Social Network Applications and Case Studies

CAP 6315Social Networks and Big Data Analytics Spring 2016

Ganna Chylikina
Computer Science Graduate Student
Florida Atlantic University
Boca Raton, United States

Maciej Medyk
Computer Science Graduate Student
Florida Atlantic University
Boca Raton, United States

Nicholas Petty
Computer Science Graduate Student
Florida Atlantic University
Boca Raton, United States

Abstract — **Social media is a new form of communication that has taken foothold in our society in recent years. It is a framework in which we communicate, express ideas, and get involved in our communities. With rapid advances in data storage, internet connectivity, and big data analysis, social networks have become not just tools for human interaction, but a powerful source of real-time information to be useful in marketing, politics, economics, biology, physical sciences, etc. by providing massive, detailed datasets for information extraction. In this publication, we reviewed recent research done on social networking websites, or with related analytic techniques that implements novel data analysis, collection, application, or presentation. We specifically focused on the topics of disaster management, political discourse, and population sentiment analysis through the lens of social network analytics. This paper discusses the involvement of social media in those areas, demonstrates what research has been made so far, and illustrates how this involvement has changed the way our society functions today.**

I. INTRODUCTION

Social networks are a new way for people to interact with each other, communicate their ideas, coordinate events and community help, discuss political discourse, and conduct business. The first area that we will discuss in this paper is how the ability of governments and communities to manage natural disasters has improved with the rise of social networking. This is primarily due to the increased communication capabilities made possible through social networks (21). A disaster in this context is defined as an event which disrupts the social fabric and makes it dysfunctional (49). Specially, earthquakes, hurricanes, diseases, and other severe geological, meteorological, and biological phenomena which damage large sections of human infrastructure and cause loss of life are the natural disasters being managed in this research. The application of social networks to disaster management can be extended to man-made disasters, like war and terrorism, but the papers under review are focused on natural events. Social media provides collectivity, connectedness, completeness, clarity, and collaboration, which are necessary components of communication in an emergency situation (5). The kind of strategic information provided by publicly generated content in these scenarios leads to correct action in the field (35). Compared to traditional means of community engagement, like television, radio, newspapers, and circulars, social networks move information much faster, reach a wider audience, and are not one-way (24). With the tools of mass communication through social media, communities are better able to prepare for disasters, respond when a disaster strikes, and provide relief to those affected.

Another area that we will discuss is how Twitter became a news platform for politicians, how they share their announcements, and how it is used for news and self-promotion. (17, 37, 38). Twitter and Facebook, in recent years, have played a vital role in organizing revolutionary movements, like Occupy Wall street, or protests during the Arab Spring in 2011, which led to regime changes (53, 54). We also will examine how elections are conducted in our democracy and how campaigns can manipulate social media in order to create momentum (37, 13, 22). Finally, we will discuss the prediction capabilities of social networks and research that was conducted in order to see if predictions based on social media are more accurate than traditional polls (32, 37, 57).

The last area that will be discussed is on how social networks have become a major part of people's lives, allowing the sharing of thoughts, impressions, opinions and sentiments about everything, from meals to life events. Moreover, the volume of such data created daily is massive. Social media communication platforms, Twitter particularly - with an active user base of more than 200 million people, allow and stimulate scientific and business communities to retrieve and analyze that knowledge. Recent researches indicates the growing interest for collecting public opinion, general mood and attitude for scientific and business purposes (26). Therefore, sentiment analysis (SA) has become a rapidly growing field of social analytics in data mining, specifically text mining. It computationally studies people's opinions, emotions and attitudes in the direction of various entities. Any individuals, events or any ongoing topics can portray the entity. Due to high interest, there are already many techniques, methods and applications have been developed and tested satisfying scientific (1, 12, 30, 55) and business interests, like stock markets, the pizza industry, brand preferences for Amazon, and NFL domains (29, 47, 48, 61). In this paper, we try to summarize the current methods and tools to perform sentiment analysis and opinion mining that have been used in recent years. Most of these applications employ three main types of approaches: machine learning, lexicon-based, and hybrid - the mix of these two. Each of them has different ways to implement a particular task depending on the chosen domain and conditions. That is why having the characterized analysis of recent trends and directions for SA is very important when giving an overview of current data mining SA methodologies.

II. RELATED WORK

Disaster management through social networks has been studied in several of the papers used as references. The papers by Kavanaugh, et al., Merchant, Simon, et al., and Chan focus on the general topic of using social media to improve management. Lindsay's paper is similar to the other general reviews, but is more in-depth regarding relief efforts through online communities. The other scholarly papers reviewed cover how social media was used, or not used, for specific natural disasters. Several online news articles were also reviewed for specific details on the disasters discussed, and general adoption of social networks for disaster management.

In political discourse, the main platform of communication and research is Twitter. Most of the research and statistics has been done on how Twitter impacts presidential elections in United States. Lindsey Meeks, in her doctoral dissertation, wrote about the woman's place in politics and how it had impacted the 2012 elections (34). Research has been made on how social media affects political elections and electoral campaigns abroad as it is discussed in an article by Tim Fowler and Doug Hagar on the impact of social media during election campaigns (13). Some work also has been done on regime changes and political awareness in authoritarian countries. Ora Reuter and David Szakonyi wrote in their paper about Russian parliamentary elections from 2011 and how usage of social media like Twitter and Facebook amplified the perception of electoral fraud (45). Lastly, a great deal of research was actually conducted about how we can predict elections based on social media activity. In a research article published in IEEE covering predictive analytics, authors described how they used Twitter and polls to establish prediction method for multiple countries, how they conducted the research, and the archived results (57).

Due to the high popularity of Twitter as a communication platform, much SA research was done based on the Twitter data covering different areas of the average life. Therefore, systemizing that knowledge, structuring the previous work is a crucial task that has to be perform to help and stimulate future explorations. In the past three years, there have been several surveys published about sentiment analysis techniques, algorithms and models. Some authors gave the theoretical explanation of sentiment analysis as a field of study, main research problems and applications (56). In addition, other authors presented very detailed overview for more than 50 papers that have been published over the last several years (33). That paper explains in depth the current trends and directions of SA; it gives a sophisticated categorization of used techniques along with their theoretical grounding. To continue, the other study made a discussion about the reasons of SA evolution and future trends that will force the new changes (4). They made a point about using multimodal sentiment analysis to enhance the existing methods. Furthermore, the authors of the following paper have done an experimental research of commonly used SA methods in terms of coverage and agreement, such as LIWC, Happiness Index, SASA, Emoticons, SenticNet, SentiStrength, etc. (42). They focused on determining positive and negative aspects (a polarity) by using two different large-scale datasets extracted from Twitter.

III. MAIN BODY

Natural disasters are an unavoidable part of human existence. Each year, they affect nearly one million and kill almost 400 people in the United States alone (14). Managing such events has three phases – preparation, response, and recovery. At all phases, social networks can be leveraged by disaster managers, victims, and the population at large to address the needs of the affected. Preparation refers to public and private planning for disasters along with building infrastructure to handle a disaster. By using social networks, planning and training can be organized, and collaborative networks can be established (5). When a disaster strikes, the immediate actions taken by those affected is the response, and is their efforts to minimize death and damage. At these times, many communication systems may be damaged, and for some, the Internet is the only option. Social networks connect victims to help, give responders situational awareness, and provide much-needed information to the general public (49). After the event has ended, recovery is the work done to return the social fabric to normal. Recovery is aided by social networking through its ability to raise awareness of victims' circumstances and collect funds (28). The primary benefit of social networks in disaster management is information sharing on a large scale, but it is not a panacea. Internet access and power are required (16), and unfortunately most planning assumes communications will be intact (50). Vulnerable groups, like the poor, homeless, and disabled, may not be reachable (36), but minorities are often more reachable with social networks than with government programs (24). The requirements of message authentication, validation, accuracy, scalability, and security are not guaranteed through these networks as well (21).

Despite these challenges, using social media is a necessary part of disaster management. The next section will review four major, recent natural disasters – two that took place before large-scale social networking, and two that took place after – and discuss how they would have benefited from social networking, or how social networks were used to improve disaster management.

Disaster	Year	Deaths (estimate)	Cost (current dollars)	Communication methods
Hurricane Andrew	1992	70	$44.5 billion	TV, radio, telephone
Hanshin Earthquake	1995	6,500	$158 billion	Radio, TV, telephone
Hurricane Sandy	2012	150	$25 billion	Text messages, Twitter, Facebook
Tohoku Earthquake	2011	20,000	$224 billion	Text messages, Twitter, Facebook, Mixi

Table 1: Overview of disasters discussed.

On August 24, 1992, Hurricane Andrew came ashore near Homestead, Florida. It was a category 5 storm, one of the most powerful ever to hit the state. Almost 70 deaths were attributed to Andrew, and did an estimated $26 billion ($44.5 billion in 2016 dollars) in damage to Florida alone (27). Over one million residents lost power and 150,000 lost telephone services. Despite this, the most common means of information movement through affected areas was radio, television, and newspapers. Famously, reporter Brian Norcross stayed live on the air for 23 hours when the storm hit, giving viewers updates on what to do and how to stay safe (3). The experience of Hurricane Andrew was a powerful lesson for the people of Florida and the United States – better communication is key in catastrophic storms, and the existing infrastructure is not sufficient. To address this weakness, many telecommunication providers developed mobile towers that can be deployed in emergencies, and towers that can stay powered by batteries for over a week (3). Although social networks were not available at the time, such an option may have proven valuable when the telephone network was not functional, or even if devices were powered by backup generators. One main problem during Hurricane Andrew was the lack of preparation, as the danger was generally underestimated. When the storm hit, bad planning further limited the ability to respond to the event, as "no one was in charge [and] no one knew what to do (27)." With the tools of social media, preparation and response to natural disasters are aided by improved communication.

The Hanshin Earthquake struck Kobe, Japan, on January 17th, 1995. It was the second largest earthquake to hit the country in the 20th century and was particularly devastating in areas with old wooden houses (51). The death toll was nearly 6,500 and the damage cost around $100 billion ($158 billion in 2016 dollars). Immediate response was slow, as communications failed and management officials did not fully understand the scope of the disaster. Additionally, rigid social structures limited cooperation between government agencies and prevented fluidity in responses (35). Preparations were found to be extremely poor, which surprised even the media. Realizing the event was a wakeup call, the Japanese government moved to establish better planning and organizational structures to deal with disasters (6). Given that social media serves well in communication support, the use of such systems would have likely aided in the management of the Hanshin Earthquake.

Hurricane Sandy swept up the northeastern coast of the United States in late November of 2012, hitting an area generally unaccustomed to strong hurricanes. The damage was extensive – over $25 billion and at least 147 deaths (10). Telephones were overloaded and power was out in many areas, but social networking played a pivotal role in response and recovery, as Internet services were for the most part still available. Twitter was especially active with disaster management efforts, with over 20 million related tweets during the storm reported by FEMA (31). The website was used by some police and fire departments to keep their communities informed, and emergency requests were sent through the social media when other means were not possible (23). Disaster managers that were able to leverage social networking were much better prepared to deal with Hurricane Sandy, and their performance during the storm was well-received by victims, prompting many lagging organizations to increase their online presence as well (60). Compared to Hurricane Andrew, Sandy was met with a much more connected populace that was better able to handle the crisis, in part thanks to social networking.

On March 11, 2011, the Tohoku Earthquake struck off the northeastern coast of Japan. The earthquake and ensuing tsunami killed over twenty thousand people and caused an estimated $224 billion in damages to buildings and infrastructure (25). Compared to the Hanshin Earthquake, this disaster's response unfolded in a much different manner due to the popularity of social networking. Twitter, Mixi, and Facebook were the major social media hubs for the country, and most crisis response communication was peer-to-peer, user-generated, and not government-controlled. As such, news of the disaster spread quickly, with social networks breaking the story 20 minutes before the mainstream media (7). Within hours of the event, multiple government agencies found that the best way to reach the public was through social media and created accounts on Twitter (7). Furthermore, one of Japan's most popular social networks, Line, was launched within four months as a solution to the country's weakened communications infrastructure (McCracken). Although the Tohoku Earthquake was extremely devastating, management of the disaster was greatly improved with the use of social networks.

Disaster management has changed dramatically with the rise of social networking. In particular, Twitter and Facebook have been able to connect millions of people almost instantaneously when a disaster occurs, and keep them engaged in the response and recovery efforts. By examining the circumstances of four major, recent disasters, it is clear that social networks have become a crucial tool in handling crises. These systems facilitate communication between affected people and responders in the immediate aftermath of a disaster. Social media platforms also now work to bring communities together to plan and prepare for emergency situations (50). They make fund raising efforts for relief reach a wider audience, as well as bringing awareness to the challenges faced by victims (28). With increased social media penetration and analytics, new options for disaster management open up. Open-sourced software enables crowdsourcing (19) to be leveraged in a crisis, and RSS and Twitter feeds can be connected to public address systems (36), providing much-needed information on emergency services. As yet unseen future applications will further enhance the ability of social networks to aid in disaster preparation, response, and recovery.

In recent years, political environments and the ability to organize and plan events have seen a transformation due to the involvement of social networks. Social media changed the way the information is shared, making it possible to track and predict campaign movements, organize protests, and manipulate perception. This is all possible due to the rapid assimilation of technology over current years. In fact, it is estimated that two out of three people in United States use social media and that search engines are used on daily basis (37).

Political video consumption by age

The % of online political users within in each group who watch political videos online. Online political users are the 55% of the voting-age population who used the internet in one way or another for political purposes in 2008.

	18-29	30-49	50-64	65+
% within each group who are online political users	72%	65%	51%	22%
Watch online video from a campaign or news organization	57	52	43	30
Watch online video that did not come from a campaign or news organization	54	44	36	26
Watched any type of political video online	**67**	**62**	**54**	**40**

Source: Pew Internet & American Life Project Post-Election Survey, November-December 2008.

One of the most popular social media services that gained foothold in news and political circles is Twitter. It is the third largest social network in the world, right after Facebook and YouTube, where 80 percent of popular tweets are created by ordinary users and more than 75 percent of users are between the ages of 15 and 25 (39). However, when we look at population as a whole only 16 percent of United States population uses Twitter and 8 percent get their news from Twitter (8). It is reported that 500 million messages are sent per day as of 2015 and that 1 percent of all accounts are responsible for 30 percent of all political discourse (37).

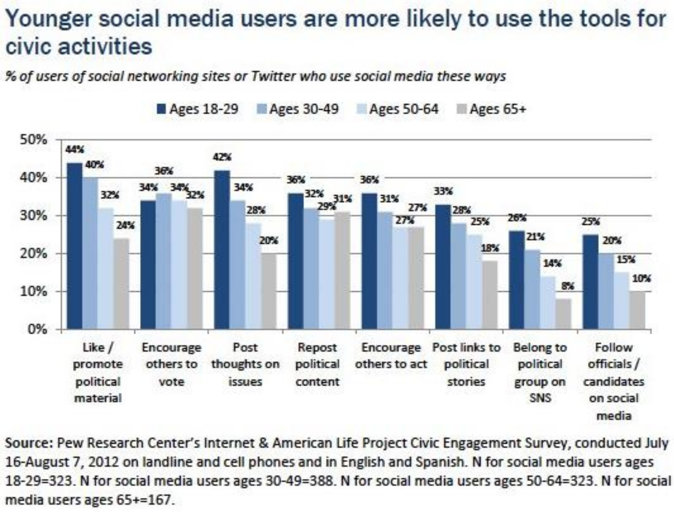
As we can see, Twitter is an enormous microblogging machine that is utilized every day by the general public, news media, and our politicians as a primary information outlet. In previous years, if a politician or a political campaign wanted to run a promotional or informative story, they had to go through newspapers or television media, who would determine if the story or announcement was newsworthy. Today politicians can bypass this channel and interact directly with reporters and public through Twitter. This speeds up the process making news announcements instantaneous. However, due to the lack of filtering, insignificant announcements many times become much larger news stories than they were meant to be as they are elevated through followers' viral retweeting.

We also can observe that the behavior of reporters also has drastically changed over recent years. Today journalists care much more about self-promotion and their brand recognition to gain following through various social sites rather than journalistic competitiveness and integrity. We can see that on the television when announcer asks the audience to follow them on Twitter or other social media (8). Many older politicians and party establishment are however concerned with social media as over the years Twitter became a platform for food fights between campaign operatives. Even that 99 percent of all of those fights are conducted and resolved without general public knowing about them they feel that this behavior brings down level of discourse and feeds the traditional media with unnecessary, murky stories. Because of this and other factors, Twitter became a news monitoring tool for reporters and staffers as it provides easier access to politicians and their staffers than communication over phone or email (9).

Social networks and particularly Twitter also established itself as a promotional campaign tool in addition to news and communication outlets mentioned above. The presidential election in 2008 showed the power of social media for the first time. The big data specialists studied the strategies employed during that campaign and studied it from two perspectives of supply and demand of information. The study noticed that social media allows politicians to bypass traditional journalistic channels to reach general public which refers to demand. The supply side shows how political campaigns can control the flow of information of social media and classify the mood of current conversation through sentiment analysis, they can shift direction of conversation (46).

Social media can be used as well for manipulation of general public in order to increase favorability perception of a candidate. In 2010 senatorial elections, a Twitter bomb was used that targeted sixty thousand user accounts and the operation was orchestrated by nine separate accounts (37). Campaigns also often use Google bombs to increase the page ranking. Tactics like Twitter or Google bombing are a type of web spamming where associations are created between anchor words and special phrases that later link to web pages or designated Twitter accounts. This type of spamming is designed to artificially increase popularity of the candidate and in crucial races where the difference is within the margin of error creating fake momentum is an often utilized tactic. Another tactic that can be used to create momentum is a fake grassroots movement called "Astroturfing." This technique tricks journalists and news outlets into creating outreach to displays of public outrage and feelings of unfairness with current coverage in order to for news media to step away from the story entirely, or at least change the tone of that story to a more favorable one (37).

In the 2012 presidential elections, we saw an even bigger use of social media than ever before, as both parties made their appeals through online campaigns. The primary on the republican side was studied for number of tweets, followers, and hashtags in order to develop better strategies to impact candidate image and political participation (40). During this election, the statistics showed that 66 percent of adults in United States who use social networking have engaged to some extent in publically oriented activity on those sites, and one out of three created a post or a link to a politically related content. Therefore, peer-to-peer sharing of political content, like user created memes, became major factor competing with both Romney's and Obama's messaging strategies, for which campaigns spend millions of dollars (41).



As we see the social networking very often has a mind of its own fueled by regular users and sometimes manipulated by campaigns or movements with resources and manpower. The messaging is instantaneous and sometimes can be greatly elevated or sometimes lost depending on circumstances and messaging of other users. There are no predefined opinion leaders and anyone with interesting, viral message may be an opinion leader. It is an outlet that young voters are most connected with; however, many think that this demographic is least likely to cast a vote and the challenge is to get them to go to the polls, but while not active in voter participation, they are the primary creators and users of the social media content (54).

Social media by appealing to young users often plays into their political idealism and feeling of social justice. Many movements have started based on this trend, most recently we could see events being organized by Occupy Wall Street which was a grassroots-driven movement with low resources organized mostly through social media (18). Many times the events organized like that lead to simple protests, sometimes they lead to spreading awareness, but sometimes they do lead to regime changes. In 2011, social networks like Facebook and Twitter were essential in organization of demonstrations in Egypt. Even after the government blocked internet use, Twitter partnered up with Google in an effort to keep demonstrators connected with the world. A Google service called "Speak to Tweet" allowed demonstrators to call the service in order to post their tweets. The service would transcribe the messages from audio to text and post them as tweets on Twitter. In the Philippines, social media was used to build political pressure to demand resignation of President Joseph Estrada (54). Those are all successful stories where social media played major role in change of the regime. Sometimes attempts are made that are not successful, like the one according to Minister Wimal Weerawansa who claimed in 2014 that United States played major role in destabilizing political environment there to overthrow the regime of Sri Lanka (59). Success of the movement is however largely dependent on political elites' acceptance of the political outcome achieved by such a movement. Many times the breakdown of a regime is a messy, long process and social media helps in creating momentum and messages, but it is simply a tool rather than recipe to victory (45).

The last way that social media is being used in the political arena is to create predictions, polls, and forecast of campaign outcomes. Twitter recently added a simple feature for all its users that allows them to create polls right from the compose screen; however, those polls are limited to Twitter accounts only (58). Polls unfortunately are just indicative of popularity and become less reliable in prediction of electoral outcomes, studies are done to see if social media could be better prediction method (32). In 2012 social media models to predict future events like movie-box-office revenues or product sales were already extremely accurate; however, predicting election results via Twitter data was more complicated as tweet chatter is originated often by small number of users, 1 percent of accounts generating 30 percent of all tweet volume; therefore, chatter rate was not the best indication of voter participation. In addition, the time period for data collection differed a lot for variety of races, as presidential races tend to go on for over a year, while less significant races have less coverage and smaller window of promotion (37). The newer studies conducted in 2015 focused as again on Twitter platform and involved sentiment analysis where negative tweets are given value of -1 and positive tweets are given value of +1 and weight was given to some words that are situated somewhere in between those to boundary values. Predictive models were built using regression algorithms, Gaussian processes, or sequential optimization for regression implemented using the Weka platform. The results that they achieved using any of those algorithms actually yielded better results than poll-based approaches with a Gaussian process leading the way. Unfortunately, the predicting process is far from perfect as there were significant differences between different models and all will need improvements to their methodology (57). As more studies and better methods are developed over time, social networks will become a major tool in measurement of current and future performance on the campaign trail.

Generally, sentiment detection in Twitter messages has been considered as any other text classification process that consists of a several phases, as presented in Figure 1.

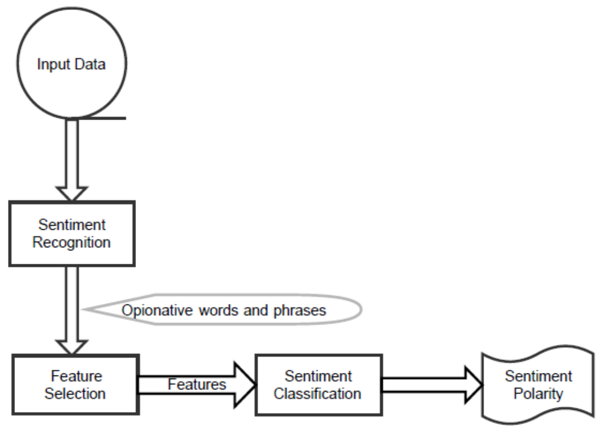


Figure 1: General text classification algorithm

The one important aspect is the methods to detect sentiments articulated in input messages. While a wide diapason of human moods are able to be detected through sentiment analysis, a lot of studies are focused on recognizing the polarity of a given text which is automatically recognize whether a tweet about a particular topic has neutral, positive or negative meaning (2, 52, 55). For example, Andrea Vanzo’s paper presented the idea of modeling the process of the polarity detection as a sequential classification task over the streams of tweets using the adopted Support Vector Machine (SVM) algorithm (2). In addition, the paper by Soujanya Poria proposed a novel paradigm for concept-level sentiment analysis that combines linguistic features, common-sense computing, and machine learning framework as SenticNet to distill the polarity by decomposing language text. Overall, there are three fundamental approaches of classification in sentiment analysis: machine learning, lexicon-based, and hybrid. Each of these can also have subcategories (42, 56). Figure 2 describes the structure of the sentiment analysis classification methods.

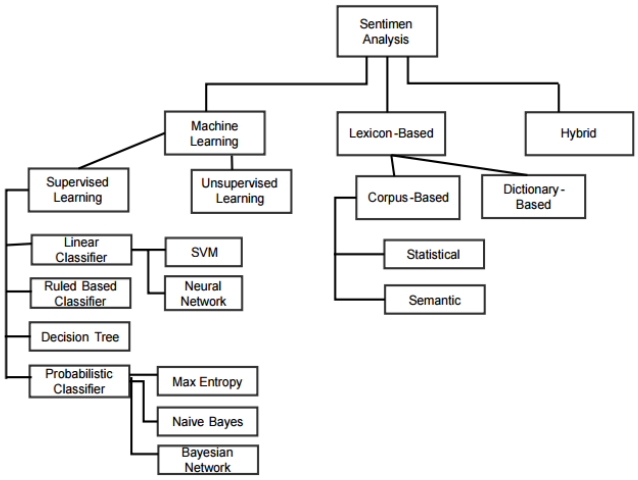


Figure 2: the structure of the sentiment analysis classification methods

The lexicon-based methods compute the opinion polarity using some opinion function words in the dataset. The machine learning methods usually train SA classifiers using special features like unigrams or bigrams. Most of the methods apply some of the supervised learning algorithms by implementing Maximum Entropy, or Support Vector Machines, or Naive Bayes. These methods require manual labeling of training sets for each specific domain. If the sentiment analysis should be done for concrete domain, in this case, supervised learning will be the dominant approach to be used. This logic utilizes many Twitter features and language usages, such as smiley and hash tags.

To be specific, machine learning methods frequently depend on supervised classification, where sentiment detection is based on a binary idea - positive and negative. This technique requires data to be labeled in order to train classifiers (43). However, the advantage of learning-based methods is the ability to gear and produce trained models for concrete purposes and domains, their lack is the presence of labeled data, and therefore, inability to apply this method on new datasets. Being that, labeling data can be expensive or even restrictive for certain tasks. Many machine learning approaches for sentiment analysis in Twitter derived by complex ways of individual tweets modeling are discussed in several works (15, 44). The paper by Hu, et al, proposed to use the individual Kernels as models for SVM implementation. Kernel functions define the overlap in terms of lexical content between tweets, thereby represented as vectors with dimensions corresponding to the different words. And components define whether the corresponding word presents in the text, and Kernel function agrees with the cosine similarity of vector pairs. Some paper proposed the study of the unsupervised sentiment analysis using emotional signals (20). To be particular, it investigated if the signals enhance the sentiment analysis by modeling two main categories of emotional signals - emotion correlation and indication. Also they aggregate these signals into a proposed unsupervised learning framework.

On the other side, lexical-based methods employ a predefined list of words, such that each word is bounded with a particular sentiment. The lexical-based methods vary according to the context in which they were created. They utilize an unsupervised approach, since it can operate without any corpus and does not need any instructions. The main logic behind the classifiers is to estimate how intense the positive and negative emotions are in particular text, and further to make a triple prediction about polarity and subjectivity, that is to say, the output result of the classifier is whether of 0, -1, +1. For instance, the paper by Aamera, et al, proposed the idea to analyze sentiment patterns according to entity-level paradigm using the Chi-square test on its output results (1). The authors of this paper first adopted a lexicon-based approach to perform entity-level sentiment analysis by performing following steps under the cleaned data: sentence segmentation, which divides a tweet into individual sentences; afterwards, tokenizing and tagging. A binary sentiment classifier then should be trained by the lexicon-based method in order to assign polarities of the sentiments to the newly defined opinionated tweets.

The last subcategory of sentiment analysis methods is hybrid, the mix of previous two. The authors of this interesting paper (12) adopted three different classifiers (SentiWordNet, Enhanced Emoticon and Improved Polarity classifiers) to determine the sentiment of each tweet in real time. The paper discusses the primary issues, such as accuracy of classification, data sparsity and sarcasm, as they affect most of the tweets to be incorrectly classified as neutral. They solved these problems by using three-way classification, by applying pre-possessing of the data which includes detection and analysis of lemmatization, slangs, abbreviations, correction and stop words removal. Pre-processing the data is the process of making the text to be ready for classification. Overall, online messages usually contain a lot of uninformative parts such as advertisement content, HTML tags, different scripts, and noise (11). In practice, sentiment methods have been widely utilized to implement a lot of applications without even understanding of their applicability in the context of online social networks, or their advantages, disadvantages, and limitations in comparison with one another. That is why having detailed and sophisticated surveys is crucial for future advances.

IV. CONCLUSION

The rise of social networking has created multiple new directions for the betterment of humanity. By leveraging the improvements they provide, disasters are able to be managed more efficiently and effectively. Governments and citizens can work together to prepare for catastrophic events, respond appropriately, and return to their normal lives with the help of social networks. Furthermore, governments can make use of social media to organize their campaigns or determine how the public views them. More ominously, this technology can be used to manipulate the media, and by extension the electorate. However, the public has access to the same networks, and can fight back using the same strategies. With social networks, political action has become more personal and far-reaching than ever before. A wide variety of methods can be used for sentiment analysis and opinion mining, and the data for this comes from social media. Blending the actual practical goals of analyzing sentiments with scientific theories of sentiments and emotions in natural language will stimulate the development of intelligent opinion-mining systems that will be capable of handling semantic knowledge, learning more complex concepts, and detecting and "feeling" emotions. Social network data analysis is a relatively new field that growing very fast, and there is still a great deal of research to be done.

REFERENCES

[1] Aamera Z.H.Khan, Dr. Mohhamad Atique Dr., V.M. Thakare. "Combining Lexicon-based and Learning-based Methods for Twitter Sentiment Analysis." *Special Issue of International Journal of Electronics, Communication & Soft Computing Science and Engineering*, ISSN: 2277-9477, (2015): 89-91. Proc. of National Conference on Advanced Technologies in Computing and Networking-ATCON-2015. N.p., n.d. Web. 01 Apr. 2016. <http://search.proquest.com/openview/3bb4518ced02bbd25b28594d28b35094/1?pq-origsite=gscholar>.

[2] Andrea Vanzo, Danilo Croce and Roberto Basili. "A Context-based Model for Sentiment Analysis in Twitter." www.coling-2014.org. *Proc. of The 25th International Conference on Computational Linguistics* (COLING 2014), Dublin, Ireland. N.p., n.d. Web. 1 Apr. 2016. <http://www.aclweb.org/anthology/C14-1221>.

[3] Beasley, Adam H. "Likely Casualty of Any Andrew-like Hurricane: Cellphones." *Miami Herald*. N.p., 31 May 2012. Web. 31 Mar. 2016. <http://www.miamiherald.com/news/special-reports/hurricane-andrew/article1940282.html>.

[4] Cambria, Erik, Bjorn Schuller, Yunqing Xia, and Catherine Havasi. "New Avenues in Opinion Mining and Sentiment Analysis." IEEE Intell. Syst. *IEEE Intelligent Systems* 28.2 (2013): 15-21. Web.

[5] Chan, Jason Christopher. "The Role of Social Media in Crisis Preparedness, Response, and Recovery." The Organisation for Economic Co-operation and Development, n.d. Web. 31 Mar. 2016.

[6] Chatfield, Akemi, and Uuf Brajawidagda. "Twitter Tsunami Early Warning Network: a social network analysis of Twitter information flows." University of Wollongong, 2012. Web. 01 Apr. 2016. <http://ro.uow.edu.au/eispapers/136/>.

[7] Cho, Seong Eun, Kyujin Jung, and Han Woo Park. "Social Media During Japan's 2011 Earthquake: How Twitter Transforms the Locus of Communication." *Media International Australia* 149 (2013): 28-40. Web. 1 Apr. 2016.

[8] Cillizza, Chris. *How Twitter has Changed Politics -- and Political Journalism*. Washington: WP Company LLC d/b/a The Washington Post, 2013. Web.

[9] Cillizza, Chris. *Is Twitter Ruining Politics?*. Washington: WP Company LLC d/b/a The Washington Post, 2014. Web.

[10] CNN Library. "Hurricane Sandy Fast Facts." CNN. Cable News Network, 3 Oct. 2015. Web. 25 Apr. 2016. <http://www.cnn.com/2013/07/13/world/americas/hurricane-sandy-fast-facts/>.

[11] Emma Haddia, Xiaohui Liua ,Yong Shib. "The Role of Text Pre-processing in Sentiment Analysis." *The Role of Text Pre-processing in Sentiment Analysis.* N.p., n.d. Web. 01 Apr. 2016. <http://www.sciencedirect.com/science/article/pii/S1877050913001385>.

[12] Farhan Hassan Khan Saba Bashir Usman Qamar. "TOM: Twitter Opinion Mining Framework Using Hybrid Classification Scheme." *Decision Support Systems*, vol. 57 (2013): 245-357. Web. 01 Apr. 2013.

[13] Fowler, Tim, and Doug Hagar. "“Liking” Your Union: Unions and New Social Media during Election Campaigns." *Labor Studies Journal* 38.3 (2013): 201-28. Web.

[14] Fox, Zoe. "Why Social Media Is the Front Line of Disaster Response." Mashable. N.p., 21 May 2013. Web. 31 Mar. 2016. <http://mashable.com/2013/05/21/social-media-disaster-response/#BMIo5McKIgq7>.

[15] Giuseppe Castellucci, Simone Filice, Danilo Croce, and Roberto Basili. “Unitor: Combining syntactic and semantic kernels for twitter sentiment analysis.” *Second Joint Conference on Lexical and Computational Semantics* (*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013), pages 369-374, Atlanta, Georgia, USA, June. Association for Computational Linguistics.

[16] Gosnell, Angela. "Social Media's Role in Disaster Response Expands." *Knoxville News-Sentinel*, 5 May 2015. Web. 31 Mar. 2016. <http://www.emergencymgmt.com/disaster/Social-Medias-Role-Disaster-Response-Expands.html>.

[17] Heaney, Michael T., and Scott D. McClurg. "Social Networks and American Politics: Introduction to the Special Issue." *American Politics Research* 37.5 (2009): 727-41. Web.

[18] HerdaĞdelen, AmaÇ, et al. "An Exploration of Social Identity: The Geography and Politics of news-sharing Communities in Twitter." *Complexity* 19.2 (2013): 10-20. Web.

[19] Howe, Jeff. "The Rise of Crowdsourcing." *Wired.com*. Conde Nast Digital, 1 June 2006. Web. 02 Apr. 2016. <http://www.wired.com/2006/06/crowds/>.

[20] Hu, Xia, Jiliang Tang, Huiji Gao, and Huan Liu. "Unsupervised Sentiment Analysis with Emotional Signals." *Proceedings of the 22nd International Conference on World Wide Web - WWW '13* (2013): n. pag. Web.

[21] Huang, Cheng-Min, Edward Chan, and Adnan A. Hyder. "Web 2.0 and Internet Social Networking: A New Tool for Disaster Management? - Lessons from Taiwan." *BMC Medical Informatics and Decision Making* 10.1 (2010): 57. Web.

[22] Huberty, Mark. "Can we Vote with our Tweet? on the Perennial Difficulty of Election Forecasting with Social Media." *International Journal of Forecasting* 31.3 (2015): 992. Web.

[23] Hughes, Amanda L., Lise A. A. St. Denis, Leysia Palen, and Kenneth M. Anderson. "Online Public Communications by Police & Fire Services during the 2012 Hurricane Sandy." *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems* - CHI '14 (2014): n. pag. Web.

[24] Kavanaugh, Andrea L., Edward A. Fox, Steven D. Sheetz, Seungwon Yang, Lin Tzy Li, Donald J. Shoemaker, Apostol Natsev, and Lexing Xie. "Social Media Use by Government: From the Routine to the Critical." *Government Information Quarterly* 29.4 (2012): 480-91. Web.

[25] Kazama, Motoki, and Toshihiro Noda. "Damage Statistics (Summary of the 2011 off the Pacific Coast of Tohoku Earthquake Damage)." *Soils and Foundations* 52.5 (2012): 780-92. Web.

[26] Lau, Raymond Y.k., Chunping Li, and Stephen S.y. Liao. "Social Analytics: Learning Fuzzy Product Ontologies for Aspect-oriented Sentiment Analysis." *Decision Support Systems* 65 (2014): 80-94. Web.

[27] Lilly, Christiana. "Hurricane Andrew: 20 Facts You May Have Forgotten (PHOTOS, VIDEO)." *The Huffington Post*. TheHuffingtonPost.com, 24 Aug. 2012. Web. 25 Apr. 2016. <http://www.huffingtonpost.com/2012/08/21/20-facts-hurricane-andrew-anniversary_n_1819405.html>.

[28] Lindsay, Bruce R. "Social Media and Disasters: Current Uses, Future Options, and Policy Considerations." *Congressional Research Service* (2011): n. pag. Web. 1 Apr. 2016.

[29] M. Ghiassi, J. Skinner, D. Zimbra. "Twitter Brand Sentiment Analysis: A Hybrid System Using N-gram Analysis and Dynamic Artificial Neural Network." N.p., n.d. Web. 01 April 2016. <http://www.sciencedirect.com/science/article/pii/S0957417413003552>.

[30] Maria Pontiki, Dimitris Galanis, John Pavlopoulos, Harris Papageorgiou, Ion Androutsopoulos and Suresh Manandhar. "Aspect Based Sentiment Analysis." *Proceedings of the 9th International Workshop on Semantic Evaluation* (SemEval 2015), Pages 486-495, Denver, Colorado, June 4-5, 2015. N.p., n.d. Web. 01 April 2016.

[31] Maron, Dina Fine. "How Social Media Is Changing Disaster Response." *Scientific American*. N.p., 7 June 2013. Web. 31 Mar. 2016. <http://www.scientificamerican.com/article/how-social-media-is-changing-disaster-response/>.

[32] McVie, Courtney M. "Exploring the Predictive Power of Social Media in Elections." ProQuest Dissertations Publishing, 2015. Web.

[33] Medhat Walaa, Ahmed Hassan, and Hoda Korashy. "Sentiment Analysis Algorithms and Applications: A Survey." *Ain Shams Engineering Journal* 5.4 (2014): 1093-113. Web.

[34] Meeks, Lindsey. "A Woman's Place: Gender Politics and Twitter in the 2012 Elections." ProQuest Dissertations Publishing, 2013. Web.

[35] Menoni, Scira. "Chains of Damages and Failures in a Metropolitan Environment: Some Observations on the Kobe Earthquake in 1995." *Journal of Hazardous Materials* 86.1-3 (2001): 101-19. Web.

[36] Merchant, Raina M., Stacy Elmer, and Nicole Lurie. "Integrating Social Media into Emergency-Preparedness Efforts." *New England Journal of Medicine* N Engl J Med 365.4 (2011): 289-91. Web. 1 Apr. 2016.

[37] Metaxas, Panagiotis T., and Eni Mustafaraj. "Science and Society. Social Media and the Elections." *Science (New York, N.Y.)* 338.6106 (2012): 472. Web.

[38] Miller, P. R., et al. "Talking Politics on Facebook: Network Centrality and Political Discussion Practices in Social Media." *Political Research Quarterly* 68.2 (2015): 377-91. Web.

[39] Park, Chang Sup. "Does Twitter Motivate Involvement in Politics? Tweeting, Opinion Leadership, and Political Engagement." *Computers in Human Behavior* 29.4 (2013): 1641. Web.

[40] Payne, J. Gregory. "Impact of Social Media in 2012 Presidential Election." *American Behavioral Scientist* 57.11 (2013): 1535-8. Web.

[41] Penney, J. "Motivations for Participating in 'Viral Politics': A Qualitative Case Study of Twitter Users and the 2012 US Presidential Election." *Convergence: The International Journal of Research into New Media Technologies* (2014)Web.

[42] Pollyanna Goncalves, Belo Horizonte, Matheus Arajo, Fabrcio Benevenuto, Meeyoung Chao. "Comparing and Combining Sentiment Analysis Methods." *Comparing and Combining Sentiment Analysis Methods.* N.p., n.d. Web. 10 April 2016. <http://dl.acm.org/citation.cfm?doid=2512938.2512951>.

[43] Prerna Chikersal, Soujanya Poria, Erik Cambria, and Alexander Gelbukh, and Chng Eng Siong. "Modelling Public Sentiment in Twitter: Using Linguistic Patterns to Enhance Supervised Learning." *Springer International Publishing Switzerland* 2015 A. Gelbukh (Ed.): CICLing 2015, Part II, LNCS 9042, Pp. 49?65, 2015ÿ(n.d.): n. pag. Web.

[44] Preslav Nakov, Sara Rosenthal, Zornitsa Kozareva, Veselin Stoyanov, Alan Ritter, and Theresa Wilson. “Semeval-2013 task 2: Sentiment analysis in Twitter.” *Second Joint Conference on Lexical and Computational Semantics* (*SEM), Volume 2: Proceedings of the Seventh International Workshop on Semantic Evaluation (SemEval 2013), pages 312-320, Atlanta, Georgia, USA, June. Association for Computational Linguistics.

[45] Reuter, Ora John, and David Szakonyi. "Online Social Media and Political Awareness in Authoritarian Regimes." *British Journal of Political Science* 45.1 (2015): 29. Web.

[46] Rotolo, Anthony. "Tweeting to Power: The Social Media Revolution in American Politics by Jason Gainous and Kevin M. Wagner. New York, Oxford University Press, 2008. 2013 Pp. Cloth, $99.00; Paper, $24.95: Book Review." *Political Science Quarterly* 130.1 (2015): 154-5. Web.

[47] Salah Bouktif, and Mamoun Adel Awad. "Ant Colony Based Approach to Predict Stock Market Movement from Mood Collected on Twitter." *IEEE Xplore*. N.p., 28 Aug. 2013. Web. 01 April 2016. <http://ieeexplore.ieee.org/xpl/login.jsp?tp=&arnumber=6785799&url=http%3A%2F%2Fieeexplore.ieee.org%2Fiel7%2F6779714%2F6785655%2F06785799.pdf%3Farnumber%3D6785799>.

[48] Shiladitya Sinha, Chris Dyer, and Noah A. Smith. "Predicting the NFL Using Twitter." *Proceedings of the Workshop on Machine Learning and*

*Data Mining for Sports Analytic*s. N.p., 27 Aug. 2013. Web. 01 Apr. 2016. <http://repository.cmu.edu/cgi/viewcontent.cgi?article=1042&context=lti>.

[49] Simon, Tomer, Avishay Goldberg, and Bruria Adini. ""Socializing in Emergencies? A Review of the Use of Social Media in Emergency Situations." *International Journal of Information Management* 35.5 (2015): 609-19. Web.

[50] Skarda, Erin. "How Social Media Is Changing Disaster Response." *Time.* Time Inc., 09 June 2011. Web. 31 Mar. 2016. <http://content.time.com/time/nation/article/0,8599,2076195,00.html>."

[51] Smith, Lydia. "Kobe Earthquake 20th Anniversary: Facts about the Devastating 1995 Great Hanshin Earthquake." *International Business Times* RSS. N.p., 16 Jan. 2015. Web. 25 Apr. 2016. <http://www.ibtimes.co.uk/kobe-earthquake-20th-anniversary-facts-about-devastating-1995-great-hanshin-earthquake-1483786>.

[52] Soujanya Poria, Erik Cambria, Gr‚goire Winterstein, Guang-Bin Huang. "Sentic Patterns: Dependency-based Rules for Concept-level Sentiment Analysis." *Sentic Patterns: Dependency-based Rules for Concept-level Sentiment Analysis. Knowledge-Based Systems* 69 (2014) 45?63, n.d. Web. 01 April 2016. <http://www.sciencedirect.com/science/article/pii/S095070511400183X>.

[53] Strandberg, Kim. "A Social Media Revolution Or just a Case of History Repeating itself? the use of Social Media in the 2011 Finnish Parliamentary Elections." *New Media & Society* 15.8 (2013): 1329-47. Web.

[54] Suarez, Sandra L. *Social Media and Regime Change in Egypt*. 32 Vol. Plainsboro: Campaigns & Elections, Inc, 2011. Web.

[55] Svetlana Kiritchenko, Xiaodan Zhu, and Saif M. Mohammad. "Sentiment Analysis of Short Informal Texts." *Journal of Artificial Intelligence Research*, vol.50 (2014): 723-762. http://www.jair.org/. Aug. 2014. Web. 01 Apr. 2016. <http://www.jair.org/papers/paper4272.html>.

[56] "Techniques and Applications for Sentiment Analysis." *Magazine Communications of the ACM.* Volume 56 Issue 4, April 2013 Pages 82-89, n.d. Web. 01 April 2016. <http://dl.acm.org/citation.cfm?id=2436274>.

[57] Tsakalidis, Adam, et al. "Predicting Elections for Multiple Countries using Twitter and Polls." *IEEE Intelligent Systems* 30.2 (2015): 10-7. Web.

[58] "Twitter Poll." *TD Magazine* 70.3 (2016): 13. Web.

[59] "US Hijacking Social Media for Regime Change - Wimal." *Daily News* 2014. Web.

[60] Webley, Kayla. "Hurricane Sandy By the Numbers: A Superstorm?s Statistics, One Month Later." *Time Inc*., 26 Nov. 2012. Web. 25 Apr. 2016. <http://nation.time.com/2012/11/26/hurricane-sandy-one-month-later/>.

[61] Wu He, Shenghua Zha, and Ling Li. "Social Media Competitive Analysis and Text Mining: A Case Study in the Pizza Industry." *International Journal of Information Management* 33 (2013) 464?472. N.p., 04 Feb. 2013. Web. 02 April 2013. http://www.sciencedirect.com/science/article/pii/S1877050913001385>.