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Processing Social Media Messages in Mass Emergency: A Survey

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Social media platforms provide active communication channels during mass convergence and emergency events such as disasters caused by natural hazards. As a result, first responders, decision makers, and the public can use this information to gain insight into the situation as it unfolds. In particular, many social media messages communicated during emergencies convey timely, actionable information. Processing social media messages to obtain such information, however, involves solving multiple challenges including: handling information overload, filtering credible information, and prioritizing different classes of messages. These challenges can be mapped to classical information processing operations such as filtering, classifying, ranking, aggregating, extracting, and summarizing. We survey the state of the art regarding computational methods to process social media messages, focusing on their application in emergency response scenarios. We examine the particularities of this setting, and then methodically examine a series of key sub-problems ranging from the detection of events to the creation of actionable and useful summaries.

General Terms: Design, Algorithms, Performance

Additional Key Words and Phrases: Social media, Crisis computing, Disaster management, Mass emergencies

1. INTRODUCTION

Crisis situations such as disasters brought on by natural hazards present unique challenges to those who study them [Stallings 2002]. Disasters create conditions that call for quick decision-making on behalf of researchers, which affects everything from data collection, to analysis, to findings. Sociologists of disaster have long documented and discussed methods for studying disaster situations [Stallings 2002]. In this paper, we present methods for studying disasters from a different—and equally as challenging—perspective: that of information processing and management. We provide an extensive analysis of the state-of-the-art approaches for automatically processing social media content during emergencies and other mass convergence events.

According to the most recent *Humanitarian Data and Trends* report from United Nations [UN OCHA 2013], between 2002–2011 there were an average of 394 disasters per year triggered by natural hazards, which affected 124.5 million people. Out of these, floods had the greatest impact, with 116M people affected every year, followed by 72M people a year by drought, 40M by storms, 9M by extreme temperatures, and 8M by earthquakes.

Crisis situations—particularly those with little to no warning (known as "sudden onset crises")—generate a situation that is rife with questions, uncertainties, and the need to make quick decisions, often with minimal information. When it comes to in-

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formation scarcity, research in recent years has uncovered the increasingly important role of social media communications in disaster situations, and shown that information broadcast via social media can enhance situational awareness during a crisis situation [Vieweg 2012]. However, social media communications during disasters are now so abundant that it is necessary to sift through hundreds of thousands, and even millions, of data points to find information that is most useful during a given event.

The goal of this survey is to provide computer science researchers and software developers with computational methods they can use to create tools for formal response agencies, humanitarian organizations, and other end users with a way to successfully identify, filter, and organize the overwhelming amount of social media data that are produced during any given crisis. Such tools can help stakeholders make time-critical—and potentially life-saving—decisions.

1.1. Social Media During Crisis Situations

Brief History. The use of Internet technologies to gather and disperse information in disaster situations, as well as to communicate among stakeholders, dates back to the late 1990s. Internet historians point to online newsgroups and email clients that were used to coordinate protests in Indonesia in 1998 [Poole et al. 2005]. In addition, there are cases of websites being set up in response to crises in 2003 [Palen and Liu 2007].

To the best of our knowledge, 2004 is the first year in which a user-generated content website was used in response to a crisis; after the Indian Ocean Tsunami of December 26 that year, an electronic bulletin board was set up and moderated for 10 days.[1] In addition, in the aftermath of Hurricane Katrina, which struck the city of New Orleans in the United States in 2005, significant emergency response activity took place on MySpace [Shklovski et al. 2010].

Today when disasters occur, many members of the public, emergency response agencies, and others use the popular microblogging service Twitter as a way to quickly communicate to a wide audience. One of the earliest known cases of people using Twitter in an emergency was during severe wildfires that took place near San Diego, California (in the United States) in 2007.[2] Since then, it has become common practice for affected populations and concerned others to use Twitter to communicate, ask questions, collect and spread information, and organize response efforts (among other tasks) [Starbird et al. 2010; Vieweg et al. 2010; Sarcevic et al. 2012; Starbird 2013; Imran et al. 2014a; Cobb et al. 2014].

Today. The growing adoption of social media during disasters has created the opportunity for information propagation that would not exist otherwise. For example, in many disaster situations, people post situation-sensitive information on social media related to what they experience, witness, and/or hear from other sources [Hughes and Palen 2009]. This practice allows both affected populations and those outside the impact zone to learn about the situation *first hand*; the "one-to-many" nature of platforms such as Twitter allow users to reach a broad audience in near real-time. The potential for millions of people to have immediate access to what is happening as a disaster unfolds is an unprecedented opportunity for greater understandings of how these events take place, and what stakeholders can do to mitigate effects, and help victims.

We know that information posted to social media platforms in time- and safety-critical circumstances can be of great value to those tasked with making decisions in these fraught situations. Previous research has shown that information which con-

[1] http://www.thefreelibrary.com/www.p-h-u-k-e-t.com+Has+Served+Its+Purpose+After+the+Tsunami\%3B+Site...-a0126803919
[2] Eric Frost, personal communication.

tributes to situational awareness is reported via Twitter (and other social media platforms) during mass emergencies [Vieweg et al. 2010; Vieweg 2012; Imran et al. 2014a]. Now, those tasked with formal response efforts—from local fire departments to international aid agencies—are working to incorporate information broadcast on social media platforms into their processes and procedures. Many emergency responders and humanitarian officials recognize the value of the information posted on social media platforms by members of the public (and others), and are interested in finding ways to quickly and easily locate and organize that information that is of most use to them [Hughes 2012].[3] Some agencies have even begun to formally incorporate social media monitoring and communication during mass emergency situations. The American Red Cross (ARC) recently opened their Social Media Digital Operations Center for Humanitarian Relief. The goals of the center are to "source additional information from affected areas during emergencies to better serve those who need help; spot trends and better anticipate the public's needs; and connect people with the resources they need, like food, water, shelter or even emotional support." [4] Though the ARC is currently one of the few (possibly the only) formal agencies to support such a center, it is likely that similar operations will begin within other organizations.

Though formal response agencies express interest in incorporating social media into their processes, obstacles exist. For example, a recent survey by the US Congressional Research Service cites administrative cost as a significant barrier to adopting social media during emergencies: "The number of personnel required to monitor multiple social media sources, verify the accuracy of incoming information, and respond to and redirect incoming messages is also uncertain ... the federal government may experience a large volume of incoming messages from the public during a disaster. Responding to each message in a timely manner could be time consuming and might require an increase in the number of employees responding to incoming messages." [Lindsay 2011] However, we respond to this argument by referring to the computational methods that can help reduce the costs that governments and other concerned organizations are concerned about; automatic methods are necessary when human computation is limited, and in the following sections, we detail what those methods entail.

1.2. Background Readings

Sociologists began researching human behavior in mass emergency situations long before the Internet, or even modern computing. With social media becoming more common during emergency response (as well as other phases of emergency), understanding its role requires an awareness of how disaster situations unfold from a sociological viewpoint. The purpose of this survey is not to provide the reader with an exhaustive list of sociology of disaster literature; we highlight a few foundational readings that are helpful for the computer science, information science, technology, and social media scholars to gain quick insight into the rich and varied field of sociology of disaster.

E.L. Quarantelli's 2002 chapter "The Disaster Research Center (DRC) Field Studies of Organized Behavior in the Crisis Time Period of Disasters" (in *Methods of Disaster Research* edited by R.A. Stallings [2002]) provides a brief history of one of the foremost disaster research institutes in the United States. Quarantelli gives background on the Disaster Research Center, and explains the strategic as well as academically-oriented decisions that were made in order to highlight the importance of studying the social science aspects of disaster.

[3]Andrej Verity, personal communication
[4]http://www.redcross.org/news/press-release/The-American-Red-Cross-and-Dell-Launch-First-Of-Its-Kind-Social-Media-Digital-Operations-Center-for-Humanitarian-Relief

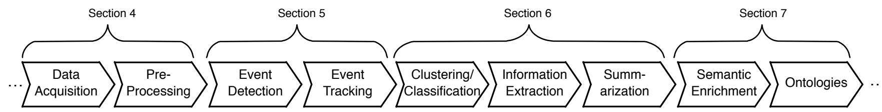

Fig. 1: Organization of the main sections of this survey.

In his edited volume "Disasters by Design," Dennis S. Mileti [1999] and the contributing authors aim to reach a general (i.e. non-academic) audience and provide background on disasters caused by natural hazards. The volume is comprised of "synthesized statements of what is known, collectively, about hazards and human coping strategies." Mileti and colleagues point to causes of disaster, which happen when three major systems—the physical, social, and built environments—interact in complex ways. The authors' goal is to give the reader a way to understand how to study disaster situations, with a final goal of helping members of the public create more resilient communities.

When it comes to combining studies of disaster with the use of social media, a recent survey by Hughes, Peterson and Palen considers the motivating factors of emergency responders regarding their use of social media data. The authors describe the challenges they face, best practices regarding the adoption of social media by formal response organizations, and also touch on instances of integrated, end-to-end systems that are currently being built to meet these needs [Hughes et al. 2014a]. In addition, an article by Palen and Liu [2007] was one of the first to provide an early assessment regarding how information and communication technology can support the participation of the public during crisis situations. Since then, many articles that focus on the role of social media in disaster have been published, but the two we mention here provide a good "first glance" to readers who are new to the field.

Our brief overview of foundational reading would not be complete without mentioning the much-discussed issue of trust and the use of social media. A recent ACM Computing Survey looks at this very topic [Sherchan et al. 2013]. The authors review the various definitions of "trust" from a variety of academic disciplines, discuss the factors that contribute to notions of trust, and combine the complex and much-scrutinized idea of trust with computing and social network research. Having a basic understanding of how trust is perceived in communications that take place through social networks is important at any time, but particularly in disaster situations when time is limited, and safety is often in question.

1.3. Scope and Organization

The overarching problem we aim to confront in this article is that of extracting time-critical information from social media that is useful for emergency responders, affected communities, and other concerned populations in disaster situations.

The following two sections briefly describe our target end user audience, and their information needs (Section 2), and end-to-end integrated systems (Section 3). The subsequent sections form the main technical part of this survey and present a systematic analysis of the computational methods we cover, as depicted in Figure 1:

— Section 4 describes methods for data acquisition and pre-processing.
— Section 5 covers (sub-)event detection.
— Section 6 outlines methods to mine and aggregate information.
— Section 7 presents how semantic technologies can be applied in this domain.

Our final section concludes the survey, and outlines current research directions.

2. USERS AND INFORMATION NEEDS

Much of the research we present here focuses on the computational aspects of processing social media messages in time- and safety-critical situations. It is additionally important to consider the end users of these technological solutions; those who benefit from having curated information that describes a disaster or crisis and enhances situational awareness include formal response agencies, humanitarian organizations, and members of the public.

2.1. Public Participation in Crises

Contrary to Hollywood renditions of disaster situations, human response to crises is not one of panic and mayhem [Mitchell et al. 2000]. Victims of disaster do not lose control, run amok, nor flee the area in fear. Instead, they make quick decisions based on the information available to them at the time, which often allow them to save their own lives as well as help those around them [Mitchell et al. 2000]. Neighbors, friends, and other members of the public are the first to respond when a disaster strikes. They rush to the scene to perform search and rescue operations, administer first aid, and perform additional critical tasks necessary in the first moments of response. Often, these "first responders" are victims of the disaster themselves [Dynes 1970]. The role of the public in disaster response efforts is critical, and with the growing use of social media to gather and disperse information, organize relief efforts, and communicate, those members of the public who can play a valuable role in these situations is no longer limited to those in the area of impact.

As [Dynes 1994] explains, emergencies do not render victims incapable of helping themselves and others, nor create a situation in which they are unable to make intelligent, personally meaningful decisions. What emergencies *do* create is an environment in which new and perhaps unexpected problems are presented, which members of the public are called upon to solve. Research in recent years on the use of social media in disasters shows how members of the public, formal response agencies, and other stakeholders have taken to online outlets to perform such tasks as communicating about hospital availability [Starbird 2013] or coordinating medical responses [Sarcevic et al. 2012] during the 2010 Haiti earthquake, and monitoring information, and communicating with the public during various crises that have taken place in the United States [Cobb et al. 2014], among many others. These users interact in complex ways including producing, distributing and organizing content [Starbird et al. 2010].

2.2. Differences in Information Needs

The recognition that social media communications are a valid and useful source of information in the moments after disaster impact is increasing among the many stakeholders who take action in disaster situations. Members of the public, formal response agencies, and local, national and international aid organizations are all aware of the ability to use social media to gather and disperse timely information in the aftermath of disaster, but the specific information they seek—and their ability to put it to use—may differ [Vieweg 2012].

Depending on the circumstances of the disaster, and what roles and duties the various stakeholders are responsible for, their specific information needs will vary. For example, in a wildfire situation that affects a community, members of a formal response organization such as local police or area firefighters can benefit from information such as where people are smelling smoke, what precautions they are taking (e.g. clearing brush, watering yards), and what traffic patterns look like. In a large-scale, sudden-onset disaster such as a typhoon or earthquake, humanitarian agencies, such as the various branches of the United Nations, or Doctors Without Borders, benefit from in-

Table I: Example systems described in the academic literature that extract crisis-relevant information from social media.

System name Data; example capabilities	Reference and URL
Twitris Twitter; semantic enrichment, classify automatically, geotag	[Sheth et al. 2010; Purohit and Sheth 2013] http://twitris.knoesis.org/
SensePlace2 Twitter; geotag, visualize heat-maps based on geotags	[MacEachren et al. 2011] http://www.geovista.psu.edu/SensePlace2/
EMERSE: Enhanced Messaging for the Emergency Response Sector Twitter and SMS; machine-translate, classify automatically, alerts	[Caragea et al. 2011] http://emerse.ist.psu.edu/
ESA: Emergency Situation Awareness Twitter; detect bursts, classify, cluster, geotag	[Yin et al. 2012; Cameron et al. 2012] https://esa.csiro.au/
Twitcident Twitter and TwitPic; semantic enrichment, classify	[Abel et al. 2012a; 2012b] http://wis.ewi.tudelft.nl/twitcident/
CrisisTracker Twitter; cluster, annotate manually	[Rogstadius et al. 2013] https://github.com/jakobrogstadius/crisistracker
Tweedr Twitter; classify automatically, extract information, geotag	[Ashktorab et al. 2014] https://github.com/dssg/tweedr
AIDR: Artificial Intelligence for Disaster Response Twitter; annotate manually, classify automatically	[Imran et al. 2014a] http://aidr.qcri.org/

formation that details the current situation "on the ground," such as where electricity has been disabled, or where people are without food and water. And in any disaster situation, members of the public play a variety of roles and take on many tasks; the information they find valuable may be very personal—i.e. hearing that a friend or loved one is safe, or it may be more broadly applicable, such as the status of a certain neighborhood or town.

Overall, the information any individual, group, or organization finds useful and seeks out in a disaster will depend upon their goals. Is it a group interested in providing food to children? Is it an organization that can set up a field hospital? Is it an individual living in a foreign country who is concerned about her or his family? The different types of information sought by these different stakeholders may be broadcast on Twitter, but to find it quickly, users rely on technological methods to sift through the millions of tweets broadcast at any given time to find that information that is useful. Further information and a deeper perspective on users of social media in disaster can be found in [Hughes et al. 2014a; Hughes and Palen 2012].

3. SYSTEMS FOR CRISIS-RELATED SOCIAL MEDIA MONITORING

Table I provides examples of existing systems described in the literature that extract crisis-relevant information from social media.[5] The systems we list have varying degrees of maturity; some have been deployed in real-life situations, while others remain under development.

Most existing systems are built around the concept of a *dashboard*, or a set of visual displays that provides a summary of social media during the crisis according to temporal, spatial, and thematic aspects. Common elements in these displays include:

— Lists/timelines showing recent or important messages, sometimes grouping the messages into clusters or categories.
— Time series graphs representing the volume of a hashtag, word, phrase, or concept over time, and sometimes marking peaks of activity.

[5]The list is not extensive, and does not include tools such as Radian6 (http://www.salesforcemarketingcloud.com/products/social-media-listening/) that have not been described in the literature, but might be relevant for other reasons—e.g. in the case of Radian6, because it is used by the American Red Cross.

— Maps including geo-tagged messages or interpolated regions, possibly layered according to different topics.
— Pie charts or other visual summaries of the proportion of different messages.

These visual elements are powered by computational capabilities that include:

— Collections of social media messages matching a given criterion, from one or multiple social media and/or SMS streams, typically with a focus on Twitter (described in Section 4).
— Natural language processing, including named entity recognition (NER) and linking of named entities to concepts (described in Section 4.4).
— Extraction of information from the messages, including geo-tagging (described in Section 4.5).
— Monitoring of the volume of messages (or sets of messages) to detect or help detect sub-events within a crisis, and sometimes the crisis itself (described in Section 5), possibly including the generation of user-defined alters when certain conditions are met.
— Clustering or automatic grouping of similar messages (described in Section 6.1.3).
— Classification of messages or groups of messages manually or automatically (see Section 6.1.2).
— Automatic translation of messages.

Though some of these systems are based on input or feedback provided by emergency responders and other officials, we note that to a large extent they are framed as a way to process social media data during crisis situations; their goal is not to address specific needs of emergency responders or other stakeholders. This focus on *processing* social media data possibly impacts the adoption of these systems by the practitioner community. Methodologies such as participatory design have been proposed to improve the matching between e.g. the needs of public information officers during a crisis, and the tools built by researchers and developers [Hughes 2014].

When the goal of meeting the specific need of users *is* stated explicitly in the design of systems, it often revolves around *enhancing situational awareness*, defined in [Endsley 1995] as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.”

For instance, *ESA* [Yin et al. 2012; Cameron et al. 2012] aims at enhancing situational awareness with respect to crises induced by natural hazards, particularly earthquakes. This is done by presenting information in time (frequency series) and space (maps), which is achieved by performing event detection, text classification, online clustering and geotagging. Similarly, *SensePlace2* [MacEachren et al. 2011] is presented as a *geovisual analytics* system, which filters and extracts geographical, temporal and thematic information from tweets in order to present them in a layered map.

In parallel to approaches that use natural language processing (NLP) techniques to enhance situation awareness, *Crisis Mapping* emerged as an alternative type of system, first by employing digital volunteers to collect, classify, and geo-tag messages [Meier 2011], and then by using the input from those volunteers to train machines to perform these tasks automatically [Imran et al. 2014a].

4. DATA CHARACTERIZATION, ACQUISITION, AND PREPARATION

Both academics and practitioners gather social media data during crisis events. In this section, we will describe the common practices used to collect, represent, and process this data.

4.1. Social Media

Social media is a general term that encompasses a variety of platforms on which user-generated content can be disseminated and consumed, and where users can grow online connections with others. This definition currently includes blogging and microblogging, online social networking sites, social media sharing platforms, and *wikis* [van Dijck 2013]. The user-generated content posted on the social media platforms include, images, videos, text, and links to other sources of information. In addition to sharing content, actions include commenting or appraising the content posted by others, and passing this information along to one's own network.

Based on a "global social media census" by Business Insider on October 2013, the ten largest online social networks in terms of monthly active users are: Facebook (a social networking site, 1,200M active users per month), YouTube (a video hosting site 1,000M), QZone China (social networking site, 721M), Sina Weibo (microblogging site, 500M), WhatsApp (mobile chat application, 350M), Google Plus (social networking site, 327M), Tumblr (microblogging site, 300M), LINE (mobile chat/talk application, 275M), Twitter (microblogging site, 240M) and WeChat (mobile chat application, 236M).[6] Of these, three are mobile-only platforms (WhatsApp, LINE, and WeChat), and all the others can be accessed through mobile applications.

4.2. Characteristics of Messages Broadcast on Social Media in Disaster

Activities such as staying in touch with friends and family, and connecting with others, have driven the growth of social media platforms.[7] Currently, different social networking sites are used for different purposes, but commonalities do exist. For instance, the top 3 activities on Twitter are to (1) post about daily activities, (2) upload and share photos, and (3) comment on posts of others; while on Facebook they are to (1) upload and share photos, (2) message with friends on a one-on-one basis, and (3) comment on posts of friends [GlobalWebIndex 2013].

In any of these platforms, an increase in social media communications can be triggered by a variety of causes, which can be divided into *endogenous* and *exogenous* [Crane and Sornette 2008]. Endogenous causes refer to phenomena in which an idea or "meme" gains popularity by a process of *viral contagion* or *information cascade*, where content spreads rapidly through a network, potentially reaching a significant fraction of all the users [Chen et al. 2013].

Exogenous causes refer to large-scale events, usually happening in the physical world, of wide interest to social media users. Emergencies and mass convergence events are examples of an exogenous cause. And during such events, we know that communication activity increases. For instance, it has been observed that mobile network usage—both in terms of phone calls and SMS—increases in emergency situations [Gao et al. 2014]. The same is true for social media usage, which "rises during disasters as people seek immediate and in-depth information" [Fraustino et al. 2012].[8]

To illustrate the types of information that affected populations broadcast specifically on the popular microblogging platform Twitter, we turn to some example messages that have been highlighted in previous literature:

— "OMG! The fire seems out of control: It's running down the hills!" (bush fire near Marseilles, France, in 2009, quoted from Twitter in [De Longueville et al. 2009])

[6]http://www.businessinsider.com/a-global-social-media-census-2013-10
[7]http://www.pewinternet.org/2011/11/15/why-americans-use-social-media/
[8]This is the idea behind Tweetping (http://tweetping.net/) and similar services, although more fine-grained methods for crisis detection exist, as we shall see in Section 5.

— “Red River at East Grand Forks is 48.70 feet, +20.7 feet of flood stage, -5.65 feet of 1997 crest. #flood09” (automatically-generated tweet during Red River Valley floods in 2009, quoted from Twitter in [Starbird et al. 2010])
— “Anyone know of volunteer opportunities for hurricane Sandy? Would like to try and help in anyway possible” (Hurricane Sandy 2013, quoted from Twitter in [Purohit et al. 2013])
— “My moms backyard in Hatteras. That dock is usually about 3 feet above water [photo]” (Hurricane Sandy 2013, quoted from Reddit in [Leavitt and Clark 2014])
— “Sirens going off now!! Take cover...be safe!” (Moore Tornado 2013, quoted from Twitter in [Blanford et al. 2014])

Though the above are only a few examples, they convey a sense of the types of information posted during an event, and show that it is varied. Vieweg [2012], points to this variation in her research that is based on a detailed study of 4 crisis events, in which she identifies 37 types of messages which are divided into 3 broad categories, corresponding to the social environment, built environment, and physical environment [Mileti 1999]. She points out that social environment messages describe anything having to do with people and their reactions to the crisis, built environment messages correspond to information and updates about property and infrastructure, and physical environment messages include updates about the hazard agent, weather, and other environmental factors (see Section 6.1.1 for details on different ways of categorizing this information).

Quantifying the amount of information found in social media based on type is even more difficult than locating that information in the first place. Important variations have been observed across crises (even for similar events) and at different stages of a crisis [Blanford et al. 2014; Imran et al. 2013a]. Olteanu et al. [2014], looked at the prevalence of three broad categories of information in tweets related to six crisis events. The results show large variabilities in the number of tweets reporting the negative consequences of an event (20%-60%), those offering or asking for donations (15%-70%) and those warning about risks or providing advice (5%-20%).

Researchers have also noted that sets of tweets can be selected and put together to represent the evolution of an event. To illustrate, Figure 2 shows a timeline of tweets derived from an analysis of Twitter activity during a major forest fire in July 2009 in the South of France [De Longueville et al. 2009]. The timeline provides a brief narrative of the event via tweets, and highlights the various phases of the fire as they are demonstrated on Twitter.

Using tweets as an indication of spatial zones during a disaster is also possible. For instance, Acar and Muraki [2011] examine the use of Twitter during an earthquake in Japan and observed that tweets from affected areas include more requests for help and more warnings, while tweets from other areas which are far from the disaster epicenter tend to mostly include other types of information, such as concern and condolences.

4.3. Data Acquisition

Most large social media platforms provide programmatic access to their content through an Application Programming Interface (API). However, the details of these APIs vary substantially from one platform to another, and also change over time. Additionally, all APIs that we are aware off are resource-limited in some way, usually in terms of number of allowed requests per unit of time.

APIs to access social media data typically belong to one of two types: those allowing to query an archive of past messages (also known as *search* APIs), and those allowing data collectors to subscribe to a real-time data feed (also known as *streaming* or *filtering* APIs). Both types of APIs typically allow data collectors to express an infor-

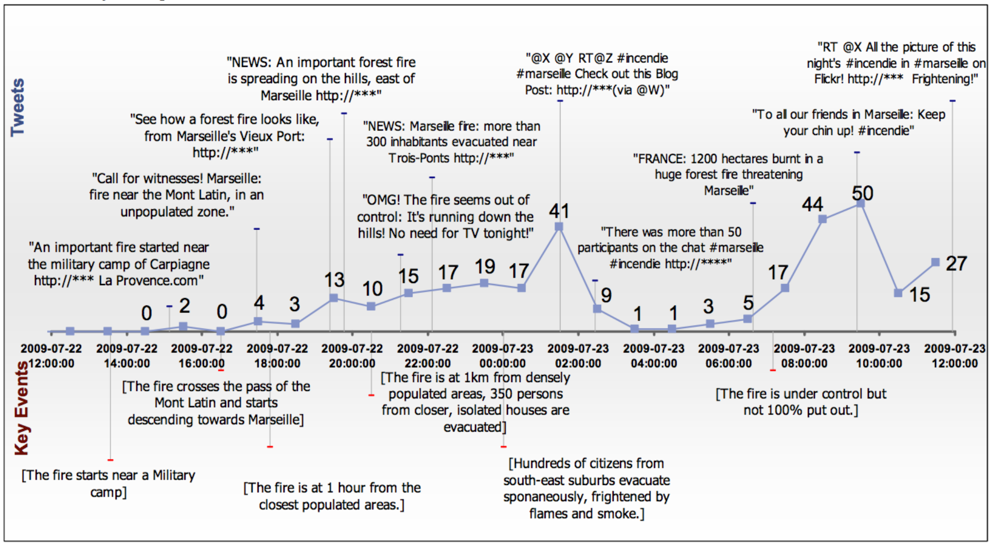

Fig. 2: Chronology of the Marseilles Fire, number of related tweets per hour and selected tweets contents. (Figure from [De Longueville et al. 2009] reproduced with permission from the authors.)

mation need, including one or several of the following constraints: (i) a time period, (ii) a geographical region for messages that have GPS coordinates (which are currently the minority), (iii) a set of keywords that must be present in the messages, which requires the use of a query language whose expressiveness varies across platforms. In the case of archive/search APIs, messages are returned sorted by relevance (a combination of several factors, including recency), or just by recency. In the case of real-time/streaming/filtering APIs, messages are returned in order of their posting time.

Data collection strategies impact the data obtained and analytic results. For instance, selecting messages in the geographical region affected by a disaster vs. selecting messages based on a keyword-based query return datasets having different characteristics [Olteanu et al. 2014].

Twitter as a key data source. Most research and most systems (such as the ones described in Section 3) use data obtained automatically from Twitter,[9] due to the existence of a streaming API providing a random sample of all public postings.[10] This is in contrast with most other social media platforms. For instance, Sina Weibo allows users to programmatically poll for the latest 20 public postings, but not to obtain them in a streaming fashion,[11] Facebook provides a stream of recent public postings through an API, but only to selected partners,[12] YouTube provides an API call for just a "most popular by country" stream,[13] while Google Plus and Tumblr do not provide this func-

[9]There are many exceptions e.g. Facebook [Bird et al. 2012], Reddit [Leavitt and Clark 2014], etc.
[10]As of April 2014, https://dev.twitter.com/docs/api/streaming
[11]As of April 2014, http://open.weibo.com/wiki/API%E6%96%87%E6%A1%A3/en
[12]As of April 2014, https://developers.facebook.com/docs/public_feed/
[13]As of April 2014, https://developers.google.com/youtube/2.0/developers_guide_protocol_video_feeds#Standard_feeds

tionality at all, allowing only to query the recent posts of a specific user (in the case of Google Plus)[14] or those having a specific tag (in the case of Tumblr).[15]

4.4. Data Pre-Processing

Most researchers and practitioners prepare social media data by *pre-processing* it, using some of the methods outlined below, before performing the actual analysis. Many pre-processing techniques are available, and the choice depends on the type of data at hand and the goals of the analysis.

Natural language processing (NLP). The text of the messages can be pre-processed by using a NLP toolkit. Typical operations include tokenization, part-of-speech tagging (POS), semantic role labeling, dependency parsing, named entity recognition and entity linking. A number of off-the-shelf implementations of these operations are available online, e.g. the Stanford NLP[16] or NLTK for Python.[17] Social media-specific NLP toolkits can also be used. For instance, ArkNLP [Owoputi et al. 2013], which is trained on Twitter data, is able to recognize Internet idioms such as "ikr" (*I know, right?*) and assign them the correct POS tag (interjection, in this case). Additionally, higher-level operations can be applied, including applying sentiment analysis methods to infer aspects of the emotion conveyed by a piece of text [Pang and Lee 2008].

Feature extraction. For many automatic information processing algorithms (e.g. machine learning), each data item must be represented accurately as an information record. The representation of choice for text is typically a numerical vector in which each position corresponds to a word or phrase—this is known as the vector space model in information retrieval. The value in each position can be a binary variable, indicating the presence or absence of that word or phrase in the message, or a number following some weighting scheme, such as tf.idf, which favors terms that are infrequent in the collection [Baeza-Yates and Ribeiro-Neto 2011]. To avoid having too many variables, textual features can be discarded by removing stopwords and functional words, or by normalizing words using stemming or lemmatization (e.g. considering "damaging" and "damage" as equivalent), or other means.

Additionally, other text-based features can be added, such as the length of the text in words or characters, and the number of question or exclamation marks. If some NLP pre-processing is performed on the text—such as part-of-speech-tagging—a feature such as *noun:fire* (instead of *verb:fire*) can be used to distinguish that the word "fire" is being used in a message as a noun ("I heard a fire alarm") instead of a verb ("They should fire him").

In the case of tweets, characteristics such as the presence of user mentions ("@user"), URLs, or hashtags can be included as features. In the case of images or video, content-based features such as colors, textures and shapes can be included (see e.g. [Liu et al. 2007] for a survey). Additionally, features such as the date of a message, tags associated with it, the number of views/comments it has received, or information about its author, are often available in a platform-dependent manner.

Obviously, one can spend a great deal of time constructing features by hand. In order to guide this exploration, both researchers and practitioners should prioritize the development and understanding of features likely to be correlated with the target variable (e.g. tweet classification). By the same token, features valuable to one target variable may not be important at all for a different target variable. Although often

[14] As of April 2014, https://developers.google.com/+/api/latest/
[15] As of April 2014, http://www.tumblr.com/docs/en/api/v2
[16] http://www-nlp.stanford.edu/software/
[17] http://www.nltk.org/

under-appreciated, feature engineering is perhaps the most important part of a modeling exercise.

De-duplication. Further reduction of the amount of data to be processed can be achieved by removing near-duplicate messages. Given that in many social media platforms the number of people re-posting a message can be interpreted as a measure of its importance, whenever removing near-duplicates it is advisable to save the number of near-duplicates that have been found (e.g. as done in [Rogstadius et al. 2013] to prioritize highly-reposted stories). De-duplication can be done by applying a clustering method (see Section 6.1.3).

Filtering. A fraction of the messages collected will not be relevant for a given crisis. This fraction depends on the specific collection method used (as discussed in [Olteanu et al. 2014]) and on other factors, such as the presence of off-topic messages using the same tags or keywords as the on-topic ones [Qu et al. 2011]. These messages can be post-filtered using human labeling or crowdsourcing, keyword-based heuristics, or automatic classification.

Additionally, many messages are posted automatically on social media for financial gain, exploiting the attention that a certain hashtag has received. These unsolicited commercial messages are known as *spam* [Gupta and Kumaraguru 2012; Uddin et al. 2014] and there are well-studied methods that can remove a substantial portion of them [Benevenuto et al. 2010]. Finally, in some cases we might want to also remove messages posted by automatic agents or social media *bots*. Their identification is similar to that of spammers.

4.5. Geo-Tagging

Determining the location to which a message refers is key to enabling filtering by geographical region and/or displaying the collected information on a map. The availability of machine-readable location information in social media messages depends on the user's device having the capacity to know its location (e.g. via GPS), on the specific client software having the capability to read this from the device, and most importantly, on the user enabling this feature explicitly (opting-in). In practice, a minority of crisis-related messages include machine-readable location information.

However, while GPS coordinates may be absent, many messages in social media do contain references to names of places (e.g. "The Christchurch hospital is operational"). *Geo-tagging* consists of finding geographical references in the text, and linking them to identifiers of places or to geographical coordinates. This can be done by using a named entity extractor to extract potential candidates, and then comparing those candidates with a list of place names. This is the approach used by e.g. [MacEachren et al. 2011] which uses Gate[18] for the first task and Geonames[19] for the second.

While building a comprehensive database of geospatial information, including place names, is an important component of geo-tagging (see e.g. [Middleton et al. 2014]), geo-tagging is not merely a dictionary look-up process because of ambiguities. These ambiguities are known as "*geo/non-geo*" and "*geo/geo*." A geo/non-geo ambiguity occurs for instance in the message "Let's play Texas Hold 'em," that does not refer to the state of Texas in the USA. A geo/geo ambiguity is found in the message "There is a fire in Paris," which may refer to the capital of France, or to any of more than a dozen places on Earth sharing the same name.

[18]https://gate.ac.uk/
[19]http://geonames.org/

In general, geo-tagging requires us to exploit contextual clues. These clues may include the general location of a crisis, information about nearby places, and location information indicated by users in their profiles. [Gelernter and Mushegian 2011].

4.6. Archived versus Live Data Processing

Depending on the urgency with which the output of an analysis is required, data may be provided to an algorithm either as an archive, for *retrospective* analysis, or as a live data feed, for *real-time* analysis. These correspond to two standard concepts in computer science: *off-line* processing and *on-line* processing.

Retrospective data analysis (*off-line processing*) starts with a batch of data relevant to an event, usually containing messages over the entire time range of interest. For example, we might consider re-constructing a timeline of events in the aftermath of an earthquake, by looking at all of the tweets from the moment of the earthquake up to two weeks after. In deciding how to build the timeline, we have the complete context of events during this two week window.

Live data analysis (*on-line processing*) is done over a stream of data relevant to the event, usually provided in real-time or with a short delay. For example, we might consider constructing a timeline of the events in the aftermath of an earthquake *as we observe new tweets*; in deciding how to build the timeline, we have an incomplete context of the events and their future repercussions.

It is possible for algorithms to lie in between, operating on small batches of data at regular intervals (e.g. hourly, daily). The trade-off between retrospective and live data is a matter of accuracy versus latency. Retrospective data analysis maximizes our context and, as a result, gives us an accurate picture of the data. However, because we have to wait for the data to accumulate, we incur latency between when an event happens and when it is processed. Live data analysis, on the other hand, minimizes the latency but, because we have partial information, we may incur lower accuracy. The choice of collection methodology depends on the use case. Crisis responders may want lower latency in order to better respond to a developing situation; forensic analysts may want higher accuracy and have the benefit of waiting for data to be collected.

While developing an algorithm, we can use retrospective data to *simulate* live data. This is a standard experimental methodology that has been used in the past for information filtering tasks [Voorhees and Harman 2005] and, more recently, for crisis informatics [Guo et al. 2013; Aslam et al. 2013].

4.7. Challenges

There are a number of challenges associated with the processing of social media messages. In this section, we group them into two high-level categories: scalability and content. We defer specific challenges (e.g. challenges to event detection) to their respective technical sections.

Scalability issues. Large crises often generate an explosion of social media activity. Data *size* may be an issue, as for crises that last several days, millions of messages may be recorded. While the text of each message can be sorted, a data record for e.g. a Twitter message (140 characters of text) is around 4KB when we consider the metadata attached to each message. Thus, a Twitter collection for a crisis is then on the order of several hundred megabytes to a few gigabytes. In addition, multimedia objects such as images and videos may significantly increase the storage space requirements.

Data *velocity* may be a more challenging issue, especially considering that data does not flow at a constant rate but experiences drastic variations. The largest documented

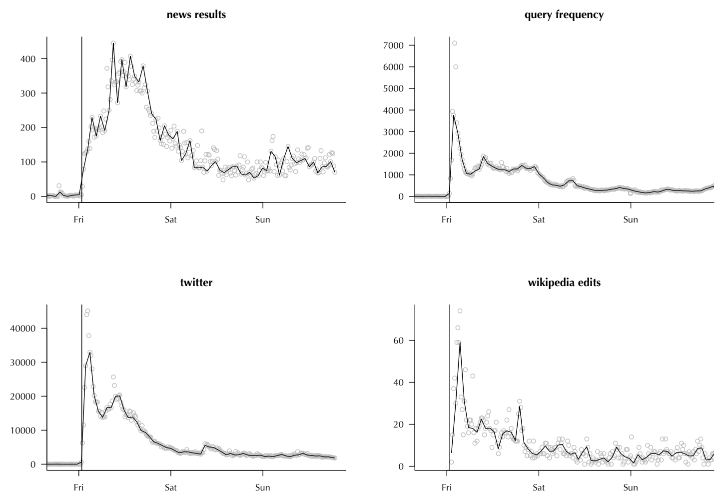

Fig. 3: Volume of content related to the 2011 Sendai Earthquake for Yahoo! News (top left), Yahoo! Search queries (top right), Twitter (bottom left), and Wikipedia (bottom right). Figure from [Guo et al. 2013, Extended version], reproduced with permission from the authors.

peak of tweets per minute during a natural hazard that we are aware of is 16,000 tweets per minute.[20]

Finally, *redundancy*, which is commonly cited as a scalability challenge, to some extent cannot be avoided in this setting. Repeated (re-posted/re-tweeted) messages are common in time-sensitive social media, even encouraged, as in some platforms messages that gain more notoriety are those who are simply repeated more.

Figure 3 depicts these scalability challenges in the content dynamics surrounding the 2011 Sendai earthquake for four text corpora: news, search queries, Twitter, and Wikipedia. Volume of content grows by many orders of magnitude across all corpora. At the same time, the velocity production is roughly four to seven times that found only a day after the event. The large relative amount of content production compared to Wikipedia edit generation suggests that the new content is also heavily redundant. In the years since the Sendai earthquake, these challenges have only grown.

Content issues. Social media messages are *brief and informal*. In addition, this type of messaging is often seen by users to be more akin to speech, as opposed to a form of writing, which—compounded with technological, cross-lingual and cross-cultural factors—implies that on the Internet "we find language that is fragmentary, laden with typographical errors, often bereft of punctuation, and sometimes downright incoherent" [Baron 2003]. This poses significant challenges to computational methods, and can lead to poor and misleading results by what is known as the "garbage in, garbage out" principle.

Messages are also highly *heterogeneous*, with multiple sources (e.g. traditional media sources, eyewitness accounts, etc.), varying levels of quality, and different languages present in the same crisis and sometimes in the same message—a phenomena known

[20]During Hurricane Sandy in 2012: http://www.cbsnews.com/8301-205_162-57542474/social-media-a-news-source-and-tool-during-superstorm-sandy/

as "borrowing," and "code switching." This makes it difficult for both machines and humans (e.g. content annotators) to understand or classify messages.

Finally, brief messages sent during a crisis often assume a shared context from which only a minor part is sometimes made explicit. The area of study in linguistics known as *pragmatics* focuses on "communication in context," and explains how people are able to infer the meaning of the communications because humans are very adept at understanding context. So, in the case of Twitter communications, a reader can understand the tweet author's intent because she or he knows the context within which that tweet is being broadcast. Current computational methods are not able to make the same inferences humans do, and thus cannot achieve the same level of understanding [Vieweg and Hodges 2014].

5. EVENT DETECTION AND TRACKING

Most systems for social media processing during crises start with *event detection*. An event is the *occurrence of something significant* which is associated with a specific *time* and *location* [Brants et al. 2003]. However, due to the online nature of social media communications, events as they play out in social media may or may not be necessarily associated with a physical location. In the context of social media, Dou et al. [2012a] define an event as: "An occurrence causing changes in the volume of text data that discusses the associated topic at a specific time. This occurrence is characterized by topic and time, and often associated with entities such as people and location".

Events typically fall into two broad categories: *predicted* (or *forewarned*) and *unexpected*. Some disaster events can be predicted to a certain level of accuracy based on meteorological or other data (e.g. this is the case with most large storms and tornadoes), and information about them is usually broadcast publicly before the actual event happens. Other events cannot be predicted (e.g. earthquakes), and in this case an automatic detection method is useful to find out about them as quickly as possible once they make impact. In this section, we study techniques available for the automatic detection of both *predicted*, and *unexpected* events.

5.1. Background on Event Detection and Discovery

A well-studied problem in Information Retrieval is detecting events in a stream of documents (see e.g. [Allan et al. 1998]). These documents can be news articles from traditional media sources, or posts on social media (e.g., tweets, Facebook posts, Flickr images). Traditionally, the *topic detection and tracking* (TDT) research community uses newswires as source data streams for event detection.

Various techniques are employed in TDT including *story segmentation*, *topic detection*, *new event detection*, *link detection*, and *topic tracking*. *Story segmentation* focuses on determining story boundaries from streaming speech recognition output, usually from radio or television broadcasts. *Topic detection* groups related documents together into cohesive topics. *New event detection* processes each new document to decide if it describes a previously-unseen story. *Link detection* detects that if two documents are similar or not. Finally, *event tracking* follows the evolution of an event/topic to describe how it unfolds.

Event detection on social media is different from the traditional event detection approaches that are suitable for other document streams. Social media data emerge more quickly, and in larger volumes than traditional document streams. In addition, social media data are composed of short, noisy, and unstructured content that often require a different approach than what is used with traditional news articles. Considering the unique characteristics of social media streams, we focus on the remainder of this section on new event detection and event tracking. Nevertheless, techniques and evaluation metrics from the TDT community provide insight into methods that might work for Twitter domain.

5.2. New Event Detection (NED)

New event detection (NED) refers to the task of discovering *the first story on a topic of interest* by continuously monitoring document streams. In the TDT community, NED is characterized as an example of "query-less information retrieval" where no prior information is available on a topic of interest [Makkonen et al. 2003]. NED makes a binary decision on whether a document reports a new topic that has not been reported previously, or if should be merged with an existing topic [Yang et al. 2009].

We will discuss NED systems according to how they process data: retrospectively or online [Yang et al. 1998] (see Section 4.6).

5.2.1. Retrospective New Event Detection. Retrospective NED refers to the process of identifying events using documents that have arrived in the past. This process often requires the use of a similarity metric for comparing documents. Metrics such as the Hellinger similarity, Kullback-Leibler divergence, and cosine similarity are among those commonly used [Kumaran et al. 2004]. For instance, Sayyadi et al. [2009] introduce a retrospective NED approach that overlays a graph over the documents, based on word co-occurrences. They assume that keywords co-occur between documents when there is some topical relationship between them. Next, a community detection method over the graph is used to detect and describe events.

Zhao et al. [2007] introduce a retrospective NED method that uses textual, social and temporal characteristics of the documents to detect events on social streams such as weblogs, message boards, and mailing lists. They build multi-graphs using social textual streams, where nodes represent social actors, and edges represent the flow of information between actors. Clustering techniques and graph analysis are combined to detect an event.

Pohl et al. [2012] describe a two-phase clustering approach to identify crisis-related sub-events in photo-hosting site Flickr and video-hosting site YouTube. During the first phase, which is to identify sub-events, clusters are formed by using only items that contain explicitly geographical coordinates. These coordinates are added automatically by the device used to capture the photo or video, or are added later by its author/uploader. Next, they calculate term-based centroids of the identified clusters using cosine distance to further describe the identified sub-events.

Another retrospective NED approach is presented in [Chen and Roy 2009], with experiments run on Flickr. It uses photos, user-defined tags, and other meta-data including time and location to detect events. This approach simultaneously analyzes the temporal and geographical distribution of tags, and determines the event type (e.g. whether it is a recurring) to form clusters. Finally, for each tag cluster, the corresponding photos are retrieved.

Ritter et al. [2012] extract significant events from Twitter by focusing on certain types of words and phrases. In their system, called *TwiCal*, they extract event phrases, named entities, and calendar dates. To extract named entities, they use a named entity tagger trained on 800 randomly selected tweets. To extract event mentions they use a Twitter-tuned part-of-speech tagger [Ritter et al. 2011]. The extracted events are classified retrospectively into event types using a latent variable model that first identifies event types using the given data, and then performs classification.

Li et al. [2012b] introduce *Twevent*, a system that uses message segments instead of individual words to detect events. The authors claim that a tweet segment, which represent one or more consecutive words in tweets, contains more meaningful information than unigrams. Overall, the *Twevent* approach works in five phases. First, the individ-

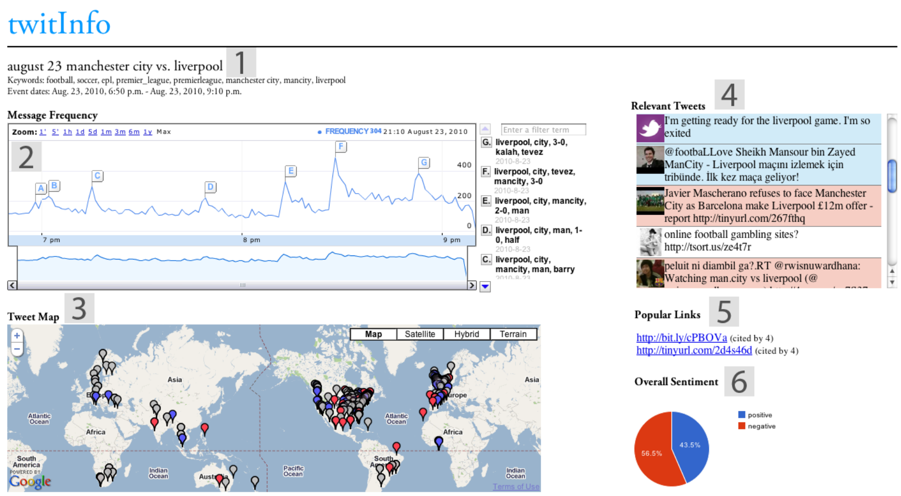

Fig. 4: The TwitInfo interface. 1: user-defined query, 2: volume of tweets over time, 3: geographical map of tweets, 4: sample of tweets, 5: popular links, 6: aggregated sentiment. (Figure from [Marcus et al. 2011] reproduced with permission from the authors.)

ual tweet is segmented, and bursty segments are identified by using the segments' frequency in a particular time window. Next, identified segments are retrospectively clustered using KNN (K-nearest neighbors) clustering. Finally, a post-filtering step uses Wikipedia concepts to filter the detected events.

5.2.2. Online New Event Detection. Online new event detection refers to the task of identifying events from online streams of documents. In contrast to the retrospective NED, the techniques that fall into this category do not use previously-seen documents or any prior knowledge about the events to be identified. Online NED is typically performed with low latency (in real-time), in the sense that the time between seeing a document corresponding to a new event and reporting that a new event has been detected is relatively short.

Methods based on keyword burst. A straightforward approach is to assume that words that show sharp frequency increases over time are related to a new event. For instance, Robinson et al. [2013] introduce a system to detect earthquakes using Twitter. The earthquake detector, which is based on the Emergency Situation Awareness (*ESA*) platform [Cameron et al. 2012], checks for the keywords "`earthquake`" and "`#eqnz`" in the real-time Twitter stream, and applies a burst detection method to analyze word frequencies in fixed-width time-windows and compare them to historical word frequencies. Unusual events are identified if the observed frequencies are much higher than those recorded in the past.

Marcus et al. [2011] introduced *TwitInfo*, a system for detecting, summarizing and visualizing events on Twitter. *TwitInfo* collects tweets based on a user-defined query (e.g. keywords used to filter the Twitter stream). It then detects events by identifying sharp increases in the frequency of tweets that contain the particular user-defined query as compared to the historical weighted running average of tweets that contain that same query. Further, tweets are obtained from the identified events to identify and represent an aggregated sentiment (i.e., classifying tweets into positive and negative classes). The authors evaluated the system on various events such as earthquakes and popular football games, as shown in Figure 4.

A similar system, *TwitterMonitor* [Mathioudakis and Koudas 2010], also collects tweets from the Twitter stream and detects trends (e.g. emerging topics such as breaking news, or crises) in real-time. The trend detection approach proposed in their paper works in two phases. During the first phase, *TwitterMonitor* identifies bursty keywords which are then grouped based on their co-occurrences. Once a trend is identified, additional information from the tweets is extracted to analyze and describe the trend. For example, the system uses Grapevine's entity extractor [Angel et al. 2009] which identifies entities mentioned in the trends.

Another Twitter-specific event detection approach introduced in [Petrović et al. 2010] uses locality sensitive hashing (LSH) for hashing a fixed number of recent documents in a bounded space, and processed in a bounded time, to increase the performance of nearest neighbors search.

With so many event detection systems, it is interesting to think about how they compare. McMinn et al. [2013] describe a corpus to evaluate event detection methods, composed of 500 news events sampled over a four-week period, and including tweet-level relevance judgments for thousands of tweets referring to these events. While existing NED systems have not been evaluated against this corpus, we anticipate this calibration of systems to occur in the future.

Beyond keyword bursts. There are well-known problems of relying on increases in the frequency of a keyword (or a segment) to detect events. For instance, consider popular hashtags such as "#musicmonday," which is used to suggest music on Mondays, or "#followfriday/#ff," which are used to suggest people to follow on Fridays. In these cases, there should be big pseudo-events detected every Monday and every Friday.

To address this problem, [Becker et al. 2011] present an approach to classify real-world events from non-events using Twitter. They use four types of features, which are temporal, social, topical, and Twitter-specific, to identify real events using the Twitter stream in real-time. First, based on temporal features (i.e., volume of messages posted during an hour), they form initial clusters using the most frequent terms in the messages. Clusters are then refined using social features (i.e., users' interactions like re-tweets, replies, mentions). Next, they apply heuristics, for example, a high percentage of re-tweets and replies often indicates a non-event, whereas a high percentage of mentions indicates that there is an event. Further, cluster coherence is estimated using a cosine similarity metric between messages and cluster centroid. Finally, as the authors report that multi-word hashtags (e.g. #musicmonday and #followfriday) are highly indicative of some sort of Twitter specific discussion and do not represent any real event, they check the frequency of such hashtags used in each cluster to further refine the results.

Weng et al. [2011] present an algorithm for event detection from tweets using clustering of wavelet-based signals. Their approach involves three steps. First, they use wavelet transformation and auto correlation to find bursts in individual words, and keep only the words with high signal auto-correlations as event features. Then, the similarity for each pair of event-features is measured using cross correlation. Finally, they use a modularity-based graph partitioning algorithm to detect real-life events. One of the strong points of this approach over the traditional event detection approaches is the capability of differentiating real-life big events from trivial ones. This is achieved mainly by two factors: the number of words, and the cross-correlation among the words related to an event.

Unlike the approaches presented above, Corley et al. [2013] present a method to detect and investigate events through meta-data analytics and topic clustering on Twitter. Various features such as re-tweets, usage of different terms, and hashtags are analyzed for a certain time period to determine a baseline, and a noise ratio. An event is detected once a particular feature value exceeds its noise boundaries, and expected threshold. Once an event has been detected, its related topics are identified using the topic clustering approach.

Domain-specific approaches. As in many natural language processing applications, approaches that are specific to a certain domain generally perform better than the approaches that are open-domain or generic.

For instance, Phuvipadawat and Murata [2010] describe a method for detecting breaking news from Twitter. First, tweets containing the hashtag "`#breakingnews`" or the phrase "`breaking news`" are fetched from the Twitter streaming API. Grouping of the extracted tweets is then performed, based on content similarity, and using a variant of the TF-IDF technique. Specifically, the similarity variant assigns a high similarity score to hashtags and proper nouns, which they identify using the Stanford Named Entity Recognizer (NER) implementation.

The authors consider three types of features associated with tweets: statistical features (i.e., number of words in a tweet, positions of a the query word within a tweet), keyword based features (i.e., the actual words in a tweet), and contextual features (i.e., words before and after a particular word entered as a query). For example, in the tweet "*...million earthquake measure...*" words "million" and "measure" are considered, given "earthquake" as a query word). In order to determine if a tweet corresponds to one of these hazards or crises, they use support vector machines (SVM)—a known supervised classification algorithm (more about supervised classification on Section 6.1.2).

Another approach for detecting newsworthy events is to incorporate data from traditional media sources. Not surprisingly, traditional media and social media have different editorial styles, perceived levels of credibility, and response delays to events. Tanev et al. [2012] find news articles describing security-related events (such as gun fights), and use keywords in their title and first paragraph to create a query. This query is issued against Twitter to obtain tweets related to the event. Dou et al. [2012b] describe *LeadLine*, an interactive visual analysis system for event identification and exploration, shown in Figure 5. *LeadLine* automatically identifies meaningful events in social media and news data using burst detection. Further, named entities and geo-locations are extracted from the filtered data to visualize them on a map through their interface.

Another domain-specific event-detection method is based on pre-specified rules and introduced in [Li et al. 2012a]. Their system, *TEDAS*, detects, analyzes, and identifies relevant crime- and disaster-related events on Twitter. First, tweets are collected based on iteratively-refined rules (e.g., keywords, hashtags) from Twitter's streaming API. Next, tweets are classified via supervised learning based on content as well as Twitter-specific features (i.e., URLs, hashtags, mentions). Additionally, location information is extracted from–using both GPS tagged and location information in tweet content. Finally, tweets are ranked according to their estimated level of importance.

Sakaki et al. [2010] detect hazards and crises such as earthquakes, typhoons, and large traffic jams using temporal and spatial information. *LITMUS* [Musaev et al. 2014] detects landslides using data collected from multiple sources. The system, which depends on the USGS seismic activity feed provider, the TRMM (NASA) rainfall feed, and social sensors (e.g. Twitter, YouTube, Instagram), detects landslides in real-time by integrating multi-sourced data using relevance ranking strategy (Bayesian model). Social media data is processed in a series of filtering steps (keyword-based filtering, removing stop-words, geo-tagging, supervised classification) and mapped based on geo

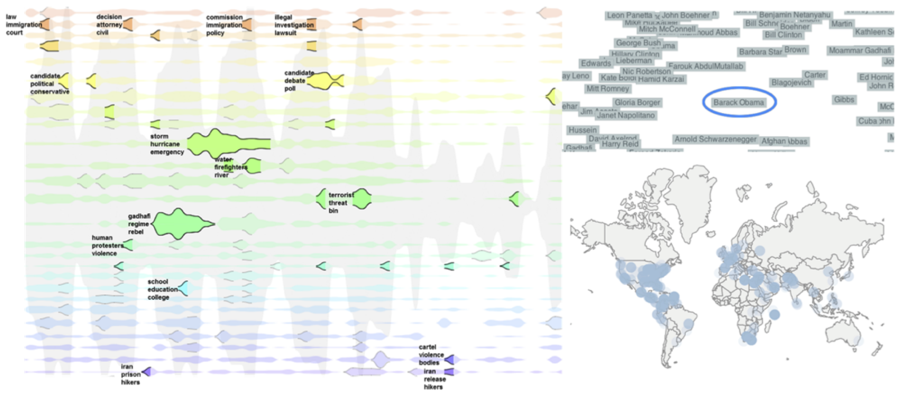

Fig. 5: The LeadLine interface. top right area shows people and entities related to the query, left area shows identified bursts, and bottom right depicts location information present in the data. (Figure from [Dou et al. 2012b] reproduced with permission from the authors.)

information either obtained from meta-data or from content. Events with high relevancy are identified as “real events.”

5.3. Event Tracking and Sub-Event Detection

Event tracking. Event tracking refers to the task of studying how events evolve and unfold. For a general discussion on the subject, see [Allan 2002; Lee et al. 2013].

The way in which emergency response agencies deal with crisis events varies as a crisis unfolds. Emergency situations typically consist of four phases: warning, impact, emergency, and recovery [Killian 2002, page 51]. During the warning phase, the focus is on monitoring the situation. Impact is when the disaster agent is actually at work, while the emergency phase is the immediate post-impact period during which rescue and other emergency activities take place. Recovery is the period in which longer-term activities such as reconstruction and returning to a “normal” state occur.

Various techniques have been proposed to identify event phases. For instance, Iyengar et al. [2011] introduce an approach to automatically determines different phases of an event on Twitter. The approach, which is mainly based on content-based features of tweets, uses an SVM classifier and a hidden Markov model. Various content-specific features such as bag of words, POS (part-of-speech) tags, etc. are used to automatically classify tweets into three phases of an event: *before*, *during*, and *after.* A disaster-specific lexicon of discriminative words for each phase of the event can also be employed [Chowdhury et al. 2013].

Sub-event detection. The detection of large-scale events has been studied with more attention than the detection of small-scale “sub-events” that happen as a crisis unfolds.

Pohl et al. [2012] show the importance of sub-event detection during crisis situations. They use multimedia meta-data (tags, and title) associated with content found on social media platforms such as YouTube and Flickr. Their framework uses a clustering approach based on self-organizing maps to detect sub-events. First, a pre-selection of the data is performed based on user-identified keywords. The selected data is then passed to a sub-event detection module that performs clustering to further split the data into sub-events.

Table II: Some of the event detection tools surveyed. The table includes the types of events for which the tool is built (open domain or specific), whether detection is performed in real-time, the type of query (open or "kw"=keyword-based), and whether it has spatio/temporal or sub-event detection capabilities. Sorted by publication year.

System/tool	Approach	Event types	Real-time	Query type	Spatio-temporal	Sub-events	Reference
TwitterMonitor	Burst detection	open domain	yes	open	no	no	[Mathioudakis and Koudas 2010]
TwitInfo	Burst detection	earthquakes, crises	yes	kw	spatial	yes	[Marcus et al. 2011]
Twevent	Burst segment detection	open domain	yes	open	no	no	[Li et al. 2012b]
TEDAS	supervised classification	crime, disasters	no	kw	yes	no	[Li et al. 2012a]
LeadLine	burst detection	open domain	no	kw	yes	no	[Dou et al. 2012b]
TwiCal	supervised classification	conflicts, politics	no	open	temporal	no	[Ritter et al. 2012]
ESA	burst detection	earthquakes	yes	kw	spatial	no	[Robinson et al. 2013]

Khurdiya et al. [2012] present a system for event and sub-event detection using Conditional Random Fields (CRF) [Lafferty et al. 2001]. Their system consists of four main modules: (1) a CRF-based event extractor to first extract actor, action, date, and location—event titles are also extracted using using CRFs; (2) an event resolution to find similar events; (3) an event compiler that characterizes events; and (4) an event reporting module which is the end-user interface used to browse events details.

Hua at al. [2013] introduce *STED*, a semi-supervised targeted-interest event and sub-event detection system for Twitter. To minimize the human effort required for labeling, they introduce an automatic label creation and expansion technique, which takes labels obtained from newspapers data and transfers them to tweets. They also propagate labels using mentions, hashtags, and re-tweets. Next, they build mini-clusters using a graph partitioning method to group words related to the event, and use supervised learning to classify other tweets using the examples provided by each mini-cluster. A final step on the classified output is to perform a location estimation using information from geo-coded tweets.

Table II lists event detection systems. The majority of them are surveyed above; additional tools are covered in the following sections.

5.4. Challenges

In addition to the discussion of general data challenges in Section 4.7, the following are particularly relevant to event detection.

Inadequate spatial information. Spatial and temporal information are two integral components of an event. Most systems that rely on Twitter data for event detection face challenges to determine geographical information of tweets that lack GPS information. In this case, automatic text-based geotagging can be used, as described on Section 4.5.

Mundane events. People post mundane events on social media sites. These data points introduce noise, which creates further challenges for an event detection algorithm to outperform. For such cases, separation of real-life big events from trivial ones is required.

Describing the events. Creating a description or label for a detected event is in general a difficult task. Often the keywords that are more frequent during the event are presented as a description for the event in the form of a list of words (e.g. { *sandy*, *hurricane*, *new york* }), but that list does not constitute a grammatically well-formed description (e.g. "*Hurricane Sandy hits New York*"). We will see one approach to address this in Section 6.2.2.

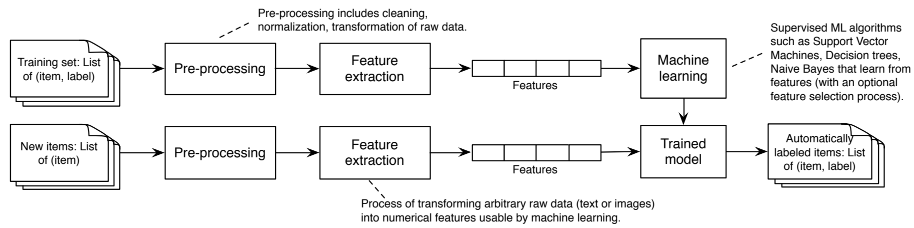

Fig. 6: Supervised classification

6. CLUSTERING, CLASSIFICATION, EXTRACTION AND SUMMARIZATION

Once we have found social messages related to a crisis event or topic, there are several ways in which we might process them. In this section, we describe some approaches. Broadly, we separate techniques into those classifying the data item as a whole and those extracting useful information from the content of one or more data items.

6.1. Classifying Social Media Items

In many situations, we are interested in classifying social media items into one or more categories. In this section, we will describe three methods of classification with decreasing levels of manual human supervision. Text classification is a large field of research, so we will cover literature relevant to disasters. Interested readers should refer to other sources for a broader discussion [Srivastava and Sahami 2009].

6.1.1. Content Categories. There is not a single standard or widely-accepted way of categorizing crisis-related social media messages. While some crisis-related ontologies have been proposed (see Section 7.2), in general, different works use different approaches.

Table III summarizes various dimensions of social media content that different research articles have used to classify information:

(1) By factual, subjective, or emotional content: to separate between facts (or combinations of facts and opinions), from opinions, or expressions of sympathy.
(2) By information provided: to extract particular categories of information that are useful for various purposes.
(3) By information source: to select messages coming from particular groups of users, e.g. eyewitness accounts or official government sources.
(4) By credibility: to filter out messages that are unlikely to be considered credible.
(5) By time: to filter messages that refer to different stages of an event, when temporal boundaries for the event are unclear.
(6) By location: to select messages according to whether they originate from or near the place that was affected by an event, or from areas that were not affected.

Other classification dimensions can be envisioned. In general, we observe that the selection of the set of categories used by researchers and practitioners is usually driven by two main factors: the data that is present in social media during crises, and the information needs of response agencies. None of these factors is static, as both can change substantially from one crisis situation to another.

6.1.2. Supervised Classification. When a set of example items in each category is provided, a *supervised classification* algorithm can be used for automatic classification. This type of algorithm 'learns' a predictive function or model from features of these examples (see Section 4.4) in order to label new, unseen data items. This set of exam-

Table III: Classification of various dimensions of content posted on social media during high impact events with description and related work references.

Classification dimension	Description/examples
By factual, subjective, or emotional content	
Factual information	*(Examples under "By information provided")*
Opinions	opinions, criticism (e.g. of government response)
Sympathy	condolences, sympathy [Kumar et al. 2013]; condolences [Acar and Muraki 2011], support [Hughes et al. 2014b]; thanks, encouragement [Bruns et al. 2012]; prayers [Olteanu et al. 2014]
Antipathy	*schadenfreude*, animosity against victims (e.g. because of long-standing conflict)
Jokes	jokes, trolling [Metaxas and Mustafaraj 2013]
By information provided	
Caution and advice	caution & advice [Imran et al. 2013b]; warnings [Acar and Muraki 2011]; hazard, preparation [Olteanu et al. 2014]; tips [Leavitt and Clark 2014]; advice [Bruns et al. 2012]; status, protocol [Hughes et al. 2014b]
Affected people	people trapped, news [Caragea et al. 2011]; casualties, people missing, found or seen [Imran et al. 2013b]; self reports [Acar and Muraki 2011]; injured, missing, killed [Vieweg et al. 2010]; looking for missing people [Qu et al. 2011]
Infrastructure/utilities	infrastructure damage [Imran et al. 2013b]; collapsed structure [Caragea et al. 2011]; built environment [Vieweg et al. 2010]; closure and services [Hughes et al. 2014b]
Needs and donations	donation of money, goods, services [Imran et al. 2013b]; food/water shortage [Caragea et al. 2011]; donations or volunteering [Olteanu et al. 2014]; help requests, relief coordination [Qu et al. 2011]; relief, donations, resources [Hughes et al. 2014b]; help and fundraising [Bruns et al. 2012]
Other useful information	hospital/clinic service, water sanitation [Caragea et al. 2011]; help requests, reports about environment [Acar and Muraki 2011]; epidemics [Imran and Castillo 2014]; consequences [Olteanu et al. 2014]
By information source	
Eyewitnesses/Bystanders	members of public [Metaxas and Mustafaraj 2013], victims, citizen reporters, eyewitnesses [Diakopoulos et al. 2012; Olteanu et al. 2014; Bruns et al. 2012]
Government	administration/government [Olteanu et al. 2014];police and fire services [Hughes et al. 2014b]; government [Bruns et al. 2012]; news organization and authorities [Metaxas and Mustafaraj 2013]
NGOs	non-government organizations [De Choudhury et al. 2012]
News Media	news organizations and authorities, blogs [Metaxas and Mustafaraj 2013], journalist, media, bloggers [De Choudhury et al. 2012];new organization [Olteanu et al. 2014]; professional new reports [Leavitt and Clark 2014]; media [Bruns et al. 2012]
By credibility	
Credible information	newsworthy topics, credibility [Castillo et al. 2013]; credible topics [Canini et al. 2011]; content credibility [Gupta and Kumaraguru 2012]; users and content credibility [Gupta et al. 2014]
Rumors	rumor [Hughes et al. 2014b; Castillo et al. 2013]
By time	
Pre-phase/preparedness	posted before an actual event occurs, helpful for the preparedness phase of emergency management [Petak 1985], pre-disaster [Iyengar et al. 2011; Chowdhury et al. 2013], early information
Impact-phase/response	posted during the impact phase of an event, helpful for the response phase of emergency management [Petak 1985], during-disaster [Iyengar et al. 2011; Chowdhury et al. 2013]
Post-phase/recovery	posted after the impact of an event, helpful during the recovery phase [Petak 1985], post-disaster information [Chowdhury et al. 2013; Iyengar et al. 2011]
By location	
Ground-zero	information from ground zero (victims reports, bystanders) [De Longueville et al. 2009; Ao et al. 2014]
Near-by areas	information from geographically closer to the affected areas [De Longueville et al. 2009]
Outsiders	information coming from other parts of world, sympathizers [Kumar et al. 2013]; distant witness (in the sense of [Carvin 2013]); not on the ground [Starbird et al. 2012]

ples is referred to as the *training set*. After a model has been learned from the training data, it is evaluated using a different, hold-out set of labeled items, not used during the training. This second set of examples is referred to as the *testing set*.

Figure 6 depicts an supervised classification approach including a few critical parts. Depending on the nature of data in hand, different pre-processing techniques can be used. In any case, the input items are transformed into feature vectors, following the methods described in Section 4.4.

Training examples. The number of training examples required to achieve good accuracy depends on many factors, including the number of categories into which messages have to be classified, and the variability of messages inside each category. Typical sizes of training sets range from a few hundred [Yin et al. 2012] to a few thousand [Imran et al. 2014a]. More examples yield better results in general, with diminishing results after a certain point. In general, the accuracy of models created using training data from one crisis decreases when applied to a different crisis, or when applied to the same crisis but at a different point in time [Imran et al. 2014b].

Feature selection. Even if messages are brief, the feature space in which they are represented is typically high dimensional (e.g. one dimension for every possible term). This introduces a number of problems including the amount of computational resources required for the data analysis, and it also increases the chances of over-fitting the training data. In this case, a *feature selection method* (e.g. mutual information) should be employed as a first step to discard input features that have little or no correlation with the given training labels. Feature selection is an active area of machine learning research and state of the art techniques can be found in modern textbooks or journals (e.g. [Guyon and Elisseeff 2003]).

Learning algorithms. After features have been extracted and selected, a machine learning algorithm can be applied. Supervised classification algorithms include, among others, naïve Bayes, support vector machines (SVM), logistic regression, decision trees, and random forests. The choice of a method is largely dependent on the specific problem setting. For instance, *ESA* [Yin et al. 2012; Cameron et al. 2012] uses naïve Bayes and SVM, *EMERSE* [Caragea et al. 2011] uses SVM, *AIDR* [Imran et al. 2014a] uses random forests, and *Tweedr* [Ashktorab et al. 2014] uses logistic regression. While in most cases algorithms are used to predict a single label for each element, adaptations of these algorithms that generate multiple labels for each element are sometimes employed (e.g. [Caragea et al. 2011]).

Ensemble/stacked classification. In some cases an explicit model of a certain factor is desired, as exemplified by the work of Verma et al. [2011]. They observe that messages that contribute the most to situational awareness are also those that are expressed using objective (as opposed to subjective) language. In this case, one can create a *stacked classifier* in which at one level certain characteristics of the message are modeled (e.g. by having a classifier that classifies messages as objective or subjective) and at the next level these characteristics are combined with other characteristics also modeled by specific classifiers (e.g. writing styles such as formal or informal), and with features from the message itself. [Verma et al. 2011] find that this approach performs better than directly using the input features.

6.1.3. Unsupervised Classification. Clustering is an *unsupervised machine learning method*; a family of methods that seek to identify and explain important hidden patterns in unlabeled data. Unsupervised machine learning methods include clustering, dimensionality reduction (e.g. principal component analysis), and hidden Markov models, among others.

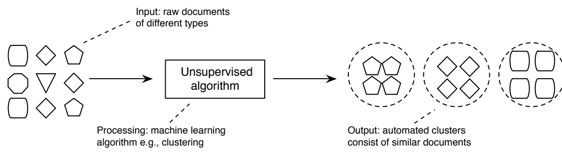

Fig. 7: Unsupervised classification

The process of performing clustering, depicted in Figure 7, begins by ingesting a set of items (e.g., documents, tweets, images) which are then processed with the objective of grouping similar items together. In general, the goal is to form clusters in such a way that elements within a cluster are more similar to each other than to the elements that belong to other clusters. Many clustering algorithms have been developed based on different approaches, examples include *K-means* (centroid-based), *hierarchical clustering* (connectivity-based), *DBSCAN* (density-based), among many others. For an overview of clustering methods, see [Zaki and Meira 2014, Part III].

In the context of dealing with social media data during crises, clustering can help reduce the number of social media messages that need to be processed/examined by humans, for instance by displaying multiple equivalent messages as a single item instead of multiple ones. This is the approach used by *CrisisTracker* [Rogstadius et al. 2013], which is a crowdsourced social media curation system for disaster awareness. The system, which collects data from Twitter based on predefined filters (i.e., keywords, geographical box), group these tweets into *stories*, which are clusters of tweets. These stories are then curated/classified by humans, whose effort can be greatly reduced if they are asked to classify entire clusters instead of single tweets. The specific clustering method employed in this case is locality-sensitive hashing, an efficient probabilistic technique that uses hash functions to detects near-duplicates in data. Another example is *SaferCity* [Berlingerio et al. 2013], which identifies and analyzes incidents related to public safety in Twitter, adopting a spatio-temporal clustering approach based on the modularity maximization method presented in [Blondel et al. 2008] for event identification. Clusters are then classified using a semantic labeling approach—using a controlled vocabulary IPSV[21]—and also based on a rank score provided by the Lucene library. [22]

In addition to clustering methods that partition the items into groups, there are *soft clustering* methods that allow an item to simultaneously belong to several clusters with varying degrees. This is the case of topic modeling methods, out of which Latent Dirichlet Allocation (LDA) is one of the most popular ones. In the crisis domain, one example is [Kireyev et al. 2009], who use topics extracted using LDA, including a weighting scheme that accounts for the document frequency (number of tweets containing a word) of the words in the tweet, as well as for the length of the tweet. When applied to data from an Earthquake in Indonesia in 2009, it detects topics that cover different aspects of the crisis such as { *tsunami*, *disaster*, *relief*, *earthquake* }, { *dead*, *bodies*, *missing*, *victims* } and { *aid*, *help*, *money*, *relief* }. There is free software available for creating these topics models, such as MALLET [McCallum 2002], which is applied to crisis data in [Karandikar 2010].

[21] http://esd.org.uk/standards/ipsv/2.00
[22] http://lucene.apache.org/

6.2. Sub-Document Analysis

In contrast to text classification schemes which make predictions about data items, sub-document analysis techniques extract granular information from the *content* of the data items. In this section we present two important of sub-document analysis in the context of crisis situations: information extraction and text summarization.

6.2.1. Information Extraction. The task of automatically extracting structured information from unstructured (e.g., plain text documents) or semi-structured (e.g., web pages) data is known as *Information Extraction* (IE). The most common information extraction task is named entity extraction, which consists of detecting regions of a text referring to people, organizations, or locations [Liu et al. 2011; Ritter et al. 2011]. This is the first step towards semantic enrichment (see Section 7.1).

In the context of crisis-related social media, information extraction can be used, for instance, to transform tweets reporting injured people in natural language (e.g. "*5 injured and 10 dead in Antofagasta*") to normalized records such as {<people-affected=5, report-type=injury, location=Antofagasta, Chile>, <people-affected=10, report-type=fatal-casualty, location=Antofagasta, Chile>}. These records are machine-readable, which means they can be easily filtered, sorted, or aggregated.

Information extraction from social media is a challenging task because of the informal writing style and the presence of many ungrammatical sentences, as we note in Section 4.7. State-of-the-art approaches to information extraction involve the use of probabilistic sequential models such as hidden Markov models, conditional Markov models, maximum-entropy Markov models, or conditional random fields. Heuristics based on regular expressions can also be applied to this problem, although these are in general less effective than probabilistic methods.

Varga et al. [2013] use linguistic patterns and supervised learning to find "trouble expressions" in social media messages. For instance, in a tweet such as "*My friend said infant formula is sold out. If somebody knows shops in Sendai-city where they still have it in stock, please let us know*," the nucleus of the problem is the sentence "*infant formula is sold out*." This extraction is then used to match tweets describing problems to tweets describing solutions to those problems.

Imran et al. [2013a; 2013b] apply conditional random fields to the extraction of information from tweets. Their method proceeds in two steps. First, tweets are classified to consider categories such as "infrastructure damage," "donations," and "caution and advice." Then, a category-dependent extraction is done, where for instance for "infrastructure damage" tweets, the specific infrastructure reported damaged is extracted, while for "donations" tweets, the item being offered in donation is extracted.

6.2.2. Summarization. Another approach to dealing with information overload involves presenting users with a text-based representation of the evolving event. Text summarization refers to the generation of a text summary of a document or set of documents [Nenkova and McKeown 2011]. Text summarization systems are optimized to generate a text summary that contain only the core topics discussed in the set of documents. Most systems produce this summary by *extracting* key sentences from the input document. This is in contrast to systems that produce a summary by *abstracting* or generating new sentences.

During crisis events, text summarization must be done in an *incremental* and *temporal* manner. Incremental text summarization, also known as *update summarization*, refers to generating a summary given: (1) the set of documents to be summarized, and (2) a reference set of documents which the user has read. The objective for the system is to produce a summary only of data the user has not already read [Dang and Owczarzak 2008]. Temporal text summarization refers to creating an extractive sum-

Table IV: Example summary from TREC 2013 Temporal Summarization Track. Updates reflect new or updated information as it is reported.

time	update
Nov 21 10:52:29 2012	Tel Aviv bus bombing; 13 injuries; reported on a bus line 142; occured on Shaul Hamelech street; No claims of responsibility.; 3 badly hurt; occured in the heart of Tel Aviv near military hdqtrs
Nov 22 20:49:57 2012	occurred in an area with many office buildings; occured in area with heavy pedestrian traffic; first notable bombing in Tel Aviv since 2006; At least 28 people were wounded; Hamas' television featured people praising the attack; Khaled Mashal, leader of Hamas, categorically rejected any connection of the bombing to his group; UN Secretary-General Ban Ki-moon deplored the attack; The White House called the bombing a terrorist attack against innocent Israeli civilians; The Russian foreign ministry termed the bombing a "criminal terrorist act"; 21 wounded in terror attack on Tel Aviv bus
Nov 26 04:33:27 2012	an Israeli Arab man was arrested on charges of planting the explosive device on the bus; Suspect was reportedly connected to Hamas; Suspect was reportedly connected to the Islamic Jihad
Nov 26 14:49:35 2012	The Romanian Foreign Minister condemned the bombing,
Nov 29 04:55:26 2012	govt rep refers to attack as terrorist attack
Nov 30 05:22:02 2012	Fears about Bus Bomb Before the Cease-Fire: Could derail peace talks
Nov 30 06:47:40 2012	The suspect remotely detonated the explosive device; suspect hid device in advance on the bus; The explosive device contained a large quantity of metal shrapnel designed to cause maximum casualties; The suspect later on confessed to carrying out the bus attack; suspect prepared the explosive device; suspect chose the target of the attack; suspect purchased a mobile phone; suspect received an Israeli citizenship as part of a family unification process

mary from a set of time-stamped documents, usually in retrospect [Allan et al. 2001; Nallapati et al. 2004; Feng and Allan 2007; 2009].

Drawing on the work from summarization research, the TREC Temporal Summarization track focuses the generating updates relating to unfolding crisis events immediately after their occurrence [Aslam et al. 2013]. Table IV presents an example of this type of summary. The focus of this initiative is to first define standardized metrics for the task and then to encourage the development of systems optimizing them. These metrics include time-sensitive versions of precision and recall, ensuring that systems are penalized for *latency*: delivering information about an event long after it occurred. In addition, the metrics include a redundancy penalty to prevent systems from delivering repetitive information. In order to optimize these metrics, systems can use staged text analysis with standard information retrieval measures [McCreadie et al. 2013]. Alternatively, systems can use regression-based combinations of features from classic text summarization literature [Guo et al. 2013; Xu et al. 2013]. Other methods are purely content-based, hierarchically clustering sentence text [Wang and Li 2010]. In the context of social media, Shou et al. [2013] propose a system for online update summarization based on incremental clustering. The performance is evaluated under experimental conditions different from the TREC track, making it difficult to compare with other results.

Although algorithms for summarization exist for crisis events, their development is still preliminary and several challenges remain. Foremost, the relative importance of different features is not well understood. To date, research has primarily used features from batch text summarization. A second challenge is scale. Many algorithms require aggressive inter-sentence similarity computation, a procedure which scales poorly.

6.3. Challenges

In addition to the discussion on generic data-related challenges on Section 4.7, the following are particularly relevant to mining:

Combining manual and automatic labeling. In a supervised learning setting, human labels are necessary, but they may be costly to obtain. This is particularly problematic in crises that attract a multilingual population, or for tasks that require domain knowledge (e.g. people who know informal, local place names in Haiti, and who speak Haitian Creole). Labeled data are not always reliable, and may not be available at the time of the disaster; in this case, a hybrid approach that mixes human labeling and automatic labeling can be employed [Imran et al. 2013c]. The selection of items to be labeled by humans can be done using *active learning*, a series of methods to maximize the improvement in classification accuracy as new labels are received.

Domain adaptation. Ideally, one would like to avoid having to re-train an automatic classifier every time a new crisis occurs. However, simply re-using an existing classifier trained on data from a previous crisis does not perform well in practice, as it yields a substantial loss in accuracy, even when the two crises have several elements in common [Imran et al. 2013a].

In machine learning, *domain adaptation* (or *domain transfer*) is a series of methods designed to maximize the accuracy of a classifier trained on one dataset, adapting it to continue to perform well on a dataset with different characteristics. To the best of our knowledge, these methods have not been applied to crisis-related social media data.

7. SEMANTIC TECHNOLOGIES IN DISASTER RESPONSE

One of the main goals of semantic technologies is to allow users to easily search through complex information spaces, and to find, navigate, and combine information. In the context of social media use during crises and mass convergence events, this is achieved by *linking* data elements to concepts in a machine-readable way, enabling the representation of a situation as a complex and interrelated set of elements.

7.1. Semantic Enrichment of Social Media Content

Semantic technologies are particularly useful in social media, because they provide a powerful method for dealing with the variety of expressions that can be used to refer to the same concept, and with the many relationships that can exist between concepts. For instance, suppose we are looking for messages related to infrastructure damage using a keyword-query search. We would think that searching for something such as "damage AND (airport OR port OR bridge OR building ...)" would be sufficient, until we notice that it is not only difficult to cover every particular type of infrastructure (airport, port, bridge, building, etc.) but also to cover every particular instance of that type (for instance, there are tens of thousands of airports in the world).

Named entity linking is a widely-used semantic technology that deals with the above problem. It operates in two phases. First, a *named entity recognizer* module detects entities—such as names of persons, places, and organizations. Second, for each named entity that is found, a *concept* is located that more closely matches the meaning of that named entity in that context.

Concepts are generally operationalized as URLs. For instance, Zhou et al. [2010] link named entities to the URLs of articles on Wikipedia. In a phrase such as "*Terminal 2 of JFK was damaged*," the named entity corresponding to the segment "JFK" would be linked to the URL https://en.wikipedia.org/wiki/John_F._Kennedy_International_Airport. There are several free, and commercial services that can be used to perform named entity linking, including Alchemy,[23] OpenCalais,[24] and Zemanta.[25]

Once an element is linked to a concept, further automatic annotation can be done by following links from the concept. Returning to our example of "*Terminal 2 of*

[23] http://www.alchemyapi.com/
[24] http://www.opencalais.com/
[25] http://developer.zemanta.com/

JFK was damaged," if we go to its Wikipedia page,[26] we can learn that "JFK" is an instance of the class "airport." The airport concept is represented in this case by the URL of a Wikipedia category page to which the JFK Airport page belongs (https://en.wikipedia.org/wiki/Category:Airports), which in turn belongs to the category of transport building and structures (https://en.wikipedia.org/wiki/Category:Transport_buildings_and_structures).

After named entity linking, messages that have been semantically enriched can be used to provide *faceted search*, a popular approach to interactively search through complex information spaces. In faceted search the information of interest can be found not only by specifying a related keyword, but also by specifying a concept or concepts associated with the items of interest. In the example, we could select "airport" from a list of buildings and structures and then find a series of social media messages that are relevant, but that do not necessarily include the specific word "airport" in them.

Abel et al. [2011], present an adaptive faceted search framework to find relevant messages on Twitter. The framework enriches tweets with semantics by extracting entities (i.e. persons, locations, organization), and then finding and linking those entities with external resources to create facets. Each facet enables search and navigation of relevant semantically related content. In follow-up work [Abel et al. 2012a; 2012b], they introduce *Twitcident*, a system that supports semantic filtering, faceted search and summarization of tweets. Another semantic-based approach is implemented in *Twitris 2.0* [Jadhav et al. 2010], which presents the reaction to events in social media by capturing semantics in terms of spatial, temporal, and thematic dimensions.

7.2. Ontologies for Disaster Management

Information technologies to support disaster response often involve interactions between software operated by different agencies, and/or provided by different developers or vendors. Allowing computer systems to communicate information in a unified way is a key challenge in general, but especially during crisis events where different agencies must address different dimensions of a problem in coordination with each other [Hiltz et al. 2011]. Interoperability at the semantic level requires centralized specifications describing machine-understandable common vocabularies of concepts and linkages between them. An effective way of achieving this is to use machine-understandable ontologies that define, categorize and maintain relationships between different concepts to facilitate common understanding, and unified communication.

Table V lists some of the ontologies that have been introduced in recent years. These ontologies have varying degrees of detail, and none of them completely covers all the aspects of a crisis. Some examples from this table:

— The *Humanitarian eXchange Language* (HXL)[28] is an ontology created in 2011 and 2012 and is currently under review; it describes 49 classes and 37 properties. The focus of HXL is mainly on four areas: organization (i.e., formal response agencies like military, charities, NGOs), disaster (i.e., classification of disasters such as natural, man-made), geography (i.e., event location, geo-location of displaced people), and damage (i.e., damages related to humans, infrastructure).
— *Management of A Crisis* (MOAC)[29] is an ontology with 92 classes and 21 properties covering four areas: disaster, damage, processes (i.e., rescue, search, evacuation processes), and resources (i.e., services, vehicles, tents). HXL and MOAC have el-

[26] Or to its related semantic resource, DBPedia [27].
[28] http://hxl.humanitarianresponse.info/
[29] http://observedchange.com/moac/ns/

Table V: Crisis ontologies, including some of the classes and attributes they cover, and the format in which they are specified (OWL: Ontology Web Language, RDF: Resource Description Framework).

Ontology Name	Coverage	Format	Reference
SOKNOS	resources, damage, disasters	OWL	[Babitski et al. 2011]
HXL	damage, geography, organization, disasters	RDF	http://hxl.humanitarianresponse.info/
SIADEX	processes, resources, geography	RDF	[de la Asunción et al. 2005]
OTN	specific to infrastructure	OWL	[Lorenz et al. 2005]
MOAC	damage, disasters, processes, resources	RDF	http://observedchange.com/moac/ns/
FOAF	emergency management people	RDF	http://www.foaf-project.org/
AktiveSA	transportation, meteorology, processes, resources, people	OWL	[Smart et al. 2007]
IntelLEO	response organizations	RDF	http://www.intelleo.eu/
ISyCri	damages, processes, disasters	OWL	[Bénaben et al. 2008]
WB-OS	features, components and information to build crisis management web sites	XML	[Chou et al. 2011]
EDXL-RM	data exchange language for resource management	XML	https://www.oasis-open.org/

ements in common: in both cases the objective is to describe different aspects of a crisis, including its effects, the needs of those affected, and the response to the crisis.
— *Integrated Data for Events Analysis* (IDEA)[30] is a framework for coding social, economic and political events. It is used in the *Global Database of Events, Language and Tone* (GDELT),[31] which is a machine-generated list of event data extracted from news reports. SOKNOS[32] is an ontology for the information integration for resource planning. The main areas it covers include damages and resources categorizations during disasters.

To support communication among different ontology-based systems, the problem of ontology heterogeneity needs to be solved by performing an *ontology mapping*, which is the process of mapping the concepts of two ontologies from the same or from overlapping domains. Many approaches have been proposed to perform ontology mapping. For instance, [Tang et al. 2006] treated this as a decision-making problem and proposed an approach based on Bayesian decision theory. For a survey on ontology mapping techniques, see [Noy 2004].

The ontologies in Table V are crisis-specific, but not social-media specific. However, they can be combined with ontologies describing social media concepts such as users, tagging, sharing, and linking. For instance, the "Semantically Interlinked Online Communities" (SIOC)[33] ontology, originally developed to model sites such as blogs and online forums, has recently been extended to support the modeling of microblogs by adding concepts such as *follower* or *follows*. An ontology specific to Twitter appears in [Celino et al. 2011] and includes user sentiments and locations, while [Passant and Laublet 2008] enables semantic tagging of social media data through an ontology called Meaning-Of-A-Tag (MOAT). For a survey on ontologies developed for social media, see [Bontcheva and Rout 2012].

8. SUMMARY AND FUTURE RESEARCH DIRECTIONS

In a relatively short time period—roughly 4 to 6 years—the research community working on the topics we have covered here has achieved a fairly high degree of maturity with respect to filtering, classifying, processing, and aggregating social media data

[30]http://vranet.com/IDEA.aspx
[31]http://gdeltproject.org/
[32]http://soknos.de/
[33]http://sioc-project.org/

during crises. However, the underlying (although sometimes explicitly stated) claim behind this line of work, i.e. that this research is *useful* for the public and/or formal response agencies, that it has the potential to save lives and/or property during an emergency, remains to be seen. Indeed, we are not aware of examples in which social media has become an integral part of the formal emergency response process of any large agency, governmental or otherwise.

There are two main directions in which we see future research going. First, continue deepening the data processing capabilities that have been the main focus of computing research on this topic thus far. Second, engage more deeply with human-centered approaches toward making the computing research the foundation of viable systems that emergency responders can implement.

8.1. Deepening Data Processing Capabilities

Extending to other types of media. Data from various sources should be processed and integrated: "The strategies of emergency services organizations must also recognise the significant interweaving of social and other online media with conventional broadcast and print media." [Bruns 2014]. There are some examples of the processing of other types of information items during crises, including short messages (SMS) [Melville et al. 2013], news articles in traditional news media and blogs [Leetaru and Schrodt 2013], and images [Abel et al. 2012a; 2012b].

Verifying information. Determining the credibility of information posted on social media is a major concern for those who process information (e.g. computer scientists, and software engineers), and for the information consumers (e.g. the public and formal response organizations) [Hiltz et al. 2011]. Automatic classification can be used to filter out content that is unlikely to be considered credible [Gupta and Kumaraguru 2012; Castillo et al. 2011]. Additionally, the public itself can be mobilized to confirm or discredit a claim through crowdsourcing [Popoola et al. 2013].

8.2. Beyond Data Processing

Designing with the users. Once social media information has been processed, how should it be presented to users? How should users interact with the data? The key to answering these question lies with the users themselves, who should be brought into the process of designing the systems, dashboards, and/or visualizations they require to serve their needs. A highly regarded methodology for achieving this is *participatory design* [Hughes 2014].

Helping governments and NGOs communicate with the public. Three days *before* Typhoon Pablo made its landfall in the Philippines in 2012, government officials were already calling users to use the hashtag `#pabloph` for updates about the typhoon. This was effective and helpful, but microformats that go beyond a single hashtag have not seen much traction in general [Starbird and Stamberger 2010]. What else can agencies do to communicate more effectively with the public? Recent work has started to consider this question [Veil et al. 2011].

From processing messages to the coordination of action. The final output of the processing of social media messages is not limited to the presentation of information in a given format. Computational methods can be applied to augment the information in a number of ways. For instance, Varga et al. [2013] match problem-tweets ("infant formula is sold out in Sendai") to solution-tweets ("Jusco supermarket is selling infant formula"), and Purohit et al. [2013] match tweets describing urgent needs of resources ("we are coordinating a clothing drive for families affected") with tweets describing the intention to donate them ("I've a bunch of clothes I want to donate"). We regard these efforts as preliminary results towards the ability to use social media as a mechanism for coordination of action in future emergency situations.

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