Communities of Sentiment around Man-Made Disasters: Lessons from the West Virginia Chemical Leak

Research-in-Progress

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Abstract

Twitter provides a platform for users to engage in microblogging around events that happen to them in their everyday lives. This research examines the sentiment of groups of users of the Twitter platform, and their reaction to a man-made disaster due to negligence instead of the typical examination within the context of a natural disaster. The groups of users’ sentiment to be analyzed include individuals, communities, businesses, and governments.

Introduction

What are the sentiments, of individuals and communities of individuals, that are the outcome of the organic growth of a discussion enabled by social media around a man-made disaster? Messages in social media manifest themselves as either positive or negative, depending on the context in which the messages are used in discourse. Hyperconnectivity afforded by social media such as Twitter played a significant role in the Arab Spring as well as in Fukushima disaster (Choudhary, Hendrix, Lee, Palsetia, & Liao, 2012; Lim, 2012; Papacharissi & de Fatima Oliveira, 2012; Tufekci & Wilson, 2012) demonstrating its potential for social movements that can lead to political and policy changes at the national level. But it is not clear what role social media plays in local man-made disasters and how sentiments of people affected by these events are reflected in social media. The objective of this research in progress is to investigate such a development.

On January 9th, 2014, it was announced that the company Freedom Industries had leaked a “large amount” of a toxic chemical into the Kanawha River of Charleston, West Virginia (Mistich, Marra, & Associated Press, 2014). Given the location of this chemical plant in relation to the water intake for the water company that supplies water to 300,000 citizens in the metro area, the water supply was contaminated with a toxic chemical, leaving those 300,000 citizens, as well as businesses in the area, without clean water for more than a week. It is critical that we understand the discourse that develops around these sudden and unanticipated disaster events with little or no advanced warnings. For example, if such an event occurred in a large city with millions of people then such an event can render emergency response ineffective. In this context, it is critical that we develop a better understanding of the discourse that develops quickly around these unanticipated disasters so that a possible early warning system can be developed to protect affected citizens and help emergency personnel. To this end, in this paper, we propose a theoretical model and provide some early analysis related to this effort.

We identify several factors from existing literature around responses to disasters. These factors include: alarm, reassurance, and doubt (Li, Vishwanath, & Rao, 2014; Speckens AEM, Spinhoven, Van Hemert, & Bolk, 2000). To further examine this discussion and to answer the research question around the organic growth aspect, this research identifies the individual, business, community, and government entities as actors engaged in discourse around the man-made disaster.

More specifically, this research has employed a script that has collected the data around several keywords pertaining to the disaster before it happened, and then modified the collection to include the keywords...
that emerged as the disaster was happening. This emergence of keywords based on the time-series collection of data can offer new insight as to how users of social media platforms share evolving information around a disaster. By collecting more keywords as more information emerges from the disaster, this also allows for the collection around a government’s response to the disaster.

With the data collected, several coding schemes are proposed based on theory, which will enable for both semantic as well as sentiment analysis of these users of social media engaged in the discussion around the water spill disaster. Since this is ongoing research, as the event is relatively new and the discussion and damage to the chemical and water company is ongoing, the focus of this paper will be around the data and the coding scheme.

The structure of the paper is as follows. The next section will talk in depth about the event that happened based on known information from the company press releases, the state government of West Virginia, and the United States National Guard, as well as form theoretical foundations that will enable coding the data. After this background discussion, the methodology for collecting the data, the structure of the data itself, and coding the data will be offered. From there, a discussion of the initial findings in the data will be presented. The paper will conclude with a section on future work, discussing the next steps in this research project.

**Background and Theoretical Foundations**

This section details the timeline of events surrounding the chemical spill into the public water system, also referred to as the disaster. By detailing the timeline of events as learned by the Associated Press, Reuters, and other news agencies, and tying them to theory, this will enable sentiment analysis and modeling of user’s perceptions from the data collected via Twitter.

**Literature Review**

With the actual events detailed, this research now turns to the literature to understand what work has been done around the topic of social media and political unrest, social media and business responses, and social media and community responses. The literature review has been conducted around the notion of influence and influencers in social media, whether it is citizen protests against a government, or the efficacy of a message via the social media medium.

The dominant topic from this literature review emerged from data collected around the 2009 protests in Egypt; that topic is that of political unrest being examined via social media data. In one study, the evolution of the revolution was tracked using twitter (Choudhary et al., 2012) and examined the frequency of tweets and retweets; in the same vein, another study looked at the patterns of news story telling via the #Egypt hashtag and employed computational discourse analysis (Papacharissi & de Fatima Oliveira, 2012). Following the domain of political unrest against a government, another study examines social media data in a broader context to include Facebook, Youtube, blogs, emails, and text messages to identify the key factors in the oppositional movements of Egypt from 2004-2011 (Lim, 2012). In another example, researchers looked at the information sharing via twitter in relation to the London Riots using descriptive statistics (Tonkin, Pfeiffer, & Tourte, 2012).

Similar to political unrest, research has been conducted around the efficacy of government-originating messages to the population via social media. In the first example in this vein of research, it was identified that emotional reactions of users engaged in social media help to explain approval rates during that same time period offering a correlation between agenda setting and political evaluation (González-Bailón, Banchs, & Kaltenbrunner, 2012). From other work, evidence is found that social media has a predictive impact on elections as well (Conover, Ratkiewicz, & Francisco, 2011; Tumasjan, Sprenger, Sandner, & Welpe, 2010).

Yet, there are business implications as well when examining the political culture of social media. Research has examined how businesses operating around and in these environments react. In one example, research examined user agreements, corporate interests, and information infrastructure around several different politically motivated interests (Youmans & York, 2012).
Next, there is the need to look at how events influence the formation of messages using social media platforms such as Twitter. Research has examined social media as a platform to check the velocity of information, and compare it to traditional media (Chua, Razikin, & Goh, 2010). Chua et al offered four findings: the performance of using spikes and bursts to detect news events was comparable, the news events detected had a measurable lag time, the news that traditional media focused on was not always of interest to social media, and lastly and most importantly, social media around a news event using a hashtag shows a proclivity towards a local context. Similarly, Weng and Lee found these bursts in their data as well, when looking for signal auto-correlations in Twitter data while trying to identify event detection (Weng & Lee, 2011).

Lastly, this research looks to examine the methods employed by the aforementioned researchers in examining their social media content. What is found is that sentiment analysis, as well as content analysis, are the dominant methodologies, while including descriptive statistics (Bae & Lee, 2012; Bollen, Mao, & Pepe, 2011; Choudhary et al., 2012; Pang & Lee, 2008; Thelwall, 2011; Tumasjan et al., 2010). From these methodologies, coding schemes are adopted, based on theoretical constructs; what is discovered is that the coding schemes typically account for both positive as well as negative messages (Bae & Lee, 2012; Bollen et al., 2011; Speckens AEM et al., 2000).

While all of the aforementioned research looks at different political, governmental, and business motives, there exists a gap: what are the sentiments around the business which causes a disaster that affects other individuals, businesses, communities, and government. Going forward, this research has identified theoretical foundations to bridge this gap and extend this line of research.

**Theoretical Foundations**

In research similar to this, examining the Twitter response to the Fukushima disaster, researchers had identified three coding categories for the data: alarm, reassurance, and doubt (Li et al., 2014). Their coding scheme was based on prior psychometric theory that examines positive and negative statements (Speckens AEM et al., 2000). In the Fukushima research, it is important to note that it was a naturally occurring incident that triggered the disaster with a massive tsunami. For the disaster that this research examines, it has been identified as negligence on behalf of the chemical company that spilled the chemical. This key difference lends itself to examination under the proposed theoretical lens since the causes are entirely man-made as opposed to naturally occurring.

In another study, researchers found that there that Twitter may contribute to situational awareness (Vieweg, Hughes, Starbird, & Palen, 2010). Situational awareness is defined as the helpful processes and strategies for those seeking awareness in emergency situations. From the work around situational awareness enabled via Twitter, it was found that there are three phases: preparation (pre-warning), warning, and response to warning, and that each of these phases have a personal and a community component around it. In the same manner, this research upon completion will look at the personal and community aspects of the situational awareness. Looking at the community metric, this can be broken down into the local community, local businesses, and government as well. These theoretical foundations offer the ground floor for preparing a sentiment analysis based on alarm, reassurance, and doubt, and identifying the origins and outcomes of those messages.
Figure 1. Theoretical Framework for Sentiment Analysis of Tweets

This research framework will be used to answer the original question, what are the sentiments around the business that caused a man-made disaster? The previous research and theory has identified there are three groups engaging in the discussion: individuals, communities (not for profit, and businesses), and government entities. The messenger will then convey a sentiment through the medium, which will then either be shared, or extended. To complete the framework, from the growth of the message onward to sentiment, this research turns to a corpus of network data and textual data gathered from Twitter. In order to test this theoretical framework, a methodology around this textual data is offered next.

**Methodology**

Given data sets like the one that is analyzed in this paper, research typically looks at the volume to tweets over a timespan, as well as the top influencers, using either retweets as a metric, or volume of tweets from that user (Acar & Muraki, 2011; Li et al., 2014; Mills & Chen, 2009). As such, and given that this research is still in its early stages, this research as it progresses will explore both of these metrics, as well as conduct a sentiment analysis on the dataset.

Sentiment analysis has been used on Twitter data in the past (Choudhary et al., 2012; Pang & Lee, 2008). Sentiment analysis, in essence, will reveal the attitude of the person sending the tweet. This type of textual data is verbose in that regard, but does require a coding scheme, as well as inter-rater reliability. The coding scheme for this data will be adopted from the theoretical foundations in that of: alarm, reassurance, and doubt. Using the identified theoretical framework, the data will be grouped upon four dimensions: personal situational awareness, community situational awareness, business situational awareness, and government situational awareness. From this grouping, the analysis can proceed by examining the social connectivity in terms of who is directly communicating with whom via the text of the data that is captured. With the groupings and the connections identified, the reach of any specific tweet within these groupings can be measured, and from that reach, the sentiment of the actor who is discussing
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it can be coded. This sentiment coding will be based on that of alarm, reassurance, and doubt. More interestingly, the sentiment of the messages from the groupings identified by awareness will also be coded.

In order to identify the sentiments around alarm, reassurance, or doubt, this research will employ a support vector machines algorithm (SVM) to analyze the data based on the prior work within these sentiments. Part of the work that remains is manually creating the training list for the SVM. By employing a SVM approach, clusters will be identified based on the timeline of events around the disaster and evidence will be offered of how these clusters of sentiments formed and shifted in the discussion of the disaster.

With this methodology, the research can then tie back to the theoretical framework to identify if the clusters around alarm, reassurance, and doubt, within the networks of individual, business, and community. This lends to a quantitative methodology, which will identify three clusters from the data and how they are networked together: individual, business, government, and community. From within these clusters, the polarity of the sentiment will also be assessed. Adding another dimension to the analysis, the research will also examine the awareness, reassurance, and doubt, and the degree to which these sentiments influence the respective networks of individual, business, government, and community.

**The Data**

*Background of Events around the Water Disaster*


On January 9th, at 8:15AM Eastern Standard Time, the Charleston Gazette which is a local newspaper to the Charleston, WV area, was reporting a liquorish smell in the air (“Timeline: West Virginia Chemical Spill - WSJ.com,” 2014). At 10:30AM on January 9th, it was discovered that there was a chemical leaking from a storage tank, upriver from the water intake for the water supply of the residents of the Charleston area. At 11:15AM, the West Virginia Department of Environmental Protection pinpoint the source of the leak to a chemical tank owned by Freedom Industries; the company responds by saying there is no risk. At 6:00PM EST, the governor of West Virginia announces that the water supply has been tainted, and that the water is undrinkable.

On January 10th, President Barack Obama issues a federal disaster declaration and deploys the National Guard to supply the area with drinkable water (Ward Jr. & Gutman, 2014). Freedom Industries holds a press conference to apologize for the spill, and state they are working with the government.

On January 11th, the water company, West Virginia American Water, states that it has developed a test to determine if the water is safe for consumption, based on 1 particle per million of the chemical in the water.

On January 12th, there are 10 people admitted to the hospitals and another 169 treated and released for symptoms associated with consuming the chemical that was spilled into the water, with reports of up to 500 more individuals calling the poison-control center.

On January 13th, the state of West Virginia announce that the chemical has largely dissipated and that the ban is being partially lifted. It was announced the same day that the chemical had reached the Ohio River and was showing up in the Chesapeake, OH water supply.

On January 14th, the West Virginia legislative body announces investigations into the chemical spill(??). On January 16th, it was learned by the Associated Press, that newly released records around the site of the chemical spill detailed five inspections of the site since 2001, but the inspections focused on air quality, not the containment of the chemical itself.

On January 17th, the water was officially restored to the 300,000 individuals who had lost their water, using the chemical test developed for safety.
While this is the official timeline of events, the doubt around the safety of the water remained, as evidenced in the data. Because this doubt remained, there is a need to apply a theoretical lens in the foundations around this data.

This research examines data collected directly from Twitter’s Search 1.1 API (“GET search/tweets | Twitter Developers,” n.d.). In order to capture the data for more than seven days, as Twitter’s API only allows for a rolling seven-day search, a small script was developed to query the Twitter Search API, and take the JSON results and store them in a local MySQL database. This script was executed every 45 seconds to query the Twitter API, and stored the last TweetID as a primary key, in order to capture the next set of tweets and ensure that there is no repetition.

<table>
<thead>
<tr>
<th>Keyword</th>
<th>Total Number of Tweets Collected</th>
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<tbody>
<tr>
<td>wv</td>
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<tr>
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<td>west virginia</td>
<td>520,842</td>
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<td>wvwaterrisis</td>
<td>30,779</td>
</tr>
<tr>
<td>Total</td>
<td>1,286,498</td>
</tr>
</tbody>
</table>

Table 1. Results of Keyword Gathering
12/1/2013-2/19/2014

The power behind this dataset is that the data scraper was already running on several of the keywords before the chemical spill was known, for the purposes of other research. Along with these keywords that are being collected, several other keywords of interest include: “coal”, “wvpol”, “wva”, “wva.”, “tomblin”, and “governor tomblin”; these keywords could yield potential as this research progresses. The relevance of this dataset can be found in the emergence of several of the keywords from the incident coupled with the script collecting data in realtime during the Search API’s seven day window. This is made evident in the “wvchemleak” and “wvwaterrisis” keywords.

The data collection is still ongoing, as at the time of this writing, it has been less than two months since the contamination of the water. Once the data is fully collected, a sentiment analysis will also be conducted and included in the results.

**Initial Results**

This research aims to create a sensing metric to assess the impact of a disaster by taking the textual information that can be found on social media and analyzing the discussion. With this particular disaster, which affected the water supply, there are two imminent implications: the first is to consumers, and the second is to businesses, which rely on clean water for operation (restaurants, fast food, etc.) With that in mind, some initial results are offered below, based on the volume of discussion around this particular disaster.

The first graph is a graph modeling the volume of tweets per day one week before the disaster, up to the disaster, and afterwards, on the keyword ‘wv.’ This graph is provided to get a sense of the volume of
tweets around the keyword ‘wv’ a week before the crisis, during the crisis, and after the crisis. The total number of tweets for this graph includes 393,837 tweets. This keyword provides evidence of the individuals engaged in a discussion around wv, whether they be associated with the government, or businesses; it provides more of a broad control and base for the data itself, as well as examining the volume of tweets to get a sense of the influence of a man-made disaster on the community discussion.

This specific graph is useful with the research is still in progress because it is a general and aggregate keyword which would involve all of the actors and sentiments around a general discussion, not contextualized to the man-made disaster. In essence, this provides a 'control' to test the sentiment on a broad scale.

The second graph is a graph modeling the volume of tweets per day one day before the disaster, up to the disaster, and afterwards, on the keyword ‘wvchemleak.’ The total number of tweets assessed was 36,170 over the duration of January 9th, 2014 to February 19th, 2014. This data allows for a closer examination of the event itself, as well as a focused keyword for more in-depth sentiment analysis. With both the #wv and the #wvchemleak dataset being collected at the same time from Twitter’s API, we get a sense of the community at large, as well as the community engaged in the discussion. This specific data set will allow for a more robust sentiment analysis.
The third graph is a graph modeling the volume of tweets per day one week before the disaster, up to the disaster, and afterwards, on the two prior keywords, wv and wvchemleak. This chart is using a stacked line graph, in order to show that there is evidence of a discussion in both the general community, as well as in the focused community.

**Figure 4. Stacked Line of #Wvchemleak and #wv hashtag frequency.**
Discussion

Based on the graph of ‘wvchemleak, it is of particular interest to see a spike above 1000 tweets that day, up from 500 the previous day when looking at the dates between January 27th and January 29th. Why this is particularly interesting, is that the President’s State of the Union address was on that day (“President Obama’s 2014 State of the Union Address | The White House,” 2014). This would suggest that there is evidence in the textual data using the #wvchemleak hashtag to suggest that the individuals who engage in using that hashtag are politically motivated. The implication that there is an underlying political motive suggests that the community of government and their response will play an important role when assessing the sentiment.

Moreover, what can be found by looking at the simple volume of tweets from this data that is currently being collected, is that the discussion about the state itself follows the same pattern as the discussion around the chemical leak. The general discussion of the broader community is also engaging in the discussion of the chemical leak. A criticism of the initial findings would suggest that a user can use both hash-tags in the same message; while that is true, it would lend further evidence that the broader community is discussing the man-made disaster.

With this evidence, the research can then turn to coding the tweets themselves based on group membership, as identified in the theoretical foundation, as well as sentiment of the tweets. What this will reveal, is not only the engagement of each group, but also how each group reacts at certain points throughout the timeline of the disaster as more information is revealed by the business that caused the disaster.

Future Work

Once the data has been collected over the duration of 90 days, an examination of the most influential messages and messengers will first take place. Parallel to this examination of the most popular messages, the aforementioned sentiment analysis will be conducted. This sentiment analysis will focus around the individual and community aspects of the messages being shared, and if those messages are focused in a positive or negative light. The community aspects will be broken down into three separate concepts: the local community, the business community, and the government. The results from this analysis will yield insight into the positivity or negativity of the users engaged in the discussion around the chemical leak via social media, and if that discussion is framing communities, businesses, and/or governments in a positive light.

The contribution of this research to practice will be three fold. First, the contribution around individual awareness and alarm of a disaster by using social media will be modeled from the data; the same goes for community as well as business awareness. Secondly, the reassurance and the dissemination of that reassurance around the disaster will also be explicated. Lastly, identification of the sentiment of doubt in the network will be explicated from the data, and the directionality of that doubt within the three clusters to be analyzed.

Conclusions

Social media has created voices for those who otherwise would not have a voice. While the context may change, the message is clear that it has empowered individuals when they feel something is wrong. Sometimes, it can be a company that has wronged individuals; sometimes it can be a government that has wronged individuals. This research aims to explore the intersection of the two, in which the government, working with a company, tries to address righting this wrong, and also explore the user’s sentiments around this effort.

References


GET search/tweets | Twitter Developers. (n.d.). Retrieved February 27, 2014, from https://dev.twitter.com/docs/api/1.1/get/search/tweets


