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Sentiment analysis during Hurricane Sandy in emergency response

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ABSTRACT

Sentiment analysis has been widely researched in the domain of online review sites with the aim of generating summarized opinions of users about different aspects of products. However, there has been little work focusing on identifying the polarity of sentiments expressed by users during disaster events. Identifying such sentiments from online social networking sites can help emergency responders understand the dynamics of the network, e.g., the main users' concerns, panics, and the emotional impacts of interactions among members. In this paper, we perform a sentiment analysis of tweets posted on Twitter during the disastrous Hurricane Sandy and visualize online users' sentiments on a geographical map centered around the hurricane. We show how users' sentiments change according not only to their locations, but also based on the distance from the disaster. In addition, we study how the divergence of sentiments in a tweet posted during the hurricane affects the tweet retweetability. We find that extracting sentiments during a disaster may help emergency responders develop stronger situational awareness of the disaster zone itself.

1. Introduction

In the field of disaster response, making social media data useful to emergency responders has been the single strongest research focus for the past several years [36]. In response to increased online public engagement and the emergence of digital volunteers, professional emergency responders have sought to better understand how they can use social media to collect intelligence [10]. Emergency decision makers see the data produced through crowdsourcing as ubiquitous, rapid and accessible, with the potential to contribute to situational awareness [38]. Starbird et al. [32] assert that bystanders "on the ground are uniquely positioned to share information that may not yet be available elsewhere in the information space and may have knowledge about geographic or cultural features of the affected area that could be useful to those responding from outside the area."

Despite the strong value to those experiencing the emergency and those seeking information concerning the emergency, responders are still hesitant to use social media data for several reasons [36]. One strong reason is insecurity and apprehension concerning the connection between the location of the disaster event and those tweeting about the disaster. Because of the nature of social media, contributors do not have to be bystanders. Responders interested in the wellbeing of physical bystanders seek methods of finding and measuring the concerns of those directly affected by a disaster. Analyzing social media data and extracting users' geo-mapped opinions and sentiments during a disaster can help emergency responders understand the dynamics of the network, e.g., the main users' concerns and panics, the emotional impacts of interactions among users, and the geographical regions that are most affected by the disaster. In addition, analyzing social media data can help obtain a holistic view about the general mood and the situation "on the ground." Through this research, we aim to design accurate approaches to geo-mapped sentiment analysis during disaster events. More precisely, using Twitter data from Hurricane Sandy as a case study, we first develop models to identify the sentiment of tweets and then measure the distance of each categorized tweet from the epicenter of the hurricane. We show that users' sentiments change according not only to the locations of the users, but also based on the relative distance from the disaster. We find that extracting sentiments during a disaster may help emergency responders develop stronger situational awareness of the disaster zone itself. We further analyze the impact of the divergence of sentiments in a tweet on the likelihood of the tweet to be re-tweeted, which affects the information spread in Twitter (also called as retweeting). Understanding how the retweet function inside Twitter works can potentially shed light into the type of information being spread during disasters in large microblogging communities. Identifying elements of a message that make it more likely to be retweeted during a disaster can better inform emergency managers on how to reach the widest audience in the fastest way.

The rest of the paper is organized as follows: Section 2 discusses the related work. Section 3 describes the sentiment classification followed

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by a geo-tagged sentiment analysis of tweets posted during Hurricane Sandy, in which sentiment classification of tweets is an important component. Section 4 describes an analysis on how the divergence of sentiments in a tweet is affecting tweets' retweetability. Section 5 concludes the paper with a summary and discussion.

2. Related work

2.1. The use of microblogged data in disaster response

Researchers have demonstrated the power of microblogging on the diffusion of news-related information [14,15]. Microblogging has been under the lens of researchers with regards to its use in disasters and other high profile events [12]. However, using microblogged feeds as information sources during a large-scale event is highly problematic for reasons including deception, focus of attention, quantification of performance, reliability, the inability to verify either the person or the information that the person posts [9,22,35]. Still, researchers are optimistic about the value of using microblogging data in disaster response. For example, several research groups have demonstrated that emergency managers and responders understand the value of social media for crisis communication [10]. In addition, there have been several studies of emergency managers and responders who have used social media to get the word out during a crisis [5,11,6,34]. More directly, there have been several research efforts to understand how emergency managers and responders have tried to influence the public's information or behavior via social media during crises [8,33]. Moreover, machine learning and natural language processing have made great leaps in extracting, processing and classifying Twitter feeds. Sakaki et al. [28] used machine learning techniques to detect earthquakes in Japan using Twitter data. Mendoza et al. [22] studied the propagation of rumors and misinformation from the Chilean earthquake using only a small set of cases. Castillo et al. [4] analyzed information credibility in Twitter. Specifically, the authors developed automatic methods to assess the credibility of tweets related to specific topics or events (although not restricted to disaster events), using features extracted from users' posting behavior and tweets' social context. Caragea et al. [3] used text classification approaches to build models for the classification of short text messages from the Haiti earthquake into classes representing people's most urgent needs so that NGOs, relief workers, people in Haiti, and their friends and families can easily access them. Li et al. [16] used a domain adaptation approach to study the usefulness of labeled data from a source disaster, together with unlabeled data from a target disaster to learn classifiers for the target and showed that source data can be useful for classifying target data. Similarly, Imran et al. [13] explored domain adaptation for identifying information nuggets using conditional random fields and data from two disasters, Joplin 2011 tornado (as source) and Hurricane Sandy (as target). Ashktorab et al. [1] used a combination of classification, clustering, and extraction methods to extract actionable information for disaster responders. In contrast to the above works, we use machine learning techniques to perform a geo-mapped sentiment analysis of tweets during the Hurricane Sandy.

2.2. Geo-mapped microblogged data in disaster response

Mapping crowd-sourced information in disaster response gained wide-scale media attention during the 2010 Haiti earthquake [31], with several challenges involved in mapping crowd-sourced communications, including the extraction of accurate location information, and the application of useful and usable cartographic representations to visually support situational awareness in crises [20]. This occurs due to the need to display large volumes of data, while avoiding information overload [20], which is complicated further by the fact that potential users of crisis maps will have different expectations influenced by their social and physical relation to the crisis event [17]. According to McClendon & Robinson [20], "Mapping social media content provides a way to gather and visualize information from what can arguably be considered the true first responders - the affected citizens who are the first to assess the situation and request assistance through social media… Future research must focus on applications that go beyond basic crowd-sourcing to develop information collections, analytical tools, coordination of communications, and mapping visualization to support all phases of disaster management."

2.3. Sentiment analysis for disaster events

There have been very few works on identifying the polarity of sentiments expressed by users in social networking sites during disaster-related events. Nagy & Stamberger [23] focused on sentiment detection in Twitter during the San Bruno, California gas explosion and fires from 09/2010. They used SentiWordNet together with dictionaries of emoticons and out of vocabulary words, and a sentiment-based dictionary to identify the basic sentiment of a tweet. Schulz et al. [30] proposed a fine-grained sentiment analysis to detect crisis related micro-posts and showed significant success in filtering out irrelevant information. The authors focused on the classification of human emotions into six classes: anger, disgust, fear, happiness, sadness, and surprise. As features, they used bag of words, part of speech tags, character n-grams (for n=3, 4), emoticons, and sentiment-based words compiled from the AFINN [25] word list and SentiWordNet [2]. Schulz et al. [30] evaluated their models on tweets related to the Hurricane Sandy from October 2012. Mandel et al. [19] performed a demographic sentiment analysis using Twitter data during Hurricane Irene. Pfitzner et al. [27] introduced the concept of *emotional divergence* which measures the diversity of the emotions expressed in a text and analyzed how likely a tweet is to be retweeted with respect to its emotional divergence value. Their dataset contains tweets from a variety of popular events related to sports, entertainment, politics and technology. Building directly on these works on sentiment analysis, we take the next logical step and focus on geo-mapped sentiment analysis of tweets from Hurricane Sandy in order to obtain a holistic view of the general mood and the situation "on the ground" during the hurricane. Our approach can help increase situational awareness and can "visually" inform emergency response organizations about the geographical regions that are most affected by a disaster. We also study the effect of emotional divergence on retweetability during Hurricane Sandy and how the emotional divergence can affect information spread.

3. Geo-mapped sentiment analysis of tweets from hurricane sandy

Through this research, we seek to find mechanisms to automatically classify the sentiment of tweets posted during the Hurricane Sandy. We formulate the problem as a classification problem and use supervised learning approaches to classify a tweet as positive, negative or neutral, based on the polarity of the emotion expressed in the tweet. Table 1 shows examples of tweets extracted from our Hurricane Sandy dataset.

The sentiment classification of tweets faces many challenges including dealing with very short texts as well as unstructured text and noisy user input, e.g., tweets contain many misspellings, "ole"

Table 1
Examples of tweets from Hurricane Sandy, labeled as positive, negative & neutral.

Tweet	Sentiment
1. "RT @User1: During this hurricane we are all going to reunite on Xbox like the good ole days"	Positive
2. "RT @User2: It doesnt look like a hurricane is coming."	Neutral
3. "User3: I got a feeling that #Sandy is about to screw up my work schedule for the week: (smh"	Negative