Identifying First Responder Communities through Social Network Analysis of Disaster-Related Traffic

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Abstract. First responder communities across disciplines are in constant pursuit of appropriate technologies and methods to help save lives, protect the public, and deliver their services more safely. Responders in the coming years will be challenged with identifying technologies that are most effective (and cost-effective) in performing duties ranging from law enforcement to emergency medical to fire fighting, and training professionals to use those technologies properly. Technology researchers can help define and deliver the needed technologies by helping to gather and understand responders' requirements in a timely way. Social media provides a bridge that could span the gap between the first responder and research communities. In this poster we present our work applying social network analysis to the problem of identifying first responders sub-communities within the universe of Twitter users and identifying current topics and active stakeholders within them. We describe the design and prototyping of a set of visualization-driven interactive tools that form a "dashboard" for interacting with aggregated data to perform focused social network analysis.

Keywords: first responders, emergency response, network analysis

1 Introduction

First responder communities across disciplines are in constant pursuit of appropriate technologies and methods to help save lives, protect the public, and deliver their services more safely. Responders in the coming years will be challenged with identifying technologies that are most effective (and cost-effective) in performing duties ranging from law enforcement to emergency medical to fire fighting, and training professionals to use those technologies properly. Technology researchers can help define and deliver the needed technologies by helping to gather and understand responders' requirements in a timely way. Social media provides a bridge that could span the gap between the first responder and research communities.
In this report we present our work on applying social network analysis to the problem of locating sub-communities of first responders within the universe of Twitter users and identifying current topics and active stakeholders within them. We describe the design and prototyping of a set of visualization-driven interactive tools that form a "dashboard" for interacting with aggregated data to perform focused social network analysis. Our objective is to create a repeatable set of methods that can be applied to the Twitter universe to carry out the initial stages of a requirements gathering process and to identify principles that are applicable to other social media platforms. Based on proof-of-concept tools utilizing live data, an infrastructure can be defined to support a more operational capability for first responder requirements analysis leveraging social networks.

By "first responder" we refer to those individuals who, in the early stages of an incident, are responsible for the protection and preservation of life, property, evidence, and the environment; as well as emergency management, public health, clinical care, public works, and other skilled support personnel that provide immediate support services during prevention, response, and recovery operations. Our interests are not specifically in the direct use of social networks for disaster response — this is an active area of study by others, including Cohen et.al — but rather in how network analysis of community interactions before, during and after disasters can be used to identify roles within the community, thought leaders, significant contributors, and their topics of discussion. Our focus has been on evaluating the effectiveness of current social media analysis techniques for the specific task of identifying first responder communities; examining tools and techniques for identifying potential requirements stakeholders within those networks; and seeking to understand current social media practices and platforms in use by the first responders community.

![Fig. 1. Depiction of Prototype First Responders Social Network Analysis Workflow](image-url)
The First Responders Social Network Analysis Workflow prototyped by the RPI team (see Figure 1) is not fully automated, but has proved effective in assisting researchers as they try to make sense of the vast quantity of information moving through Twitter at any given moment. The end goal is to identify stakeholders in the community with whom we can engage for whatever participatory design task is deemed necessary for a particular requirements gathering activity. The TWC RPI visualization tools therefore present aspects of first responder related Twitter data and metadata in a manner that reduces the overall information the researcher must process, enabling the researcher to identify both Twitter users of interest and topics and times of interest so that the tools parameters may be altered as necessary to keep up with the quickly-changing environment of social media.

2 Identifying Communities

The TW RPI team employed the Twitter Search API to locate tweets containing one or more hashtags from a list of 17 hashtags known to be relevant to and identified by the first responder community. The first event studied, the February 2013 east coast winter storm unofficially named "Nemo," provided an opportunity to collect data over the span of several days. Since Nemo was an anticipated event — those expecting to be affected by the storm knew it ahead of time — citizens and officials were able to prepare, and the Twitter conversation developed well before the storm hit. The second event the RPI team studied was the Boston Marathon bombing on April 15, 2013. Conversations on Twitter regarding this tragedy naturally evolved in a different manner, as the event was sudden and unexpected.

Plots of tweet volume over time may help identify time intervals that are likely to contain discussions of significant events. To this end, Figure 2 displays Twitter activity over a period of nine days in February 2013. Each column in the chart represents the total number of tweets to a specific hashtag for a specific date and time. Each vertical bar represents roughly two hours, with taller bars indicating a higher tweet volume during that time period.

With this interactive visualization users are able to "zoom" the horizontal time axis in order to focus on dates and times of interest and view the data.
Fig. 2. Plotting Nemo: Twitter volume over nine days for a specific hashtag

at a higher temporal granularity. Conversations on social media are in constant flux, and events can cause rapid changes. In prolonged disaster situations such as winter storm Nemo, a rise or fall in Twitter volume related to a particular hashtag can be an indicator of an evolving situation. In sudden and unexpected events such as the Boston Marathon bombings, a sudden increase in tweets may even be one of the first indicators to an outside researcher that something has occurred.

A dramatic increase in the volume of tweets including a particular hashtag indicates an increase of interest and a deliberate effort by the community to have engage in a conversation about that topic. Certain hashtags that are in constant use, such as #wx for weather reports, may grow in response to particular events. In the case of Winter Storm Nemo, the event was expected and those concerned had time to tweet prior to the event as well as during it.

Interest can arise over time in anticipation of an event, as in the case of the winter storm or suddenly in response to an unexpected event, such as the Boston Marathon bombing. Visualizing tweet volume over time for hashtags related to an event can help pinpoint chronologically when an event emerges as an important topic on Twitter. The interactive tool depicted in Figures 3 and 4 demonstrates one way users can interact with the results of topic models based on analysis of the Twitter data. In this tool each pie slice represents an emergent topic, named using the most prevalent hashtags occurring in that topic. The popup list of hashtags (on the right in Figure 3 and detailed in Figure 4) enables the user to see other hashtags that are more loosely related to the topic.

6 Topic models are algorithms for discovering the main themes that pervade a large and otherwise unstructured collection of documents and can be used to organize the collection according to the discovered themes. See esp [?].
The interface depicted in Figures 3 and 4 is based on probabilistic topic modeling applied to Twitter data related to the Boston Marathon bombing. The topic modeling evaluation is performed on the server using MALLET, an open source machine learning and text analysis tool developed by UMass Amherst. Since Twitter users may include multiple hashtags in a single tweet, topic modeling enables the user of the visual interface to view clusters of commonly co-occurring hashtags. In this way, users are able to identify other hashtags that might indicate a topic of interest.

See [http://mallet.cs.umass.edu/](http://mallet.cs.umass.edu/)
3 Identifying Hashtags of Interest

The selection of hashtags participants in Twitter conversations choose to use, and/or whether they use hashtags at all, depend upon their awareness and sense of urgency; flexibility in selecting which tags to follow is therefore important when attempting to identifying stakeholder communities. While some hashtags can be anticipated — "#wx" is based on a standard telegrapher’s code for weather — others are often suggested by companies or agencies in anticipation of an event or they may arise spontaneously as events unfold. To ensure that Twitter data is over the most complete and most relevant subset of tweets, some machine-learning analysis can help the user identify other hashtags that are topically related to the users area of interest.

Fig. 5. ICo-occurance matrix of Twitter users and Nemo hashtags of interest

[Diagram of ICo-occurance matrix]

8 The Weather Channel announced names and related hashtags for 2013-2014 winter storms at the beginning of the winter storm season. See http://bit.ly/1rdRmgF
Figure 5 presents a co-occurrence matrix with rows labelled by the Twitter account names of frequent users (along the left side) and columns labelled by hashtags (along the top). The color intensity of each cell indicates the relative frequency with which a given user has tweeted using a particular hashtag. Cells with darker intensity indicate more tweets, while lighter cells indicate fewer or no tweets. Browsing to an individual cell (i,j) will display the exact value of that intersection, e.g. the number of times user @j tweeted to hashtag #i. A summation across a given row correlates roughly to a user’s overall volume of tweets within the sample set, but this measure is not exact since a single tweet may contain multiple hashtags.

From a dataset of tweets gathered based generally on hashtags related to winter storm Nemo, a tool developed by the RPI team was used to count the occurrences of each hashtag in tweets from each Twitter user. Users were filtered by weighted entropy and a subset of users was selected to provide the most coverage over the hashtags of interest. For example, a user tweeting to #wx, #ny, and #travel is of greater interest than a user tweeting only to one of these tags. Once the users were selected and the counts of each hashtag occurrence determined, the parser generated a JSON file of this data. A visualization tool utilizing the popular d3.js library then generated the matrix based on this data.

The co-occurrence matrix is useful for gaining insights into overall frequency of hashtag use, as well as the activities of certain users. For example, #storm received more activity than #snowstorm in this subset of the data, and although @rightnowio feed had more tweets overall, @Ainiecarr tweeted to a greater variety of hashtags.

Initial parsing serves to identify Twitter users who frequently tweet to multiple hashtags among those determined to be of interest by the researcher. This is important because a prolific tweeter to a single general hashtag such as #traffic may not be discussing how the winter storms effects on it necessarily, but if their activity intersects with other hashtags known to be relevant such as #nemo, then they may be a better candidate.

The co-occurrence matrix alternately may be used to identify Twitter users’ interests or to identify hashtags of interest to individual Twitter users. This enables users of the tool to develop a more fine-grained understanding of individual topics, which can help pinpoint users of interest for further requirements gathering. For example, if a particular requirements gathering activity must focus specifically on New York City, the matrix visualization can help break down who among a set of prolific Twitter users included #nyc more frequently than hashtags related to other locations such as #boston or #ct.

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9 A custom parser implemented in Python

10 Explanation: The top twenty users were filtered by weighted entropy to produce a list of hashtags (number of times the user mentioned all hashtags) * (log2[counted number of hashtags they used on the list]). This resulted in a JSON file containing the co-occurrence matrix data, which was used to drive a d3.js visualization.

11 See [http://d3js.org/](http://d3js.org/)
4 Multi-modal Visualization Tools

Visualizations based on topic modeling and other numerical analysis such as those described earlier are useful for discovering patterns and trends in Twitter traffic and therefore may be important tools for identifying communities within the Twitterverse, but there may be situations where examination the network dynamics and specific context of Twitter conversations is necessary. In particular, it may be necessary to provide ways for users to move seamlessly from macro-scale visualizations to the micro-scale of individual tweets. To accommodate this span of analysis, "multi-modal" data visualizations are required. Figures 6 and 7 present one such tool, wherein at one level — "macro" — the propagation and reweeting of themes can be dynamically observed, while at another level — "micro" — individual tweets and associated media content can be examined.

Through colleagues we obtained 300,000 geocoded tweets mentioning Boston starting at the moment of the bombing. The selection criteria was that there was some mention of Boston, but necessarily an occurrence of hashtags. In order to depict reweet activity, we obtained reweet of the approximately 5000 original tweets that were reweeted at least once, as determined by searching on tweet ID; this produced approximately 10,000 retweets.

Each node in the graph represents an individual Twitter user. The size of a node at any given point in the animation relates to the number of retweets.
up to that point in (depicted) time. The animation plays back "live," based on
tweet timestamps. Nodes are colored based on hashtags; each node is assigned
one color based on the most popular hashtags within the data set.

![Figure 7.](figure7.png)

**Fig. 7.** Multi-modal visualization of Twitter activity during and after the Boston
Marathon bombing (details)

Examining this visualization more closely (Figure 7b) we see a snapshot rep-
resentation of users and their retweet activity during the first minutes and hours
after the Boston marathon bombing. We see in particular the difference in node
size, corresponding to the number of times that user had been retweeted during
the subset of the sample dataset depicted at that moment by the animation.
User nodes are linked by edges that represent actual retweet events.

This visualization is animated, with retweet activity replayed in proportional
real time. As each retweet "happens," the link is highlighted (and faded out
as time passes) and the tweet text is displayed below the graph. If the tweet
contains a photograph, the image and the tweet are displayed above the graph.
For convenience we display the network as a force directed graph; due to the large
aspect ratio and the fact that the graph is highly disconnected, each connected
subgraph is distributed randomly across the visual space by anchoring one node
per graph. This maintains an even distribution of nodes across the visual space
and avoids clumping into an ellipse. Tweets and user nodes are color-coded by
the hashtag used in the most recent retweet.

This tool demonstrated the potential value of "multi-model" visualization,
i.e. showing multiple views at once — the content of individual tweets, including
linked media, as well as the overall network — and over time, enabling users to better understand how certain pieces of information went viral.

5 Fitting Social Network Analysis into the Emergency Management Lifecycle

Ideally, communities of stakeholders from each phase of the emergency management lifecycle should be studied, so that potentially unique requirements may be gathered for each step. Of the four characteristic phases of disaster management — mitigation, preparedness, response, recovery — the "response" phase arguably provides the largest volume of data on Twitter, as evidenced by the volume of tweets increasing during and immediately after events in the northeastern United States related to Nemo, and nationwide after Boston; unfortunately it also produces the most "noise." Ideally, data collection across social networks should be happening constantly, both to provide rich context for potential events and because it is simply impossible to predict many disaster situations that first responders must deal with.

While data collection ideally can happen at any stage, the stage of most interest to a requirements gathering process itself is probably mitigation. As noted in [?], "(the mitigation) phase includes any activities that prevent an emergency, reduce the likelihood of occurrence, or reduce the damaging effects of unavoidable hazards. Mitigation activities should be considered long before an emergency." It is yet unclear how social networks might be monitored to identify communities of stakeholders during the mitigation phase using our current methods.

6 Passive vs Active monitoring of Twitter Activity

Passive monitoring provides a more coarse-grained sample of the Twitter data stream. Since disasters rarely can be anticipated, passive monitoring of user activity allows us to constantly monitor a "default" set of known first responder hashtags at all times so when an event such as a natural disaster does happen, it is likely we’ll have a useful if not perfect sample dataset.

Active monitoring, usually conducted after the fact in the event of a natural disaster, provides a deeper examination of user activity, including a focused examination of retweets and an investigation of "spontaneous" hashtags that emerge throughout the event. Active monitoring may extend to actual contact with stakeholders and included examination of incident reports or journaling and interactive, "flash" interviews. Incident reporting involves the candidate stakeholder filling out the details of their incident response through an online form or mobile app. Alternatively, an investigator may contact the candidate based on their monitored Twitter activity. Questions that might be considered during such an investigating include what usability requirements the subject is considering for their system.
7 Applying the Data Dashboard to Requirements Gathering

In this report we have described a set of prototype tools for analyzing social networks to identify communities of first responder participants and popular topics of discussion. We have focused on tools that leverage Twitter data, a convenient source of social media data produced by first responders.

The TWC RPI social network “dashboard” of network analysis and visualization tools can be used by requirements developers to interactively explore the social network activities of first responders, identify key contributors, collect information on key issues, and collect requirements “snippets” or user stories [?] from the community’s Twitter activity.

8 Discussion and Conclusions

The social network analysis and visualization tools the TWC RPI team has explored to date demonstrate methods of passive social network monitoring that help users discover ongoing topics of conversation among first responders on Twitter. These tools may be useful for understanding trends that stakeholders have expressed interest in through their engagement, but are somewhat limited in their ability to connect and engage the researcher with those end users. Future work should include extending these tools to expose and make actionable detailed user information, including which users are most active on pertinent hashtags, with an end goal being that those users who are highly involved in relevant conversations are stakeholders of interest in the first responder community.

Twitter is a rapidly-changing communications ecosystem, and the time-sensitive nature of any Twitter sample dataset requires that visualization tools such as our be more adept at filtering to specific time periods of interest. Future work should improve the researcher’s ability to browse in time; this will help shed light on the topics and the users discussing them at any particular moment, but will also enable the researcher to study how those conversations shift and evolve over time.

Recent events have demonstrated [?] that passive experiments and studies using social network data without user knowledge and consent may backfire when conducted contrary to user expectations, if not accepted policies. Further work in this area should carefully examine the social implications of this work and in particular seek to understand at what point, if any, researchers should seek informed consent from potential stakeholder candidates.

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