# An Overview of Sentiment Analysis in Social Media and its Applications in Disaster Relief

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**Abstract.** Sentiment analysis refers to the class of computational and natural language processing based techniques used to identify, extract or characterize subjective information, such as opinions, expressed in a given piece of text. The main purpose of sentiment analysis is to classify a writer's attitude towards various topics into positive, negative or neutral categories. Sentiment analysis has many applications in different domains including, but not limited to, business intelligence, politics, sociology, etc. Recent years, on the other hand, have witnessed the advent of social networking websites, microblogs, wikis and Web applications and consequently, an unprecedented growth in user-generated data is poised for sentiment mining. Data such as web-postings, Tweets, videos, etc., all express opinions on various topics and events, offer immense opportunities to study and analyze human opinions and sentiment. In this chapter, we study the information published by individuals in social media in cases of natural disasters and emergencies and investigate if such information could be used by first responders to improve situational awareness and crisis management. In particular, we explore applications of sentiment analysis and demonstrate how sentiment mining in social media can be exploited to determine how local crowds react during a disaster, and how such information can be used to improve disaster management. Such information can also be used to help assess the extent of the devastation and find people who are in specific need during an emergency situation. We first provide the formal definition of sentiment analysis in social media and cover traditional and the state-of-the-art approaches while highlighting contributions, shortcomings, and pitfalls due to the composition of online media streams. Next we discuss the relationship among social media, disaster relief and situational awareness and explain how social media is used in these contexts with the focus on sentiment analysis. In order to enable quick analysis of real-time geo-distributed data, we will detail applications of visual analytics with an emphasis on sentiment visualization. Finally, we conclude the chapter with a discussion of research challenges in sentiment analysis and its application in disaster relief.

**Keywords.** Sentiment Analysis, Disaster Relief, Visualization, Social Media

# 1 Introduction

With the explosive growth of social media (e.g. blogs, micro-blogs, forum discussions and reviews) in the last decade, the web has drastically changed to the extent that nowadays billions of people all around the globe are freely allowed to conduct many activities such as interacting, sharing, posting and manipulating contents. This enables us to be connected and interact with each other anytime without geographical boundaries, as opposed to the traditional structured data available in databases. The resulted unstructured user-generated data mandates new computational techniques from social media mining, while it provides us opportunities to study and understand individuals at unprecedented scales [1, 2, 3, 4, 5, 6, 7]. Sentiment analysis (a.k.a opinion mining) is one class of computational techniques which automatically extracts and summarizes the opinions of such immense volume of data which the average human reader is unable to process. This ocean of opinionated postings in social media is central to the individuals' activities as they impact our behaviors and help reshape businesses. Nowadays, not only individuals are no longer limited to asking friends and family about products but also businesses, organizations and companies do not require to conduct surveys or polls for opinions about products, as there are tons of user reviews and discussions in public forums on the Web. There are thus numerous immediate and practical applications and industrial interests of collecting and studying such opinions by using computational sentiment analysis techniques, spreading from consumer products, services, healthcare, and financial services to social events, political elections and more recently crisis management and natural disasters.

Social media has pervasively played an increasing role and they have become an important alternative information channel to traditional media in the last five years during emergencies and disasters, where they rank as the fourth most popular sources to access necessary information during emergencies [8, 9]. In particular, individuals and communities have used social media for many tasks from warning others of unsafe areas to fund raising for disaster relief [8]. The days of one-way communication where only official sources used to provide bulletins during emergencies are actually gone. In 2005 for instance, when Hurricane Katrina slammed the U.S. gulf coast, there was no Twitter for news update while Facebook was not that much famous yet. Compare, for example, Hurricane Katrina to the Haiti earthquake on January 2010. During latter, people used Twitter, Facebook, Flicker, blogs and YouTube to post their experience in form of texts, photos and videos during the earthquake which resulted in donating 8 million U.S. dollars to the Red Cross which vividly demonstrates the power of social media in propagating information during emergencies [10]. Hurricane Sandy on 2012, is another example to show the positive impact of social media during disasters. By that time, using social media had become an important part of disaster response. There are numerous similar examples that show how social media have come to the rescue in disaster situations including Hurricane Irene, California gas explosion on 2010, Japan earthquakes, Genoa flooding and more recently Ebola. Social media could be actually leveraged to keep the problem informed, help locate loved ones, and express support or notify authorities during emergencies and disasters. Sentiment analysis of disaster related posts in social media in could help to detect posts that contribute to the situational awareness and better understand the dynamics of the network including users' feelings, panics and concerns by identifying the polarity of sentiments expressed by users during disaster events to improve decision making. Sentiment information could also be used to project the information regarding the devastation and recovery situation and donation requests to the crowd in better ways.

Interactive tools such as visual analytic methods could help us to make a large amount of complex information more readable and interpretable, if integrated by computational approaches, as the effectiveness of most computational techniques is limited due to several factors [11]. Interactive visual analytics provide intuitive ways of making sense of large amount of posts available in social media. These techniques are now widely used in social media data and contribute in many areas of exploratory data analysis. Despite most social media visualization approaches which rely solely on geographical and temporal features, there are some systems which are able to exploit the sentiments of the data such which help improving visualization. Besides disaster related data management in social media, the ability to drawing out important features could be used for better and quick understanding of situation which leads to rapid decision making in critical situations. Moreover, the data produced by social media during disasters and events, is staggering and hard for an individual to process. Therefore, visualization is needed for facilitating pattern discovery.

The goal of this chapter is to give the reader a concrete overview of sentiment analysis in social media and how it could be leveraged for disaster relief during emergencies and disasters. In particular, we cover state-of-the-art sentiment analysis approaches and highlight their contributions and shortcomings and then discuss the application of social media and sentiment analysis in disaster relief and situational awareness. We conclude the chapter by detailing applications of visual analytics with an emphasis on sentiment analysis and then discussing the research challenges in sentiment analysis and disaster relief. By the end of this chapter, the reader is expected to learn about the sentiment analysis and disaster management concepts as well as the state-of-the-art approaches and the applications of visual analytics in these contexts.

# 2 Sentiment Analysis

Sentiment analysis (a.k.a sentiment classification, opinion mining, subjectivity analysis, polarity classification, affect analysis, etc.) is the multidisciplinary field of study that deals with analyzing people's sentiments, attitudes, emotions and opinions about different entities such as products, services, individuals, companies, organizations, events and topics and includes multiple fields such as natural language processing (NLP), computational linguistics, information retrieval, machine learning and artificial intelligence. It is set of computational and NLP based techniques which could be leveraged in order to extract subjective information in a given text unlike factual information, opinions and sentiments are subjective [12].

Despite the recent surge of interest in sentiment analysis since the term was coined by Nasukawa et al. [13] in 2003, the demand for information on sentiment and opinion during decision-making situations dates back to long before the widespread use of the World Wide Web. Opinions are central to almost all human activities as they could influence our behaviors specially when making a decision. For example, many of us may have asked their friends to recommend a dishwasher or to explain who they might vote for during elections, or even requested reference letters from colleagues regarding job applications. Now, opinions and experiences of numerous people that are neither our acquaintances nor professional critics are readily available thanks the Internet and the Web [14]. This is not limited to individuals only; businesses, organizations and companies are also eager to know consumers' opinions about their products and services. In the past, when a business needed consumer opinions, it conducted surveys and opinion polls. Nowadays, one is no longer limited to asking friends and family or conducting surveys for opinions about products; instead one can use volumes of user reviews and discussions in public forums on the Web [12]. Indeed, the Web has dramatically changed the way that people express their opinions about products, services, companies, individuals and social events. There are now many Internet forums, discussion groups, blogs and even micro-blogs that are well suited for the users to freely post reviews about products and express their views on almost anything online. These users-generated contents and word-of-mouth behavior are sources of information with many immediate and practical applications.

The research on sentiment analysis appeared even earlier than 2003 [15, 16, 17, 18, 19, 20], while there were also some other earlier work [21, 22] on beliefs as frontiers or later work [23, 24, 25, 26, 27, 28, 29, 30] on interpretation of metaphors, sentiment adjectives, subjectivity, view points, affects and related areas [12, 14]. In contrast to the long history of linguistics and NLP, the area of analyzing people's opinions and sentiments has been virtually untrodden before the year 2000. However, since then, the literature witnessed literally hundreds of studies [31, 32, 33, 34, 35, 36, 37, 38, 39] due to several factors, including: (1) the rise of machine learning techniques in natural language processing and information retrieval; (2) access to datasets for training machine learning techniques because of the World Wide Web and specifically review-aggregation Websites, and; (3) realizing the huge applications in industry that the area started to offer [14]. This rapid growth of sentiment analysis and, more importantly its coincidence with the explosive popularity of the social media, have made the sentiment analysis the central point in the social media research [12].

Research on sentiment analysis has been investigated from different perspectives. Perhaps the most popular perspective is to categorize these studies into three levels, document level, sentence level, and entity and aspect level [12] described as follows:

- **Document level**: The aim here is to determine the overall sentiment of an entire document. For example given a product review, the task is to determine whether it expresses positive or negative opinions about the product. This level looks at the document as a single entity, thus it is not extensible to multiple documents.

- **Sentence level**: This level of analysis is very close to subjectivity classification and the task at this level is limited to the sentences and their expressed opinions. Specifically, this level determines whether each sentence expresses a positive, negative or neutral opinion.

- **Entity and aspect level**: Instead of solely analyzing language constructs (e.g. documents, paragraphs, sentences), this level (a.k.a feature level) provides finer-grained analysis for each aspect(or feature) i.e., it directly looks at the opinions for different aspects itself. The aspect-level is more challenging than both document and sentence levels and consists of several sub-problems. It finds different available sentiment

Sentiment analysis methods could be categorized into two groups, language processing based and application oriented methods. We describe the state-of-the-art approaches in each category and highlight their contributions. Then we conclude this section with a brief overview on visual analytics approaches in sentiment analysis.

## 2.1 Language Processing Based Methods

Meanwhile, some other works have addressed sentiment analysis from two different aspects, namely, lexicon-based, and linguistic analysis. The most obvious yet important indicators of sentiments are sentiment or opinion words such as $good$, $amazing$, $poor$, $bad$ as well as some phrases and idioms which are used to express positive or negative opinions. A sentiment lexicon (a.k.a opinion lexicon) is the list of such words and phrases and is necessary but not sufficient for sentiment analysis. In addition to exploiting lexicons, linguistic based approaches also use the grammatical structure of the text for sentiment classification. There are two kinds of lexicon generation methods, namely, dictionary based [32, 33, 40] and corpus-based [31] approaches. The first category starts with a small set of opinion words and expands the lexicon through bootstrapping a certain dictionary while the second category generates the opinion lexicon through learning the dataset. For example, authors et al. [32] propose to employ predefined syntactic templates to capture links between opinion words and their targets. The links can then be used to infer more opinion words. Wu et al. [41] further extended the link structure to syntactic trees and expand the opinion lexicon accordingly. Kouloumpis et al. [31] investigate the utility of linguistic features including lexicon and part of speech for sentiment analysis of microblogging posts by deploying AdaBoost.MH model [42]. The authors then concluded that sentiment lexicon features demonstrate better performance. Another lexicon based method is proposed by Thelwall et al. [33] that authors study the relation between importance of events and sentiment intensity of messages posted in Twitter. Time series based analysis of sentiment can be used to predict offline phenomena of online topics or investigating the role of sentiment in important online events.Thelwall et al. [33] incorporate SentiStrength algorithm [43], which simultaneously assigns positive and negative scores to the token in the text, to extract the intensity of posts sentiments. The algorithm assigns scores to the tokens in a dictionary which includes common emoticons while modifier words or symbols can boost the score. The final score is the maximum score among all tokens' scores. The authors conclude with the observation that negative sentiment intensity of microblogging posts increases with the importance of the event.

## 2.2 Application Oriented Methods

Pervasive real-life applications of sentiment analysis and opinion mining are one reason that sentiment analysis is now a popular research problem. Due to these offered applications by sentiment analysis, many activities specially those of industries have risen in recent years which have spread to almost every possible domain including products, services, healthcare, financial services, social events and political elections. Sentiment analysis also helps to understand opinions of people regarding different online topics. It has many applications in social media and many works have been done recently in applying sentiment analysis methods to social media data. These applications include, but are not limited to, movie reviews [17], product reviews [44, 12], App reviews [45], stock market predictions [46] and trend detection [47]. For example, Pang et al. [17] discuss the performance of machine learning classifiers including Naïve Bayes [48], maximum entropy [49] and support vector machines [50] in the specific domain of movie reviews. They use various feature extractors based on unigrams and bigrams. Star ratings are also used as polarity signals in training data. Another application of sentiment analysis is in stock market prediction [46], investigating whether the stock market could be predicted using public sentiment expressed in daily Twitter posts. The authors use OpinionFinder [51] and Google-Profile of Mood States(GPOMS) tools to measure users sentiments and mood to further analyze resulted time series and the effect of public mood states on prediction of stock market. In spite of these applications and the abundance of public information available for sentiment analysis, finding opinion Websites on the Internet and processing the information contained in them is still a tedious task for the average human reader. Therefore, automated sentiment analysis systems are critical. One good example of such a system is the Stanford CoreNLP toolkit [52] which is an extensible and annotation-based NLP processing pipeline that provides several core natural language analysis steps, from tokenization to coreference resolution.

There are also some other studies that leverage network information into sentiment analysis applications. For example, some works exploit social network information [34, 35] to improve sentiment analysis performance. Authors in [34] incorporate user-user relations including follower/followee network corresponding into the principle of homophily [53] and "@"-network which shows the attention of users to each other, i.e. mentions network. They propose a semi-supervsied model using a factor-graph model to leverage social network information for user-level sentiment polarity classification. Tan et al. show considering both homophily and attention at the same time could result in a significant improve even when representative information is very sparse, as long as demonstrating a strong correlation between users shared opinions. Another work [35] confirms the existence of two social theories *sentiment consistency* and *emotional contagion* in microblogging data. Sentiment consistency [54] refers to sentiment consistency of messages posted by the same user in comparison to two different random users' posts. Emotional contagion [55] suggests that messages posted by two friends have more similar sentiment than those of random users in the network. The proposed method, then, integrates the social theories using sentiment relations between tweets as a regularization parameter into the definition of traditional supervised classification method and finally uses optimization techniques to solve the problem. In order to handle noisy and short texts in microblogging data, Hu et al. [35] utilizes sparse learning method lasso [56] for the classification feature space.

Different from these works, some efforts have been made to exploit emoticons [36, 37, 57]. For example, Go et al. [57] apply machine learning classifiers using distant supervision to consider microblogging post with emoticons as training data. Distant supervision is introduced by Read [58] which shows that emoticons could be used as sentiment labels to reduce dependencies in machine learning techniques. In a similar attempt, Zhao et al. [36] train a Naïve Bayes classifier on a dataset from Weibo[1] using emoticons as noisy label information. Another work by Hu et al. [37] further investigate using emotional signals in the sentiment analysis problem. Emotional signals refer to any information in the data which reveals the sentiment polarity of a post such as emoticons, product ratings or some words which carry clear semantic meaning. Emotional signals can be grouped into two categories: emotion indication and emotion correlation. The former refers to the signals that strongly demonstrate the sentiment of a post or word, like emoticons or product ratings, and the latter includes posts that demonstrate the correlation between post or words such as synonym correlation or sentiment consistency theory. This theory states that two co-occurred words are more likely to be sentiment consistent rather than two random words. The proposed method, first verifies the existence of two representative emotional signals, emoticons and sentiment consistency. Then it models them with regularization factors considering both post- and word- level aspects of them and exploits them in the orthogonal nonnegative matrix tri-factroization model (ONMTF) [59] for sentiment classification.

There exist some other studies for sentiment classification that are different from the previous methods. For instance, the impact of human factors such as textual, topical, demographical, spatial and temporal features on the attitude and sentimentality of posts is studied by Kucuktunc et al [40]. This study proposes to use posts on Yahoo! Answers[2], a large online question answering system and uses [43] as a sentiment extraction tool to extract sentiments and further deploys gradient boosted decision trees [60, 61] to predict the attitude a question will provoke in answers. As an another example, Hu et al. [62] propose a method to identify sentiments of segments and topics of event related tweets which have received praise or criticism. Their framework decomposes the tweet-vocabulary matrix into four factors to demonstrate the relation of tweets with different segments, topics and sentiments so that it could characterize the segment and topics of events via aggregated Twitter sentiment. To compensate the learning process, three types of prior knowledges have been exploited in their method including sentiment lexicon, manually labeled tweets and tweet/event alignment using [63]. Balahur et al. [64] apply sentiment analysis methods for news opinion mining since it is different from that of other text types in clarifying target, separation of good and bad news from good and bad sentiment, and analysis of explicitly marked opinion. Recent work of [38], presents three neural networks to exploit and learn sentiment-specific word embedding (SSWE) for sentiment classification on Twitter without any manual annotations. In more details, they apply sentiment-specific word embedding for Twitter sentiment analysis under a supervised learning framework. In this study, instead of hand-crafting features, authors incorporate the continues representation of word and phrases as the feature of a tweet. Another study [39], compares three different approaches including $replacement$, $augmentation$ and $interpolation$ for exploiting semantic features for Twitter sentiment analysis and concludes that the best results are achieved by interpolating the generative model of words given semantic concepts into the unigram language of model of

[1] http://Weibo.com
[2] http://answers.yahoo.com

the Naïve Bayes classifier.

In Table 1, we summarize some of the recent studies with their datasets along with their proposed approaches and their best reported accuracies.

| Paper | Dataset | Approach | Evaluation |
|---|---|---|---|
| [17] | IMDb Movie Review | Support vector machine | 82.9%(Accuracy) |
| [31] | iSieve Twitter dataset | AdaBoost.MH | 75%(Accuracy) |
| [32] | Customer Review Dataset | Others | 70%(FScore) |
| [33] | Twitter dataset | SentiStrength | |
| [34] | Twittes dataset on Different Topics | Graphical models incorporating users relation network | 80%(Accuracy) |
| [35] | Stanford Twitter Sentiment; Obama-McCain Debate | Incorporating sociological sciences into multiple sentiment classification | 79.6%(Accuracy) |
| [36] | Weibo Tweets | Incorporating emoticons into Naive Bayes classifier | 58.3%(FScore) |
| [37] | Stanford Twitter Sentiment; Obama-McCain Debate | Leveraging emotional signals in ONTMF[59] | 72.6%(Accuracy) |
| [38] | Twitter sentiment classification benchmark dataset in SemEval | Neural networks | 86.48%(FScore) |
| [39] | Stanford Twitter Sentiment; Obama-McCain Debate; Health Care Reform | Incorporating semantics features into Naive Bayes | 84.25%(Accuracy) |
| [40] | Yahoo answers | SentiStrength | 0.4939 (RMSE) |
| [57] | Self crawled Twitter dataset | Incorporating emoticons in support vector machine | 83%(Accuracy) |
| [62] | Denver Debate Twitter dataset; ME Speech Twitter dataset | Matrix factorization by leveraging prior knowledge of lexicon, sentiment and alignment of tweets to the events | 76.8%(Accuracy) |
| [64] | news articles quotes | SentiWordNet | 82.0%(Accuracy) |

**Table 1: Best results reported by different studies using different approaches on different data sets. Some studies may have reported different accuracies in their original papers.**

## 2.3 Sentiment Visualization

Visual analytics focuses on providing an intuitive way of making sense of large amount of posts available in social media. It is widely used in social media data and contributes in many areas of exploratory data analysis, such as geographical analysis [65], information diffusion [66] and business prediction [67]. While most social media visualization approaches rely on geographical and temporal features, some systems exploit the semantic of the data such as sentiments to improve visualization. For example, there exist some Websites that provide mashup applications to visualize and analyze tweets, including TrendsMap[3], Twitalyzer[4], and Geotwitterous[5], some of which provide sentiment analysis as well. In the remainder of this section, we explore some of the existing systems and tools that are able to visualize sentiment.

IN-SPIRE [68] is a visual analytic tool for blog analysis which helps users to harvest blogs and classify them with respect to their contents. IN-SPIRE supports sentiment visualization of blogs and streaming contents. The sentiment of lexicons are categorized into positive/negative, virtue/vice, power coop/conflict and pleasure/pain according to Gregory et al. [69] and is visualize as a rose plot. Each pair of category is shown with a different shade of a same color. Moreover, the size of petals are different in terms of the amount of sentiment. For example, Fig.1 depicts sentiment distribution in two event-related and music-related blogs regarding the September $11^{th}$ attacks.

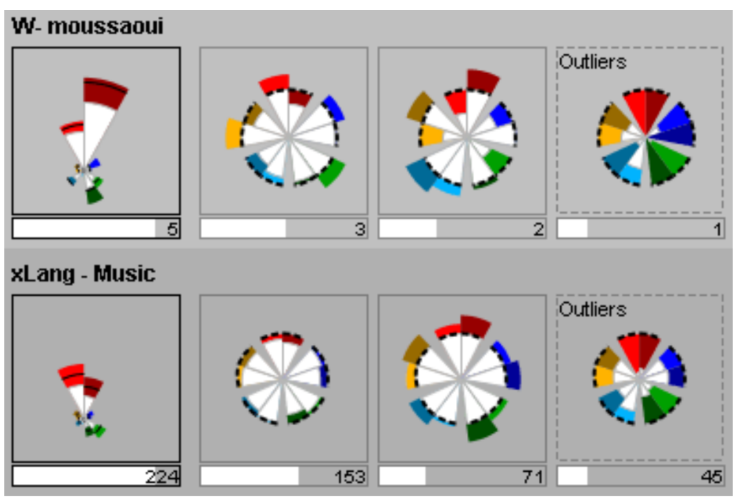


**Figure 1: Sentiment Distribution of two blog topics using IN-SPIRE. The sentiment of lexicons categorized into different groups visualize as a rose plot with different colors. Reprinted with permission from [68]**

[3]http://trendsmap.com/
[4]http://www.twitalyzer.com/
[5]http://ouseful.open.ac.uk/geotwitterous/

As another example of sentiment visualization prototype, Pulse [70], simultaneously detects topic and sentiment of a document in the sentence-level in the following way. It first constructs a tree-map [71] to visualize the clusters and their associated sentiments. Each cluster is depicted by a box whose size indicates the number of sentences in it and also its red or green color translates into the positive or negative sentiment respectively. Naive Bayes classifier with Expectation Maximization (EM) and bootstrapping [72] are finally applied to find the sentiment of the sentence. Fig.2 shows a screenshot of Pulse user interface system. Oelke et al [73] develops a tool that analyzes and visualizes customer feedbacks using a 2-D

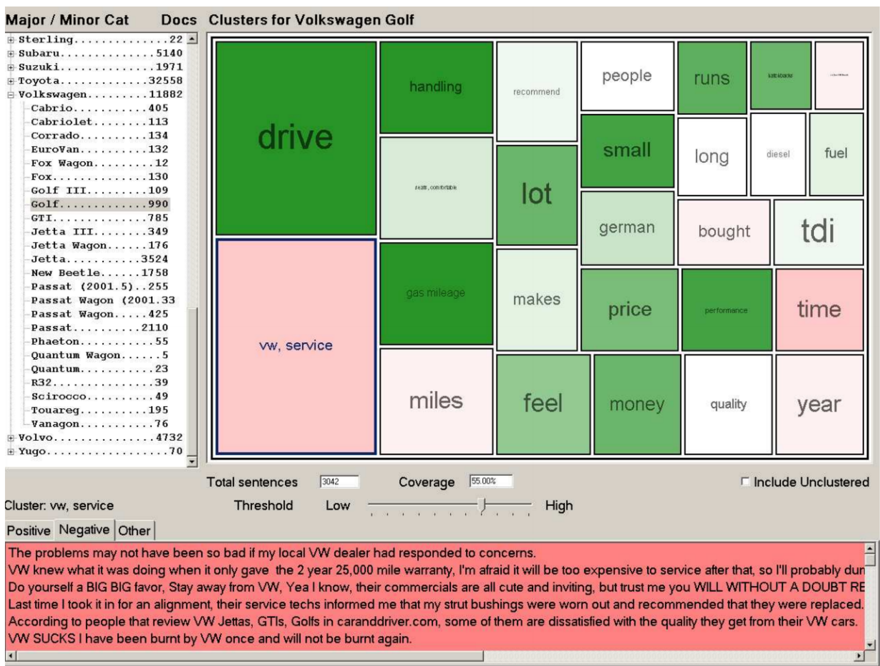


**Figure 2: Screenshot of Pulse user interface. Each cluster of corespondent tree-map is shown with a box whose size indicates the number of sentences in it. Positive and negative sentiments are shown with red and green color respectively. Reprinted with permission from [70]**

matrix to show the sentiment overview of customer feedbacks. Then it clusters the reviews and uses special thumbnails to provide their relationship. It uses a circular correlation map to analyze the correlations among different aspects of the dataset such as numerical ratings, sentiment orientations and product features of the reviews.

Similarly, VISA [74], is an extension to the generic text visualization tool TIARA [75] with the further sentiment analysis abilities which helps average human reader to understand sentiments of a huge amount of textual data. The novel concept of this tool is sentiment tuple which is the core of the data model and acts as an interface between backend sentiment analysis system and the frontend visualization. This tuple of feature, aspect, opinion, and polarity helps the system to incorporate any external sentiment analysis method results which could be easily transformed into this representation. VISA is also a mashup visualization which shows the temporal sentiment dynamics, comparison of sentiment among different topics, document snippet to provide details about the context of sentiment and chart visualization for different structured features for more accurate sentiment perception. It deploys three domain-specific $entity$, $word$, and $opposite$ dictionaries to determine features, aspects and polarity of the document.

Eventscape tool [76] combines time, visual media, mood, and controversy by performing topic modeling and clustering to determine events and topics and arranging them in time. It uses ANEW dictionary to find emotion valence and arousal of document text. It shows sentiment diversity of documents by focusing on interactive colour-coded timeline, lists of tweets, and mood maps. TwitInfo [77] is also a system for summarizing and visualizing event on Twitter and has a timeline based display which allows users to brows a large collection of tweets. It plots the geographical data coupled with sample tweets, color-coded for sentiment. TwitInfo uses Naive Bayes classifier on unigram features following the strategy of go et al. [57] to classify tweets as positive and negative. It also introduces a normalization procedure for sentiment summarization to guarantee that sentiment methods produce correct results. MediaWatch [78] creates sentiment flow diagrams to analyze the evolution of sentiment over time with an innovative color-coding display. It uses aggregated sentiment polarity method as a sentiment detection algorithm. A screenshot of the MediaWatch on climate change data is shown in Fig.3. Shook et al. [79] propose a geospatial visual analytics method, TwitterBeat, which analyze large volume of textual data to capture the sentiment to display it in emotional heatmaps. Fig.4 depicts a sample of TwitterBeat on US sentiment feed.

# 3 Sentiment Analysis for Disaster Relief

Recent years have witnessed an increase in severity and frequency of natural disasters [80]. Many natural disasters around the globe, have killed people and impacted human lives worldwide. Consequently there is a critical need to use a mechanism to best allocate investment for prevention, preparedness, response, and recovery to enhance safety and reduce the cost and social effects of emergencies and disasters [81]. In the following subsections, first we describe the application of social media during disasters and emergencies as one of such mechanisms and then explain how sentiment analysis can be deployed for disaster relief and finally review some of the state-of-the-art visual analytics techniques used to accommodate the task of disaster management.

## 3.1 Social Media in Disaster Relief

Social media have become an important alternative information channel to traditional media during emergencies and disasters. They have been used for many tasks including warning others of unsafe areas and fund raising for disaster relief [8]. Social media help to

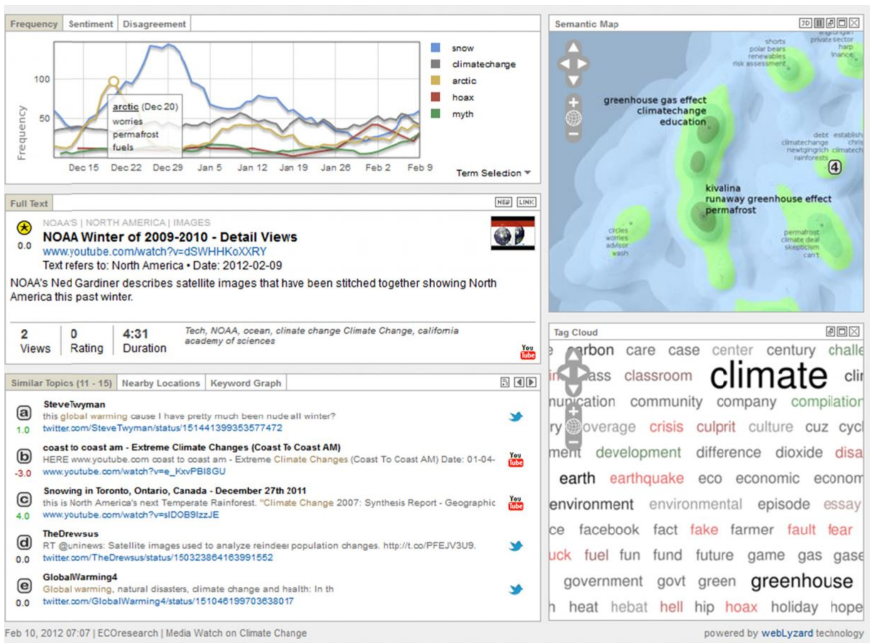

Figure 3: Screenshot of the MediaWatch on climate change data. Sentiment flow diagram is shown to analyze evolution of sentiment over time. Reprinted with permission from [78]

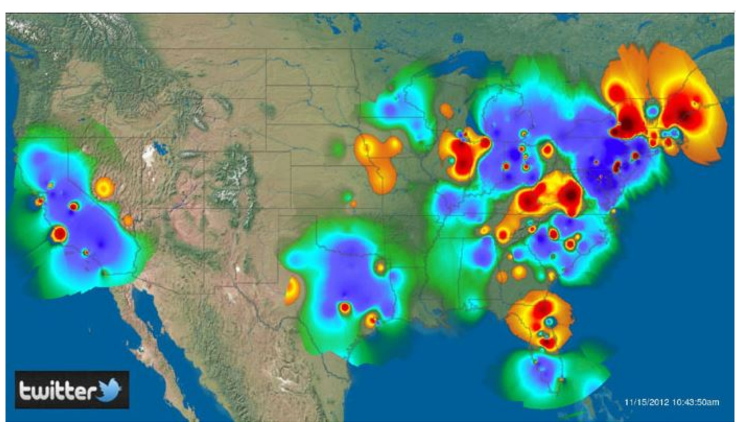

Figure 4: Heat Maps of US Sentiment on Twitter. Reprinted with permission from [79]

keep informed, locate loved ones, express support or notify authorities during emergencies and disasters. Due to popularity and diverse areas of discussion of social media, it has been used recently as a tool by first responders-those who provide first hand aids- for disaster relief and crisis management. Microblogging systems are used by millions around the world to broadcast just about anything. Therefore they can be used in disaster management as they provide an information platform with easy accessibility. For example Twitter was used to provide real time situation updates during major disasters [82, 83, 84, 85]. [86] used 2008 Sichuan Earthquake in 2008 as a case study to show that individuals use social media to gather and disperse useful information regarding the disasters. [87] also provides a study on how microblogging systems could be used to facilitate disaster response.

The applications of social media in disaster management can be roughly categorized into two groups, situational awareness and information sharing [88]. Situational awareness means identifying, processing, and comprehending critical elements of an incident or situation to provide useful insight into time- and safety-critical situations [8, 89]. It assists first responders in assessing the amount of damage, victims' locations and needs. Information sharing also shows how people behave and share information in social media regarding the disasters and could be used for directing needed resources into public. Both situational awareness and information sharing help to accelerate disaster response and alleviate both property and human losses in crisis managements.

Analyzing and identifying posts related to the disaster [9, 90], detecting posts originated from within a crisis region [91], studying automatic methods for extracting information [92, 85, 93, 94, 95, 96, 97, 98, 99] and behavioral analysis methods during disasters [87, 100, 101] are among different methods used to improve situational awareness. There are also some applications and analysis tools which help humanitarian and disaster relief organizations to track, analyze, and monitor microblog event related posts such as [102, 103, 104, 105, 106, 107, 108].

## 3.2 Applications of Sentiment Analysis in Disaster Relief

Sentiment analysis of disaster related posts in social media is one of the techniques that could gear up detecting posts for situational awareness. In particular, it is useful to better understand the dynamics of the network including users' feelings, panics and concerns as it is used to identify polarity of sentiments expressed by users during disaster events to improve decision making. It helps authorities to find answers to their questions and make better decisions regarding the event assistance without paying the cost as the traditional public surveys. Sentiment information could also be used to project the information regarding the devastation and recovery situation and donation requests to the crowd in better ways. Using the results obtained from sentiment analysis, authorities can figure out where they should look for particular information regarding the disaster such as the most affected areas, types of emergency needs [109].

Many methods have been proposed to analyze the role of sentiment analysis in disaster management where most of them deploy variant machine learning techniques [109, 89, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121] and other techniques such as swarm intelligence [122]. The datasets used for evaluations includes the social media posts related to events such as Hurricane Sandy, Hurricane Irene, Red River flood in 2009 and 2010, Haiti earthquake, California gas explosion, and Terrorist attack in Mumbai.

One of the earlier machine learning based works for disaster management using sentiment analysis is proposed by Verma et al. [89]. In particular, they build a classifier to automatically detect situational awareness tweets by categorizing them to several dimensions including subjectivity, personal or impersonal style and linguistic style (formal or informal) using combination of hand-annotated and automatically linguistic features. Subjectivity features could be used to assess the amount of emotion a user expressed in her tweets for situational awareness and information extraction. This study, uses OpinionFinder [123, 124] to extract subjectivity of tweets as a linguistic features for their developed classifier. Similarly, authors in [109] use Bayesian Networks to detect sentiment of tweets of California gas explosion based on combination of sentiment ontology, emoticons,frequent lists of sentiment words SentiWordNet [125] and AFINN [126]. In addition to classifying sentiments of tweets into positive and negative, study of Nagy et al. [109] could be used to detect information-based tweets as a way to increase credibility of the post. Using different features such as bag of words, pruning features and lexicon based ones, authors in [110] train a sentiment classifier to categorize messages based on level of concern. Then they leverage trained classifier for understanding public perception towards disasters by investigating relation of sentiment and demographic features including location, gender and time. The authors use Hurricane Irene dataset for evaluation.

Dong et al. [111] develop a prototype to automatically collect, analyze and visualize live disaster related social media data from Twitter and also studies how individuals on Twitter react to disaster. Finally they utilize Granger causality analysis [127] to correlate positive/negative sentiments of users on Twitter with distance of Hurricane Sandy approaching the disaster location. Another study on Hurricane Sandy is [112] where proposes a fine-grained sentiment analysis using machine learning classifiers, SVM, Naive Bayes Binary and Multinomial model to distinguish crisis-related micro-posts from irrelevant information. In particular, all of the tweets have been preprocessed to remove irrelevant terms and features and extract general categories from microposts using OpenCalais API[6] and also to handle abbreviations based on noslang dictionary[7]. Then, several features are extracted including bag of words, part of speech tags, n-grams, emoticons, and sentiment features which are obtained from AFINN and SentiWordNet word list. The proposed method identifies seven emotion classes anger, disgust, fear, happiness, sadness, and surprise. Likewise, after collecting Hurricane Sandy relevant tweets, authors in [113] annotate the tweets with one of four sentiment labels, positive, fear, anger and other using SVM and Naïve Bayes. As opposed to [112, 109], Caragea et al. [114] classify tweets sentiments into three classes of positive, negative and neutral associating tweet geo-location to demonstrate general mood on the ground. Authors identify the sentiments of tweets by applying machine learning techniques on the combination of bag of words and sentiment features such as emoticons, acronyms and polarity clues as the feature representation provided to the classifier. Then they assigns locations of tweets to their sentiments to show how sentiments of users change

[6]http://www.opencalais.com

[7]http://noslang.com

with respect to relative distance from the disaster. Mapping disaster information helps response organizations to have a real time map which shows population's response to disaster using sentiment analysis as a measure.

Using Japan earthquakes as a case study, Vo et al. [117] track crowd emotions during earthquake in microblog posts. The authors consider 6 different emotion classes namely calm, unpleasantness, sadness, anxiety, fear, and relief. Then it deploys two machine learning classifier for identifying earthquake related tweets and also classification of them based on the expressed emotions. By tracking crowd sentiment, Vo et al. [117] conclude that fear and anxiety are two emotions that users express right after the events while calm and unpleasantness are not exposed clearly during small earthquakes but in the large tremor. As an another case study of sentiment analysis for disaster management, authors in [116] apply sentiment analysis methods on Kenya Westgate Mall attack dataset to assess and understand how emergency organizations use social media to improve their responses. They study the difference between sentiment of posts published by emergency organizations and managers and deploy document-level sentiment analysis of TwitterMate which utilizes Alchemy API[8] [39]. Authors also apply statistical t-test to confirm that managers posts have more positive sentiment than organizations' as they are considered more approachable by the public due to the positive language of their posts. Similar to other machine learning techniques, considering eight types of emotions including accusation, anger, disgust, fear, happiness, sadness, surprise, and no emotion, Torkildson et al. [118] classify Gulf Oil Spills event related tweets using ALOE [128] which deployed SVM.

Buscaldi et al. [119] use subjectivity, polarity and irony detection tool named as IRADABE proposed in [129] (which is based on SVM) to identify event related tweets. They assumed that subjective tweets are more likely from a person who is involved in the event, ironic tweets are posted after the event to criticize or blame and event-related tweets have more negative sentiments rather than day-to-day ones. The authors extracted tweets related to 2014 Genoa Floodings to analyze how sentiment analysis and natural language processing methods affect extracting useful information. Another study [120] investigates the impact of disasters on the underlying sentiment of social media streams. In more details, it explores the underlying trends in positive and negative sentiment with respect to the disasters and geographically related sentiments. In particular, it first proposes an uncertainty measure to evaluate the disagreement among multiple sentiment classifiers SentiwordNet [130], SentriStrength [131] and CoreNLP [132] using vote entropy and then uses a committee vote scheme to decide on a Tweet's sentiment class [133]. Due to the vast amount of information published in social media during an event, problem reports and corresponding aid messages were not successfully exchanged most of the time. Therefore, many resources would be wasted and victims would not received necessary aids. So discovering matches between problem reports and aid agencies facilitate communication between victims and humanitarian organizations.Varga et al. [121] try to solve problem of aid and problem report messages recognition and matching using machine learning techniques by considering different features such as lexicon, semantic and sentiment features.

Furthermore, information flow during catastrophic events such as hurricanes is a critical

[8]http://www.alchemyapi.com/

part of disaster management.In an attempt, authors in [115] analyze sentiments of over 50 million tweets before, during and after Hurricane Sandy to study people's behavior changes in Twitter based on the times hurricane reached different cities in terms of number of published posts and expressed sentiments in their tweets. They observe that sentiment of tweets deviate from those of normal ones and conclude that analyzing sentiments from tweets, along with other metrics enables use of sentiment sensing for detecting and locating disasters. Authors use three different methods, Topsy [134], Linguistic Inquiry and Word Count(LIWC) [135] and SentiStrength as sentiment detection algorithms. Other than machine learning techniques, there exist some other methods which are developed for sentiment analysis in disaster management. For example, Chakraborty et al. [122] model the evolution of social dynamics, sentiment, opinion and views of people after a major event. They use swarm intelligence technique to identify the dynamic and time bound property of social events.

## 3.3 Visual Analytics

Besides disaster related data management in social media, the ability to drawing out important features is essential for better and quick understanding of situation which leads to rapid decision making in critical situations. Moreover, the data produced by social media during disasters and events, is staggering and hard for an individual to process. Therefore, visualization is needed for facilitating pattern discovery [136]. Using visualization, people can find their answers regarding the disasters more quickly and they will figure out where they should look for to find their answers more easily.

Some of the methods that have been introduced previously such as [111, 113, 114, 118, 120], develop visualization tools to increase meaningfulness of analysis. Dong et al. [111] develop a prototype to visualize automatically collected and analyzed live disaster data from Twitter using word clouds, spatial maps and dynamic online activity graphs. Fig.5 is an example of how the proposed visualization tool utilized on Hurricane Sandy dataset. Authors in [113] simply visualize proportion of messages classified with different labels and [114] maps sentiment of disaster-related tweets to their locations and visualize it on a geographical map to have a real time analysis of population's response to disaster.Fig.6 shows maps of tweets sentiment analyzed by [114] in global and regional scale. Another study [118] displays the frequency of emotion labels during different hours of each event while example tweets of each label are also shown to make sense about the event. Authors in [120] develop a visual analytics framework for analyzing and modeling sentiment on disaster related Twitter data. They particularly uses Ebola Twitter dataset in order to evaluate their visual analytic framework. The proposed framework is particularly useful for exploring the patterns of sentiment distributions and also comparing between the distributions. Fig.7 depicts results of sentiment analysis and visualization on Ebola dataset where blurred circles show high sentiment uncertainty.

The main challenge in crisis-related social media data visualization, is the immediate analysis of data for emergency management. For example, Calderon et al. [105] design a visual analytics prototype to support real-time analysis of sentiment in social media in emergency management. The proposed model addresses three domain-specific issues as follows:


**Figure 5: Visualization Tool applied on Hurricane Sandy corpus. Reprinted with permission from [111].**

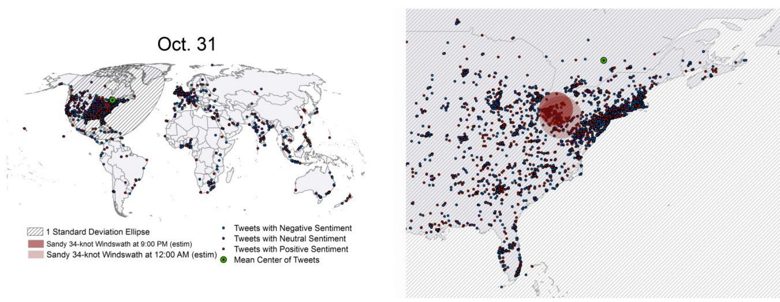


**Figure 6: Maps of Positive, Neutral, and Negative Tweets at global and regional scale during Hurricane Sandy. Reprinted with permission from [114].**

dealing with high volume of generated social media data during disaster, real-time extraction of relevant features and analysis and visualization of social media streams in the absence of critical attributes e.g. geo-location when real-time analysis is needed. It uses animation to represent time update considering the dynamic nature of stream data. SentiStrength [132] is applied as an algorithm for sentiment analysis.Fig.8 shows screenshots generated by the proposed dynamic visualization prototype.

We summarize the recent works in application of sentiment analysis in disaster relief with highlighting their datasets, approaches and reported accuracies in table 2. We distinguish between studies with and without visualization abilities.

# 4 Discussions and Future Directions

This chapter presented an overview of sentiment analysis in social media and how it could be leveraged for disaster relief during emergencies and disasters. We covered state-of-the-art sentiment analysis approaches and highlight their contributions and then discussed the application of social media and sentiment analysis in disaster relief and situational aware-

| Paper | dataset | Approach | Evaluation | Visualization |
|---|---|---|---|---|
| [89] | OK Fire; Red River flood 2009-2010; Haiti earthquake | Maximum Entropy | 88% (Accuracy) | |
| [105] | Hurricane Sandy | SentiStrength | 20% (Accuracy for animation visualization) | ✓ |
| [109] | California gas explosion and resulting fires | Bayesian Networks | 94.9% (FScore) | |
| [110] | Hurricane Irene | Maximum Entropy | 84.27% (Accuracy) | |
| [111] | Hurricane Sandy | Granger Causality Analysis | - | ✓ |
| [112] | Hurricane Sandy | Binary Naïve Bayes | 65.8% (Accuracy) | |
| [113] | Hurricane Sandy | Support Vector Machine | 75.3% (Accuracy) | ✓ |
| [114] | Hurricane Sandy | Support Vector Machine | 75.91% (Accuracy) | ✓ |
| [115] | Hurricane Sandy | Topsy, LIWC, SentiStrength | - | |
| [116] | Kenya Westgate Mall attack | Alchemy API | - | |
| [117] | Japan Earthquakes | Multinomial Naïve Bayes | 87.8% (FScore) | |
| [118] | Gulf Oil Spill | Support Vector Machine | 91% (Accuracy) | ✓ |
| [119] | 2014 Genoa Floodings | IRADABE Tool | 66% (Accuracy) | |
| [120] | Ebola | SentiWordNet, SentiStrength, CoreNLP | - | ✓ |
| [122] | Terrorist attack in Mumbai | Swarm Intelligence Technique | - | |

**Table 2: Recent approaches in the application of sentiment analysis in disaster relief along with their datasets and applied methods. Methods applying visualization are check marked. Some studies may have reported different accuracies in their original papers.**

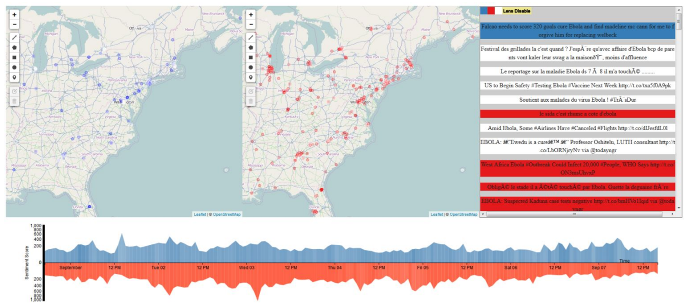

**Figure 7: Sentiment analysis and visualization overview on Ebola Twitter dataset. The two maps are used for geo-comparison view. The list on the right depicts ordered Tweets by retweet count. The bottom view is entropy sentiment river. Reprinted with permission from [120].**

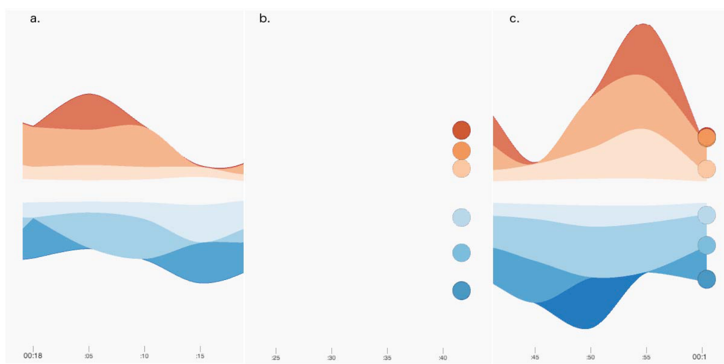


**Figure 8: Screenshots from 3 animations used to represent a stream of emergency-related tweets classified by sentiment analysis. Reprinted with permission from [105].**

ness, while we also detailed applications of visual analytics with an emphasis on sentiment analysis. In this section we discuss some of the challenges facing the studies in sentiment analysis and its application in disaster relief, as well as visual analytics, as potential research directions for further considerations.

Despite few works that have exploited network information such as followee-follower networks and @-networks for more accurate sentiment analysis, majority of the works have not incorporated such useful information; they have considered the problem of sentiment analysis with solely taking into account the lexicon or linguistic based features. One potential avenue of future work is to deploy extra information such as emotional correlation information including spatial-temporal patterns and homophily effect as a measurement of sentiment of social media posts. For example, during winters, people in Florida are expected to be happier than people in Wisconsin. Also, homophily effect suggest that similar people might behave in a more similar way than other people regarding a specific event. Moreover, as the task of collecting sentiment labels in social media is extremely time consuming and tedious, unsupervised or semi-supervised approaches are required to reduce the cost of sentiment classification. Although some studies have addressed this issue, the literature is premature in this realm and still lacks strong contributions. For example, future studies could explore the contributions of other available emotion indications in social media such as product ratings and reviews.

Most studies in disaster relief have used plain machine learning techniques with simple lexicon features. Therefore, more complex machine learning based approaches along with stronger features are required. Furthermore, leveraging the findings of psychological and sociological studies on individuals' behaviors (e.g. hope, fear) during disasters, could be another interesting research direction. This additional information could help better understand people's behaviors and feelings during disasters and also help decision makers know how they can handle this situation. Investigating how this information could be preprocessed to be immediately usable by corresponding authorities, is another interesting future research direction. Furthermore, visualization techniques need to be improved to allow for real time visual analytics of disasters related posts in order to help first responders easily track the changes during disasters and make proper and quick decisions.

# 5 Acknowledgments

This material is based upon the work supported by, or in part by, Office of Naval Research (ONR) under grant number N000141410095, the NSF under Grant Number 1350573, and the U.S. Department of Homeland Security's VACCINE Center under Award Number 2009-ST-061-CI0001.

# References

[1] Reza Zafarani, Mohammad Ali Abbasi, and Huan Liu. *Social media mining: an introduction*. Cambridge University Press, 2014.

[2] Jure Leskovec, Daniel Huttenlocher, and Jon Kleinberg. Predicting positive and negative links in online social networks. In *Proceedings of the 19th international conference on World wide web*, pages 641–650. ACM, 2010.

[3] G. Beigi, M. Jalili, H. Alvari, and G. Sukthankar. Leveraging community detection for accurate trust prediction. In *ASE International Conference on Social Computing*, June 2014.

[4] Jiliang Tang, Xia Hu, and Huan Liu. Social recommendation: a review. *Social Network Analysis and Mining*, 3(4):1113–1133, 2013.

[5] Hamidreza Alvari, Alireza Hajibagheri, and Gita Sukthankar. Community detection in dynamic social networks: A game-theoretic approach. In *Advances in Social Networks Analysis and Mining (ASONAM), 2014 IEEE/ACM International Conference on*, pages 101–107. IEEE, 2014.

[6] Michaela Goetz, Jure Leskovec, Mary McGlohon, and Christos Faloutsos. Modeling blog dynamics. Citeseer, 2009.

[7] Hamidreza Alvari, Sattar Hashemi, and Ali Hamzeh. Discovering overlapping communities in social networks: A novel game-theoretic approach. *AI Communications*, 26(2):161–177, 2013.

[8] Bruce R. Lindsay. Social Media and Disasters: Current Uses,Future Options, and Policy Considerations. Technical report, Congressional Research Service, September.

[9] Alfredo Cobo, Denis Parra, and Jaime Navón. Identifying relevant messages in a twitter-based citizen channel for natural disaster situations. In *Proceedings of the 24th International Conference on World Wide Web Companion*, pages 1189–1194, 2015.

[10] Huiji Gao, Geoffrey Barbier, and Rebecca Goolsby. Harnessing the crowdsourcing power of social media for disaster relief. *IEEE Intelligent Systems*, (3):10–14, 2011.

[11] Shamanth Kumar, Fred Morstatter, and Huan Liu. *Twitter data analytics*. Springer, 2014.

[12] Bing Liu. *Sentiment Analysis and Opinion Mining*. Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, 2012.

[13] Tetsuya Nasukawa and Jeonghee Yi. Sentiment analysis: Capturing favorability using natural language processing. In *Proceedings of the 2nd International Conference on Knowledge Capture*, K-CAP '03, pages 70–77, New York, NY, USA, 2003. ACM.

[14] Bo Pang and Lillian Lee. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2(1-2):1–135, January 2008.

[15] Sanjiv Das and Mike Chen. Yahoo! for amazon: Extracting market sentiment from stock message boards. In *Asia Pacific Finance Association Annual Conf. (APFA)*, 2001.

[16] Satoshi Morinaga, Kenji Yamanishi, Kenji Tateishi, and Toshikazu Fukushima. Mining product reputations on the web. In *Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*, pages 341–349, 2002. Industry track.

[17] Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. Thumbs up?: sentiment classification using machine learning techniques. In *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*, pages 79–86. Association for Computational Linguistics, 2002.

[18] Richard M. Tong. An operational system for detecting and tracking opinions in on-line discussion. In *Proceedings of the Workshop on Operational Text Classification (OTC)*, 2001.

[19] Peter D. Turney. Thumbs up or thumbs down? semantic orientation applied to unsupervised classification of reviews. *CoRR*, cs.LG/0212032, 2002.

[20] Janyce Wiebe. Learning subjective adjectives from corpora. In Henry A. Kautz and Bruce W. Porter, editors, *AAAI/IAAI*, pages 735–740. AAAI Press / The MIT Press, 2000.

[21] Gary Carlson. Review of "subjective understanding, computer models of belief systems by jaime g. carbonell"; umi research press, ann arbor michigan copyright 1981. *SIGART Bull.*, (80):12–12, April 1982.

[22] Yorick Wilks and Janusz Bien. Beliefs, points of view and multiple environments. In *Proc. the International NATO Symposium on Artificial and Human Intelligence*, pages 147–171, New York, NY, USA, 1984. Elsevier North-Holland, Inc.

[23] Marti Hearst. Direction-based text interpretation as an information access refinement. In Paul Jacobs, editor, *Text-Based Intelligent Systems*, pages 257–274. Lawrence Erlbaum Associates, 1992.

[24] Alison Huettner and Pero Subasic. Fuzzy typing for document management. In *ACL 2000 Companion Volume: Tutorial Abstracts and Demonstration Notes*, pages 26–27, 2000.

[25] Warren Sack. On the computation of point of view. In *Proceedings of the Twelfth National Conference on Artificial Intelligence (Vol. 2)*, AAAI'94, pages 1488–, Menlo Park, CA, USA, 1994. American Association for Artificial Intelligence.

[26] Janyce Wiebe and Rebecca Bruce. Probabilistic classifiers for tracking point of view. In *Working Notes of the AAAI Spring Symposium on Empirical Methods in Discourse Interpretation*, 1995.

[27] Janyce M. Wiebe. Identifying subjective characters in narrative. In *Proceedings of the 13th Conference on Computational Linguistics - Volume 2*, COLING '90, pages 401–406, Stroudsburg, PA, USA, 1990. Association for Computational Linguistics.

[28] Janyce M. Wiebe. Tracking point of view in narrative. *Comput. Linguist.*, 20(2):233–287, June 1994.

[29] Janyce M. Wiebe, Rebecca F. Bruce, and Thomas P. O'Hara. Development and use of a gold-standard data set for subjectivity classifications. In *Proceedings of the 37th Annual Meeting of the Association for Computational Linguistics on Computational Linguistics*, ACL '99, pages 246–253, Stroudsburg, PA, USA, 1999. Association for Computational Linguistics.

[30] Janyce Wiebe and William J. Rapaport. A computational theory of perspective and reference in narrative. In Jerry R. Hobbs, editor, *ACL*, pages 131–138. ACL, 1988.

[31] Efthymios Kouloumpis, Theresa Wilson, and Johanna Moore. Twitter sentiment analysis: The good the bad and the omg! *ICWSM*, 11:538–541, 2011.

[32] Guang Qiu, Bing Liu 0001, Jiajun Bu, and Chun Chen. Expanding domain sentiment lexicon through double propagation. In Craig Boutilier, editor, *IJCAI*, pages 1199–1204, 2009.

[33] Mike Thelwall, Kevan Buckley, and Georgios Paltoglou. Sentiment in twitter events. *Journal of the American Society for Information Science and Technology*, 62(2):406–418, 2011.

[34] Chenhao Tan, Lillian Lee, Jie Tang, Long Jiang, Ming Zhou, and Ping Li. User-level sentiment analysis incorporating social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1397–1405. ACM, 2011.

[35] Xia Hu, Lei Tang, Jiliang Tang, and Huan Liu. Exploiting social relations for sentiment analysis in microblogging. In *Proceedings of the sixth ACM international conference on Web search and data mining*, pages 537–546. ACM, 2013.

[36] Jichang Zhao, Li Dong, Junjie Wu, and Ke Xu. Moodlens: an emoticon-based sentiment analysis system for chinese tweets. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1528–1531. ACM, 2012.

[37] Xia Hu, Jiliang Tang, Huiji Gao, and Huan Liu. Unsupervised sentiment analysis with emotional signals. In *Proceedings of the 22nd international conference on World Wide Web*, pages 607–618. International World Wide Web Conferences Steering Committee, 2013.

[38] Duyu Tang, Furu Wei, Nan Yang, Ming Zhou, Ting Liu, and Bing Qin. Learning sentiment-specific word embedding for twitter sentiment classification. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics, ACL 2014, June 22-27, 2014, Baltimore, MD, USA, Volume 1: Long Papers*, pages 1555–1565, 2014.

[39] Hassan Saif, Yulan He, and Harith Alani. Semantic sentiment analysis of twitter. In *The Semantic Web–ISWC 2012*, pages 508–524. Springer, 2012.

[40] Onur Kucuktunc, B Barla Cambazoglu, Ingmar Weber, and Hakan Ferhatosmanoglu. A large-scale sentiment analysis for yahoo! answers. In *Proceedings of the fifth ACM international conference on Web search and data mining*, pages 633–642. ACM, 2012.

[41] Liang Wu, Yuanchun Zhou, Fei Tan, Fenglei Yang, and Jianhui Li. Generating syntactic tree templates for feature-based opinion mining. In *Advanced Data Mining and Applications*, pages 1–12. Springer, 2011.

[42] Robert E Schapire and Yoram Singer. Boostexter: A boosting-based system for text categorization. *Machine learning*, 39(2):135–168, 2000.

[43] Mike Thelwall, Kevan Buckley, Georgios Paltoglou, Di Cai, and Arvid Kappas. Sentiment strength detection in short informal text. *Journal of the American Society for Information Science and Technology*, 61(12):2544–2558, 2010.

[44] Minqing Hu and Bing Liu. Mining and summarizing customer reviews. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 168–177. ACM, 2004.

[45] Bin Fu, Jialiu Lin, Lei Li, Christos Faloutsos, Jason Hong, and Norman Sadeh. Why people hate your app: Making sense of user feedback in a mobile app store. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1276–1284. ACM, 2013.

[46] Johan Bollen, Huina Mao, and Xiaojun Zeng. Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1):1–8, 2011.

[47] P. Hennig, P. Berger, C. Lehmann, A. Mascher, and C. Meinel. Accelerate the detection of trends by using sentiment analysis within the blogosphere. In *Advances in Social Networks Analysis and Mining (ASONAM), 2014 IEEE/ACM International Conference on*, pages 503–508, Aug 2014.

[48] Christopher D Manning and Hinrich Schütze. *Foundations of statistical natural language processing*. MIT press, 1999.

[49] Kamal Nigam, John Lafferty, and Andrew McCallum. Using maximum entropy for text classification. In *IJCAI-99 workshop on machine learning for information filtering*, volume 1, pages 61–67, 1999.

[50] Nello Cristianini and John Shawe-Taylor. *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press, 2000.

[51] Theresa Wilson, Paul Hoffmann, Swapna Somasundaran, Jason Kessler, Janyce Wiebe, Yejin Choi, Claire Cardie, Ellen Riloff, and Siddharth Patwardhan. Opinionfinder: A system for subjectivity analysis. In *Proceedings of hlt/emnlp on interactive demonstrations*, pages 34–35. Association for Computational Linguistics, 2005.

[52] Christopher D Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven J Bethard, and David McClosky. The stanford corenlp natural language processing toolkit. In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 55–60, 2014.

[53] Miller McPherson, Lynn Smith-Lovin, and James M Cook. Birds of a feather: Homophily in social networks. *Annual review of sociology*, pages 415–444, 2001.

[54] Robert P Abelson. Whatever became of consistency theory? *Personality and Social Psychology Bulletin*, 1983.

[55] Elaine Hatfield, John T Cacioppo, and Richard L Rapson. *Emotional contagion*. Cambridge university press, 1994.

[56] Jerome Friedman, Trevor Hastie, and Robert Tibshirani. *The elements of statistical learning*, volume 1. Springer series in statistics Springer, Berlin, 2001.

[57] Alec Go, Richa Bhayani, and Lei Huang. Twitter sentiment classification using distant supervision. *CS224N Project Report, Stanford*, 1:12, 2009.

[58] Jonathon Read. Using emoticons to reduce dependency in machine learning techniques for sentiment classification. In *Proceedings of the ACL student research workshop*, pages 43–48. Association for Computational Linguistics, 2005.

[59] Chris Ding, Tao Li, Wei Peng, and Haesun Park. Orthogonal nonnegative matrix t-factorizations for clustering. In *Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 126–135. ACM, 2006.

[60] Jerome H Friedman. Greedy function approximation: a gradient boosting machine. *Annals of statistics*, pages 1189–1232, 2001.

[61] Jerry Ye, Jyh-Herng Chow, Jiang Chen, and Zhaohui Zheng. Stochastic gradient boosted distributed decision trees. In *Proceedings of the 18th ACM conference on Information and knowledge management*, pages 2061–2064. ACM, 2009.

[62] Yuheng Hu, Fei Wang, and Subbarao Kambhampati. Listening to the crowd: automated analysis of events via aggregated twitter sentiment. In *Proceedings of the Twenty-Third international joint conference on Artificial Intelligence*, pages 2640–2646. AAAI Press, 2013.

[63] Yuheng Hu, Ajita John, Fei Wang, and Subbarao Kambhampati. Et-lda: Joint topic modeling for aligning events and their twitter feedback. In *AAAI*, volume 12, pages 59–65, 2012.

[64] Alexandra Balahur, Ralf Steinberger, Mijail Kabadjov, Vanni Zavarella, Erik Van Der Goot, Matina Halkia, Bruno Pouliquen, and Jenya Belyaeva. Sentiment analysis in the news. *arXiv preprint arXiv:1309.6202*, 2013.

[65] Junghoon Chae, Dennis Thom, Harald Bosch, Yun Jang, Ross Maciejewski, David S Ebert, and Thomas Ertl. Spatiotemporal social media analytics for abnormal event detection and examination using seasonal-trend decomposition. In *Visual Analytics Science and Technology (VAST), 2012 IEEE Conference on*, pages 143–152. IEEE, 2012.

[66] Jian Zhao, Nan Cao, Zhen Wen, Yale Song, Yu-Ru Lin, and Christopher M Collins. # fluxflow: Visual analysis of anomalous information spreading on social media. *Visualization and Computer Graphics, IEEE Transactions on*, 20(12):1773–1782, 2014.

[67] Yafeng Lu, Feng Wang, and Ross Maciejewski. Business intelligence from social media: A study from the vast box office challenge. *Computer Graphics and Applications, IEEE*, 34(5):58–69, 2014.

[68] Michelle L Gregory, Deborah Payne, David McColgin, Nicolas Cramer, and Douglas Love. Visual analysis of weblog content. In *ICWSM*, 2007.

[69] Michelle L Gregory, Nancy Chinchor, Paul Whitney, Richard Carter, Elizabeth Hetzler, and Alan Turner. User-directed sentiment analysis: Visualizing the affective content of documents. In *Proceedings of the Workshop on Sentiment and Subjectivity in Text*, pages 23–30. Association for Computational Linguistics, 2006.

[70] Michael Gamon, Anthony Aue, Simon Corston-Oliver, and Eric Ringger. Pulse: Mining customer opinions from free text. In *Advances in Intelligent Data Analysis VI*, pages 121–132. Springer, 2005.

[71] Marc A Smith and Andrew T Fiore. Visualization components for persistent conversations. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 136–143. ACM, 2001.

[72] Kamal Nigam, Andrew Kachites McCallum, Sebastian Thrun, and Tom Mitchell. Text classification from labeled and unlabeled documents using em. *Machine learning*, 39(2-3):103–134, 2000.

[73] Daniela Oelke, Ming Hao, Christian Rohrdantz, Daniel Keim, Umeshwar Dayal, Lars-Erik Haug, Halldór Janetzko, et al. Visual opinion analysis of customer feedback data. In *Visual Analytics Science and Technology, 2009. VAST 2009. IEEE Symposium on*, pages 187–194. IEEE, 2009.

[74] Dongxu Duan, Weihong Qian, Shimei Pan, Lei Shi, and Chuang Lin. Visa: a visual sentiment analysis system. In *Proceedings of the 5th International Symposium on Visual Information Communication and Interaction*, pages 22–28. ACM, 2012.

[75] Furu Wei, Shixia Liu, Yangqiu Song, Shimei Pan, Michelle X Zhou, Weihong Qian, Lei Shi, Li Tan, and Qiang Zhang. Tiara: a visual exploratory text analytic system. In *Proceedings of the 16th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 153–162. ACM, 2010.

[76] Brett Adams, Dinh Phung, and Svetha Venkatesh. Eventscapes: visualizing events over time with emotive facets. In *Proceedings of the 19th ACM international conference on Multimedia*, pages 1477–1480. ACM, 2011.

[77] Adam Marcus, Michael S Bernstein, Osama Badar, David R Karger, Samuel Madden, and Robert C Miller. Twitinfo: aggregating and visualizing microblogs for event exploration. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 227–236. ACM, 2011.

[78] Alexander Hubmann-Haidvogel, Adrian MP Brasoveanu, Arno Scharl, Marta Sabou, and Stefan Gindl. Visualizing contextual and dynamic features of micropost streams. 2012.

[79] E. Shook, K. Leetaru, Guofeng Cao, A. Padmanabhan, and Shaowen Wang. Happy or not: Generating topic-based emotional heatmaps for culturomics using cybergis. In *E-Science (e-Science), 2012 IEEE 8th International Conference on*, pages 1–6, Oct 2012.

[80] Debby Guha-Sapir, Femke Vos, Regina Below, and Sylvain Ponserre. Annual disaster statistical review 2010. *Centre for Research on the Epidemiology of Disasters*, 2011.

[81] Yelena Mejova, Ingmar Weber, and Michael W Macy. *Twitter: A Digital Socioscope*. Cambridge University Press, 2015.

[82] Mark Glaser. California wildfire coverage by local media, blogs, twitter, maps and more. *PBS MediaShift*, 2007.

[83] Kate Starbird, Leysia Palen, Amanda L Hughes, and Sarah Vieweg. Chatter on the red: what hazards threat reveals about the social life of microblogged information. In *Proceedings of the 2010 ACM conference on Computer supported cooperative work*, pages 241–250. ACM, 2010.

[84] Jeannette Sutton, Leysia Palen, and Irina Shklovski. Backchannels on the front lines: Emergent uses of social media in the 2007 southern california wildfires. In *Proceedings of the 5th International ISCRAM Conference*, pages 624–632. Washington, DC, 2008.

[85] Sarah Vieweg, Amanda L Hughes, Kate Starbird, and Leysia Palen. Microblogging during two natural hazards events: what twitter may contribute to situational awareness. In *Proceedings*

*of the SIGCHI conference on human factors in computing systems*, pages 1079–1088. ACM, 2010.

[86] Yan Qu, Philip Fei Wu, and Xiaoqing Wang. Online community response to major disaster: A study of tianya forum in the 2008 sichuan earthquake. In *System Sciences, 2009. HICSS'09. 42nd Hawaii International Conference on*, pages 1–11. IEEE, 2009.

[87] Yan Qu, Chen Huang, Pengyi Zhang, and Jun Zhang. Microblogging after a major disaster in china: a case study of the 2010 yushu earthquake. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, pages 25–34. ACM, 2011.

[88] Takeshi Sakaki, Fujio Toriumi, Kenji Uchiyama, Yoshikazu Matsuo, Kazuma Shinoda, Kazuhiro Kazama, Seiji Kurihara, and Itsuki Noda. The possibility of social media analysis for disaster management. In *Humanitarian Technology Conference (R10-HTC), 2013 IEEE Region 10*, pages 238–243. IEEE, 2013.

[89] Sudha Verma, Sarah Vieweg, William J Corvey, Leysia Palen, James H Martin, Martha Palmer, Aaron Schram, and Kenneth Mark Anderson. Natural language processing to the rescue? extracting" situational awareness" tweets during mass emergency. In *ICWSM*. Citeseer, 2011.

[90] Teun Terpstra, A de Vries, R Stronkman, and GL Paradies. Towards a realtime twitter analysis during crises for operational crisis management. In *Proceedings of the 9th international ISCRAM conference, Vancouver, Canada*, 2012.

[91] Fred Morstatter, Nichola Lubold, Heather Pon-Barry, Jürgen Pfeffer, and Huan Liu. Finding eyewitness tweets during crises. *arXiv preprint arXiv:1403.1773*, 2014.

[92] Muhammad Imran, Shady Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. Practical extraction of disaster-relevant information from social media. In *Proceedings of the 22nd international conference on World Wide Web companion*, pages 1021–1024. International World Wide Web Conferences Steering Committee, 2013.

[93] Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. Earthquake shakes twitter users: real-time event detection by social sensors. In *Proceedings of the 19th international conference on World wide web*, pages 851–860. ACM, 2010.

[94] Hongmin Li, Nicolais Guevara, Nic Herndon, Doina Caragea, Kishore Neppalli, Cornelia Caragea, Anna Squicciarini, and Andrea H Tapia. Twitter mining for disaster response: A domain adaptation approach.

[95] Muhammad Imran, Shady Mamoon Elbassuoni, Carlos Castillo, Fernando Diaz, and Patrick Meier. Extracting information nuggets from disaster-related messages in social media. *Proc. of ISCRAM, Baden-Baden, Germany*, 2013.

[96] Soudip Roy Chowdhury, Muhammad Imran, Muhammad Rizwan Asghar, Sihem Amer-Yahia, and Carlos Castillo. Tweet4act: Using incident-specific profiles for classifying crisis-related messages. In *10th International ISCRAM Conference*, 2013.

[97] Brandon Truong, Cornelia Caragea, Anna Squicciarini, and Andrea H Tapia. Identifying valuable information from twitter during natural disasters. *Proceedings of the American Society for Information Science and Technology*, 51(1):1–4, 2014.

[98] Zahra Ashktorab, Christopher Brown, Manojit Nandi, and Aron Culotta. Tweedr: Mining twitter to inform disaster response. *Proc. of ISCRAM*, 2014.

[99] Anirban Sen, Koustav Rudrat, and Saptarshi Ghosh. Extracting situational awareness from microblogs during disaster events.

[100] Marcelo Mendoza, Barbara Poblete, and Carlos Castillo. Twitter under crisis: Can we trust what we rt? In *Proceedings of the first workshop on social media analytics*, pages 71–79. ACM, 2010.

[101] Ntalla Athanasia and Ponis T Stavros. Twitter as an instrument for crisis response: The typhoon haiyan case study.

[102] Alan M MacEachren, Anthony C Robinson, Anuj Jaiswal, Scott Pezanowski, Alexander Savelyev, Justine Blanford, and Prasenjit Mitra. Geo-twitter analytics: Applications in crisis management. In *25th International Cartographic Conference*, pages 3–8, 2011.

[103] Shamanth Kumar, Geoffrey Barbier, Mohammad Ali Abbasi, and Huan Liu. Tweettracker: An analysis tool for humanitarian and disaster relief. In *ICWSM*, 2011.

[104] Fred Morstatter, Shamanth Kumar, Huan Liu, and Ross Maciejewski. Understanding twitter data with tweetxplorer. In *Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1482–1485. ACM, 2013.

[105] Nadya Calderon, Richard Arias-Hernandez, Brent Fisher, et al. Studying animation for real-time visual analytics: A design study of social media analytics in emergency management. In *System Sciences (HICSS), 2014 47th Hawaii International Conference on*, pages 1364–1373. IEEE, 2014.

[106] Alan M MacEachren, Anuj Jaiswal, Anthony C Robinson, Scott Pezanowski, Alexander Savelyev, Prasenjit Mitra, Xiao Zhang, and Justine Blanford. Senseplace2: Geotwitter analytics support for situational awareness. In *Visual Analytics Science and Technology (VAST), 2011 IEEE Conference on*, pages 181–190. IEEE, 2011.

[107] Donghao Ren, Xin Zhang, Zhenhuang Wang, Jing Li, and Xiaoru Yuan. Weiboevents: a crowd sourcing weibo visual analytic system. In *Pacific Visualization Symposium (PacificVis), 2014 IEEE*, pages 330–334. IEEE, 2014.

[108] Fabian Abel, Claudia Hauff, Geert-Jan Houben, Richard Stronkman, and Ke Tao. Semantics + filtering + search = twitcident. exploring information in social web streams. In *Proceedings of the 23rd ACM Conference on Hypertext and Social Media*, HT '12, pages 285–294, New York, NY, USA, 2012. ACM.

[109] Ahmed Nagy and Jeannie Stamberger. Crowd sentiment detection during disasters and crises. In *Proceedings of the 9th International ISCRAM Conference*, pages 1–9, 2012.

[110] Benjamin Mandel, Aron Culotta, John Boulahanis, Danielle Stark, Bonnie Lewis, and Jeremy Rodrigue. A demographic analysis of online sentiment during hurricane irene. In *Proceedings of the Second Workshop on Language in Social Media*, pages 27–36. Association for Computational Linguistics, 2012.

[111] Han Dong, Milton Halem, and Shujia Zhou. Social media data analytics applied to hurricane sandy. In *Social Computing (SocialCom), 2013 International Conference on*, pages 963–966. IEEE, 2013.

[112] Axel Schulz, T Thanh, H Paulheim, and I Schweizer. A fine-grained sentiment analysis approach for detecting crisis related microposts. *ISCRAM 2013*, 2013.

[113] Joel Brynielsson, Fredrik Johansson, and Anders Westling. Learning to classify emotional content in crisis-related tweets. In *Intelligence and Security Informatics (ISI), 2013 IEEE International Conference on*, pages 33–38. IEEE, 2013.

[114] Cornelia Caragea, Anna Squicciarini, Sam Stehle, Kishore Neppalli, and Andrea Tapia. Mapping moods: geo-mapped sentiment analysis during hurricane sandy. *Proc. of ISCRAM*, 2014.

[115] Yury Kryvasheyeu, Haohui Chen, Esteban Moro, Pascal Van Hentenryck, and Manuel Cebrian. Performance of social network sensors during hurricane sandy. *PLoS one*, 10:e0117288–e0117288, 2015.

[116] Tomer Simon, Avishay Goldberg, Limor Aharonson-Daniel, Dmitry Leykin, and Bruria Adini. Twitter in the cross firethe use of social media in the westgate mall terror attack in kenya. 2014.

[117] BKH Vo and NIGEL Collier. Twitter emotion analysis in earthquake situations. *International Journal of Computational Linguistics and Applications*, 4(1):159–173, 2013.

[118] Megan K Torkildson, Kate Starbird, and Cecilia Aragon. Analysis and visualization of sentiment and emotion on crisis tweets. In *Cooperative Design, Visualization, and Engineering*, pages 64–67. Springer, 2014.

[119] Davide Buscaldi and Irazú Hernandez-Farias. Sentiment analysis on microblogs for natural disasters management: a study on the 2014 genoa floodings. In *Proceedings of the 24th International Conference on World Wide Web Companion*, pages 1185–1188. International World Wide Web Conferences Steering Committee, 2015.

[120] Yafeng Lu, Xia Hu, Feng Wang, Shamanth Kumar, Huan Liu, and Ross Maciejewski. Visualizing social media sentiment in disaster scenarios. In *Proceedings of the 24th International Conference on World Wide Web Companion*, pages 1211–1215. International World Wide Web Conferences Steering Committee, 2015.

[121] István Varga, Motoki Sano, Kentaro Torisawa, Chikara Hashimoto, Kiyonori Ohtake, Takao Kawai, Jong-Hoon Oh, and Stijn De Saeger. Aid is out there: Looking for help from tweets during a large scale disaster. In *ACL (1)*, pages 1619–1629, 2013.

[122] Bishwajit Chakraborty and Sean Banerjee. Modeling the evolution of post disaster social awareness from social web sites. In *Cybernetics (CYBCONF), 2013 IEEE International Conference on*, pages 51–56. IEEE, 2013.

[123] Ellen Riloff and Janyce Wiebe. Learning extraction patterns for subjective expressions. In *Proceedings of the 2003 conference on Empirical methods in natural language processing*, pages 105–112. Association for Computational Linguistics, 2003.

[124] Janyce Wiebe and Ellen Riloff. Creating subjective and objective sentence classifiers from unannotated texts. In *Computational Linguistics and Intelligent Text Processing*, pages 486–497. Springer, 2005.

[125] Andrea Esuli and Fabrizio Sebastiani. Sentiwordnet: A publicly available lexical resource for opinion mining. In *Proceedings of LREC*, volume 6, pages 417–422. Citeseer, 2006.

[126] Finn Årup Nielsen. A new anew: Evaluation of a word list for sentiment analysis in microblogs. *arXiv preprint arXiv:1103.2903*, 2011.

[127] Clive WJ Granger. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, pages 424–438, 1969.

[128] Michael Brooks, Katie Kuksenok, Megan K Torkildson, Daniel Perry, John J Robinson, Taylor J Scott, Ona Anicello, Ariana Zukowski, Paul Harris, and Cecilia R Aragon. Statistical affect detection in collaborative chat. In *Proceedings of the 2013 conference on Computer supported cooperative work*, pages 317–328. ACM, 2013.

[129] Irazú Hernandez-Farias, Davide Buscaldi, and Belém Priego-Sánchez. Iradabe: Adapting english lexicons to the italian sentiment polarity classification task. In *First Italian Conference on Computational Linguistics (CLiC-it 2014) and the fourth International Workshop EVALITA2014*, pages 75–81, 2014.

[130] Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In *LREC*, volume 10, pages 2200–2204, 2010.

[131] Richard Socher, Alex Perelygin, Jean Y Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the conference on empirical methods in natural language processing (EMNLP)*, volume 1631, page 1642. Citeseer, 2013.

[132] Mike Thelwall, Kevan Buckley, and Georgios Paltoglou. Sentiment strength detection for the social web. *Journal of the American Society for Information Science and Technology*, 63(1):163–173, 2012.

[133] Ido Dagan and Sean P Engelson. Committee-based sampling for training probabilistic classifiers. In *Proceedings of the Twelfth International Conference on Machine Learning*, pages 150–157, 1995.

[134] Topsy labs (2012) topsy website., Available: http://www.topsylabs.com. Accessed 2012 Nov 20.

[135] James W Pennebaker, Martha E Francis, and Roger J Booth. Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Associates*, 71:2001, 2001.

[136] Daniel M Best, Joseph R Bruce, Scott T Dowson, Oriana J Love, and Liam R McGrath. Web-based visual analytics for social media. Technical report, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2012.