Classification of People’ s Emotions during Natural Disasters

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Nann Hwan Khun[a)], Thi Thi Zin[b)], Mitsuhiro YOKOTA[b)], Hninn Aye Thant[c)]

Abstract

Identifying the polarity of sentiments expressed by users during disaster events have been widely researched. At a recent time, social media has been successfully used as a proxy to gauge the impacts of disasters in real-time. With the growing of microblog sites on the Web, people have begun to express their opinions and emotions on a wide variety of topics on Twitter and other similar social services. We proposed a visual emotion analysis framework for natural disasters. The proposed framework consists of two components, emotion analysis modeling and geographic visualization. This emotion analysis modeling is mostly targeted in case of determining the emotions of Twitter users pre, peri and post natural disasters to help first responders for better managing the situations such as mental health of survived victims and fund raising after severe natural disasters. This geographic visualization system can help people for better understanding the changes of emotion reactions along with the duration of natural disasters and mostly interested regions of Twitter users on these natural disasters. In this research, the situations in California Fire which is happened in 2018 November is experimented for emotion analysis because the affected people often show their states and emotions via big data social media environment.

Keywords: Emotion analysis, Social media visual analytics, Natural disaster, Twitter, California fire, Support vector machine

1. INTRODUCTION

Sentiment analysis is the process of discovering the opinion of user about some topic or the text in attention. Nowadays, people use microblogging sites to express their opinions and emotions about any topic imaginable. There are many popular microblogging sites like Facebook, Twitter, LinkedIn and Amazon etc. It has been useful in various domains like political, business, health and educational domain. Emotional expressions are the focus of a considerable amount of research on social media. The social media service in our research is Twitter that allows users to send and read instant text-based messages or 'tweets'. Evidence exists that Twitter can be used to identify the sentiment of Twitter messages based on text classification [1].

With the strong development of social media, tracking emotions becomes easier, faster and more reliable than using the traditional public surveys or polls. Social media may also provide information where traditional surveys are restricted because of limited financial resources.

Fig. 1. News about California Camp Fire

Information from social media websites has potential to aggregate traditional survey techniques as it provides compact measurements of behavior over time, while taking advantage of large population sample sizes. The applications of sentiment analysis

a) Master DDP Student, Energy and Electronics Course, Graduate School of Engineering, University of Miyazaki (Master Student, University of Technology (Yatanarpon Cyber City), Myanmar)
b) Professor, Dept. of Electrical and Systems Engineering, Faculty of Engineering, University of Miyazaki
c) Professor, Dept. of Information Science, Faculty of Information and Communication Technology, University of Technology (Yatanarpon Cyber City), Myanmar

are vast and powerful. The former US President, Obama, administration used sentiment analysis to investigate public opinion related with policy announcements and campaign messages ahead of 2012 presidential election and found that it was very useful.

The new user-centralized Web services hosts a large volume of data created by various users. Users are now becoming co-creators of web content, rather than being passive consumers. The social media is now a major part of the Web. The user contributions to social media range from blog posts, tweets, reviews and photo/video uploads etc. A large amount of the data on the Web is unstructured text. Opinions declared in social media as reviews or posts create an important and interesting area worth exploration. With development in accessibility of opinion resource such as product reviews, blog reviews, social network posts, the new challenging task is to drill large volume of texts and design suitable algorithms to understand the opinion of others.

Natural disasters happen with regularity around the globe and are increasing with the growing influence of environmental climate change. Tracking crowd emotions towards natural disasters could provide valuable situational awareness for not only authorities to manage bad situations but also for psychological scientists to understand human behaviors in such situations. However, research to date lacks the detection of specific emotions from social media, especially in the disaster context.

Therefore, we proposed a time-series data visualization for emotion analysis using geo-located Twitter data during California Camp Fire, the deadliest and most destructive wildfire in California history to date. We aimed to extract basic emotions from Twitter for emotion analysis during fire dates, from November 11 to November 20, 2018. Assessing emotional reactions over time may shed light on when disasters are considered most severe within affected communities [2]. Finally, originating locations of the Twitter posts are visualized on the Geo-map. We have constructed our emotions based on Ekman’s six basic emotions [3]: happiness, surprise, sadness, anger, fear and disgust. Nevertheless, happiness emotion is too positive to fit in such bad fire situations; we removed and substituted with calm emotion in order to show positive emotion in such situations.

2. SOME RELATED WORKS

There are generally three types of approaches for sentiment analysis of texts: (a) using a machine learning based classifier such as Naïve Bayes, SVM or Neural Networks with suitable feature selection scheme; (b) using the unsupervised semantic orientated scheme of obtaining relevant n-grams of the text and then labeling them and consequently the document; and (c) using the SentiWordNet based publicly available library that provides positive, negative and neutral scores for each word. Some of the relevant past works on sentiment classification can be found in [4] and [5].

Therefore, we in here attempt to improve the overall system accuracy by exploiting new shape feature extraction method. Sentiment analysis and emotion analysis are the tasks of identifying the attitude and emotion classes of the investigated document [6]. Different domains for sentiment analysis were educational, political, environmental and social etc. Feature-based classification approach has been used from the first applications of sentiment analysis on movie reviews to current sentiment and emotion analysis applications on social media [7]. Abinash Tripathy et al. [8] have performed sentiment analysis on movie review dataset. They have compared results of different classification algorithms and found that SVM classifier outperforms every other classifier in predicting the sentiment of a review or tweet.

While social media mining has been used in different disaster scenarios, one of the most important aspects to understand social responses is to gauge people’s opinion for improved disaster management. There are a few works on sentiment analysis in crisis contexts such as hurricanes [9], and gas explosion [10]. Visual analytics is widely used in social media data analysis and contributes in many areas of exploratory data analysis such as geographical analysis, information diffusion and business prediction.

In [12], the authors targeted the 2011 Great East Japan Earthquake for emotion analysis over Tokyo area and used Twitter posts only written in Japanese language. Since English language plays a bridging role than other languages, our research focus on English Twitter posts and we get rich data. The authors proposed a novel visual analytics framework for sentiment visualization of geo-located data [13].

3. PROPOSED METHOD

The proposed system is mainly composed of five components: data collection, data preprocessing, feature extraction, emotion classification and visualization. The architectural overview of the proposed system is shown in Fig. 2.

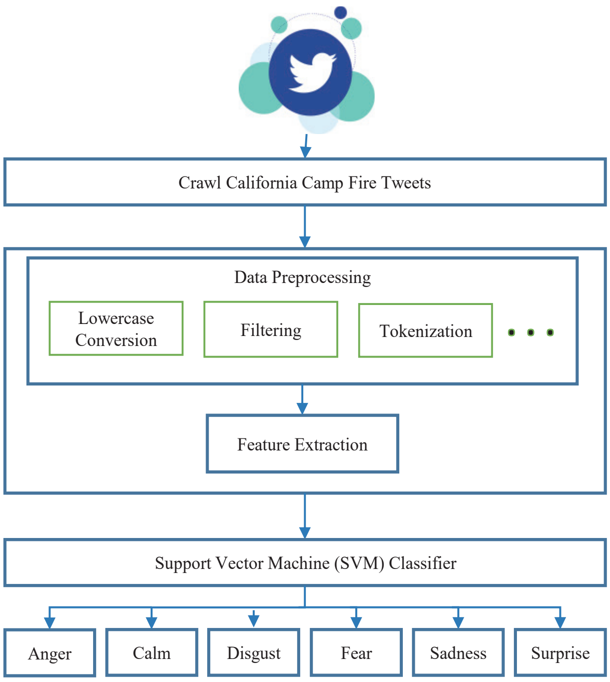

Fig. 2. Architectural Overview of the Proposed System

3.1 Data Collection

The amount of data that one has to deal has exploded to unimaginable levels in the past decade. Since big data analysis mainly involves collecting data from diverse sources, it becomes available to be used up by analysts and finally deliver useful data to the organizational business. The process of transforming large amounts of unstructured raw data, retrieved from different sources to a useful data product for organizations forms the core of big data analysis. This system is to work on collecting data from Twitter and structuring it to be used in a machine-learning model.

The twitter data programmatically can be accessed by creating an application in Twitter that interacts with the Twitter API. In order to search for particular tweets, Oauth protocol is used for Authentication. Then, we get a consumer key, consumer secret, access token and access token secret that should always be kept private. After obtaining these four keys, we connect to the Twitter Streaming API and start downloading Tweets. One tweet contains 140 characters at most and these tweets from various Twitter users' status. In this way, the system crawls the real tweets related with California Camp Fire data.

3.2 Data Preprocessing

Data preprocessing is very important stage, which transforms the raw data into the valuable data for doing analytical process. Real-world data is often incomplete, inconsistent, and lacking in certain behaviors or trends. Data preprocessing is a proven method of solving such issues. Data preprocessing prepares raw data for further processing. Both training phase and testing phase are required to pass this data preprocessing stage to get the desired goal. In this system, six preprocessing steps are performed using Natural Language Toolkit techniques.

- Convert all text to lowercase – this avoids having multiple copies of the same words.
- Removal of usernames, links and special symbols – because they do not add any extra information while treating text data. Do not intend to follow the short urls and determine the content of the sites.
- Word-tokenization – this divides the text into a sequence of words. It plays a large part in the process of lexical analysis.
- Stop-words Removal – removal of non-informative words like a, an, the etc. This is mainly to improve the accuracy of the results and to reduce the redundancy of computation.
- Lemmatization – this converts the word into its root word, rather than just stripping suffixes.
- Spelling Correction – this step is also performed since tweets usually contain misspelled words.

3.3 Feature Extraction

Transforming the input data into the set of features is called Feature Extraction; a process of representation figures calculated from textual data. If the features can be appropriately chosen, we can expect that the features set will be performed the desired task using the reduced description instead of the full size input. There are many methods that have been proposed for keyword feature extraction. TF-

IDF, one of the simplest approaches, is a binary representation that is commonly used and only counted how many times a word appears in a document with a weighting scheme of textual data. Term Frequency – Inverse Document Frequency (*tf-idf*) is a popular feature extraction method, which echoes the importance of a word in a particular document among the corpus. It is a numeric statistical approach, which is often considered as a weighting factor in information retrieval and text mining. is taken as the following equation:

$$tf\text{-}idf = tf * idf \tag{1}$$

Term Frequency (*tf*) is simply the ratio of the count of a word present in a sentence, to the length of the sentence and is expressed as in (2) and Inverse Document Frequency (*idf*) is defined as in (3).

$$tf = \frac{\text{number of times term } t \text{ appears in the particular row}}{\text{number of terms in that row}} \tag{2}$$

$$idf = log(N/n) \tag{3}$$

where, N is the total number of rows and n is the number of rows in which the word was present. Our system limited to 10000 features to be selected to perform emotion analysis. Then, SVM will classify the emotion of the tweets based on these features. Table 1 shows the example of how *tf-idf* score is calculated if we have two Tweets T1 and T2.

For example,
T1: The fire is still burning.
T2: The fire surrounding them was hot and white.

Table 1. *tf-idf* calculation for T1 and T2

Words	*tf*		*idf*	*tf-idf*	
	T1	T2		T1	T2
and	0	1/8	log(2/1)	0	0.038
burning	1/5	0	log(2/1)	0.060	0
fire	1/5	1/8	log(2/2)	0	0
hot	0	1/8	log(2/1)	0	0.038
is	1/5	0	log(2/1)	0.060	0
still	1/5	0	log(2/1)	0.060	0
surrounding	0	1/8	log(2/1)	0	0.038
the	1/5	1/8	log(2/2)	0	0
them	0	1/8	log(2/1)	0	0.038
was	0	1/8	log(2/1)	0	0.038
white	0	1/8	log(2/1)	0	0.038

3.4 Emotion Classification

Sentiment analysis is generally a process of determining the emotional accent depending on a series of expressed words, used to mine an understanding of the attitudes, opinions and emotions expressed within a given text. It can also be said as the stem of natural language processing or machine learning methods. Machine learning uses algorithms to solve the sentiment analysis as a regular text classification problem that makes use of syntactic or linguistic features. The classification used to predict a class label for every instance of unknown class.

There are two sentiment analysis techniques such as supervised and unsupervised techniques. This system performs emotion analysis by using supervised technique, Support Vector Machine (SVM) because it has been shown to be highly effective at traditional text categorization. SVM trains the features in order to build the classifier model. The classifier model performs that the output features of Feature Extraction stage as which classified different emotion features with their weights. SVM is used for training and testing the extracted features and also evaluating the emotion category as shown in Fig. 3. By this way, testing phase performs well easily and classifies accurately six different emotion classes: anger, calm, disgust, fear, sadness and surprise.

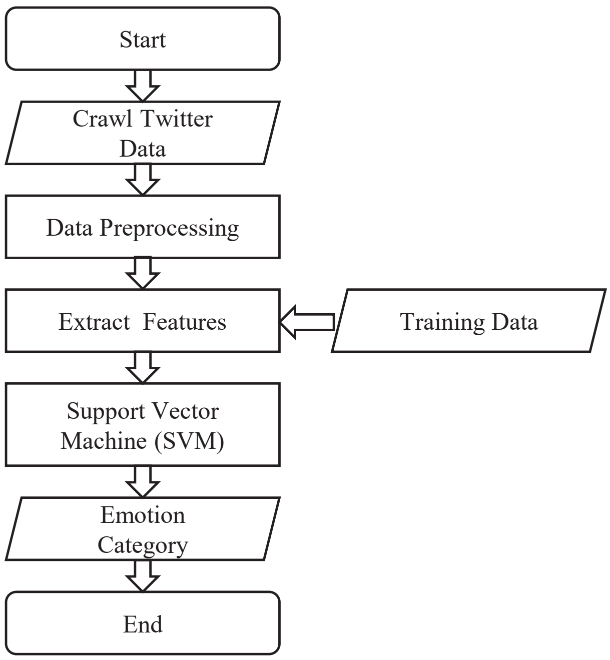

Fig. 3. System Design

3.5 Visualization

Data visualization is a general term that usually aims for any effort to help people understand the significance of data by placing it in a visual context. It is the graphical display of abstract information for data analysis and communication in a way that leads to understanding for action.

A word cloud is a novelty visual representation of text data or to visualize free form text. Fig. 4 is a Word Cloud representation in order to have a global vision related with California Camp Fire Twitter dataset. The more the word occurs, the bigger the font size is.

Twitter provides various APIs, and tweets generally come as JSON objects that include the tweet text along with metadata, such as time, location (coordinates) associated with the tweet (if provided by the user). Since there are four primary ways in which geolocation is commonly performed on Twitter users and messages, we used JSON 'Place' object that encodes a location associated with the tweet. Fig. 5 is obtained based on these geographic coordinates.

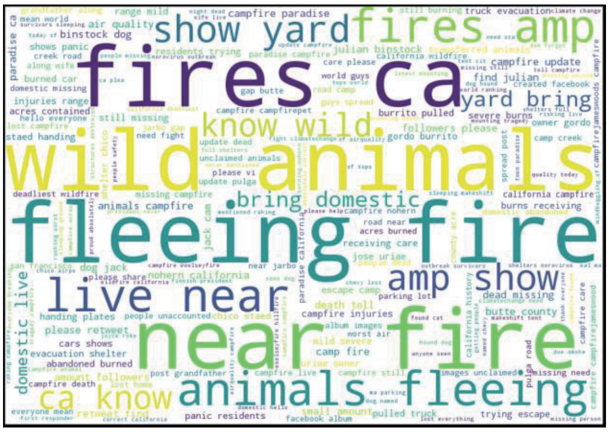

Fig. 4. Word Cloud related with California Camp Fire Twitter Dataset

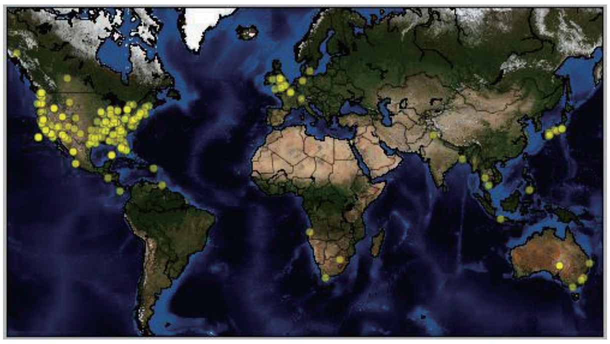

Fig. 5. Visualization of California Camp Fire Twitter Dataset on Geo-map

This system shows the real geolocation of Twitter users, who posted about California Camp Fire, with yellow spots on the geo-map as shown in Fig. 5. However, it does not cover all the users since only a few tweets contain geolocations.

4. EXPERIMENTAL RESULTS AND DISCUSSION

Our system works on the California Camp Fire Twitter corpus [11] that consists of 588674 tweets during ten fire days (November 11 to November 20, 2018). Depending on extracted tweets with emotional keywords, we divided into 80% training and 20% testing tweets and the accuracy of this system is 83%. Table 2 shows the performance parameters of our system.

Table 2. Performance Parameters

Classified Labels	**Actual Labels**	
	Positive	Negative
Positive	True Positive (*TP*)	False Positive (*FP*)
Negative	False Negative (*FN*)	True Negative (*TN*)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad , \quad \text{Recall} = \frac{TP}{TP+FN}$$

$$F-\text{measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

We applied an advanced sentiment analysis on Twitter tweets during ten fire dates, from November 11 to November 20, 2018, to extract basic emotions. The system shows the emotion analysis result of this fire by using bar graph. Fig. 6 shows the amount of emotion changes within ten fire dates. From this, we can see that Tweets are mostly posted on the first days of fire and the most influent emotion during first two days is Fear emotion. A clear notice of this fire is that Fear emotion is always dominant when fire started and rapidly decreases to nearly correlated with Sadness emotion. The emotions significantly variate on 13 November and shows Sadness emotion becomes higher. Sadness emotion changes from lower than Fear from the first dates of fires to higher than this emotion on 13 November that shows Twitter users relief steadily from Fear emotion and changes to Sadness emotion. Therefore, it can be said that the most influent emotion during these fire days is Sadness emotion.

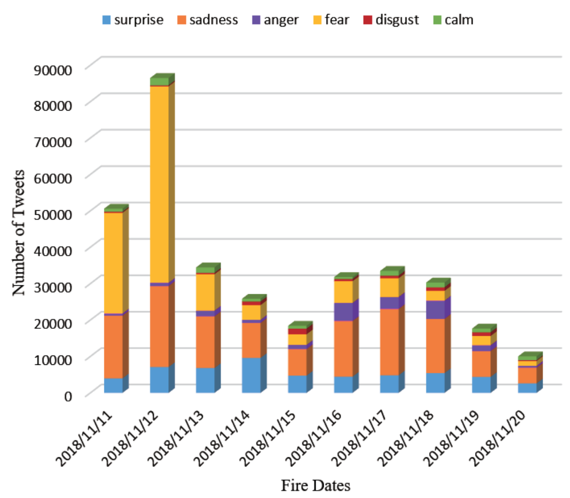

Fig. 6. Emotions detected in Twitter data over the time of California Camp Fire between November 11 and November 20, 2018.

5. CONCLUSION

In this paper, we have presented a visual emotion analysis framework for natural disasters. California Camp Fire is firstly focused for emotion analysis during fire dates, from November 11 to November 20, 2018. We used the Support Vector Machine classifier, which is a well-known machine-learning algorithm and mostly used in text and statistics of data analysis. To interact with this algorithm, python' natural language toolkit (NLTK) library is mainly used and developed this system.

Emotions in the time interval of fire dates reveal the insights of Twitter users during such hard time. Fear emotion always correlate with the occurrence of big natural disasters. Sadness emotion will dominant after a few days of Fear because of natural disasters. As time goes by, however, Twitter users become calmer. There are also some kinds of work for further extending on this system by combining machine-learning process with big data solutions to get more accurately results relate with emotion.

ACKNOWLEDGEMENTS

I must express my gratitude to Prof. Pyke Tin, the Former President of University of Computer Studies, Yangon (Myanmar) and currently Visiting Professor at University of Miyazaki (Japan), for all the insightful research discussions, understandable explanations, valuable advice, supportive suggestions and kindness to me.

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