Social Networks in Emergency Response

Dashun Wang[1,2], Yu-Ru Lin[3,4], and
James P. Bagrow[5,6]
[1]Center for Complex Network Research,
Northeastern University, Boston, MA, USA
[2]Center for Cancer Systems Biology,
Dana-Farber Cancer Institute, Boston, MA, USA
[3]College of Computer and Information Science,
Northeastern University, Boston, MA, USA
[4]Institute for Quantitative Social Science,
Harvard University, Cambridge, MA, USA
[5]Engineering Sciences and Applied
Mathematics, Northwestern University,
Evanston, IL, USA
[6]Northwestern Institute on Complex Systems,
Northwestern University, Evanston, IL, USA

Synonyms

Collective response; Communication Network; Data mining; Disaster; Emergency; Event detection; Spatiotemporal analysis; Social networks

Glossary

Emergency An unexpected and often dangerous situation, typically affecting multiple individuals and requiring immediate action

Social and Communication Networks Networks of people interacting with each other through web-based (e.g., Twitter) and mobile-based (e.g., mobile phone) technologies

Social Media Web-based tools that enable people to communicate and interact with each other in various media forms including text and multimedia. Examples of these tools include emails, instant messengers (IM), blogs, microblogs (e.g., Twitter), vlogs (e.g., YouTube), podcasts, forum, wikis, social news (e.g., Digg), social bookmarking (e.g., Delicious), and social networks (e.g., Facebook, MySpace, and LinkedIn)

Definition

Modern datasets derived from telecommunication technologies such as online social media and mobile phone systems offer a great potential to understand the behaviors of large populations during emergencies and disasters. This entry reviews recent studies using large-scale, modern data to understand emergency and disaster response, covering work focused on social network activity during earthquakes and disease outbreaks and mobile phone communications following bombing and other emergency events. The key techniques and research trends are also discussed.

Introduction

Large-scale emergencies and disasters are an ever-present threat to human society. With growing populations and looming threat of global climate change, the numbers of people at risk will continue to grow. Thus there is a great need to optimize response efforts from search and rescue to food and resource disbursement. Human dynamics research offers a promising avenue to understand the behaviors of large populations, and modern datasets derived from cutting-edge telecommunications such as online social media and pervasive mobile phone systems bring a wealth of potential new information. Such massive data offers a promising complement to existing research efforts in disaster sociology, which primarily focus on eyewitness interviews, surveys, and other in-depth but small-scale data (Rodríguez et al. 2006).

Yet most current human dynamics research is focused primarily on data collected under normal circumstances, capturing baseline activity patterns. Here we review a number of studies pushing the envelope of modern data into the realm of unexpected deviations in these population behaviors. We discuss research focused on massive datasets from social network activity during earthquakes and disease outbreaks to mobile phone communications following bombings, power outages, and more.

We review a number of recent studies using large-scale, modern data to understand emergency and disaster response. We begin with a review quantifying how expectations of communication in today's world may influence our perception of the severity of an emergency. We then cover works focused on social media and mobile phones. These works use Twitter, a prominent online social media service, to understand more about disease outbreaks and the impact of earthquakes. The mobile phone studies feature a number of emergencies, including earthquakes, bombings, and a plane crash. The results of these studies have the potential to revolutionize disaster response in the future, with the critical goal of saving lives.

Historical Background

Connectivity and information access through global telecommunications have become increasingly pervasive due to modern technologies such as mobile phones and the Internet. People are becoming increasingly reliant on these communication modes and so an important question asked by Sheetz et al. (2010) is as follows: what do people expect about their access to these communication channels when an emergency occurs? They explored how the expectation of the availability of these communication technologies may influence their perceptions of how they would use these technologies during and after a crisis.

To answer this question, the authors conducted online surveys and follow-up interviews with Virginia Tech students, faculty, and staff (participants). This university suffered a tragic attack on April 16, 2007, and the authors reported that local cellular networks were overwhelmed by traffic. Surveying witnesses and survivors at the university allows the authors to study how the perceptions of information access meshed with the unfortunate events that occurred.

Through these surveys and interviews, they found that participants have a range of expectations for connectedness in normal activities. Most participants did not expect to be able to immediately contact someone. This held even for strong social ties, for example, a student trying to reach his or her parents. Most importantly, the authors discovered that participants who do have high expectations of connectivity (and also tend to be more extroverted individuals) were more likely to report problems with connectivity than users with lesser expectations. These problems can lead these people to form overestimate of the severity of the crisis, compared with individuals who have lower expectations for their communication and are thus less likely to find communication loss a cause for concern. This means that an individual's personal traits may directly influence how he or she estimates the severity of a crisis.

While the authors admitted that they had a small sample size and that their interview methods may not be perfect, this study is an important step towards further understanding the interplay between modern telecommunications and emergency events.

Emergencies and Social Media

Today, social media such as Twitter and Facebook have been popularly used as everyday communication tools. Millions of people use "tweets" or Facebook "statuses" to inform family, friends, colleagues, or any others about information, opinion, and emotions about events just happening, leading to the great potential of using social media for monitoring and rescue purposes. Twitter allows users to send and receive tweets (140-character messages) via text messages and Internet-enabled devices, providing the public with detailed anecdotal information about their surroundings. Given the real-time nature of Twitter and the emerging social networking technologies, social media has the potential to fundamentally alter our discussions of emergencies. We briefly review some of the recent work on detecting disease outbreaks and earthquake response with Twitter.

Twitter and Disease Outbreaks

Various studies have shown the potential of using Twitter data to monitor the current public health status of a population, as people often tweet when they feel ill or recognize disease symptoms. Quincey and Kostkova (2010) collected tweets that contained instances of the keyword "flu" in a week during the swine flu pandemic. Their study suggests that the copresence of other words in tweets can be used by public health authorities to gather information regarding disease activity, early warning, and infectious disease outbreak. For example, in the majority of the collected tweets, the word "swine" was present along with "flu"; the words "have flu" and "has flu" may indicate that the tweet contains information about the users or someone else having flu. The words "confirmed" and "case(s)" perhaps indicate a number of tweets that are publicizing "confirmed cases of swine flu." Culotta (2010) collected over 500,000 influenza-related tweets during 10 weeks and analyzed the correlation between these messages and the Centers for Disease Control and Prevention (CDC) statistics. The paper reported a correlation of 0.78 by leveraging a document classifier. Chew and Eysenbach (2010) collected over 2 million tweets containing the keywords "H1N1," "swine flu," and "swinflu" within 8 months in 2009. Using manual and automated content coding, they found temporal correlation of Twitter activity with major news stories and H1N1 incidence data. In addition, they found that the majority of these tweets contained resource-related posts (e.g., links to news websites). Gomide et al. (2011) analyzed how the dengue outbreaks in 2009 were mentioned on Twitter. Using a linear regression model, they showed promising results to predict the number of dengue cases by leveraging tweet content and spatiotemporal information. Signorini et al. (2011) tracked time-evolving public sentiments about H1N1 or swine flu and studied the probability of using Twitter stream for real-time estimation of weekly influenza-like illness (ILI) statistics generated by CDC.

There has also been work addressing the technical challenges of collecting tweets that are related to health or disease. Zamite et al. (2011) proposed a system architecture for collecting and integrating epidemiological data based on the principles of interoperability and modularity. Prier et al. (2011) proposed using a Latent Dirichlet Allocation (LDA) model to effectively identify health-related topics in Twitter. Paul and Dredze (2011) collected two billion tweets related to illness, disease symptoms, and treatment from May 2009 to October 2010. They proposed a probabilistic aspect model to separate tweets related to health from unrelated tweets. Aramaki et al. (2011) collected 300 million tweets from 2008 to 2010. They applied the Support Vector Machines (SVMs) to find tweets related to influenza with a correlation of 0.89 % compared with Google Flu Trends (Ginsberg et al. 2008). These tools offer the means to transform the overwhelming flood of big data into more manageable information.

Besides social media, there are also other solutions to estimate a population's health from Internet activity, most notably Google Flu Trends service, which correlates search term frequency with influenza statistics reported by the CDC (Ginsberg et al. 2008).

Twitter and Earthquakes

In recent years, tremendous effort has been made towards leveraging Twitter to study earthquakes, mainly falling into two lines of research: real-time detection (Sakaki et al. 2010; Guy et al. 2010; Earle et al. 2012) and crisis management (Hughes and Palen 2009; Caragea et al. 2011; Li and Rao 2010; Mendoza et al. 2010).

Early earthquake detection and the delivery of timely alerts is an extremely challenging task. Depending on peculiarities of the earthquake, from size to location, alerts may take between 2 and 20 min to publish, owing to the propagation time of seismic energy from the epicenter to seismometers and the latencies in data collection and validation. Therefore, it has been practically impossible for affected populations to know about an earthquake before it arrives. This situation is changing, however, thanks to the pervasive use of Twitter. Users submit their tweets via text messages and Internet-enabled devices, and these messages are available to their followers and the public within seconds, making Twitter an ideal environment for the dissemination of breaking news to large populations. Therefore, by using populations as social sensors, Twitter may be a viable tool for rapid assessment, reporting, and potentially real-time detection of a hazard event. Sakaki et al. (2010) investigated events such as earthquakes and typhoons in Twitter and proposed an algorithm to monitor tweets and to detect earthquakes. They extracted features such as keywords in a tweet by semantic analysis and used Support Vector Machines (SVMs) to classify a tweet into a positive or negative class. By regarding a tweet as a social sensor associated with location information, the authors transformed the earthquake detection problem into an object detection problem in ubiquitous and pervasive computing. They derived a probabilistic model by applying Kalman filtering and particle filtering to estimate the epicenter of an earthquake and the trajectories of a typhoon. They then deployed an earthquake reporting system in Japan, which delivers earthquake notifications to their users faster than the announcements broadcast by Japan Meteorological Agency. Meanwhile, researchers from the US Geological Survey (USGS) reported an earthquake detection system that adopts social network technologies, called Twitter Earthquake Detector (TED) (Guy et al. 2010; Earle et al. 2012). They downloaded tweets that contain the words "earthquake," "gempa," "temblor," "terremoto," or "sismo" from August to the end of November 2009. Based on tweet-frequency time series, they used a short-term-average, long-term-average algorithm to identify earthquakes, finding 48 earthquakes around the globe with only 2 false triggers in 5 months of data. The detections are faster than seismographic detections, with 75 % occurring within 2 min. These results demonstrate the efficiency of using Twitter as a detection tool, potentially achieving better and more accurate results when combined with existing systems.

The rich semantics of tweets and Twitter's broadcasting nature also hint at the potential of using Twitter for rapid emergency response tools to assist in intervention and crisis management. Caragea et al. developed a reusable information technology infrastructure, called Enhanced Messaging for the Emergency Response Sector (EMERSE) Caragea et al. (2011). The system is aimed at classifying tweets and text messages automatically, together with the ability to deliver relevant information to relief workers. EMERSE has four components, including an iPhone application, a Twitter crawler, machine translation, and automatic message classification. The system analyzed the information about the Haiti earthquake relief and provided their output to NGOs, relief workers, and victims and their friends and relatives in Haiti. To use Twitter as an emergency response tool, it is important to assess the information quality of tweets during an emergency situation. Li and Rao (2010) studied Twitter usage following the Sichuan earthquake in China in 2008. They focused on five information quality dimensions: timeliness, accessibility, accuracy, completeness, and collective intelligence, arguing that Twitter is an effective tool for information dissemination in critical moments following earthquake and its broadcasting nature plays an important role in emergency response. Mendoza et al. (2010) studied the dissemination of false rumors and confirmed news following 2010 Chile earthquake, finding that false rumors tend to be questioned much more than confirmed news. Their study indicates the possibility of using Twitter to detect rumors after an earthquake to make the rescue efforts more efficient.

Emergencies and Mobile Phones

In addition to social media websites, the pervasive adoption of mobile phones provides another potentially even more detailed avenue to monitor large populations. Mobile phone records usually include fine-grained longitudinal mobility traces and communication logs. The data allows greater opportunity to study personal social networks through their relationship with physical space, compared to the online social networks (e.g., "friends" and "followers" on Twitter). Mobile phones are well established in many areas, even in third world countries such as Rwanda (Kapoor et al. 2010). Leveraging their presence to assist in emergency response has great potential to save lives. Here we review two recent papers focused on mobile phones and emergencies. The first studied an earthquake that occurred in central Africa (Kapoor et al. 2010). The second analyzed a corpus of events including non-emergency controls such as music festivals occurring in Western Europe (Bagrow et al. 2011).

An Earthquake in Central Africa

To understand how effective mobile phones are at understanding emergency situations, a number of studies have been conducted. Kapoor et al. (2010) studied a 5.9 magnitude earthquake that occurred February 3, 2008, in Lake Kivu region of the Democratic Republic of Congo Kapoor et al. (2010). The dataset is the cellular activity patterns of mobile phone users in Rwanda. They used daily call volume on a per tower basis, and they also had the geographic coordinates of the towers. Their goal was to determine the location of the epicenter algorithmically using only the cellular data and to assess or predict what areas of the country are most in need of aid due to the earthquake.

To study these problems, they assumed that (i) cell tower traffic deviates in a statistically significant manner from normal activity levels and trends when an event occurs, (ii) areas that are more disturbed by the event will display traffic deviations for longer periods of time, and (iii) disruptions are inversely proportional to the distance from the catastrophe.

To detect an event they assumed the typical daily traffic on a tower obeys a gaussian distribution and they used a negative log-likelihood score to compare the current traffic with this distribution. The higher this score, the more likely there was an anomalous event on that day. They demonstrated that this score spikes on the day of the event, although they did not discuss a specific algorithm to automatically flag scores (e.g., introducing a threshold score such that an event is anomalous when its score exceeds that threshold).

To estimate the location of the event, they assumed the activity levels at a tower during the event follow a normal or gaussian distribution but that the mean of this tower's distribution is now a function of the distance from the epicenter. Specifically they used for tower i a distance-dependent mean $m_i + \alpha D_i(e_x, e_y)^{-1}$, where m_i is the normal mean traffic for i, α is some configurable scaling parameter, and $D_i(e_x, e_y)$ is the geographic distance of tower i from an epicenter located at coordinates (e_x, e_y). They determined this epicenter (e_x, e_y) (and also α) using well-established maximum likelihood estimates, that is, they found the epicenter and scaling parameters that maximize the sum of the log's of all the tower's probabilities.

The other problem they wish to address is to predict what areas are most in need of emergency aid. To do this, they want to predict whether a particular tower will experience a significant increase in traffic some number of days after the event. They accomplished this by building a classifier which allows them to estimate this persistence probability. Since it is reasonable to assume that areas with higher populations are likely to require more aid, they built an "assistance opportunity score" for a location by taking the product of the persistence probability estimate for that location and the population at that location. Such a score allows emergency responders to potentially prioritize aid efforts.

The authors also pointed out an important issue when using mobile phone data to study these problems: the density of towers, and therefore information, is not uniform. Cities have many more towers than rural regions, and this leads to far greater granularity in areas of high population and greater information uncertainty in areas with fewer towers. They exploited this fact to estimate what areas are most valuable to survey manually for information after an event, by prioritizing surveys towards areas with more uncertainty. They did this by devising a simple mechanism to drive down the entropy in the information that may be gained from the system, and they even incorporated geographic distances since it is more expensive in terms of time and effort to survey more remote regions.

All of their methods were validated by comparison with the February 3 earthquake and were shown to work rather well. For future work they discussed a number of interesting advancements such as incorporating richer models of geographic terrain.

Mobile Phones and Disasters

Bagrow et al. (2011) performed a data-driven analysis of a number of emergencies, including bombings, a plane crash, and another earthquake. This work reported a number of empirical discoveries regarding the response of populations in the wake of emergencies (and non-emergency control events such as festivals), as measured from the country-wide data of a single mobile phone provider in Western Europe. The assumptions made by Kapoor et al. (2010) are further justified by their work.

They found that emergencies trigger a sharp spike in call activity (number of outgoing calls and text messages) in the physical proximity of the event, confirming that mobile phones act as sensitive local "sociometers" to external societal perturbations. In Fig. 1a, we plot the relative call volume $\Delta V / \langle V_{\text{normal}} \rangle$ as a function of time, where $\Delta V = V_{\text{event}} - \langle V_{\text{normal}} \rangle$, V_{event} is the number of calls made from nearby towers during the event, and $\langle V_{\text{normal}} \rangle$ is the average call volume during the same time period of the week (Figure adapted from Bagrow et al. (2011)).

The anomalous traffic starts to decay immediately after the emergency occurs, suggesting that the urge to communicate is strongest right at the onset of the event. There was virtually no delay between the onset of the event and the jump in call volume for events that were directly witnessed by the local population, such as the bombing, the earthquake, and the blackout. Brief delay was observed only for the plane crash, which took place in an unpopulated area and thus lacked eyewitnesses. In contrast, non-emergency events, like the festival and the concert, displayed a gradual increase in call activity.

The temporally localized spikes in call activity (Fig. 1a) raise an important question: is information about an event limited to the immediate vicinity of the emergency or do emergencies, often immediately covered by national media, lead to spatially extended changes in call activity (Petrescu-Prahova and Butts 2008)? To investigate this, Bagrow et al. inspected the change in call activity in the vicinity of each event's epicenter, finding that for the bombing, for example, the change in call volume is strongest near the event and drops rapidly with the distance r from the epicenter. To quantify this effect across all emergencies, they integrated the call volume over time in concentric shells of radius r centered on the epicenter. The observed decay in anomalous traffic was approximately exponential, $\Delta V(r) \sim \exp(-r/r_c)$, allowing one to characterize the spatial extent of the reaction with a decay rate r_c (we present their results for the plane crash in Fig. 1b). The observed decay rates ranged from 2 km (bombing) to 10 km (plane crash), indicating that the anomalous call activity is limited to the event's vicinity. An extended spatial range ($r_c \approx 110$ km) was seen only for the earthquake. Meanwhile, non-emergencies are highly localized: they possess decay rates less than 2 km. This systematic split in r_c between the spatially extended emergencies and well-localized non-emergencies persisted for all explored events.

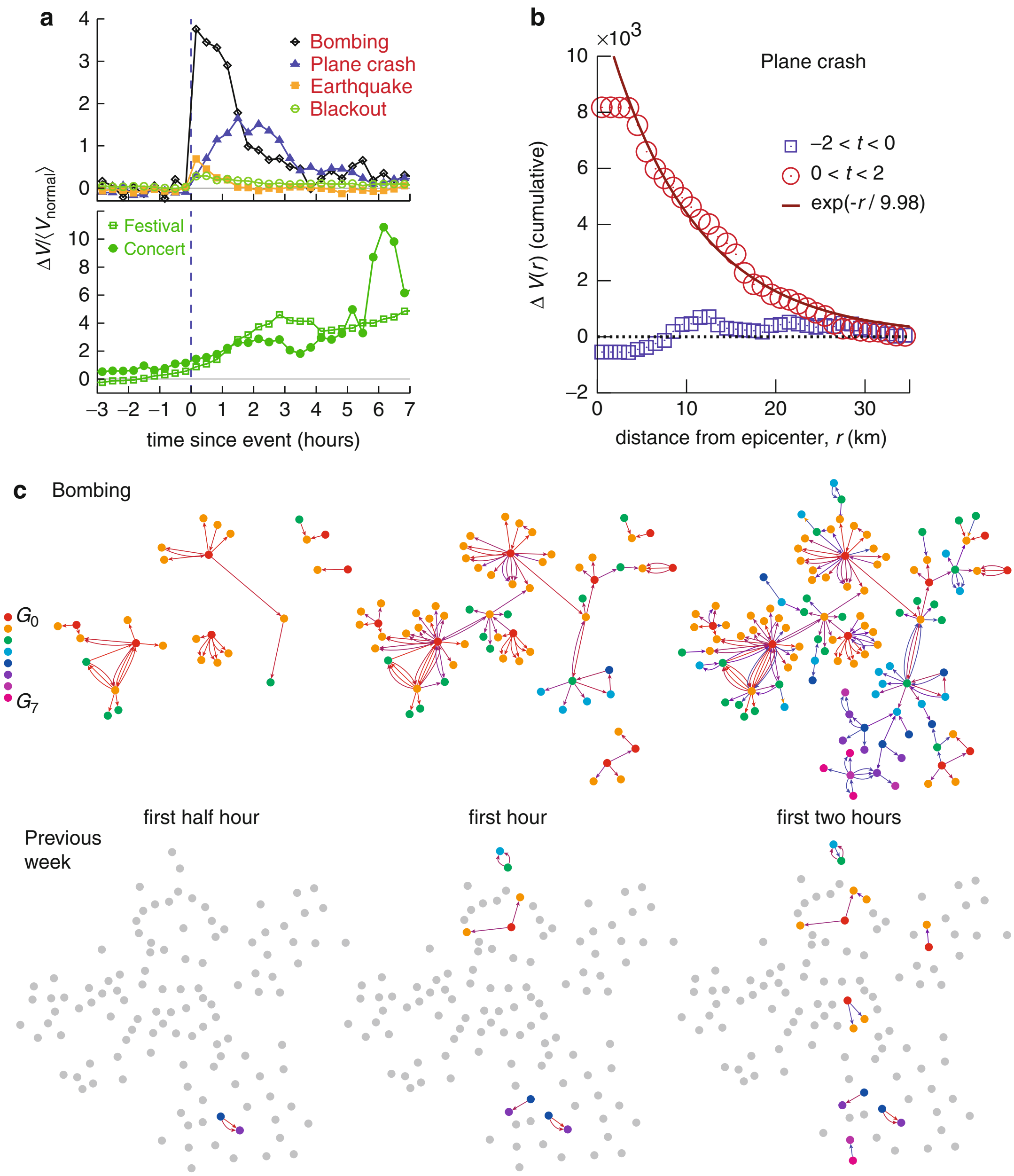
Despite the clear temporal and spatial localization of anomalous call activity during emergencies, one expects some degree of information propagation beyond the eyewitness population. To study how emergency information diffuses through a social network, Bagrow et al. used mobile phone records to identify those individuals located within the event region, forming a population called G_0 as well as a group called G_1 consisting of individuals outside the event region but who receive calls from the G_0 group during the event, a G_2 group that receive calls from G_1, and so on. They reveal that the G_0 individuals typically engage their social network within minutes and that the G_1, G_2, and occasionally even the G_3 group show an anomalous call pattern immediately after an emergency. We present their illustration of a segment of this contact network for the bombing in Fig. 1c. The authors proceeded to further quantify and control for this social propagation and showed that the bombing and plane crash have significant propagation up to the third and second neighbors of G_0, respectively. They found that other emergencies, the earthquake and blackout, displayed relatively little propagation. This seems reasonable given the less severe nature of those events (the earthquake was relatively minor).

Finally, we also presented a breakdown of a number of measurable features for each emergency and non-emergency and showed that these features may be used to distinguish anomalous call activity due to benign events such as music festivals from spikes in call volume that indicate a dangerous event has occurred. Using such factors may allow first responders to more accurately understand rapidly unfolding events and may even allow them to actively solicit information from mobile phone users likely to be near the event.

Key Techniques

We summarize the key techniques that have been used in the above-mentioned studies.

Event Detection. The first challenge in large-scale emergency studies is to determine and collect a subset of data relevant to emergencies under consideration. With Twitter or other social media data where the communication content is



Social Networks in Emergency Response, Fig. 1 Temporal, spatial, and social response during emergencies. **a** The time dependence of call volume $V(t)$ after four emergencies and two non-emergencies. We plot the relative change in call volume $\Delta V / \langle V_{\mathrm{normal}} \rangle$, where $\Delta V = V_{\mathrm{event}} - \langle V_{\mathrm{normal}} \rangle$, V_{event} is the call volume on the day of the event, and $\langle V_{\mathrm{normal}} \rangle$ is the average call volume during the same period of the week. **b** The total change in call volume during 2-h periods before and after the plane crash, as a function of distance r from the epicenter of the crash. Following the event, we see an approximately exponential decay $\Delta V \sim \exp r / r_{\mathrm{c}}$ characterized by decay rate r_{c}. **c** Part of the contact network formed between mobile phone users in the wake of the bombing. Nodes are colored by group, with G_0 representing phone users calling from the event region, G_1 the recipients of those calls, etc. As time goes by more users are contacted as information propagates. Those same users make little contact during a corresponding time period the week before (Figure adapted from Bagrow et al. (2011))

available in text format, most studies begin with a simple keyword matching, that is, collecting data that contained instances of the relevant keywords such as "flu," "H1N1," and "earthquake." The initial collections could be refined by manual and automated classification process. Classification techniques such as Support Vector Machines (SVMs) have been employed (Aramaki et al. 2011; Sakaki et al. 2010), and topic clustering methods such as Latent Dirichlet Allocation (LDA) can be used to improve the classification (Paul and Dredze 2011; Prier et al. 2011). Validation of this body of work is often conducted based on authority reports such as Centers for Disease Control and Prevention (CDC) statistics (Signorini et al. 2011) (for disease outbreaks) or US Geological Survey (USGS) reports (Guy et al. 2010; Earle et al. 2012) (for earthquakes). While the messages disseminated in social media might be inaccurate, there has been work on determining the quality of information sources (Li and Rao 2010; Mendoza et al. 2010). Further, by applying time-series analysis and spatiotemporal pattern analysis (e.g., Kalman filtering and particle filtering in Sakaki et al. (2010)), researchers have developed powerful earthquake detectors with performance comparative to existing earthquake detection systems.

Event Prediction and Forecasting. The development of event prediction and forecasting is still in its early stage. Gomide et al. (2011) used a linear regression model to predict the number of dengue cases. The earthquake detectors (Sakaki et al. 2010; Guy et al. 2010; Earle et al. 2012) that reported earthquakes faster than the seismographic detection can be used as early warning system. There has been work on developing information infrastructure which has the ability to deliver relevant information to users once events are detected (Caragea et al. 2011).

Spatiotemporal Pattern Recognition of Events. Unlike social media data, the content of communication is often unavailable in mobile phone data, and hence the identification of emergency events in mobile phone data relies on analyses of spatial and temporal anomalies of call logs. The main challenge of this research is to construct reasonable null model in order to recognize anomaly events. Bagrow et al. (2011) proposed using pre-emergency normal activities as well as the activities during non-emergency events to contrast the activities of emergency events. Based on this approach the epicenter of an emergency event can be identified. Kapoor et al. (2010) used a similar methodology to identify event epicenters as well as to predict the locations in need of emergency aid.

Future Trends

Foundational work understanding the sociology of disaster was limited in scale by available data but surveys and interviews can ask a number of in-depth follow-up questions. To understanding population response from, for example, mobile phone call volume alone is potentially more challenging as such data, while perhaps being more objective, is also far shallower. This begs the question: can more depth be found in communications data? The wealth of textual information available within social media such as Twitter can be leveraged to learn more context about how populations respond to emergencies, and advances in data mining and natural language processing techniques offer the promise of even greater information. This may allow researchers to separate relevant information from spurious activity, improving the accuracy and precision of information available to rescuers.

One can reasonably expect a degree of noise from any communication system, as users will be focused on diverse topics. Yet when something of overwhelming importance occurs, such as an emergency, it seems reasonable to expect that event to capture the majority of user attention. This may lead to a communication system that is less noisy and more focused as the severity of the event increases, in the sense that an increasing fraction of the system's communication will be about that event. Given this, it may be worth trying to develop (rigorous) bounds on how much useful information can be successfully extracted from such a system during and immediately following an event. This could allow quantitative benchmarking of algorithms designed to assist rescuers by comparing, for example, how much emergency information was extracted by an algorithm with the maximum amount possible.

Meanwhile, it will be crucial going forward to develop algorithms that combine and help understand multiple data sources—such as cell phone call volume, twitter messages, and perhaps even security cameras, all from a given geographic locale. This trend towards greater data availability and unification will only continue as more advanced and entirely new forms of telecommunication come into widespread use. Without methods to handle the increased diversity and volume of communication, rescuers may be unable to capitalize on the extra information provided by future telecommunications.

Conclusion

We have reviewed a number of works focused on the use of communications data, from social media to mobile phones, to understand how people react to emergencies and disasters. This problem is of critical importance: in many areas of the world, more people than ever are at risk, as both human populations and threats due to climate change continue to grow. Hopefully tools derived from social media and other communication datasets will help rescuers improve their emergency and disaster response by providing accurate, useful, and timely information in the wake of such events.

Cross-References

► Actionable Information in Social Networks, Diffusion of
► Counter-Terrorism, Social Network Analysis in
► Disaster Response and Relief, VGI Volunteer Motivation in
► Extracting Individual and Group Behavior from Mobility Data
► Modeling and Analysis of Spatiotemporal Social Networks
► Social Network Datasets
► Social Networking in the Telecom Industry
► Spatiotemporal Proximity and Social Distance
► Temporal Networks

References

Aramaki E, Maskawa S, Morita M (2011) Twitter catches the flu: detecting influenza epidemics using twitter. In: Proceedings of the conference on empirical methods in natural language processing, Edinburgh. Association for Computational Linguistics, pp 1568–1576

Bagrow JP, Wang D, Barabási A-L (2011) Collective response of human populations to large-scale emergencies. PLoS ONE 6(3):e17680

Caragea C, McNeese N, Jaiswal A, Traylor G, Kim H, Mitra P, Wu D, Tapia A, Giles L, Jansen B, et al (2011) Classifying text messages for the Haiti earthquake. In: Proceedings of the 8th international ISCRAM conference, ISCRAM, Harbin, vol 11

Chew C, Eysenbach G (2010) Pandemics in the age of twitter: content analysis of tweets during the 2009 h1n1 outbreak. PLoS One 5(11):e14118

Culotta A (2010) Towards detecting influenza epidemics by analyzing twitter messages. In: Proceedings of the first workshop on social media analytics, Washington, DC. ACM, pp 115–122

Earle P, Bowden D, Guy M (2012) Twitter earthquake detection: earthquake monitoring in a social world. Ann Geophys 54(6):708–715

Ginsberg J, Mohebbi M, Patel R, Brammer L, Smolinski M, Brilliant L (2008) Detecting influenza epidemics using search engine query data. Nature 457(7232):1012–1014

Gomide J, Veloso A, Meira W, Almeida V, Benevenuto F, Ferraz F, Teixeira M (2011) Dengue surveillance based on a computational model of spatio-temporal locality of twitter

Guy M, Earle P, Ostrum C, Gruchalla K, Horvath S (2010) Integration and dissemination of citizen reported and seismically derived earthquake information via social network technologies. In: Proceedings of the 9th international conference on advances in intelligent data analysis, Tucson, pp 42–53

Hughes A, Palen L (2009) Twitter adoption and use in mass convergence and emergency events. Int J Emerg Manag 6(3):248–260

Kapoor A, Eagle N, Horvitz E (2010) People, quakes, and communications: inferences from call dynamics about a seismic event and its influences on a population. In: Proceedings of AAAI artificial intelligence for development (AI-D'10), Stanford

Li J, Rao H (2010) Twitter as a rapid response news service: an exploration in the context of the 2008 china earthquake. Electron J Inf Syst Dev Ctries 42(0)

Mendoza M, Poblete B, Castillo C (2010) Twitter under crisis: can we trust what we rt? In: Proceedings of the first workshop on social media analytics, Washington, DC. ACM, pp 71–79

Paul M, Dredze M (2011) You are what you tweet: analyzing twitter for public health. In: Proceedings of the 5th international AAAI conference on weblogs and social media (ICWSM), Barcelona

Petrescu-Prahova M, Butts CT (2008) Emergent coordinators in the World Trade Center disaster. Int J Mass Emerg Disasters 28(3):133–168

Prier K, Smith M, Giraud-Carrier C, Hanson C (2011) Identifying health-related topics on twitter. In: Proceedings of the 4th international conference social computing, behavioral-cultural modeling and prediction, College Park, pp 18–25

Quincey E, Kostkova P (2010) Early warning and outbreak detection using social networking websites: The potential of twitter. Electronic Healthcare. Springer Berlin Heidelberg, 21–24

Rodríguez H, Quarantelli E, Dynes R (2006) Handbook of disaster research. Springer, New York

Sakaki T, Okazaki M, Matsuo Y (2010) Earthquake shakes twitter users: real-time event detection by social sensors. In: Proceedings of the 19th international conference on world wide web, Raleigh. ACM, pp 851–860

Sheetz S, Kavanaugh AL, Quek F, Kim BJ, Lu S-C (2010) The expectation of connectedness and cell phone use in crises. J Emergen Manag 7(2):124–136

Signorini A, Segre A, Polgreen P (2011) The use of twitter to track levels of disease activity and public concern in the us during the influenza a h1n1 pandemic. PLoS One 6(5):e19467

Zamite J, Silva F, Couto F, Silva M (2011) Medcollector: multisource epidemic data collector. In: Transactions on large-scale data-and knowledge-centered systems IV. Springer, Berlin/Heidelberg, 7(2):124–136