On Critical Event Observability using Social Networks: A Disaster Monitoring Perspective

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***Abstract*—The proliferation of social networks with large-scale information dissemination capabilities, such as Twitter, significantly increases the degree of observability of critical events, such as natural or man-made disasters. This paper analyzes the extent to which critical physical events indeed are observable, thanks to social networks, as well as the extent to which the offered view into event state that affects the state's own evolution. As a case study, we investigate the gas shortage that ensued around New York City in the aftermath of Hurricane Sandy in November 2012. Both ground truth data regarding the shortage as well as Twitter data describing it are collected. Results suggest that the social network responds to the shortage in a manner that enables (noisy) reconstruction of actual damage evolution. Non-linear models of social response tend to fit the data better, suggesting that the response switches from an initial rational reaction to a subsequent panic reaction that is largely a function of its own history, as opposed to that of the physical event. Deriving a good model of this (over)reaction is therefore critical for correct reconstruction of the actual damage. Similarly, the paper presents models for actual damage and demonstrates that combining social response with actual damage can improve the damage modeling capability.**

I. Introduction

Critical events, such as hurricanes, civil unrest, or use of weapons of mass destruction offer a large damage footprint. Damage assessment becomes an important component of successful recovery and damage control efforts. This requires some degree of observability into the physical state of the event. Often accurate state assessment is hard to attain in post-disaster scenarios, due to impaired communication and insufficient resources. The advent of social networks, such as Twitter, offers an opportunity to observe such events through the social lens of participants, survivors, and their online networks. This paper investigates the evolution and the degree of observability of the state of physical events offered by the social networks.

As a running case study, the paper focuses on gas shortage around New York city in the aftermath of hurricane Sandy. This hurricane hit the city at the end of October 2012. It was the second costliest on record (after Katrina) and the worst in 2012. A severe gas shortage ensued. The All Hazards Consortium logged the status of hundreds of gas stations in the area during the month of November, archiving daily gas availability at each station. In addition, tweets were collected in real time from the area that include the word "gas". Sentiment analysis was performed on the tweets to determine if they are positive or negative. This analysis offered an opportunity to plot the average sentiment regarding the gas crisis as reflected on Twitter. We henceforth call the measured sentiment, the Twitter social response. Using this data set, the question the paper addresses is one of understanding how social response evolves as a function of actual damage, and the degree to which damage evolution may be reconstructed from observing social response. Two observations are relevant at this point. First, in the absence of broadcast communication media, each individual can observe only a limited physical locale. Social media, such as Twitter, offer a much broader view of the event, albeit with some delay and distortion. It is interesting to model how this broader view impacts social response. Past studies [1] have shown that in social media, speed has tended to trump accuracy, i.e. a false rumor stated early spreads more widely than a later correction, which is an observation we make in this paper as well. Second, the view offered via social media, itself, has impact on user behavior, and hence occasionally changes the profile of damage propagation. This is especially true of outages, where human over-reaction, for example, can increase demand and hence exacerbate the outage. Three related families of questions are addressed:

First, what model best expresses the relation between damage and Twitter social response? Thinking of damage as input and response as output of an auto-regressive moving average (ARMA) model with delay, is response affected more by the input terms (i.e., by actual damage) or by past output terms (i.e., previous sentiment)? What is order of the model and how big is the delay term? In other words, how far back do terms that affect current sentiment go? Is the model linear or not? A linear model would indicate that humans react to different levels of damage in a consistent manner. Non-linear response would indicate that human behavior changes. For example, in a state of panic, social response might become disproportionate to actual damage. Hence, the structure of the model gives interesting insights into the nature of human response on social networks.

Second, can the actual physical damage evolution be inferred from the observed social response on a social network like Twitter? The answer depends very much on the shape of the model discussed above and the amount of noise present in the raw data. Given the model and noise terms, what are the bounds on accuracy of physical damage reconstruction? Moreover, the order of the model and the magnitude of the delay term affect how quickly damage can be observed. If sentiment is a “delayed reaction” then it carries less information on current input and more on past input.

Third, does the evolution of sentiment on the social network actually affect damage propagation itself? In our example, the propagation of a gas shortage follows supply and demand dynamics, where supply has been impaired by damage attributed to the disaster. Are these dynamics consistent with the same demand curves observed prior to the disaster or does the demand curve needed to explain outage dynamics change after the disaster as a function of the sentiment? The latter would indicate that the sentiment does affect future evolution of damage propagation, due to a different demand profile.

Our paper is organized as follows: Section II describes the dataset we use in our study. Section III and IV present in details the social sentiment and gas shortage modeling, respectively. Model experiments with the dataset are conducted in each of these sections. We discuss the related work in section V. Finally, we conclude the paper and discuss future direction in section VI.

II. DATASET

During the aftermath of hurricane Sandy, a number of gas stations in the areas around New York and New Jersey were closed due to high demand. The All Hazard Consortium recorded daily fuel availability of gas stations in these regions, along with their addresses, longitudes, and latitudes. We converted this data into a time series of actual *damage* with values ranging from 0 to 1. Here, *damage* is defined as the fraction of the number of gas stations that are out of gas among all surveyed gas stations aggregated by day in overall (global) or local regions. Besides, people during this period used Twitter to broadcast their own observation of fuel availability at the gas station and related information such as waiting time. We first collected tweets from Twitter containing the words *gas* over 22 days of November, 2012 in the areas around New York and New Jersey. We subsequently filtered out those that do not contain location information and performed sentiment analysis [2] on the remaining tweets to decide whether they are positive or negative. This results in a total of 711 tweets with the negativity sentiment ranging from 0 (not negative) to 1 (extremely negative). Thus, we obtain a time series of social sentiment with values corresponding to the average sentiment aggregated by day in global or local regions. More details about the process of retrieving Twitter data can be found in [3].

III. SOCIAL SENTIMENT MODELING

The first question we attempt to answer is the relation between the Twitter social response, S, and actual damage, D. In particular, what is the structure of the model that describes this relation? We start with a linear ARMA model that attempts to predict today's social response using the history of actual damage and the history of previous response values, as given by the equation below:

$$S(t) = \sum_{i=d_D}^{d_D+n_D-1} a_i D(t-i) + \sum_{j=1}^{n_S} b_j S(t-j)$$

where d_D denotes the delay time on actual gas shortage time series, n_D denotes the number of days looking back on actual gas shortage time series from d_D, and n_S denotes the number of days looking back on actual social sentiment time series.

In the above difference equation, the time index represents a day. Using z-transform, this becomes:

$$\frac{S(z)}{D(z)} = z^{-d_D} \frac{a_{(d_D)} + a_{(d_D+1)} z^{-1} + ... + a_{(d_D+n_D-1)} z^{-n_D+1}}{1 - b_1 z^{-1} - ... - b_{n_S} z^{-n_S}}$$

Table I depicts the root mean square error (RMSE) from fitting the data to models of different order, n_D, n_S, and a different delay term, d_D (days). It can be seen in Table II that the second order model with 4 parameters and RMSE=0.065 is approximately the threshold of diminishing return. Beyond that model, increasing order or delay does not yield much improvement.

Params	n_D	d_D	n_S	d_S	RMSE
5	2	1	3	1	0.066
4	2	1	2	1	**0.065**
3	1	2	2	1	0.065
2	1	2	1	1	0.079

TABLE I. COMPARISON OF DIFFERENT LINEAR MODELS

Delay	n_D	n_S	d_S	RMSE
$d_D = 1$	**2**	**2**	**1**	**0.065**
	2	3	1	0.066
	3	2	1	0.070
	3	3	1	0.070
$d_D = 2$	2	2	1	0.075
	2	3	1	0.075
	3	2	1	0.089
	3	3	1	0.090

TABLE II. DIMINISHING RETURN

Figure 1 shows the accuracy of the aforementioned prediction model. The horizontal axis shows the calendar day (starting November 2nd, 2012). Three curves are compared on the Y-axis; namely, (i) the shortage (red) curve, depicting the fraction of gas stations that are out of gas of those surveyed in our data set, (ii) the panic (green) curve, depicting Twitter sentiment, and (iii) the sentiment (purple) curve as predicted from the shortage curve using our model. Model parameters indicate that the largest influence on today's sentiment is attributed to damage 2 days ago and social response in the previous day. This observation suggests that social response is a delayed function of actual damage. Moreover, social response feeds on itself; it is more an auto-regressive function of its own past state than a function of actual damage. Twitter sentiment today is more a reflection of Twitter sentiment in the recent past, than that of actual damage status in the past.

An observation that can be made from Figure 1 is that the model predicting social response trails behind the real response curve. The gap can be closed only if the model places a bigger weight on more recent damage data, such that response to the onset of damage becomes faster. Models with faster response to damage (red curve), however, perform poorly as they significantly underestimate the response at the trailing end of the curve when actual damage becomes low. This suggests nonlinear behavior. Initially, social response follows damage more closely. This is an indication of a state of rational behavior. In later days, however, response switches to a regime,

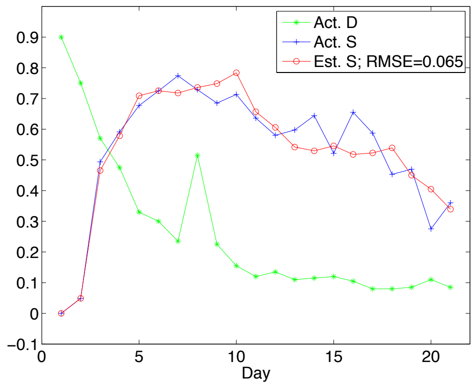


Fig. 1. Predicting Social Sentiment based on historical Twitter Sentiment and actual Damage. D and S stand for Damage and Sentiment, respectively. Params: 2-day back Sentiment, 2-day back Damage with delay=1

where it becomes more of an auto-regressive function of itself and less a function of input. This is an indication of panic, where sentiment no longer follows actual damage but rather responds more strongly to sentiment in the recent past.

IV. GAS SHORTAGE MODELING

A. Basic Model

Knowing the above model, it becomes possible to do the reverse estimation as well. Namely, given the panic curve alone, it becomes possible to estimate real damage. Such estimation is shown in Figure 2. In this figure, the inferred shortage curve is derived from the panic curve alone and without any direct measurement of actual damage. The inferred shortage does track actual damage faithfully in the first week. It deviates in later days when a damage spike occurs, which is attributed to a second storm that followed Sandy, although it does recognize that an increase in damage occurred. Its predictive performance decreases in the last week, where the predicted damage fluctuates significantly.

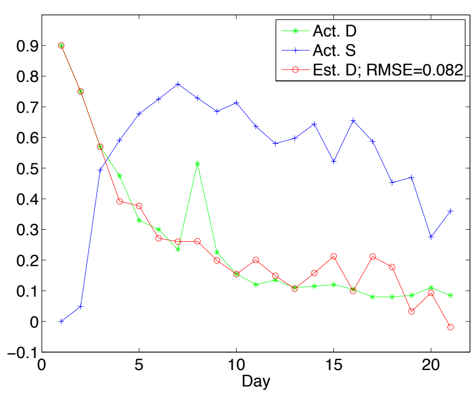


Fig. 2. Predicting damage from Twitter Sentiment. D and S stand for Damage and Sentiment, respectively. Params: 3-day back Sentiment with delay=1.

B. Improved Model

One of the reasons why the above model does not fit actual data well is the ARMA model only takes into account the actual sentiment and does not consider the actual damage, which essentially could be obtained with some delay. In this section, we present another improved model for predicting damage, which will take actual damage with some delay as another input source. Additionally, we further study the effect of the delay of actual damage on the performance of the model.

Here, the ARMA model that we use for predicting damage is the one with multiple input sources. It takes into account actual damage (D), and observed social sentiment (S), as given in the equation below:

$$D(t) = \sum_{i=d_D}^{d_D+n_D-1} a_i D(t-i) + \sum_{j=d_S}^{d_S+n_S-1} b_j S(t-j)$$

where d_D denotes time-delay (in day unit) on actual damage time series; n_D denotes number of days looking back on actual damage time series from d_D; d_S denotes delay time on actual sentiment time series; and n_S denotes number of days looking back on actual sentiment time series from d_S. If the input value does not exist as the input delay is too far in the past, we consider it as 0. The number of parameters for the above model is the sum of n_D and n_S.

Params	n_D	d_D	n_S	d_S	RMSE
5	4	1	1	1	0.067
4	**1**	**1**	**3**	**1**	**0.074**
3	2	1	1	1	0.076
2	1	1	1	1	0.085

TABLE III. COMPARISON OF MODELS

Table III shows the performance of our models with different parameter settings. From this table, we choose the model with 4 parameters and RMSE=0.074 to further study the effect of time-delay on actual damage since its parameter is small enough to alleviate the effect of over-fitting. An example in learning the regression's coefficients with $1-$day delay yields the following model:

$$D(t) = 0.368 * D(t-1) + 0.487 * S(t-1) - 0.172 * S(t-2) - 0.148 * S(t-3)$$

As compared to the model parameters for predicting social sentiment, which stresses more importance on past social sentiment than on actual damage, model parameters here indicate that damage is a response of both past actual damage and social sentiment. This means that in the event of gas shortage people might respond to both the damage they see locally and the observation they have over social media.

Past damage data, however, is not always available. Figure 3 and 4 shows the effect of delay from 1-3 and 4-5 days of the actual damage on the fitness of model. The x-axis represents time (in days), and the y-axis, from 0 to 1, represents both the fraction of gas stations that are out of gas of all the gas stations (for the damage curve) and social sentiment (for the sentiment curve). Looking at these figures, we may see that with settings of small delay-time, the prediction is influenced by a combination of both past actual damage and social sentiment. This behavior can also be seen with the subsequent settings yet the regression performance is a bit compromised as the past values do not exist for the initial values in the actual damage time series. The negative effect of delay is demonstrated in Figure 5, where the larger the delay values, the poorer the performance of the models.

It can be concluded that physical damage can be inferred

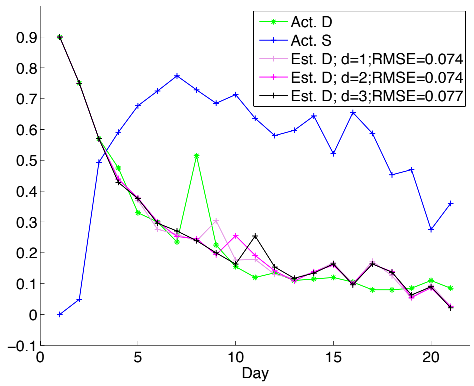


Fig. 3. Predicting damage with delay from 1-3 on actual Damage. D and S stand for Damage and Sentiment, respectively. Params: 1-day back actual Damage; 3-day back Sentiment with delay=1

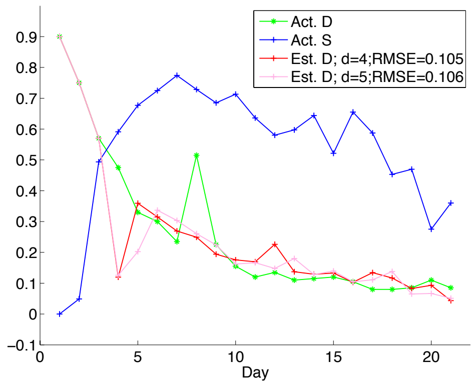


Fig. 4. Predicting damage with delay from 4-5 on actual Damage. D and S stand for Damage and Sentiment, respectively. Params: 1-day back actual Damage; 3-day back Sentiment with delay=1

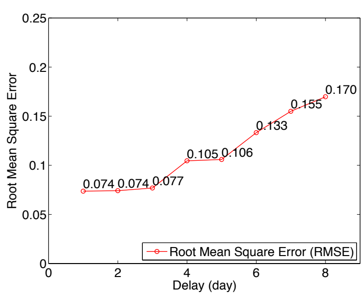


Fig. 5. RMSE of models with different delays on actual Damage time series. 1-day back actual Damage; Params: 3-day back Sentiment with delay=1

using a combination of delayed actual damage and social response. The above experiment shows that actual damage plays an important role in the physical damage reconstruction, whose inference has better performance than the one using social response alone. However, in order for the physical damage to be inferred in a timely manner, the delay of actual damage needs to be adequately small. Yet, it is still unknown whether the model can be applied for local damage and whether there exists a relationship between damage observation in different regions. These will be explored in the following part.

C. Regional Damage Modeling

To better understand the importance of past damage and social response towards human behavior in the extreme condition as gas shortage, we further break down the data into regions and see whether the model relating damage and sentiment also holds for individual regions. We choose New York and New Jersey as two typical regions since they were severely damaged by hurricane Sandy. Social sentiment and damage data are computed by taking the average of social sentiment and the number of closed gas station in these regions. Following the model for predicting damage, we apply the same learned function to individual regions in the following ways: Predicted regional damage as a function of a) Actual regional Damage, regional Sentiment b) Actual regional Damage, global Sentiment c) Actual global Damage, regional Sentiment d) Actual global Damage, global Sentiment.

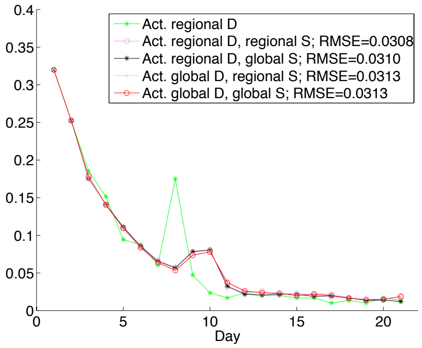
Region	Model	Params=2	Params=3	Params=4	Params=5
New Jersey	Model a)	0.0349	0.0307	0.0301	0.0278
	Model b)	0.0351	0.0309	0.0303	0.0277
	Model c)	0.0345	0.0313	0.0306	0.0279
	Model d)	0.0344	0.0312	0.0306	0.0279
New York	Model a)	0.0323	0.0296	0.0284	0.0271
	Model b)	0.0326	0.0297	0.0285	0.0273
	Model c)	0.0275	0.0269	0.0267	0.0223
	Model d)	0.0280	0.0272	0.0270	0.0220

TABLE IV. REGIONAL MODELS COMPARISON

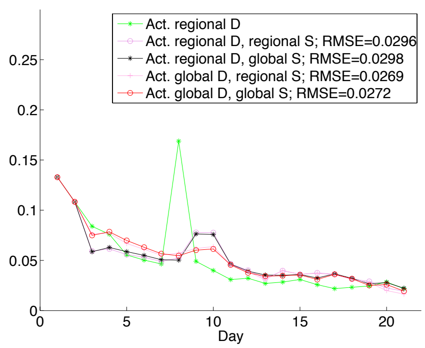
Figures 6a and 6b demonstrate the predicted outputs of New Jersey and New York data corresponding to the four models above. Figure 6d and 6e show the models of New Jersey and New York in more details. Table IV shows the comparison of the errors of the four models for New Jersey and New York.

The models corresponding to the two regions vary in their fitness, which relate less to social sentiment and more to the actual damage source. One of the reasons is that social sentiment on Twitter actually propagates across different regions. Thus, the sentiment in these regions correlates with each other and the model fitness is not heavily affected by this difference. Moreover, the models for New Jersey have lower error in the group that take regional damage as a source, which could be attributed to the fact that people in this region are affected by what they see around them. Whereas, in New York, models that take global damage as an input source have lower error. One hypothesis for this is that people in New York actually respond more to the damage in New Jersey, or more clearly, the heavy damage of New Jersey by hurricane Sandy actually affects the propagation of damage in New York. For this hypothesis, we check the following models: Damage of New York as a function of a) Actual New Jersey Damage, regional Sentiment b) Actual New Jersey Damage, global Sentiment; and: Damage of New Jersey as a function of c) Actual New York Damage, regional Sentiment d) Actual New York Damage, Global Sentiment.

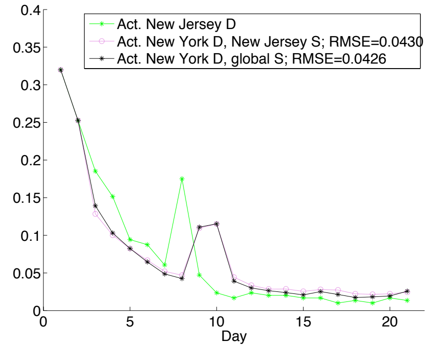
Figures 6c and 6f show the models of New York and New Jersey in details. From these figures, New York models as a function of New Jersey damage have lower error than these of global damage. Whereas, New Jersey models as a function of New York damage have higher error than these of New Jersey damage. This implies that people respond more strongly to the damage of New Jersey. This is actually consistent with the fact that damage of New Jersey was higher than that of New York [4], [5]. It seems that people not only react to what they observe around them but also to the damage in regions that are more severely damaged.



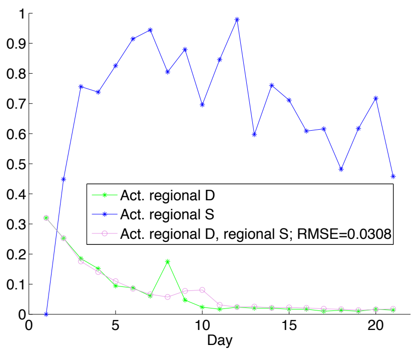
(a) New Jersey damage models comparison.



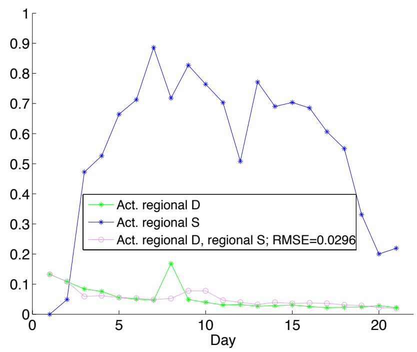
(b) New York damage models comparison.



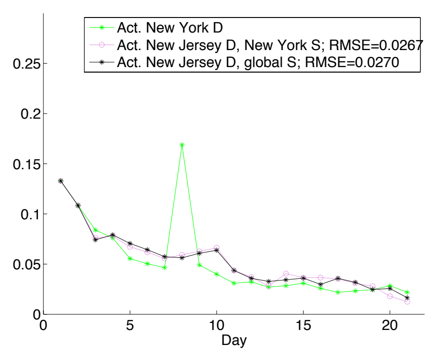
(c) New Jersey damage models as a function of New York damage; New Jersey and global sentiment.



(d) New Jersey damage model.

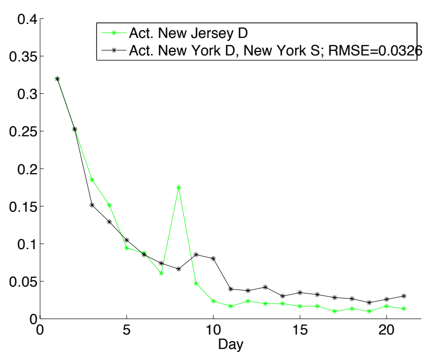


(e) New York damage model.

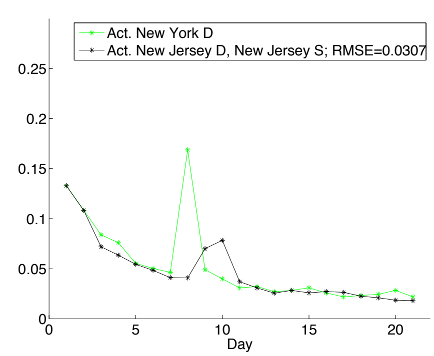


(f) New York damage models as a function of New Jersey damage; New York and global sentiment.

Fig. 6. Regional Damage Models. D and S stand for Damage and Sentiment, respectively. The model in each curve has the lowest error with respect to the number of parameters. The parameters in each of the estimated curves are identical, where $n_D = 2, n_S = 1, d_D = 1, d_S = 1$.



(a) Estimating New Jersey damage using the model built with New York data.



(b) Estimating New York damage using the model built with New Jersey data.

Fig. 7. Cross-validation test. Models are derived using data of one region and tested using data of another region. The parameters in the estimated curves are identical, where $n_D = 2, n_S = 1, d_D = 1, d_S = 1$.

D. Cross-Validation

In this section, we perform cross-validation to verify the generalizability of our models. The idea is to build a model from one data set and test its regression capability on the other one. In specific, we perform the following two experiments: a) Training a model to infer regional damage in New York based on the regional social responses in New York and then use that model to infer regional damage in New Jersey. b) Training a model to infer regional damage in New Jersey relied on the regional social responses in New Jersey and then use that model to infer regional damage in New York.

Figures 7a and 7b plot our experimental results. Pictorially, it can be observed that the damage predictions are well inferred in both experiments, with a slightly better regression on estimating the New York damages by using the New Jersey model. These results imply that our learning parameters are not over-fitting despite the relatively limited number of data samples.

V. Related Work

Social media analysis is a recent extension of media analysis, a seventy-year old branch of social science, that attempts to gauge the influence and impact of newspaper, TV, radio and other media on people's actions and attitude [6], [7]. An example of such media analysis is to study the event of War of the Worlds radio broadcast in 1938, which convinced millions of people that Martians had attacked the Earth [8]. The questions to be addressed include: What causes some people to believe and subsequently act while the others not? What characteristics of media are the matters? How can populations be manipulated through the sophisticated use of media? Other examples of research in media impacts may be found in [1].

Time-series analysis has been studied extensively for various prediction tasks. A number of effective methods including ARMA, ARIMA [9] and their variations such as ARMAX, ARIMAX, etc. have been developed. Amodeo *et al.* [10] combine probabilistic and seasonal ARIMA models to perform event prediction. Many models in [11] also use these methods for predicting evolution and explaining burst in electricity loads and prices. The key difference between the above studies and our work in this paper is the condition in which the events happen. While other works study the data collected in common conditions, our work focuses on extreme events, like the case in which a large number of gas stations were closed due to the hurricane Sandy. This could negatively impact human behavior and would subsequently exacerbate the condition. In previous studies of extreme events, very limiting works have been conducted. Ganti *et al.* [3] use a modification of susceptible-infected-recovered model to model the spread of damage in a social network. Nonetheless, this work solely focuses on human behavior within the social network without considering real-life situation. Thus, it is fundamentally different from the one we address in this paper. On the other hand, a number of studies have been done on predicting user behavior and sentiment in various social networks. Zhong *et al.* [12] attempt to predict users' behaviors by transfer-learning the knowledge in a composite network. Zhang *et al.* [13] develop a method based on a dynamic continuous factor graph model for modeling and predicting users' emotions in social networks. Yang *et al.* [14] propose an emotion prediction method for individuals based on user interest and social influence. These models take advantage of online social relationships and observations to uncover user behavior and sentiment. However, in the case of extreme events, as demonstrated in our work, users' online behaviors can be significantly impacted by what they observe in real-life and vice versa. Therefore, these methods are not able to reveal such essential and complex interactions.

VI. Conclusions and Future Work

In this paper, we have explored the problem of event modeling using information from social networks, specifically for the social sentiment and actual gas shortage in the aftermath of hurricane Sandy. We showed that social sentiment exhibits non-linear behavior. Specifically, social sentiment follows closely actual damage at the initial stage of the event, but it gradually puts more importance on its own past values. Moreover, the model built upon both social sentiment and (previously seen) gas shortage fits the damage degrees better than the ones that simply regress on social sentiment. The results further suggest that the current damage is best approximated by a balanced combination of actual damage in the past and current social response. When further breaking the data down into individual regions, such as New York and New Jersey, the model approximating the actual damage tends to be highly correlated with the regional damage rather than both the local and global social sentiments. Particularly, the model strongly corresponds to the region that is more severely affected by the hurricane event.

Acknowledgments

Research reported in this paper was sponsored by the Army Research Laboratory and DTRA and was accomplished under Cooperative Agreement W911NF-09-2-0053, and DTRA grant HDTRA1-10-1-0120. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory, DTRA, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on.

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