-selection of the data from different repositories using the user supplied keywords. In future the pre-selection module will be extended to data through the streaming interface. This will provide the opportunity to follow the event in real-time. Such an approach is useful for keeping the relief workers and the people updated about the natural hazard. However in this paper to prove the concept, static analysis of the proposed approach is being done for detecting sub-events through social media platforms using the YouTube data contents.

Next module, after pre-selection of the social media documents, is to form clusters for sub-event detection. Sub-events during a particular event are the smaller events separated by time or location.

After the identification of the sub-events it is necessary to analyze them. This is performed by labeling module. The last module performs the summarization of the documents associated with the sub-events. And as a whole it gives the summarization of entire event which can be included into the situational report.

4. Sub-event detection

This paper focuses on the sub-event detection module of the social media data exploration framework discussed in earlier section. The approach discussed over here is a two-step process.

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In the first step clusters formed by taking different features of social media documents individually. In the second step the clustering solutions obtained in the first step are combined to give a single clustering solution. Each of these clusters obtained in final clustering solution represents a sub-event.

Using different features of the documents like the title, description, location, uploading or creating date and time, etc. and their similarity measures different set of clusters can be generated. Let us say ($F_1,\dots,F_k$) are the features of the documents and using their appropriate similarity measures different clustering solutions ($C_1,\dots,C_k$) can be formed as shown in the Fig. 4. Here single pass centroid similarity technique [10] is used, which works as follows,

1. Given a threshold τ, a similarity function F and the data points to cluster $D_1,\dots,D_n$, this algorithm considers each data point D_i in turn and computes its similarity $F(D_i,c_j)$ against each cluster c_j, for $j=1,\dots,m$, where m is the number of clusters (initially $m=0$).
2. If no cluster is found with the centroid whose similarity to D_i is greater than τ then a new cluster is formed containing data point D_i and with the centroid value as the value of D_i.
3. Otherwise, D_i is assigned to the cluster which gives maximum value for $F(D_i,c_j)$ and after adding D_i to cluster j new value of c_j is computed. Depending on the feature of data point being considered, the centroid for the cluster is either the average *tf-idf* score per term (for textual features such as title, description, tags), the average number of days (for date), or the mid-point (for location) of all data points in that cluster.

For each of the clustering unit associated with each metadata or feature of the social media data the threshold parameters can be tuned during the training phase. Each clustering unit is trained using a labeled data set annotated with the sub-events of the event and the performance of each clustering unit is evaluated at different thresholds and the one which yields the highest performance is chosen. To measure the performance of the clustering unit Normalized Mutual Information (NMI) score is used. NMI measures how much information is shared between the two sets of partition. In the case under consideration it is useful to measure how much common information is shared in between the actual ground truth and the clustering result obtained using the clustering unit. Hence it measures the performance of the clustering unit.

In the approach discussed over here the performance metric is used for two purposes. One is to determine the threshold values for each clustering unit and second is to determine the weights $(W_1,\dots,W_k)$ to be assigned to each clustering unit or feature. These weights are also determined during the training phase. The weight assigned to each of the clustering unit is determined based on the accuracy of the feature of the social media data in determining the document similarity. In other words weight assigned to the feature is based on its significance. The weights assigned are normalized so that their sum is equal to one. Once the clustering unit thresholds and weights have been determined they can be used on the unseen data.

The clustering solutions $(C_1,\dots,C_k)$ obtained from the clustering units can be seen as the voter which votes taking into consideration whether the pair of data points fall in the same cluster or not in their clustering solution. The function used in weighted binary vote works as follows,

1. For the pair of documents (D_i,D_j) and the clustering unit C, a function $F_C(D_i,D_j)=1$, if D_i and D_j are in same cluster when clustered using the clustering unit C and $F_C(D_i,D_j)=0$, if D_i and D_j falls in different clusters.
2. Then the score $\Sigma_C\ F_C(D_i,D_j)\cdot W_C$ is computed, where W_C is the weight of the clustering unit C.
3. The score computed in step 2 is used to determine the similarity between the documents while combining the clusters using single-pass incremental clustering with the threshold tuned in the similar manner as done in the clustering units.

At the end of this phase the set of clusters $(S_1,\dots,S_e)$ is obtained where each cluster corresponds to the sub-events in the particular event.

5. Experiments and results

In this study the data posted for Mississippi river floods (5th – 20th May, 2011) and their features are used and are collected using the YouTube API. The data consists of sub-events observed at different cities located on its banks including Memphis, Greenville, Vicksburg, Natchez and Helena. The features associated with each video include title, description, date and location information. Location information in both textual representation and latitude-longitude representation has been considered. To train the algorithm the data set is divided into two sets. One of these set is used for training the algorithm and are supplied in increasing order of date to the algorithm to tune the threshold

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and weights. While the other half of the dataset is supplied to the algorithm in increasing order of date and the performance is evaluated by computing the Normalized Mutual Information (NMI) score of the obtained results and the ground truth.

The *tf-idf* values for the textual features like description and title and term occurrence for the textual representation of location is calculated. For experiment MATLAB was used for implementing the single pass incremental clustering algorithm. For tuning the thresholds the training data are provided and the NMI score is calculated for each clustering unit separately. The thresholds are varied within the range of [0,1] and is set at the value which gives maximum NMI score. The weights of the clustering units are set proportional to their NMI score such that the sum of the weights of all the clustering units equals to one. Then the test data is used for testing the algorithm.

For evaluation of the approach comparison is made between the NMI scores obtained by the clusters formed by taking all the features individually and the ground truth with the NMI score obtained between the clusters formed by combining the clusters using above discussed technique and the ground truth.

The pie chart in Fig. 3 shows the most suitable weights assigned to each clustering unit for given data. However these weights tend to change with change in type of data.

Fig. 4 shows the chart comparing the NMI scores of different clustering unit taking individual features. NMI score of 0.603 is obtained by taking textual location information and is highest amongst the performance obtained by taking each feature individually. While the last bar shows the NMI score of 0.7087 obtained by taking multiple features into account using the approach discussed in this paper. So it can be said that clustering the documents using multiple features of the social media document gives higher performance than taking individual features for detecting the sub-events in some natural hazard event.

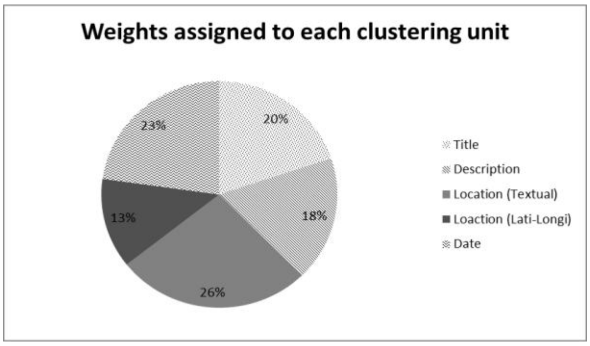

Fig. 2 **Suitable weights for each clustering unit**

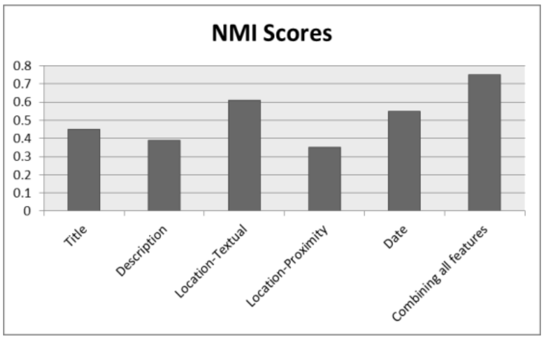

Fig. 3 **Comparison of NMI Scores taking different features individually and combined result**

6. Conclusion

Research shows that social media data contains vast information describing any event. And by facilitating the searching of sub-events for the social media data of a particular event the relief and rescue activities during natural hazards can be enhanced. Manually detecting sub-events is a difficult task. Traditional topic detection techniques for news articles cannot be used for sub-event detection with social network data. Also other existing sub-event detection techniques for social network data are computationally very expensive. Also from the results it can be concluded that we cannot rely only on any one particular feature for social network data. Here the approach discussed in this work helps in sub-event detection considering multiple features of social media data into account.

YouTube data was used for experiments but the approach discussed over here is not constrained only to the YouTube data and can also be used with other social media data. However based on the type of features of the data, the similarity measures and weights of the feature based clustering units tend to change.

Also the evaluation metric plays an important role in the working of the approach. Hence future work includes testing of the approach with different data sets from other social networking sites and other types of emergency situations, using different evaluation metric.

Work has to be done in determining some technique which can facilitate sub-event detection at different levels of granularity.

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Appendix:

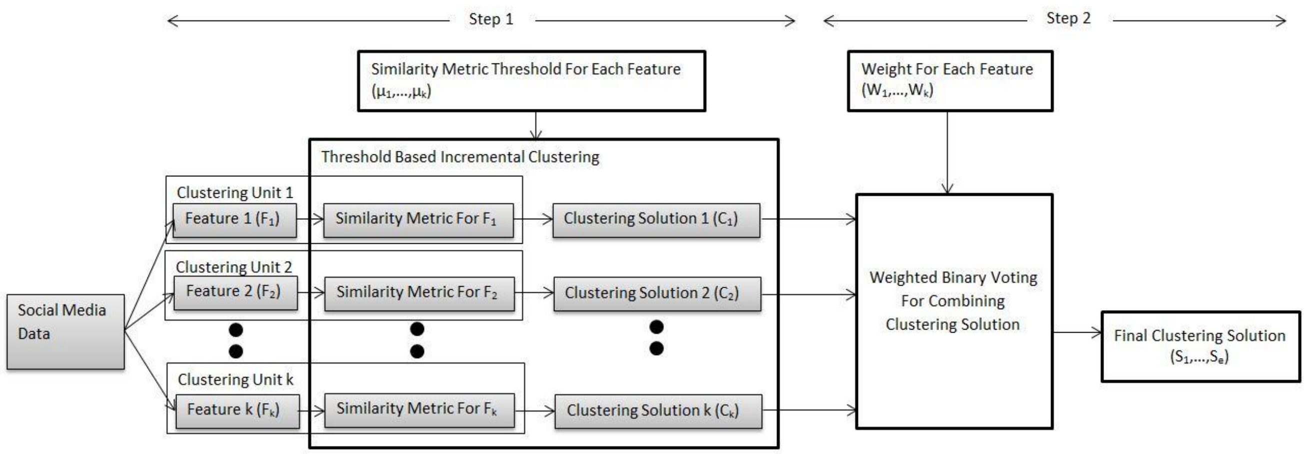

Fig. 4 Conceptual overview of sub-event detection