The Ripples of Fear, Comfort and Community Identity During the Boston Bombings

Yu-Ru Lin[1]
[1] University of Pittsburgh

Abstract
The Boston Marathon bombing event presents a rare opportunity to study how a massive disruptive event triggers emotional contagion. In this work, we use over 180 million geocoded tweets over an entire month to study how Twitter users expressed shared fear, comfort and community identity, over time and across different cities following the bombings. We quantify the level of shared fear by using the sentiment and time-series analyses. The expressions of comfort and community identity are studied based on the emergent use of two hashtags widely adopted after the bombings: #prayforboston and #bostonstrong. We found that these emotional responses varied with their geographical distances from the Boston area. However, statistical analyses show that users' direct experience of being in Boston predicts the shared fear better, and users' social networks are more effective in predicting the occurrences of expressing comfort and community identity. Our study has implication in identifying potentially vulnerable population, and predicting the perceived threat in the face of future massive disruptive events such as terrorist attacks.
Keywords: emergency response, collective activity, crisis management, emergent use of communication tools, social media and social networks
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Contact: yurulin@pitt.edu

1 Introduction

The bombing at the Boston Marathon on April 15, 2013 resulted in 3 deaths and more than 250 casualties. Over the subsequent week, the search for and apprehension of the suspects resulted in an area-wide manhunt and "lockdown" of Boston and neighboring suburbs.

Local and national news outlets continuously reported on the tragedy and the on-going threat. Intensive social media discussion were triggered by news reporting and by people witnessed or participated in the event in all sorts of ways. Over the first week, Boston area residents were immersed in the stories and aftermath of the bombings.

The news and social media response was soon intermingled with prideful news commentary about the heroic responses of Bostonians. Boston-area residents continue to be reminded of the event by media reports of the alleged bomber who was tried in a Boston court and "Boston Strong" community events such as the "Run to Remember" memorial foot-race and music concerts. Outside Boston, people showed support for Boston and the victims of the bomb attack. In New York, Yankees fans stood in the baseball stadium singing "Sweet Caroline," the Boston Red Sox anthem. In Chicago, more than 200 runners gathered for a run of solidarity. A week after the Boston Marathon, thousands of marathon runners in London wore a black ribbon in solidarity with the people of Boston. People around the country and over the world expressed concerns and comfort through Facebook and Twitter.

The marathon bombing presents a rare opportunity to examine how a serious, real-life, community-wide threat stirs up a shared perception of risk, a sense of empathy, as well as a sense of togetherness, solidarity or community identity.

In this work, we use Twitter communications related to the Boston bombings to study the extent to which people share fear, express comfort and community identity with the affected population during a massive destructive event. Social media sites like Twitter and Facebook has shown profound increases in traffic and information sharing during major events. The widespread use and semi-transparency of social media, Twitter in particular, makes people's public expressions more available to analysis than was conceivable a few years ago. On one hand, Tweet communication streams integrate the representative scope of polls and surveys with the free-form responses of focus groups and interviews; on the other hand, Twitter users are embedded within their usual social contexts rather than artificial contexts created by polls, focus groups, and other survey methods. The scope and sensitivity of Twitter has thus become an attractive means of measuring and assessing the responses of the public to events and information (Lin, Margolin, Keegan, & Lazer, 2013).

Twitter data have been mined in real time for temporal cues during political events (O'Connor, Balasubramanyan, Routledge, & Smith, 2010; Lin, Margolin, Keegan, Baronchelli, & Lazer, 2013), economic events (Bollen, Mao, & Zeng, 2011; O'Connor et al., 2010), and sports events (Nichols, Mahmud, & Drews, 2012). In particular, the massive outpouring of political communication on social media sites permits analysis of sentiment and topics during political events such as elections (O'Connor et al., 2010; Tumasjan, Sprenger, Sandner, & Welpe, 2010) and debates (Lin, Margolin, Keegan, & Lazer, 2013; Metaxas & Mustafaraj, 2012; Diakopoulos & Shamma, 2010). Twitter data have also been utilized as early detection systems for emerging public health problems (Aramaki, Maskawa, & Morita, 2011; Chew & Eysenbach, 2010; de Quincey & Kostkova, 2010). There has been considerable effort leveraging Twitter data for real-time emergency detection (Sakaki, Okazaki, & Matsuo, 2010; Guy, Earle, Ostrum, Gruchalla, & Horvath, 2010; Earle, Bowden, & Guy, 2012) and crisis management (Caragea et al., 2011; Li & Rao, 2010; Mendoza, Poblete, & Castillo, 2010). The use of Twitter during disaster events have been examined (Hughes & Palen, 2009; J. Sutton, Palen, & Shklovski, 2008; J. N. Sutton, 2010), and studies have shown that Twitter supports backchannel communication to address the information dearth problem in the face of disaster, though the spread of misinformation is also a concern (J. Sutton et al., 2008; J. N. Sutton, 2010). Recent study suggested social media may also offer potential psychological benefit for affected populations through participating in social media conversation (Keim, 2011).

In the context of an emergency or disaster, disruptive events refer to events which interrupt the normal functions of a community or business, and may result in harm (McAslan, 2011). In a disruptive event, a layperson's assessment of potential harm (i.e., perceived risk) is as important as the actual magnitude of harm assessed by experts, because people respond to their perceived risk, rather than the actual likelihood and severity of harm (McAslan, 2011), and their judgments can be biased by the perceived threat (Baumann & DeSteno, 2010). Using the case of Hurricane Katrina, Comfort showed how policy makers failed to communicate the urgency of the danger to their respective agencies without recognizing the severity of the threat and its likely consequences (Comfort & Haase, 2006).

The consequence following extraordinarily upsetting events have profound impact on people with direct or indirect exposure to the events and could affect how people function over time (Maguen, Papa, & Litz, 2008). For example, after the events of 9/11, although individuals may not have PTSD (post-traumatic stress disorder) or depression, they may ride the bus or fly less frequently or reduce social interactions with other people in public. The immediate and consequential psychosocial vulnerability may be overcome by community resilience, which has been characterized by prior research as a typical collective behavior, such as the emergent togetherness, solidarity, unity or "community spirit" observed in the 2005 London bombings (Drury, Cocking, & Reicher, 2009). Community resilience, including comforting and helping each other, is the ability of a human system to absorb disturbance and still retain its basic function and structure (Drury et al., 2009; McAslan, 2011).

This work fills an important gap in prior research on the understanding of shared sense after a massive disruptive event. A massive disruptive event often has far-reaching impact on large population, including victims, witnesses, and people not directly affected by the event. Most prior work focuses on the psychological impact on the directly affected population or the communication within the local community. (Drury et al., 2009; J. Sutton et al., 2008; J. N. Sutton, 2010). In this work, we attempt to characterize the Twitter communication among and outside local community in response to the Boston bombing event. We examine the two key components, perceived threat and community resilience, within and beyond the local community in Boston during this massive disruptive event. Using Twitter communication streams, we study people's perceived threat based on the detected fear expression in their public tweet messages, and we study community resilience based on the emergent use of words signaling comfort and community identity in their tweets. We believe the study will contribute to an understanding of how shared perception of risk and community resilience may be developed for potentially vulnerable population.

We focus on three research questions:

- To what extent Twitter users express fear that shares common characteristics with the affected population? How can we characterize the level of shared fear?
- To what extent Twitter users express comfort and community identity?
- What factors may explain different level of shared fear, and different level of interests in expressing comfort and community identity?

We discuss our method and analysis results in the following sections.

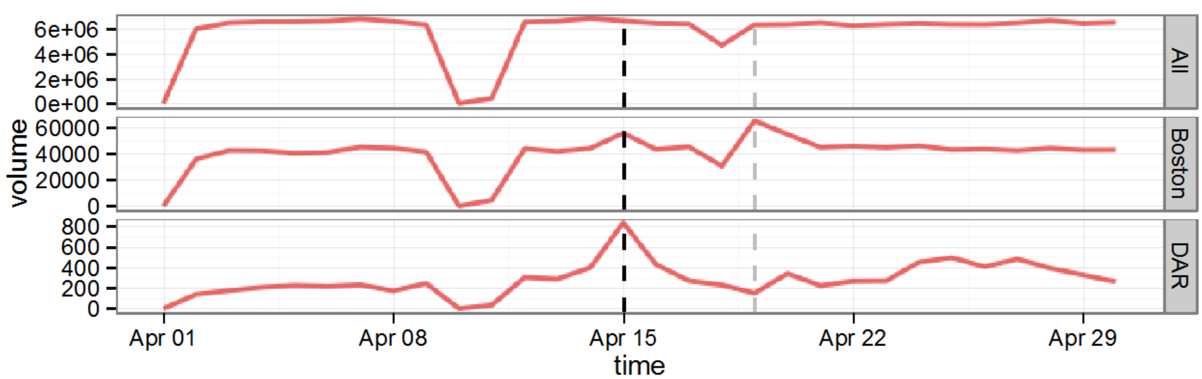

Figure 1: **Tweet daily volume in dataset.** The plot shows the daily number of geocoded tweets (volume) in our dataset. Tweets without geocodes are removed. From top to bottom: the total daily volume, the daily volume of tweets within the Boston area, and the daily volume of tweets within the direct affected region (DAR). The vertical dashed lines indicate the day of Boston bombings (April 15; black line) and the day of manhunt (April 19; gray line). The tweets posted on April 1, 10 and half-day on April 11 were missing due to data collection process errors.

2 Method and Results

2.1 Data Description

This project uses nearly all geotagged tweets collected from the Twitter Streaming API (Mostak & Lewis, 2012). Fig. 1 shows the total number of geocoded tweets (volume) per day over the month of April in the dataset. Tweets without geocodes (latitude and logitude) are removed. The vertical dashed lines indicate the day of Boston bombings (April 15; black line) and the day of manhunt (April 19; gray line). Due to data collection process errors, tweets posted on April 1, 10 and half-day on April 11 were missing. In the following analysis, volumes in the three missing days are excluded when reporting aggregated statistics. The total volume before, during and after the bombing day are 6.59M tweets/day on average, 6.69M tweets, and 6.36M tweets/day on average. Within the Boston area, the volume before, during and after the bombing day are 42370 tweets/day on average, 56131 tweets, and 45668 tweets/day on average.

Following the news reports (What *we know about the Boston bombing and its aftermath,* 2013), we manually identified direct affected region that covers the area of the two blasts. We refer to this approximately 0.55 km2 direct affected region as "DAR." Within DAR, the volume before, during and after the bombing day are 234 tweets/day on average, 832 tweets, and 331 tweets/day on average.

2.2 Detecting Fear

To study users' expression of fear, we incorporate sentiment analysis to extract different sentiments from the text in users' tweet messages. We use a concept-based affective lexicon SentiSence (de Albornoz, Plaza, & Gervas, 2012) to extract two different kinds of sentiments, fear and joy. Examples of fear related keywords include 'fearful', 'unkind', 'craziness', 'crime', 'shudder', 'suffocate', 'dreadfully', 'terror', 'fatal', 'crash', 'anxiously', 'erupt', etc. and joy related keywords include 'satisfied', 'cheerful', 'comfortableness', 'cruise', 'pleased', 'happiness', 'joyful', 'belonging', 'exult', 'rejoicing', 'eagerly', 'fortunate', etc. We compute the relative strength of a sentiment within a region as follows. Let L be the list of all words in the sentiment lexicon, and L_{fear} and L_{joy} be the lists of fear- and joy-related words, respectively. The degree of a kind of sentiment $c \in \{fear, joy\}$ in a tweet i, denoted as $s_{i,c}$, is given by

$$s_{i,c} = |W_i \cap L_c| / |W_i \cap L|,$$

where W_i is the words in the text content of tweet i. The sentiment index $S_{RT,c}$ of a region R within a particular time interval T is given by

$$S_{RT,c} = \frac{1}{m} \sum_{t_i \in T, g_i \in R} \left(s_{i,c} / \sum s_{i,\acute{c}} \right),$$

where t_i and g_i are the timestamp and geocode of tweet i, respectively, and $m = |i : t_i \in T, g_i \in R|$. Based on the above calculation, the fear index (or joy index) is a normalized measure of the relative strength of fear (or joy) regardless of number of tweets posted within a region and a time interval.

Fig. 2 show the hourly fear and joy indices within DAR and the Boston City, from April 10 to 30. Compared with joy indices, the fear indices exhibit greater sudden increases around April 15 and April 19, corresponding to the times of blasts and the subsequent manhunt. The substantial difference between the two indices suggest a particular emotional expression, fear, was trigger in response to the event.

(a) DAR (b) Boston

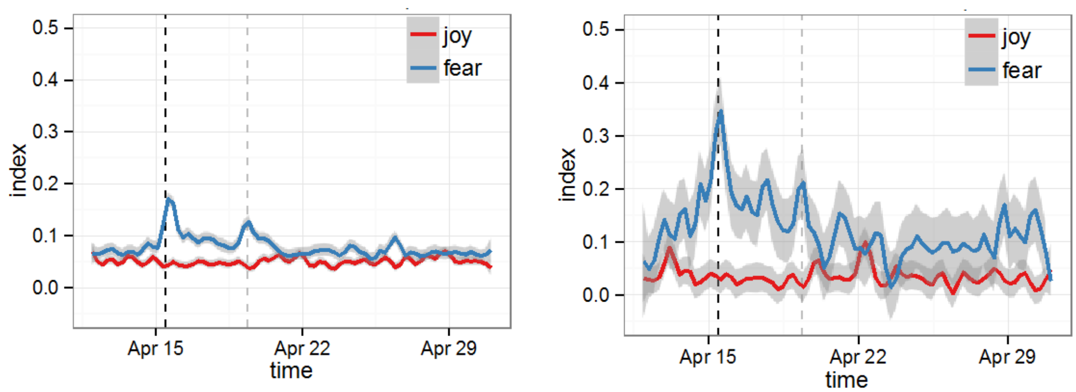

Figure 2: **Sentiment indices over time in (a) the direct affected region (DAR) and (b) the City of Boston.** The hourly sentiment indices of fear and joy before, during and after the Boston bombings are shown in smooth fitted curves over time (in UTC) with shaded area indicating a 95% confidence region. The vertical dashed lines around April 15 and 19 indicate the times of bombings and manhunt, respectively. The spikes in the level of fear correspond to the Boston bombings and the subsequent events, while the level of joy does not exhibit a sudden increase and is relatively stable over the period.

In Fig. 3 we show the sentiment indices in Boston and other three cities, New York City, Washington and Chicago, over the same time period. We observe similar, though slightly weaker, spike patterns in all three cities. In these cities, the first peaks on April 15 have a six- to eight-hour delay compared with the first peak in Boston. The highest fear level in Boston is at least 1.5 times the fear level in other cities. This indicates the local community in Boston had stronger and quicker emotional response.

We observe a small increase of joy in DAR on April 22, which correspond to the day when the suspect, Dzhokhar Tsarnaev, was charged (Markon, Horwitz, & Johnson, 2013). The increase of joy is not obvious within the Boston City and other major cities. This may suggest that the local community from the directly affected region retained higher attention on the bombing related events.

To understand the extent to which a city shares the fear in response to the event, we compute the *fear correlation* between Boston and the given city in terms of the correlation between the two cities' timeseries of fear indices. Fig. 4(a) shows the fear correlation between the Boston City and other major cities. The cities are ordered from top to bottom based on the correlation values. We can see some non-US cities, including London, Paris and Moscow, exhibit higher level of fear correlation than many US cities, suggesting the level shared fear may vary depending on various social, economic and political connections among the cities.

In Fig. 5(a) we plot the cities' fear correlation with Boston against their geographical distance from Boston. The decline of correlation along the distance suggests a ripple of shared fear may vary with the geographical proximity between cities.

(a) Boston (b) New York City (c) Washington (d) Chicago

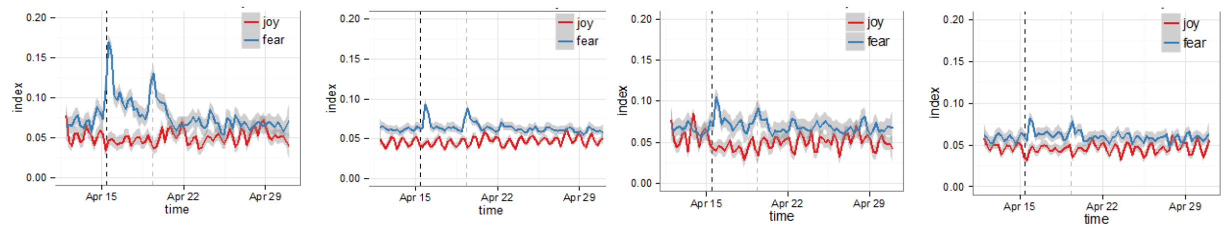

Figure 3: **Sentiment indices over time in (a) Boston, compared with those in (b) New York City, (c) Washington and (d) Chicago.** Similar but slightly weaker spike patterns were observed in New York City, Washington and Chicago over the same time (in UTC).

(a) Fear correlation (b) Comfort (#prayforboston) (c) Community identity (#bostonstrong)

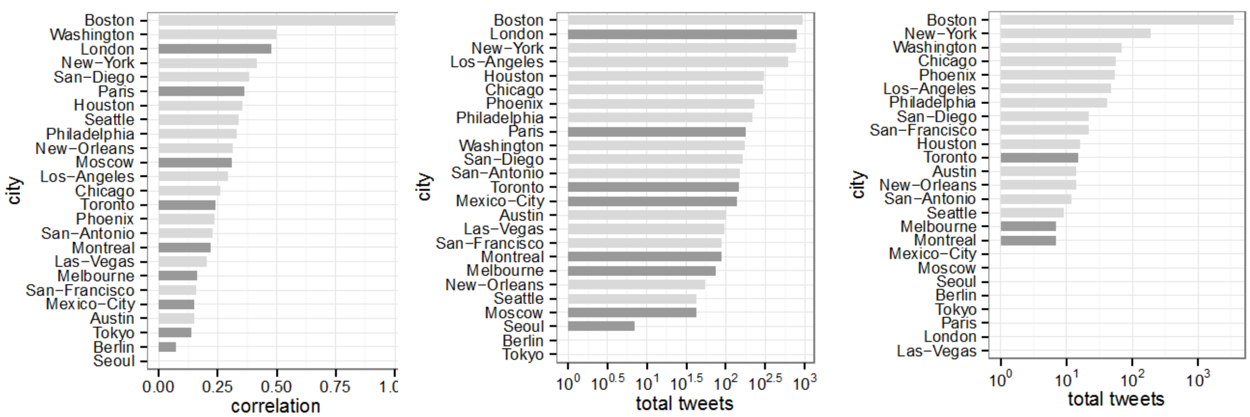

Figure 4: **Expression of fear, comfort and community identity in response of the Boston bombings.** (a) The temporal correlation of detected fear in a city with respect to the fear in Boston. Non-US cities are colored in dark gray. (b) The total number of tweets (volume) containing the #prayforboston hashtag in a city. (c) The total number of tweets (volume) containing the #bostonstrong hashtag in a city. In all three plots, the cities are ordered based on the variable of interest (x-value), from the highest to the least

2.3 Comfort and Community Identity

In Twitter, hashtags are ubiquitous and flexible annotations, allowing users to track ongoing conversations, signal membership in a community, or communicate non-verbal cues like joy and sadness. Hashtags often reflect eccentric topics and their emergence is happenstance. Over the two weeks of Boston Marathon, bombings and subsequent events, we observe new hashtags such as #bostonmarathon, #prayforboston, #bostonstrong were created and quickly adopted by many users in their tweet conversations. These hashtags serve different conversational purposes. For example, #bostonmarathon is a topical hashtag, most popular on April 15 and was used mainly in Boston area to indicate any Boston-Marathon-related conversations.

We focus on the emergent use of hashtags #prayforboston and #bostonstrong. The two hashtags were widely adopted after the bombings. The first hashtag #prayforboston became popular immediately after the bombings, used by both Boston and non-Boston users, to send comfort messages to Bostonians. The second hashtag #bostonstrong was populated two days after and gained its highest popularity around

April 20 due to the "Boston Strong" community events. This hashtag reflects a sense of community identity of Bostonians.

Interestingly, the two hashtags also appeared widely in tweets from other cities. Fig 4(b,c) show the number of tweets containing the two hashtags. Outside Boston, the level of interests for Twitter users in expressing comfort (in terms of #prayforboston volume) and community identity (in terms of #bostonstrong volume) vary with cities. The hashtag #prayforboston had a wider reach than the hashtag #bostonstrong – among the 25 cities considered in this analysis, #prayforboston appeared in 23 cities, while #bostonstrong only appeared in 17 cities. Similar to the detected fear, the use of the two hashtags exhibit a ripple effect corresponding to the geographical proximity of cities, as shown in Fig. 5(d,g).

2.4 Social Networks and Personal Visits

To further understand the ripple effect of expressing fear, comfort and community identity, we study these expressions in relation to other social factors. We identify two social factors:

- Social tie is the strength of social connections between Boston and a given city. We quantify the social tie strength between two cities A and B based on the number of replies sent within approximately two weeks before the event (from April 2 to 14), with a condition that the reply sender and receiver were observed in cities A and B or B and A on the same day of the reply. A user can be observed in a city if the user posts a tweet with geocode within the region of the city.
- Personal visit is the amount of travel users made between cities. We use personal visit between Boston and a given city to quantify the direct experience or actual familiarity of being in the Boston City. We first extract a transition flow for each individual user within the two-week pre-event period (from April 2 to 14). The transition flow is a temporal ordered list of cities where the given user was observed through geocoded tweets. The amount of travel between two cities A and B is then measured based on the number of transitions between A and B or B and A by aggregating all individual transition flows. In addition to the two social factors, we consider the following two control variables:
- Geo-distance is the geographical distance between Boston and a given city, measured in kilometers.
- *Tweet activity* is the expected Twitter activity of a city regardless of the event. This quantity serves as a baseline variable when explaining the level of response to the bombing events. We quantify this baseline tweet activity by the number of tweets posted from a city within the two-week pre-event period.

In Fig. 5 we plot the fear correlation, the volume of #prayforboston and #bostonstrong against the geo-distance, social tie and personal visit between Boston and other cities. The fear correlation is computed based on fear indices between April 10 and 20. The volumes of hashtags are calculated as total number of tweets containing the hashtags posted between April 15 and 30. The first-order correlations are shown on top of each scatterplot. Among the three factors, personal visit has the highest association with shared fear and the volume of #bostonstrong, while social tie has the strongest relation with the volume of #prayforboston. The first order correlations suggest the strength of social tie may well predict people's level of interest in expressing comfort during the event. On the other hand, the number of personal visit to the city may serve a strong predictor for the level of shared fear and level of interest in expressing community identity. We use multivariate linear regression analysis to examine the impact of different factors. We examine linear models for three response variables: the level of shared fear, the volume of #prayforboston (comfort) and the volume of #bostonstrong (community identity). Using different combination of predictors, we test the following models:

- baseline model: has a single predictor, tweet activity
- geo model: has two predictors, tweet activity and geo-distance
- social model: has two predictors, tweet activity and social tie
- visit model: has two predictors, tweet activity and personal visit
- geo-social model: has three predictors, tweet activity, geo-distance and social tie
- geo-visit model: has three predictors, tweet activity, geo-distance and personal visit
- full model: has four predictors, tweet activity, geo-distance, social tie and personal visit

We report the out-of-sample R^2 in Table 1. The results indicate that personal visit is a strong predictor for the level of shared fear between Boston and a given city. When predicting the shared fear, the visit model outperforms social and geo models by 22% and 104%, respectively. In predicting the interests of expressing comfort and community identity, both social tie and personal visit are strong predictors. The social and visit model outperform the geo model by at least 62%. Social tie has slightly higher predictive power than personal visit. The social model improves visit model by 5.8% in predicting the volume of #bostonstrong, and by 6.8% in predicting the volume of #prayforboston. Due to the small sample size (25 cities in total), the models with more predictors are likely overfitting.

	baseline	geo	social	visit	geo-social	geo-visit	full
shared fear	0.087	0.127	0.213	**0.260**	0.160	0.189	0.133
#prayforboston	0.090	N/A	**0.512**	0.479	0.191	0.176	0.120
#bostonstrong	0.335	0.340	**0.577**	0.545	0.104	0.398	0.259

Table 1: **Prediction performance**. Out-of-sample R^2 for models of predicting shared fear, volume of #prayforboston (comfort), volume of #bostonstrong (community identity).

3 Discussion and Future Work

In this work, we characterize the Twitter communication among the local and global communities during and after a massive disruptive event – the Boston bombings. Drawing from the crisis management literature, we identified two key components in a massive disruptive event: the perceived threat and community resilience. Using about 180 million, nearly all geotagged tweets, we study Twitter users' perceived threat in terms of their fear expression in tweets and compute the temporal correlation between Boston and other cities. We study community resilience based on the emergent use of two hashtags widely adopted after the bombings: #prayforboston signaling comfort, and #bostonstrong signaling solidarity and community identity. We observed that the level of shared fear, the interests of expressing comfort and community identity vary with the geographical proximity between cities. Using correlation and linear regression analyses, we found that users' direct experience of being in the city of Boston, quantified in terms of the amount of travel to Boston, predicts the shared fear better than other factors. In terms of predicting the interests of expressing comfort and community identity, both social network, measured based on replied tweets, and direct experience, outperform the geographical proximity by at least 62%. Our analyses has implication in identifying potentially vulnerable population, and predicting the perceived threat in the face of future massive disruptive events such as terrorist attacks.

Our current work presents several limitations. First, we rely on a concept-based affective lexicon to extract fear expression. The lexicon cannot capture fear signals in non-English words or in more dynamic forms (such as emoticons, acronyms and community invented expressions). Second, we focused on 25 major US and non-US cities. Our results may not generalize to the majority of smaller cities or neighboring cities. As part of future work, we plan to (1) develop a more sophisticated fear detection framework for extracting shared fears, (2) characterize the shared fears at multi-scale of time and space, (3) extend our analyses to a more comprehensive sample of large, medium and small US cities, and incorporate the social, political and economic attributes of these cities in the analyses, (4) use human-coded content analysis to analyze the communication patterns in a smaller sample (e.g., focus on tweets posted in the direct affected region) to triangulate the analyses from big data sample, and (5) compare the Boston bombing event with other types massive disruptive events such as hurricanes and school shootings.

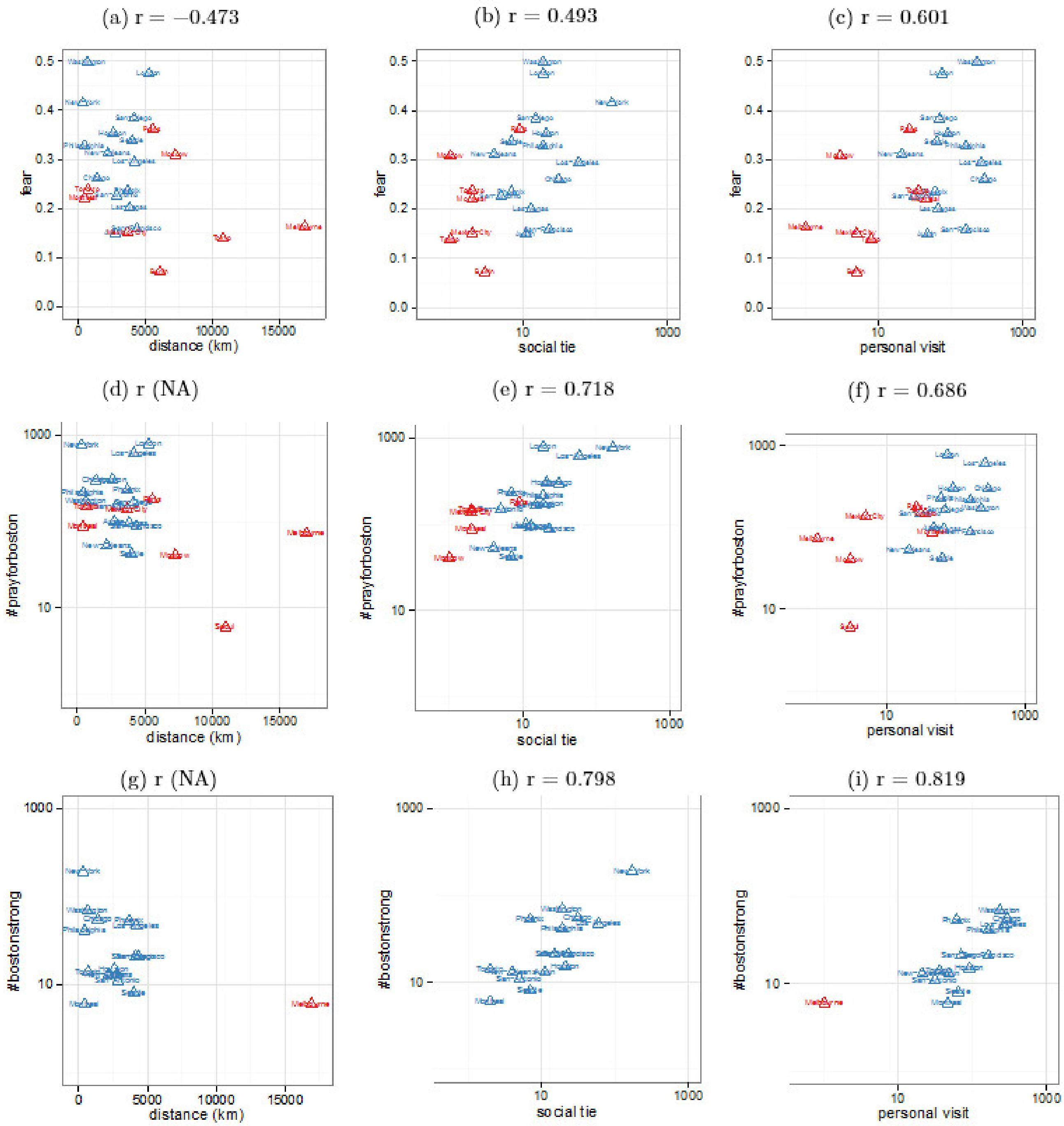

Figure 5: **The expression of fear, comfort and community identity in relation to geo-distance, social ties and personal visits.** (a-c) are scatterplots of the fear correlation with Boston against distance in kilometers, number to replies, and number of personal visit, respectively. (d-f) are scatterplots of #paryforboston volume (total number of tweets containing the hashtag) against the three factors. (g-i) are scatterplots of #bostonstrong against the three factors. In all plots, non-US and US cities are colored in red and blue, respectively. The correlation coefficients are reported on top of the scatterplots except for (d,g) which have influence of outliers.

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