IMPROVING SENTIMENT ANALYSIS OF DISASTER RELATED SOCIAL MEDIA CONTENT

by

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IMPROVING SENTIMENT ANALYSIS OF DISASTER

RELATED SOCIAL MEDIA CONTENT

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ABSTRACT

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Social media platforms have become the most accessible public communication and broadcast channels. Recently, the world has witnessed the prevailing usage of social media for communication during disasters. Being able to monitor and predict public opinions on social media during disasters allows us to evaluate crisis communication theories in order to design more efficient and effective communication mechanisms during the crisis. However, this potential is yet to be materialized due to difficulties in sentiment analysis of social media content. We propose to augment the effectiveness of such analysis by incorporating social relations in sentiment classification models. This thesis extends previous work substantially by looking at social relations of different nature, focusing on different communication goals at each stage of disaster management. This study provides a quantitative analysis of social media sentiments during disaster utilizing improved sentiment analysis and feature extraction techniques.

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CHAPTER I:

INTRODUCTION

Disasters cause major disruptions in human life created by natural hazards and accidents. A society's vulnerabilities to disasters stem from its choices such as, how it builds its infrastructure, agriculture; how it structures its government and financial systems; and how it uses land and natural resources. These vulnerabilities are dealt with using a disaster management strategy, which involves risk reduction, damage mitigation, and recovery. Effective communication is a key to successful disaster management strategy. Communication strategies in disaster management deal with information dissemination and information gathering by governments and non-government organizations (NGOs).

With the exponential growth of social media (e.g. blogs, micro-blogs, and social networks) in the last decade, the web has drastically changed. Nowadays, billions of people all around the globe are freely allowed to conduct many activities such as interacting, sharing, posting, and manipulating contents. This enables us to be connected and interact with each other anytime without geographical boundaries, as opposed to the traditional approaches to communicate and collaborate. The resulted unstructured user-generated data provides us opportunities to study and understand individuals at unprecedented scales. But it also mandates new computational techniques to analyze and make sense. Social media is increasingly being used as a medium for disaster communication. During Hurricane, Harvey victims turned to social media such as Twitter and Facebook, as local 911 service failed to respond to the demand (Rhodan 2017). American Red Cross finds social media as a crucial component of a disaster communication strategy. In a 2010 survey, 90% of respondents felt that the public expects some action based on social media applications (American Red Cross 2010). However, unlike 911 or emergency services, social media is not being monitored 24/7.

Despite social media's wide adoption in disaster management, its potential for information extraction and aggregation, and effective information dissemination is largely untapped.

Disaster management organizations from around the world would like to monitor sentiments during pre-disaster, impact, and post-disaster phases to assist recovery and provide disaster relief. The sheer volumes of social media data present opportunities and challenges for sentiment analysis of these noisy and short texts. Sentiment analysis has been extensively studied for commercial applications such as, product and movie reviews, which differ substantially from social media posts from platforms such as Facebook or Twitter. Unlike standard texts with many words that help gather sufficient statistics, the posts on Twitter only consist of a few phrases or one to three sentences. For example, Twitter has 280 characters limit per post and only 140 characters limit per post prior to November 2017. Due to these character limitations, it is common to find users using abbreviations or acronyms that rarely appear in conventional text documents. For example, messages like, "wooow", "LOL", "OMG :-(", "smh", are intuitive and popular on social media, but some are not actually English words. It is difficult for machines to accurately identify the semantics of these messages, though they provide convenience in quick and instant communications for human beings. Existing methods rely on pre-defined sentiment vocabularies, which are highly domain-specific (Barbosa and Feng 2010; Go et al. 2009; Liu 2012; Mukherjee, Venkataraman, et al. 2013; Wiebe and Cardie 2005).

One approach to achieve integrated and intelligent disaster management is through emotion-driven analysis of communication. Such an approach would involve the application of advanced text mining, feature extraction, and sentiment analysis to test the effectiveness of interweaved communication of public, respondents, and disaster management agencies, based on established communication theories. The literature review in this paper provides an overview of past and present achievements, propositions, and analytical techniques used for disaster related sentiments. The purpose and focus of this study are to identify the challenges involved in sentiment classification, formulate them as research problems and present a novel approach to improve the quality of sentiment classification in disaster-related communication. This study reviews the potential use of implicit network information to improve sentiment classification (Shivarkar and Wei 2018), extended from the studies using explicit social relations to improve sentiment classification (Hu, L. Tang, et al. 2013; Tan et al. 2011). In this study, we test and evaluate the effectiveness of incorporating disaster-related implicit social relations in sentiment classification. We focus on communication of two major organizations in disaster management – Federal Emergency Management Agency (FEMA) and American Red Cross – during Hurricane Harvey. The findings of this work can provide insights to designing a framework to improve the quality of communication between the public and disaster management agencies.

CHAPTER II:

LITERATURE REVIEW

Disaster Management

The words “disaster” and “crisis” are used interchangeably in general conversations. However, crisis often refers to a situation involving important decisions to be made in a short period of time within an organization. While disasters tend to be with long-term after effects and community-based. Disasters and crisis often have an interdependent relation, where failing to handle a crisis can lead to disasters and disasters can spawn a crisis for organizations when the public becomes concerned about how well organizations managed the disaster.

The United Nations Office for Disaster Risk Reduction defines disaster as “a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources” (UNISDR 2018). Disasters occur due to inability to handle hazards, accidents, or attacks; such inability is only one of the societal vulnerabilities that leave humankind susceptible to disasters. Unpredictability, uncertainty, unfamiliarity, and velocity of hazardous incidents elevate the severity of disasters.

To identify such vulnerabilities, organize and manage resources to reduce risk, mitigate the impact and facilitate relief are the facets of disaster management. Disaster management is highly dependent on accurate information collection and interpretation. The disaster communication strategy must evaluate information and aggregate it semantically. In modern times, the information management system facilitates disaster communication strategies. These modern information systems provide disaster respondents the tools to analyze data and detect information patterns and trends.

Identification of such patterns can be done accurately by applying established communication theories.

Disaster Communication Strategies

Communication during a disaster can be broken down into four fundamental temporal phases of disaster, which are Warning, Impact, Response, and Relief. The information being communicated, and its motivation varies in each phase. For example, in the warning phase of a disaster, communication is focused on providing early warnings and predictions. However, communicating early-warning alone does not guarantee the understanding of risks or reaction by the citizens for various reasons. Risk communication customized to local culture/customs is the key. Communication is a crucial component of disaster response because the effectiveness of disaster management strategy depends on effective communication. This relation has been constantly highlighted in disaster management research: “Citizens who do not have adequate information to assess the situation, the risks, and possible actions, might make choices that — observing from a greater distance, with more overview — may be perceived as sub-optimal.” (Helsloot and Ruitenberg 2004).

A 2016 survey provides compiled evidence of the importance of communication activities in an emergency with a comprehensive content analysis of emergency debriefing reports spanning six years. The study identifies important communication activities as education and pre-disaster engagement, warnings, communication planning, information, and engagement. It found that social media related activities and community engagement pressing issues in recent post-disaster studies (Ryan 2017). In a more generalized sense, we can narrow down to three major issues in communication, technological, sociological, and organizational. Effective communication in emergency response should involve solutions for all three issues (Manoj and Baker 2007).

Technological issues address robustness and interoperability issues. Emergency communication must be facilitated with the same effectiveness and efficiency despite the geographical location, adverse conditions, a major interruption of societal functions, and failure of existing infrastructure. Implemented communication systems should be fault-tolerant and robust, and it should be interoperable with existing infrastructure and information systems.

Sociological issues include information veracity and trust concerns. It affects the public, respondents, and government agencies alike when trusting information from an unknown, unverified source. Inaccurate or harmful information can put stakeholders at severe risk. Other sociological issues include maintaining sensitivity and empathy towards the emotions of the affected public while communication information, for the message to be well-received by the public.

Organizational issues stem from a lack of integration between an organization with different motivation, responsibilities, and organization structure. Cross-organizational communication should take place irrespective of the organizational structure, without any information gaps. The problem arises especially when groups are required to work in unfamiliar authority and organizational hierarchy; without any prior training to work under more dynamic, flat, and ad-hoc organization structure.

Crisis Communication Theories

Disaster communication is a two-way process of information exchange about nature, severity, and control of a risk. Communities depend on communication to assimilate and build a collective understanding of present and emerging threats from risks during a disaster. Researchers study communication patterns to describe best practices and build crisis and risk communication models (Fischhoff 1995). Crisis communication models are used to describe, predict, and test a multitude of variables and interacting entities. This section includes the review of various crisis communication models and theories.

Crisis and Emergency Risk Communication (CERC) is a communication model that emerges from incorporating traditional notions of health and risk communication in crisis and disaster communication. CERC aims to help manage complex events in uncertain, chaotic environments. This model was developed after the September 11 attacks. CERC model assumes that crisis will develop in predictable and systematic ways — from initial risk to the recovery. The systematic approach allows reducing uncertainty and allows crisis managers to anticipate communication problems. CERC is divided into five stages, (i) pre-crisis, (ii), initial event, (iii) maintenance, (iv) resolution, and (v) evaluation (Reynolds and Seeger 2005). CERC recommends a set of actions and responsibilities for effective communication at every stage of a disaster. Some examples of these responsibilities are monitoring and recognition of emerging risks, general public understanding of risk, and establishing empathy, reassurance, and reduction in emotional turmoil. The CERC framework allows us to explore disaster management and communication problems where the potential successful use of sentiment analysis is unrealized.

Situational Crisis Communication Theory (SCCT) is an evidence-based framework which provides a mechanism for anticipating how stakeholders will react to a crisis in terms of the reputational threat posed by the crisis. SCCT suggests that crisis management should be a proactive function of an organization, which should be in a continual process of learning from previous crisis to be better prepared to prevent future crisis entirely by protecting the public from harm by providing, instructing, and adjusting information. To achieve this, a tested and robust communication strategy is needed. Though SCCT is geared towards organizational crisis and reputational threat. It remains highly relevant for government agencies and organizations that deal with disaster response (Coombs 2007). Agencies such as FEMA, Red-Cross are required to keep their reputation from being harmed, as reputation is crucial for trust building and encouraging greater public engagement. Mishandling emergency situations can spawn a crisis for an organization and in turn spell a disaster. SCCT is based on **Attribution Theory** (Coombs 2007). According to the theory, the disaster-affected public is motivated to assign causes to their distrust and hostility towards an organization. SCCT suggests many response strategies based on crisis type, crisis history, prior reputation to the crisis. Crisis types could be in the form of natural disasters, technical errors, intentional harm, or malpractices. However, before opting for any response strategy, the organization must formulate an accurate overview of public response and emotions. This is where Situational Theory of Publics (STP) and the Heuristic-Systematic Model can be useful.

Situational Theory of Publics (STP) is a theory proposed by J. E Grunig, explains specific public's' active or passive communication behavior as a function of three situational variables: problem recognition, constraint recognition, and level of involvement; this behavior is public's propensity to seek information on a given issue actively or process it passively. STP model has been shown to be effective in helping understand the nature of the public and their specific behaviors (Grunig 2010). Further research extended to the situational theory of problem-solving by introducing an additional variable, communicative action in problem-solving, which involves a potential problem-solver increasing active or passive information seeking, selecting, and giving (Kim and Grunig 2011). To summarize, STP allows understanding of how public process risks messages and guide the development of appropriate risk messages.

Heuristic-Systematic Model allows communicators to identify and understand the connections between a person's need and motivation for obtaining and processing information. The model is divided into two parts, heuristic and systematic. The heuristics define how publics use superficial cues of the source to process information; the systematic part of the model looks at how public comprehensively analyze information to understand it, and the overall model states that public will use superficial cues and/or comprehensive strategies depending on the situation (Griffin et al. 2002).

The effectiveness of social media in disaster management has been a topic of debate. Therefore, there is a need to develop better strategies to avoid the mistakes experienced in social media pioneering years. There is a series of research addressing this issue. However, this discipline and its theories are still in infancy without theoretical models that accurately reflect the current social media landscape, communicators will be at a disadvantage for proactively managing disaster communication using evidence-based approaches such as SCCT over social media.

Crisis Communication Models for Social Media

Social Mediated Crisis Communication Model (SMCC) helps crisis managers to understand the creation, consumption, and dissemination of information using social media and related sources. The research studies show crisis information forms. Source and origin play a crucial role in influencing what response public expects from an organization during a crisis (Jin et al. 2014; Liu et al. 2011).

SMCC (Figure 1) considers five factors — crisis origin, crisis type, infrastructure, message strategy, messages form — that affect how organizations respond to crises via various modes of communication. SMCC suggests that crisis messages strategies and crisis emotions are a function of crisis origin. Researchers based this suggestion on SCCT, where crisis origin affects attribution of responsibility and limiting what crisis response strategies are available to the organization.

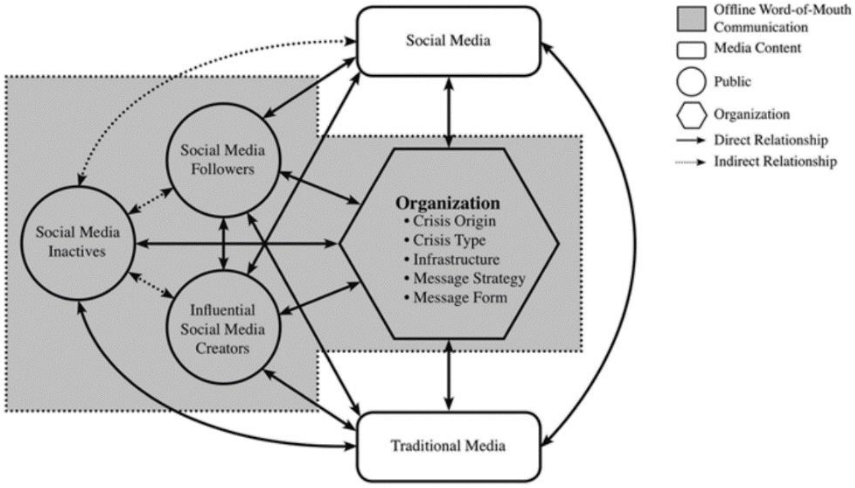

Figure 1 Social-mediated Crisis Communication Model

SMCC categorizes crisis emotions as attribution-independent emotions (anxiety, apprehension, and fear), attribution-dependent emotions (disgust, contempt, and anger), and self-attributed emotions (embarrassment, guilt, and shame). Results of the study find that crisis origin affects how the public perceives the organization's crisis strategy; also, the study confirmed that publics feel more attribution-dependent emotions when crisis origin is internal. These SMCC findings can be used as a guideline for design and development of a framework for monitoring attribution-dependent emotions from public response to the communicated information.

Importance of Crisis Communication Theories in Sentiment Analysis

Sentiments and emotions play a pivotal role in understanding disaster communication management. They allow people to convey complex information about their feelings, perception, and opinions. A sleuth of studies find many methods proposed by researchers to analyze the role of sentiment analysis in disaster management where most of them deploy variant machine learning techniques (Brynielsson et al. 2013; Buscaldi and Hernandez-Farias 2015; Caragea et al. 2014; Dong et al. 2013; Lu et al. 2015; Mandel et al. 2012; Nagy et al. 2012; Schulz et al. 2013; Torkildson et al. 2014).

The datasets used for evaluations include the social media posts related to events such as Hurricane Sandy, Hurricane Irene, Red River floods in 2009 and 2010, Haiti earthquake, and California gas explosion. Most of the research in this domain is focused on sentiment classification algorithms and demonstrate its applicability in disaster management. However, sentiment and text classification problems are not limited to the efficiency and accuracy of machine learning algorithms. The most lacking aspects in these studies are, (i) how sentiment classes and their boundaries are defined, (ii) how sentiments are aggregated and presented at a meaningful level, and (iii) how proposed sentiment analysis technique can be used and integrated with established disaster management and communication practices.

This is where crisis communication theories and models play a crucial role, we reviewed and studied theories and models such as SCCT, SMCC and Attribution Theory to extend our understanding of sentiment classes and their relation with emotions expressed in given text. In this study, we modeled our sentiment class boundaries based on recommendations in these models. We present our model of sentiment classes in CHAPTER IV.

Social Media & Disaster Communication

Social media has a wide range of interactive tools and technologies that facilitate users to generate, manipulate, influence or link rich multimedia content. Social media is a potent tool to enable dialogue between multiple parties in a short period. The public turns to social media because of its cost, ease of use, and accessibility. It is a popular communication tool for Americans and primary tool of social communication for young adult Americans (Liu et al. 2011). Research has shown that governments, organizations, and the public are increasingly using social media for disaster communication to varying degree of success (Sakaki et al. 2013; Sheppard et al. 2012; Vanderford et al. 2007). Social media served as a crucial component in disaster response and recovery during the 2017 hurricanes. Social media helped the continuity of disaster communication as the local 911 system was overwhelmed by demand. The severity of the disaster was beyond the capability of local emergency services to handle (Leefeldt 2017; Texas Monthly 2017; The New York Times 2017). Often times the first respondents are not trained professionals but bystanders, when professional help is not available people have to rely on help from the community; this is where social media proves itself to be reliable and far more effective disaster communication tool compared to traditional communication channels (American Red Cross 2010b). Similarly, community building, demand resolution, and information sharing enable social media to provide emotional support in post-disaster situations (Choi and Lin 2009).

Table 1 Social media types

Social Media Group	Example
Social Networking	Facebook, Google+
Micro-blogging	Twitter
Blogging	Medium, Blogger, Wordpress.com
Photo/Video Sharing	Instagram, Snapchat
Chatting	WhatsApp, WeChat
Discussion/Forums	Disqus, Reddit
Podcasts/Music	iTunes, Soundcloud
Social Reviews/Rating	Yelp, Google Businesses
Location Based Networking	Nextdoor

Though academic studies overwhelmingly focus on Twitter and Facebook, the sphere of social media encompass a wide range of platforms and media formats. These varied social media platforms exhibit different use patterns depending on disaster phase and user motivations. For example, WhatsApp and WeChat are very popular for interpersonal communication even though many other social media platforms facilitate the same functionality. Table 1 lists examples of social media platforms by the group, while Table 2 lists the functions of social media in disaster management according to their temporal phase (Houston et al. 2015).

Table 2 Functions of social media during disasters

Disaster social media use	**Disaster phase**
Provide and receive disaster preparedness information	Warning
Provide and receive disaster warnings	Warning
Signal and detect disasters	Warning → Event
Send and receive requests for help or assistance	Impact
Inform others about one's own condition and location and learn about disaster affected individual's condition and location	Impact
Document and learn what is happening in the disaster	Impact → Recovery
Deliver and consume news coverage of the disaster	Impact → Recovery
Provide and receive disaster response information; identify and list ways to assist in the disaster response	Impact → Recovery
Raise and develop awareness of an event; donate and receive donations; identify and list ways to help or volunteer	Impact → Recovery
Provide and receive disaster mental/behavioral health support	Impact → Recovery
Express emotions, concerns, well-wishes; memorialize victims	Impact → Recovery
Provide and receive information about (and discuss) disaster response, recovery, and rebuilding; tell and hear stories about the disaster	Impact → Recovery
Discuss sociopolitical and scientific causes and implications of and responsibility for events	Recovery
(Re)connect community members	Recovery
Implement traditional crisis communication activities	Warning → Post-event

Government and Citizen Communication

Government agencies are increasingly turning towards social media platforms and diversifying their social media outreach to improve the efficiency of information dissemination. An academic research shows that despite the interactive nature of social media government agencies primarily engage in one-way communication with the public over Twitter (Waters and Williams 2011). This is one of the forms of communication asymmetry. Communication asymmetry is a important issue in government-public communication, even though modern public relation focuses on symmetrical relationship-based approach (Kavanaugh et al. 2012). However, government-public communication is not limited to Twitter and public engagement by the agency may change depending on its scope, whether its national, federal or local. There is also a need to verify if communication asymmetry has a negative effect on how information is received by the public. Though, governments have improved their use of social media in recent years, many issues still remain unaddressed (Ryan 2017).

Social Media & Citizens

Modern social media is accessible, portable, cost-effective, and convenient to use. Social media is a large network of billions of users worldwide. For a common citizen, social media is an economical and most effective way to reach other individuals, groups or communities. Also, an individual from a group is more likely to use social media platform, if other members of the group use that social media platform. If such a pattern exists in groups with many individuals, it is considered a social norm. Besides convenience and personal involvement, third-party influence, such as personal recommendations, promotes social media usage. Americans primarily use social media to stay connected with their friends, family, and community, with approximately 66% reporting it as the main reason for use (Austin et al. 2012).

Common reasons and concerns for using social media in a disaster are summarized in Table 3.

Table 3 Reasons and concerns for social media use during disasters

Reasons	Concerns
Seek information in a timely manner	Privacy and security concerns
Share information	Information accuracy concerns, Rumors
Express opinions	Knowledge deficiencies
Seek emotional support for healing	Limited information accessibility

Social Media & Government

Government primarily uses social media passively to disseminate information and occasionally seek user feedback. This remains a common practice among government agencies, including the Federal Emergency Management Agency (FEMA). Though FEMA suggests many proactive communication practices (Andrea Barron and Winn 2009), such practices are rarely witnessed in their social media strategies (Kavanaugh et al. 2012; Waters and Williams 2011). Long series of research covered in this literature review has suggested many applications for government agencies to use social media for disaster management. However, many of such application remain either speculative or in their infancy. For example, local governments tend to have a limited understanding of social media's costs and benefits and fail to recognize and target their desired audience on social media (Kavanaugh et al. 2012). For example, many social media analytics studies focus on technical problems such as algorithm complexities and accuracies, while we see very few proposed algorithms that were successfully adopted in real-world applications. This happens mainly due to the lack of research in the evaluation of these techniques, their practicality in real-world scenarios, and an information system design that can effectively exploit proposed techniques to deliver high-level insights to disaster managers. Even though advanced data analysis tools are available to researchers, Government agencies may not be able to employ proposed technologies without proper information system. Kavanaugh finds that there is a lack of well-engineered off-the-shelf solutions for disaster-related social media analytics tools and services that can be used by governments (Kavanaugh et al. 2012).

Successful social media integration can allow government agencies to take advantage of advanced big data analytical tools available (Felt 2016). Though many such suggestions of social media integration to allow information flow from public to agencies, government agencies remain reluctant to use public information in decision-making. This is mainly due to (i) volume of social media data and streams can render analytical tools ineffective to provide insight in a short amount of time. (ii) amount of noise in social media data can affect the accuracy of any such insight. (iii) information veracity problems such as managing rumors and the accuracy of information, trusting and verification of public information are largely unsolved (Gupta, Lamba, and Kumaraguru 2013; Gupta, Lamba, Kumaraguru, et al. 2013; Kavanaugh et al. 2012; Mehta et al. 2017).

Social Media Analytics for Disaster Management

Social media analytics aims to leverage the vast amount of data available on social media platforms. The term ‘Social Media Analytics’ is usually used as an umbrella term for various analytical methods, techniques, and theories. It is an interdisciplinary field where theories from various disciplines such as social sciences, political science, psychology, or geology are tested, verified, and applied using computer science and statistical methods. These analytical techniques are used to obtain valuable insight from social communication which is facilitated by social media platforms.

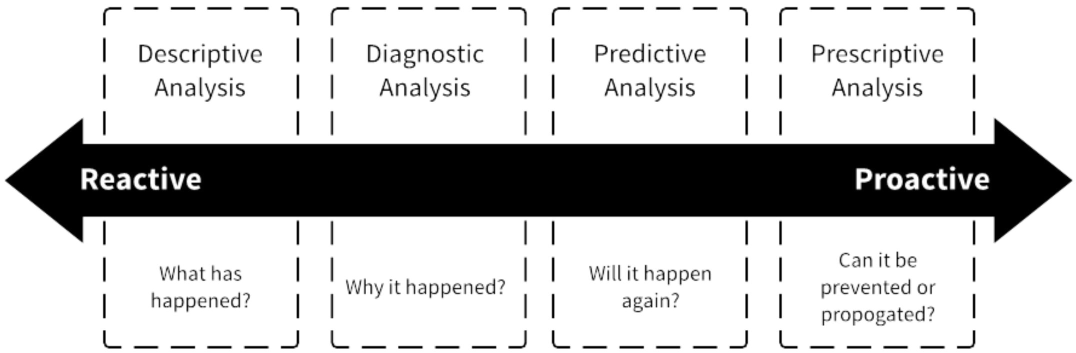

Figure 2 Categories of Social Media Analytics (Khan 2015)

Social media platforms are some of the biggest sources of data generation, for example, mere 140 character long tweets amount for over 12 terabytes data every day; while Twitter is ranked at number nine with 317 million active users (Chaffey 2017). Given the ability to obtain data from social media platforms, most of the data generated on such public platforms are available for analysis. Social media data has the potential to provide insights into diverse topics. However, this potential and value of data can only be realized if this data is properly analyzed. Social media data analysis is primarily used for understanding past patterns (reactive analysis) or predicting future trends and occurrences (proactive analysis). Figure 2 shows the detailed categorization of social media analytics by its function.

Social Media Analytics Techniques

Social media analytics are utilized in each temporal phase of disaster management, to address specific research problems. Researchers employ a wide range of analytical techniques to test or validate their hypothesis. Most of the social media data is human generated and unstructured, which limits the options for techniques available for analysis. Gaining insights from such data relies upon effective data exploration. For social media analytics, visual analytics is a popular method of data exploration. (Chen et al. 2017). One example of data exploration is to understand user behavior enabled information diffusion patterns based on the spatial and temporal distribution of information. Data exploration helps researchers to understand the semantics of user behavior and its effects on information diffusion. The semantics of user behavior is defined by the topics, keywords, and sentiments of content (Stieglitz and Dang-Xuan 2013; Viégas and Wattenberg 2013; Wu et al. 2011). Such data exploration methods are based on network or graph analysis techniques; while these are not the only analysis techniques that researchers use.

Exploratory & Visual Analytics

Visual analytics techniques can be categorized into a graph (network), geospatial, and text visualization. Graph visualizations focus on social media entities such as users and organizations and their social relationships and interests, communication. Combination of different entities and various relationships form complex and highly connected graphs which allow rich information extraction using analysis such as community analysis, connectivity analysis, etc. However, insights from graphs are difficult to assimilate unless they are visualized. While graph analytics mainly focus on entities and relations, text visualization techniques focus on the content itself. In text visualization, various aspects such as topics, keywords, and sentiments are visualized. In the context of social media messages, keywords are the most important words in the text; keywords can be extracted from text based on its frequency of occurrence. Topics are the summarized subjects from social media content. While keyword visualizations illustrate word-level semantics of text, visualizing topics in the social media illustrate topic-level semantics, which is highly summarized and derives the themes of contents. Sentiments are summarized from the message with the attitude, emotions, and opinions of social media users. Effective extraction of features such as sentiments, text semantics depends on text mining (Cao and Cui 2016).

Text Mining

In the context of social media analytics, **text mining** refers to the process of extracting interesting information and knowledge from unstructured natural language text. Text mining is heavily based on statistics, computational linguistics, data mining, and machine learning. These data mining methods are used to handle specific tasks:

Information Retrieval is a text analysis on a document level. It focuses on classification and identification of documents based on patterns in its contents. Being a traditional way of analysis, Information retrieval uses statistical measure and methods heavily.

Information Extraction focuses on the extraction of specific information from text documents and building traditional databases from the information. Extraction of information is based on pattern detection. Researchers are increasing employing machine learning techniques to improve pattern detection.

Natural Language Processing (NLP) is used to achieve a better understanding of natural language using computational methods. NLP focuses on identifying the part of speech, entities, dependencies, sentence boundaries to process and understand the text by the way humans write it and mean it. Combined with statistical and computational methods, NLP allows detailed linguistic analysis that allows effectively extract information from varied sources and genres of text.

Sentiment / Opinion Mining are extended techniques from NLP that extract and summarize attitude, opinions, and emotions about news, event, organization, product, or a service from a text document. Social media and World Wide Web have provided citizens a platform to freely express their opinions. The vast amount of social media postings by citizen contain valuable information about their sentiments and behaviors; incorporating this information in decision-making can help reshape organizations and their reputation (Liu 2012).

Graph Analytics

Graph Analytics are derived from graph theory. A graph is a mathematical construct, where graph G is denoted as a pair $G (V, E)$. In $G (V, E)$, V represents the set of vertices and E represents the set of edges. Vertices and edges are the fundamental building blocks of graphs. In social media, analytics vertices represent entities such as users, organizations, etc. Edges connect vertices and represent the relation between two vertices, such as friendship, following, etc. These edges can be undirected or directed depending on the nature of the relation. Both vertices and edges also have properties; for example, edge properties can indicate the magnitude of relations. Graph analytics in social media aims to understand these individual entities and their relations embedded in the interconnected networks. The social media networks can be conveniently represented using graphs. Such studies allow researchers to understand the relationship between entities, social structure, social position, and role. Measuring different structural properties of a social media network can also help researchers to better understand information flow hierarchies, which is important to analyze effective dissemination of information. (Nisar 2013; Stieglitz and Dang-Xuan 2013). To conduct graph analysis on social media for disaster management, we must first define measures for quantifying centrality, interactions, relations, dependencies in correspondence to disaster communication models. The input graph for such analysis must be formed from the extracted information from social media content.

Apart from communication patterns in disaster situations, graph analytics are also effective in analysis of geospatial information, information diffusion patterns. Therefore, researchers also employ these techniques in understanding information diffusion patterns to achieve effective information dissemination (Stieglitz and Dang-Xuan 2013) and the spread of rumors, spam, and fake information, to provide effective rumor management (Gupta, Lamba, and Kumaraguru 2013; Gupta, Lamba, Kumaraguru, et al. 2013; Mukherjee, Kumar, et al. 2013; Mukherjee, Venkataraman, et al. 2013).

Application of Social Media Analytics in Disaster Management

A wide range of research covers disaster management, disaster communication, and social media analytics. However, use of social media analytics in disaster management is still in its infancy. Researchers have applied and tested various applications of social media analytics in disaster management to varying degrees of success. Table 4 is a collection of the research reviewed in this study; it consists of identification of research in categories and classes we identified in the literature review. Categorization of research is done by application of social media analytics, techniques used, types of analysis, and applicable phase of disaster management.

Table 4 Summary of research in social media analytics for disaster management

Application	Techniques	Type of Analysis	The Phase of Disaster Management	Paper
Crisis Mapping	Geospatial Analysis, Text Mining, Visual Analytics	Descriptive Analysis	Impact	(Sampson et al. 2016)
Crisis Mapping	Geospatial Analysis, Visual Analytics	Descriptive Analysis	Impact	(Rosser et al. 2017)
Trust/Reputation Management	Text Mining	Prescriptive Analysis	Response	(Busa et al. 2015)
Rumor Management	Text Mining, Graph Analytics	Predictive Analysis	Response	(Gupta, Lamba, and Kumaraguru 2013)
Sentiment Mining	Text Mining	Diagnostic Analysis	Relief	(Cohn et al. 2004)

Application	Techniques	Type of Analysis	The Phase of Disaster Management	Paper
Urban Resilience	Geospatial Analysis, Text Mining	Diagnostic Analysis	Relief	(Brajawidagda et al. 2016)
Rumor Management	Graph Analysis, Visual Analytics	Predictive Analysis	Impact	(Gupta, Lamba, Kumaraguru, et al. 2013)
Crisis Mapping	Text Mining, Visual Analytics	Descriptive Analysis	Impact	(Anbalagan and Valliyammai 2017)
Crisis Mapping	Text Mining, Visual Analytics	Descriptive Analysis	Impact	(*Improving Disaster Response and Recovery : Social Media Analytics and Reporting Toolkit* n.d.)
Crisis Mapping, Situational Awareness	Text Mining, Visual Analytics	Descriptive Analysis	Impact	(Kumar et al. 2011)
Crisis Mapping	Text Mining, Sentiment Analysis	Descriptive Analysis	Impact	(Teodorescu 2015)
Crisis Mapping	Text Mining, Geospatial Analysis	Descriptive Analysis	Impact	(Middleton et al. 2014)
Sentiment Mapping	Text Mining, Sentiment Analysis	Prescriptive Analysis	Response	(Beigi et al. 2016)
Crisis Mapping	Geospatial Analysis	Descriptive Analysis	Impact	(MacEachren et al. 2010)
Crisis Reporting	Text Mining	Prescriptive Analysis	Response	(Starbird and Stamberger 2010)
Event Detection	Text Mining	Predictive Analysis	Warning	(Earle et al. 2011)
Event Detection	Text Mining	Predictive Analysis	Warning	(Cameron et al. 2012)
Urban Resilience	Text Mining, Visual Analytics	Descriptive Analysis	Impact	(Aulov et al. 2014)

Out of all research reviewed, text mining is the most common approach opted. Traditional information retrieval and machine learning based text classification are techniques that are commonly used in these text mining applications. Though these techniques do not always focus on sentiment or opinion analysis, their experience of social media data, approach to research design, and findings can be exploited to improve the effectiveness of sentiment and opinion mining techniques in disaster management.

While text mining is the most common technique used by researchers, very few studies employ advance text mining and natural language processing techniques. Word level analysis and extracting topic level semantics of the social media content is a reoccurring theme in crisis mapping and event detection applications. These applications have mostly focused on basing their analysis on keyword extraction and hashtag usage. From the review of these studies, we can summarize the most prevalent limitations in current research as follows: (i) Lack of variety in social media data sources, (ii) Limited use of textual analytics, (iii) Limited focus on the effectiveness of communication itself, iv) Lack of interdisciplinary approach to research problems.

Importance of Understanding Public Opinion and Sentiments

Monitoring public opinion and sentiments in crisis communication can be done to understand public response to information released by an organization. Sentiment analysis is not just limited to the polarity of the thoughts expressed in a text document. For example, consider these two texts from social media:

example (i): *A tree has fallen on the West Mall, slowing down traffic... Stuck in one place for 30 min :(#HurricaneHarvey*

example (ii): *FEMA's denied most individual aid with unrealistic proof standards & non-Spanish speaking, sketchy assessors. Internet-based FEMA processes prevesnt ppl with limited access from even applying*.

Though both examples, (i) and (ii) are labeled as ‘Negative’, the magnitude of negative sentiments in both examples are different. These examples also differ in the emotions expressed. While example (i) has non-attributed emotions, example (ii) has strong attributed emotions expressed towards FEMA. To better understand sentiments, other aspects such as sentiment strength, context, granularity, complexity, and subjectivity should also be reviewed.

Sentiment Polarity: Sentiment polarity refers to sentiment or opinion is positive or negative. Instead of a binary class, many researchers opt for fuzzy logic to represent sentiment polarity. It is usually captured as a value between the range of -1 to 1 or 0 to 1. Where, -1 or 0 represents maximum negative sentiment possible, and 1 represents maximum positive sentiment.

Sentiment Context: Though an opinion may be expressed in a conversation or social media thread, the sentiment of the opinion may not necessarily belong to conversational context. The context of the sentiment could be topical or inter-personal.

Sentiment Granularity: Sentiment in the text can be analyzed at various levels, a document may hold different sentiment in each sentence, and multiple sentiments in one sentence. The sentiment granularity refers to the level and position of observed sentiment in the semantic structure of the text. Sentiments can be observed in individual words, sentences, paragraphs, and whole documents. Understanding the sentiment granularity at a lower level of text semantics is crucial to accurately assign a sentiment to a larger body of text describing a topic.

Sentiment Complexity: Text can contain sentiments of mixed polarity and strengths at various levels of granularity. Traditional sentiment analysis which tries to assign a generalized sentiment value to the entire body of text often ends up losing detailed information about complex sentiments expressed in the text.

Sentiment Strength: Sentiments are expressed in various degrees of magnitude. A negative sentiment can range from general disappointment to an outcry. Depending on domain and application sentiment strengths should be carefully accounted into the analysis.

Sentiment Subjectivity: Sentiment subjectivity describes the subject sentiment is expressed towards. For example, a service, a product, or a piece of information. Not to be confused with sentiment context describes where sentiment belongs, for example to a specific conversation or general topic.

Monitoring and mining emotions and sentiments from public responses can help us to better summarize topics of conversation, identify critical issues, and issues that are affecting public opinion the most. Insights such as these can aid an organization to proactively craft their disaster management and communication strategy. We continue to review sentiment classification details in CHAPTER IV.

Potential and Opportunities

The current inclination of research in social media analytics is towards facilitating disaster management tasks using social media. There is little to no research in using social media analytics to improve crisis communication. The field of disaster management and disaster communication is interdisciplinary. However, most of the social media analytics application leverage the established disaster communication theories or test their validity in social media-driven communication. Therefore, the potential of social media analytics for disaster management remains largely unrealized. Use of advanced text mining techniques such as natural language processing is fairly limited in these applications. With the use of advanced computational, statistical, and analytical techniques; there are opportunities to test, verify, validate current models of crisis communication in the context of social media communication by (i) Monitor Public Opinion and Sentiments: monitoring and evaluating public response to an organization's communication, (ii) Detect and Predict Anomalies: detect emotion and sentiment patterns of public responses and its impact factors such as social media platform, information source over public perception of information, (iii) Improving Public Response: prescribe a model for social media information dissemination strategy to improve public response to organization's information dissemination.

However, in practice, the realization of these opportunities is highly dependent on the quality and reliability of sentiment classification and opinion mining of social media texts. In this study, we will focus on the improvement of sentiment classification in disaster management scenarios. Apart from textual content, social media also allows users to connect. These connections can be established explicitly (user-based) or implicitly (content-based). Those networks formed depict some types of social relations. The dynamics of peoples' opinions and their social relations are bi-directional. People who are socially related are more likely to share similar opinions about certain topics, and similar minds tend to flock together (Hatfield et al. 2014). More specifically, homophily (McPherson et al. 2001) and social influence (Marsden and Friedkin 1993) are the two processes that enable emotional contagion. The former suggests that people befriend those who are alike, and the latter says friends tend to become similar over time. Based on these theories, we could speculate that connected social media users may hold similar opinions (Thelwall et al. 2010). Studies (Hu, L. Tang, et al. 2013; Tan et al. 2011) have shown that when social relations are incorporated into the learning model, performance of sentiment classification can be improved significantly. Both studies used Twitter data, taking into consideration the user-user networks formed on the platform. This approach remains largely untested for disaster-related applications of sentiment analysis. Presenting us with a wide range of possible research opportunities to evaluate new techniques and potential of latent and implicit data.

In this chapter, we reviewed extensive research from various disciplines – such as communication, disaster management, computer science, and information systems – as well as interdisciplinary studies that bridge the gap between these disciplines. The extensive literature review presents the current state of research and allowed us to identify potential opportunities for research. However, integrating ideas from different disciplines is a challenging task.

CHAPTER III:

RESEARCH METHODOLOGY

The nature of this research requires a multidisciplinary approach; however, such an approach is not new to information systems research. In our study, we reviewed literature from several disciplines apart from computer science and information systems, such as communications, disaster management, social science, and even psychology. We adopt and apply theories from these disciplines, established theories which are often adopted in disaster communication studies. These theories allow us to improve our understanding of the domain of application and provide a theoretical background to our proposed work. However, this multidisciplinary approach also introduces new difficulties as they opt for diverse types of research methods. For example, the social science and communication studies are largely inductive, focused around generating a theory, based on qualitative methods of research and are theoretical in nature. While computer science and data analytics focus on empirical, deductive, and quantitative approach. This study focuses on improving sentiment classification techniques that can be used to test and verify the crisis communication models and its variable using big data-driven analytical methods. In the subsection below, we state our research problems and questions.

Research Problems

Social media texts greatly vary in content, size, and format. Unlike normal documents, they also tend to have grammatical noise, irrelevant features, and out-of-vocabulary words and are generally shorter and less topic-focused. Classifying and clustering these sorts of texts pose new challenges. Because of the short length, they do not provide enough word cooccurrence or shared context for a good similarity measure. Therefore, normal machine learning methods usually fail to achieve the desired accuracy due to the data sparseness caused by noisy data. For example, word “people” and its often-misspelled variant on social media “ppl” represent the same concept for the human readers. However, they are two separate features in the bag-of-words representation of data. We identify such features as noisy textual features. These noisy features cause extremely high dimensionality regardless of the data representation and feature selection, making training effective classification boundaries difficult. Various lexical preprocessing techniques such as stemming and lemmatization are often used to reduce dimensionality in bag-of-words representation. However, they often cause heavy information loss in texts that are noticeably short, to begin with. Making it exceedingly difficult to deal with short and noisy texts. In our literature review, we identified alternative techniques, such as using network information as features in sentiment classification. We also identified a need of representing sentiments in classes that are relevant to disaster-related applications as well as presenting them at meaningful aggregated level. We use these opportunities to present the following research problems.

A. Meaningful Sentiment Classes and Aggregation

We discussed the complexities of sentiments in our literature review. Though capturing as many as aspects of sentiments, – such as strength, subjectivity, and emotion –is more meaningful and useful in real-world applications, many researchers opt for binary classification of sentiments. One of the major reasons for that is lack of appropriately labeled data. Labeling data with sentiment classes, complexity and strength is an extremely labor-intensive task. It is also susceptible to misinterpretation, and difference of opinion of people labeling the data, therefore such labeling task also requires formalizing sentiment class complexities and training the volunteers for labeling tasks. Data labeling also gets more difficult as more sentiment classes and sentiment strength is introduced. Therefore, binary classification remains a popular choice in sentiment analysis studies. However, generalizing complex sentiment classes to binary polarity has its own problems, and these problems are hardly addressed in most studies.

In most binary class definitions, two sentiment classes are defined, ‘Positive’ and ‘Negative’. However, it is difficult to define what positive and negative means. In the case of product or movie reviews, ‘positive’ means ‘to like something’ and ‘negative’ means ‘to hate something’. Positive and negative can also be defined in many different ways. For disaster-related context, we identify sentiments such as ‘relief’, ‘anxiety’, ’outrage’, etc. Emotions are associated with ‘anxiety’ are different than that of ‘hate’. Therefore, there is a need of formally defining sentiment classes and guidelines to generalize them, depending on the domain of application.

Research Approach

We utilize qualitative, inductive research methods to describe complex disaster-related sentiment classes. We explore possibilities and methods for sentiment class definition using established theories and existing research. We verify suitable emotions and sentiment classes by reviewing samples from our data.

Research Questions

1) *How sentiments can be presented at a meaningful level for disaster management?*
    a. *How sentiment classes can effectively be defined to represent disaster-related emotions?*
    b. *How complex sentiment classes can be generalized to binary polarity?*

B. Feature Extraction of Implicit Social Relations

In our literature review, we identified research opportunity to network information as a feature in sentiment classification. While explicit network data does not need complicated extraction effort, as it adheres to a certain structure or schema and has a formal definition. However, implicit relations are not formally defined; they can be latent or can only be inferred from the data. Extracting different implicit relations will require the use of different techniques, in this study we only consider social relations of emergent citizen groups and discussion topics. While emergent citizen groups can be inferred from explicit social media data or community detection, detecting talked about issues is a complicated problem. Though there are techniques such as topic modeling to extract latent topics in corpora. However, they often suffer from noise and fragmentation. In this study, we plan to evaluate and improve the utilization of topic modeling techniques for extracting implicit social relations in data.

Research Approach

In this study, we use a combination of descriptive and exploratory quantitative data analysis techniques to look at implicit relations and evaluate topic modeling techniques. In order to extract content-based networks, we need to extract issues and topics being discussed over social media and form linkages between content, replies, and users. There are similarity and ranking algorithms for this purpose. However, while dealing with large heterogeneous data, text retrieval techniques might fall short. Other approaches to model our topics include employing statistical and semantic analysis techniques such as Latent Dirichlet Allocation (LDA), Probabilistic Latent Semantic Analysis (PLSA), Latent Semantic Analysis (LSA). Extracted topic information can be used to model social relations formed around them. However, the effectiveness of these techniques to extract relevant crisis-time topics needs to be evaluated.

Research Questions

2) *How implicit social relation between emergent citizen groups and issues can be extracted effectively?*

a. *What data represent the issue discussed in a collection of social media posts?*
b. *How accurately do topics describe issues discussed during a disaster?*

C. Incorporating Implicit Information in Sentiment Classification

Once we successfully extract implicit network information from the data, the problem to encode it as a feature and incorporating it into a classification. We explore and evaluate approaches to build machine learning models that can effectively incorporate encoded network features.

Research Approach

In this study, we look at network information of group-topics and incorporate it in the sentiment classification task. We use quantitative research methods to test approaches of building machine learning models and evaluate the accuracies of these models. Results of these evaluations can help us find and determine what emotions define collective goals and attitudes of emergent citizen groups. To achieve it, we ask the following questions:

Research Questions

3) *Can implicit network information be used to improve sentiment classification accuracy?*
    a. *Does group-issues social relation correlate with sentiment labels?*
    b. *How much do implicit network features contribute to model accuracy?*
4) *How network information can be encoded as a feature in a classification problem?*
    a. *What are possible ways to combine numerical or categorical features with textual features?*
    b. *What algorithms or techniques are effective for classification using these techniques?*

Research Plan

We address three problems and their subproblems in this research. These problems are interdisciplinary and are tackled using mixed research methods. In this section, we present the workflow of our research and identify prerequisite tasks completed before tackling a research problem.

1. **Data Collection**

   We start our research by collecting data from various platforms. The process involves collecting data using official APIs, web scraping, storing the data and converting unstructured data into structured data. This process has been presented in CHAPTER IV

2. **Defining Emotion Model**

   We continue our research by exploring and testing numerous ways to formalize sentiment classes and their components. We present our considerations and final model in CHAPTER V.

3. **Data Cleaning**

   Before we start labeling, we clean the data in order to reduce noise, remove unwanted documents, and reduce the dimensionality of final feature vectors. This process has been presented with its detail in CHAPTER VI

4. **Data Labeling**

   Data labeling is the most labor-intensive task in this research. The process of labeling and considerations are presented in CHAPTER VI.

5. **Data Exploration**

   In CHAPTER VII, we present continued research using data exploratory techniques to describe the data. We test and evaluate appropriate topic modeling techniques to detect disaster-related issues.

6. Classification & Results

Finally, we explore considerations for modeling and encoding network features and building classification models and processes that allow us to effectively incorporate implicit social relations in the sentiment classification problem.

Challenges

Social media analytics is analogous to big data analytics in some factors. The key factors of big data such as volume, velocity, variety, and veracity can be used to summarize challenges in social media analytics. All processes in any type of social media analysis can be categorized in phases such as discovery, aggregation, preparation, and analysis. Each factor brings its own challenges in each phase of the social media analysis as shown in Figure 3.

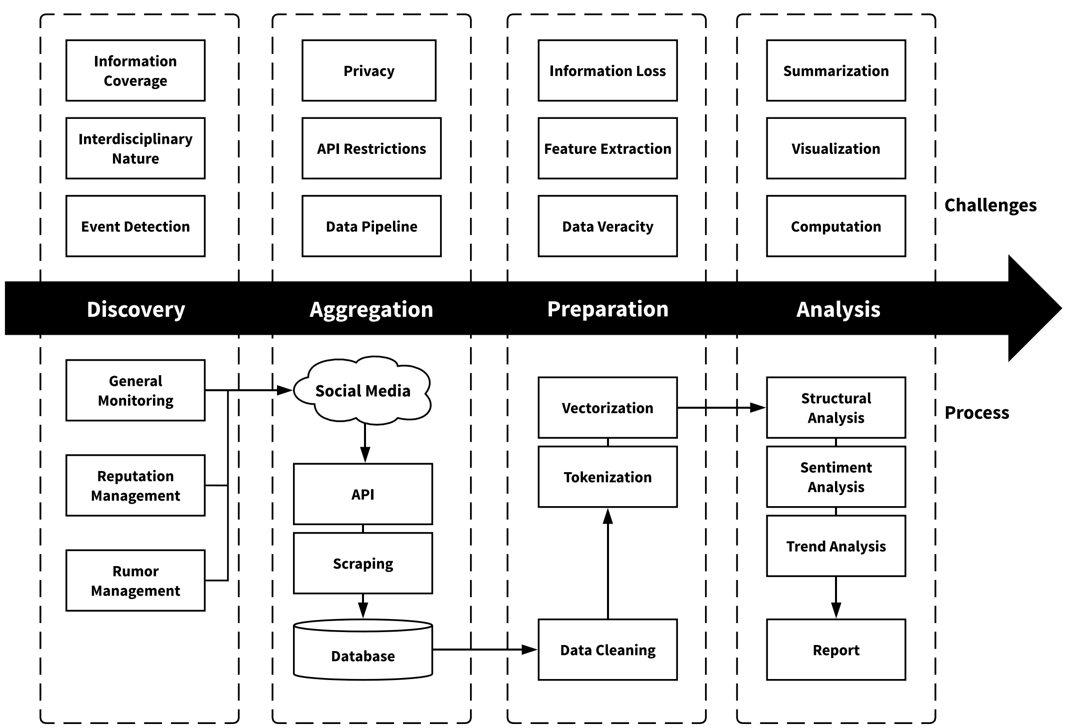

Figure 3 Summary of challenges in social media analytics

Interdisciplinary Nature

Social media analytics is used by researchers from diverse backgrounds and goals. Disciplines such as communication, psychology, linguistics, marketing, etc. have its own merits and prejudices. Disaster management itself is interdisciplinary requiring domain experts from various fields. Researchers suggest that computer science techniques and social science theories should be combined to solve real-world problems using social media analytics. It also posits a critical approach that makes use social theory to ask critical questions early in the research process (Tinati et al. 2014). Information Systems (IS) has a history of combining the different paradigms. The information systems discipline can provide a unique perspective in this area. As IS researchers often use a combination of qualitative and quantitative methods in a mixed-methods approach (Venkatesh et al. 2013, p., 2016). Similarly, our research focuses on qualitative and quantitative methods from social science, communications, and computer science.

Data Availability

The availability of social media data is hindered by platform policies and privacy laws. For example, Twitter data used to be popular for academic research. However, Twitter introduced new API restrictions in 2011 which significantly reduced the availability of the data to be used in academic research. Twitter data can be purchased using expensive enterprise access to Twitter API. Other methods such as web scraping are only able to fetch data that is available on Twitter web frontend. A platform such as Facebook allows access to data using API. However, the availability of data depends on the privacy settings of users, groups, and pages. To improve the amount of data available for academic studies, data related to a specific topic can be collected from different aggregated from various social media platforms.

Data Quality

Though social media data is available in large volumes, little of that data is suited to be used for any analytical purposes. Prior to any analysis data must be structured, without inconsistencies and errors. Social media data is user-generated, unstructured, and noisy, which renders data cleaning and preparation difficult in most cases. Poor data quality is one of the major factors that cause reluctance towards adopting social media analytics for generalized practices with wide coverage of data sources, data types, and topics. Social media data and topic-based filtering of social media data are also influenced by other external and concurrent events. While preparing data for analysis any irrelevant data is considered as noise. Noise in social media data consists of political and general opinions, rumors, unreliable sources, spam, content from different topics. The problem of low-quality data can be tackled by incorporating data cleaning and filtering stage in data preparation phases. Filtration of textual social media data presents the most difficult challenge as it relies on complex text mining and natural language processing. In a literature review, we notice that cleansing data of diverse types of noises and inconsistencies is also a popular research problem in social media analytics and disaster communications research.

Information Bias and Coverage

For the following study, data is collected and aggregated from multiple social media platforms, mainly from Twitter and Facebook. As of 2018, Twitter and Facebook continue to remain some of the most popular public social media platforms in the United States of America, with 68% US adults using Facebook and 45% using Twitter (Pew Research Center 2018). Figure 4 shows the active monthly users for most popular mobile social media platforms in the US.

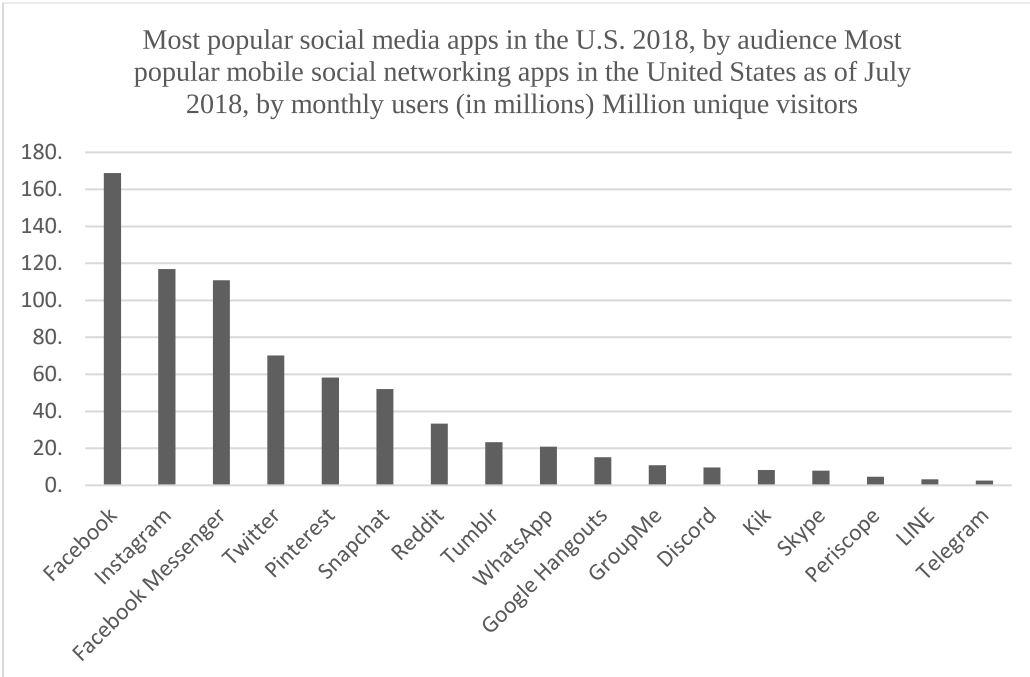

Figure 4 Social media market share in the U.S.A. (statista.com 2018)

The information bias for each research problem and challenge differs largely based on its nature. For example, if a research problem focuses on people to people communication during a crisis, the information from public platforms such as Twitter and Facebook will not be usable, as private conversations take place on more private communication platforms such as WhatsApp, Facebook Messenger, or WeChat. However, the current scope of this study is limited to looking at sentiments expressed on official social media channels used by FEMA and American Red Cross.

Another, information bias issue is that this study does not deal with any Non-English texts. In a state such as Texas, where a significant number of people speak Spanish as a first language, omitting these responses can affect the sentiment information or insight at a higher level. However, it does not affect objectives of this study, which are to test and evaluate the use of implicit social relations to improve sentiment classification.

For a research problem focusing on different sentiment and information diffusion patterns, the public response on different social media platforms should not be analyzed separately, since many people use multiple social media platforms and often share information from one platform to another. Therefore, data for the same organization over two different social media platforms is needed. However, that does not ensure a fair comparison of use patterns and purpose for social media platforms such as Twitter, Facebook, and Reddit vary largely. Organization social media policy can also cause a difference in how its different social media accounts are handled and for what purpose. For example, an organization may use Facebook for more interactive communication, while using Twitter handle for information dissemination. Data from various platforms can be used to verify, validate information or study differences between use patterns and purposes. However, while dealing with data from various sources cannot be used for analysis under the same rules. Prior to combining and using different sources for data, it is important to understand the relationship between different platforms across various organizations.

Due to these factors, the study focuses on collecting data from various platforms and for various organizations, groups, and communities; over a long period of time. This is important in order to reduce information bias as much as possible.

Limitations

Communication patterns and differences between social media platforms may render sentiment analysis difficult. For example, on Twitter, a conversation takes place on a topic or a hashtag, this conversation is largely homogenous and continuous. However, on Facebook, conversations are strictly structured as threads of statuses, replies, and comments. On Facebook, conversations take place on pages belonging to individual users, groups, or organizations, instead of one global stream like Twitter. Making these conversations often shorter and isolated, but more closely related to the topic than Twitter. These shorter conversations can have their own context and can exhibit a stark difference in sentiment polarity depending on the topic discussed.

Irony, humor, sarcasm, and other subtleties of human speech are harder to detect and classify correctly; as a result, they can negatively affect the accuracy of the sentiment analysis. The research around the classification of such facets of natural language is largely in its infancy.

The study mainly focuses on the analysis of conversations taking place in English. People from different regions or with the first language other than English might be effusive in their use of language. Exclusion of conversations taking place in any other language than English is also one of the limitations of this study.

CHAPTER IV:

DATA COLLECTION

Facebook is a social networking platform that allows its users to create dedicated pages or groups. Users can share their thoughts, opinion, and information in form of text or multimedia – known as posts – on these pages or groups. Other Facebook users can comment on these posts, share, or like. The Figure 9 and Figure 10 shows an example of such a Facebook post. Facebook allows access to this data using its official API, known as Graph API. This API is available for free can be used to fetch data from entire Facebook Pages and Groups. Facebook Pages and Groups consist of posts and comments written by its members.

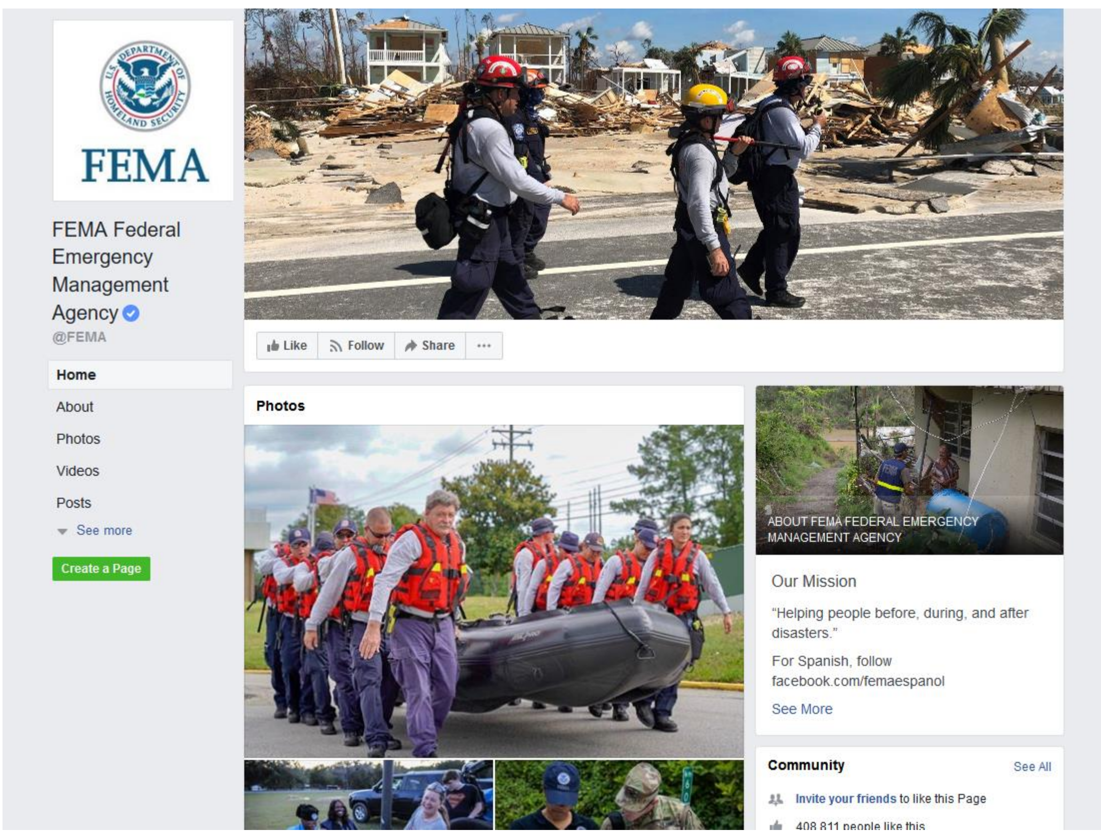

Figure 5 FEMA's Official Facebook page

Facebook Pages are used to represent organizations, products, services; while Facebook Groups are used by communities and allow for greater interactions. Therefore, organizations such as FEMA (see Figure 5), EPA, Red Cross, etc. use Facebook Pages, while citizen groups prefer Facebook Groups. Each Facebook Page or Group post each fetched and processed into CSV file with following fields – comment id, status id, parent id, message, author, published date, number of reactions, number of likes, number of loves, number of wows, number of funny reactions, number of sad reactions, number of angry reactions, number of special reactions.

Twitter is a micro-blogging client. Unlike Facebook, it does not have dedicated pages, groups, or communities. On Twitter, every user has a "feed". A feed is a stream of Tweets or Twitter posts from the user and posts from other Twitter users they follow, an example shown in Figure 6.

Figure 6 FEMA's Official Twitter feed

Users can reply to other Tweets forming threads. Examples of the Twitter post and Twitter thread can be seen in Figure 7 and Figure 8. Such data can be acquired, either by official Twitter API or by scraping Twitter front-end. Though enterprise API access provides full access to Twitter data, including all metrics, user public profiles, and public posts, it is not available for free for data that is over seven days older. For data that is older than 7 or 30 days, paid access to Twitter API is needed. Alternatively, Twitter data that is older than 7 or 30 days can be accessed by using any Twitter user account over the Twitter website. Since Twitter data is largely public, most of it can be scraped from the web. Twitter advanced search also allows users to search Tweets with specific text, hashtags, mentions, and locations. However, scraping modern websites is often difficult and inconvenient than accessing data via API, as scraped data must be filtered and structured prior to building a dataset. Such dataset of tweets consists of the user's name, id, likes, replies, retweets, text, and timestamp. Tweets can be fetched on per user, per topic, or per conversation basis. For this study, we focus on aggregating tweets related to the topic and tweets posted by governmental agencies such as FEMA.

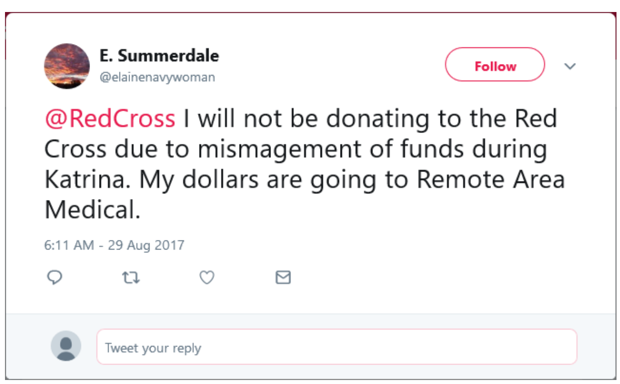

Figure 7 Twitter example post / Tweet

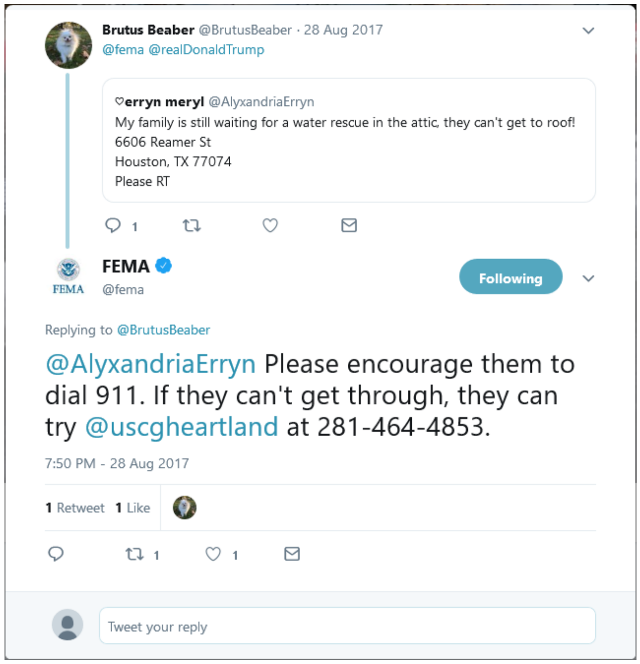

Figure 8 Twitter example post / Tweet

Figure 9 Facebook Example Post 1

Figure 10 Facebook Example Post 2

Data Collection Techniques

Facebook allows access to their data and functionality through an Application Programming Interface (API). Facebook’s new API is known as Graph API. This API allows users to access all public data and data they have permission to view on Facebook. This API is a Representational State Transfer (REST) API and is facilitated using Hyper Text Transfer Protocol (HTTP).

Using official APIs is the cleanest and most straightforward method to fetch data. APIs are designed to be used programmatically and any programming tool and language able to imperatively send, receive and parse HTTP requests are able to fetch copious amounts of data from the API in the relatively short amount of time, as API provide information in semi-structured or in schema-on-read formats such as JSON or XML. Following is an example of a JSON record of fetched Tweet. Note, that the long fields are truncated.


```
{
   "contributors":null,
   "truncated":false,
   "text":"RT @aaronjayjack: Displaced dog jumped into my jeep. Please share
to help find owner! #harvey #hurricane #displacedpets
https://t.co/0C6Ve9\u2026",
   "is_quote_status":false,
   "in_reply_to_status_id":null,
   "id":901774900481970176,
   "favorite_count":0,
   "source":"<a href=\"http://twitter.com/download/iphone\"
rel=\"nofollow\">Twitter for iPhone</a>",
   "retweeted":false,
   "coordinates":null,
   "entities":{
      "symbols":[ ],
      "user_mentions":[
         {
            "indices":[3, 16],
            "screen_name":"aaronjayjack",
            "id":9299392,
            "name":"Aaron Jayjack",
            "id_str":"9299392"
```

```
         }
      ],
      "hashtags":[
         { "indices":[86, 93], "text":"harvey" },
         { "indices":[94, 104], "text":"hurricane" },
         { "indices":[105, 119], "text":"displacedpets"}
      ],
      "urls":[ ]
   },
   "in_reply_to_screen_name":null,
   "id_str":"901774900481970176",
   "retweet_count":9193,
   "in_reply_to_user_id":null,
   "favorited":false
}
```

Next, the parser is required to parse the schema-on-read data from the API response and convert it into flattened tabular format. We store this data in tabular format as comma separated values (CSV) files. Following is an example of CSV record.

```
"index","id","text","is_quote","quote_id","is_reply","replyto_id","replyto_use
rid","is_rt","retweet_id","favorites","retweets","user_id","lang","created_at"

"0","901774900481970176","RT @aaronjayjack: Displaced dog jumped into my jeep.
Please share to help find owner! #harvey #hurricane #displacedpets
https://t.co/0C6Ve9â?","False","","False","","","True","901491384124817408","0
","9193","3005788947","en","Sun Aug 27 11:54:25 +0000 2017"
```

We stored user, hashtag, and mentions information in separate CSV files.

For our study, we developed our parser using Python 3- and third-party libraries such as *Requests* and *ujson*.

Like Facebook, Twitter also provides an API to provide access to its data and platform. However, Twitter API is monetized. At basic tier, Twitter allows access to its API free of cost. We developed our parsers from Twitter using Python 3, Requests, ujson and BeautifulSoup4.

Storage

While collecting data, first JSON or XML responses are needed to be stored. The most common practice is to store each JSON response on a single line in a plain text file.

This practice makes parsing large files easier as line readers can be used to parse single valid JSON entry at a time. It is often avoided to store large JSON objects, as entire JSON object has to be loaded into memory to parse it. Below is an example of nested JSON entries per file.

```
[{id: 1, column1: ‘value1’, column2: ‘value2’, column3: false … }]
[{id: 2, column1: ‘value1’, column2: ‘value2’, column3: { id: 10, column1:
‘value1’… } … }]
```

This JSON file can be parsed and converted as following CSV, flattening the nested JSON entries as independent rows in CSV

```
id, column1, column2, column3, …
1, value1, value2, false …
2, value1, value2, 10 …
10, value1, value2, false …
```

Though CSVs are tabular documents and can be stored using relational databases, CSV datasets are often ‘flattened’ or denormalized form. Therefore, it only makes sense to store extremely large CSVs that cannot be loaded into memory for processing.

Data Set

We collected data from several social media platforms. From Facebook, we collected content from official pages of local news platforms, and organizations such as the Federal Emergency Management Agency (FEMA), and American Red Cross. We also managed to get data from emergent citizen groups formed on Facebook during disastrous events such as recent Hurricanes, Harvey, and Irma. The Facebook dataset records contain data about the individual posts, comments, and their metrics such as likes, shares, and reactions. Dataset from Twitter is a collection of Tweets from relevant topic discussions, and conversations taking place around official handles of government and non-profit organizations and news platforms. In addition, the collected data allows us to extract networks such as follower-followee, commenter-commented, @-network, and #-

network. These datasets serve as the domain-specific datasets. We also collected region specific Tweets during Hurricane Harvey. This dataset includes Tweets from a wide range of topics during disasters, including off-topic and irrelevant Tweets. This dataset serves as a background dataset.

Data Cleaning

Extremely large data collections were randomly sampled for more manageable data sizes for a supervised classification study. In initial data cleaning, we conduct basic exploratory analysis to find and drop irrelevant records or documents. We drop the records that match the following criteria.

- Non-English social media posts
- Promotional posts / advertisements
    - Bots / Spammers
- Extremely short and isolated social media posts
- Media only posts, posts with no text

This cleaning phase does not include dealing with noise and errors in the text itself. Since labeling is time-consuming and labor-intensive, we only label texts that are as relevant as possible. Table 5 gives a brief record of total data collected, how much was sampled and how much were selected for the study after cleaning the sampled data.

Table 5 Selected datasets from the final collection

Dataset	**Collected**	**Sampled**	**Selected**	**Selected Duration**
Twitter	1181999	30000	22632	08/20/2017 – 10/30/2017
FEMA – Facebook	5976	5976	5976	08/20/2017 – 10/30/2017
FEMA – Twitter	104031	30000	26751	08/20/2017 – 10/30/2017
Red Cross – Facebook	8630	8630	8630	08/20/2017 – 10/30/2017
Red Cross – Twitter	15297	10000	8670	08/20/2017 – 10/30/2017
Total			**72659**	

CHAPTER V:

SENTIMENT & EMOTION MODELING

In sentiment analysis sentiment is commonly defined as a positive or negative opinion, emotion, or speculation expressed about a subject. This is a simplified representation of model suggested by Wiebe et al. (Wiebe and Cardie 2005), (p, e, a, o) where p is state experienced by *e* and *a* is experiencer's attitude towards object *o*. Opinion mining comprises different methods to extract expressed opinions from given corpora. Sentiment or polarity classification is a method of opinion mining that works with predefined classification labels.

Sentiment Classification

Sentiment classification, also referred to as polarity classification, is one of the most common objectives of sentiment analysis, where the multi-tiered classes of interest ranging from positive to negative are defined. Within corpora, each corpus or document has to be assigned one of the defined sentiment classes based on the contents of the document. Classification of sentiments can be achieved using diverse ways; one uses sentiment lexicon (a list of words with known sentiment polarity), others may use supervised machine learning to build a "model" of the language used for each polarity. Figure 11 gives an overview of distinct categories of sentiment classification techniques.

In the lexicon-based approach, the lexicon is compared with the document to identify words or terms present in the lexicon with its associated sentiment information. This approach is proven inflexible and inefficient in many applications. As this approach highly depends on the vocabulary coverage of the lexicon, it often performs poorly while dealing with diverse topics, wiring styles, and context.

Machine learning techniques build classifier models that are trained with corpora that are limited to a context and application. When an unlabeled document is provided to this model it assigns a predicted label to the document. This approach classifies text based on the features in each document, the decision boundary on the polarity of the sentiment is based upon features that capture the peculiarities of the language used in it. Due to this machine learning implementations are difficult to generalize for a wide range of corpora. For example, if a document is provided to a trained model which has not observed emotion terms from the corpora it will not classify the document with a high confidence value. The flexibility of machine learning techniques for text classification depends on text representation techniques and machine learning algorithms used to train classifier models.

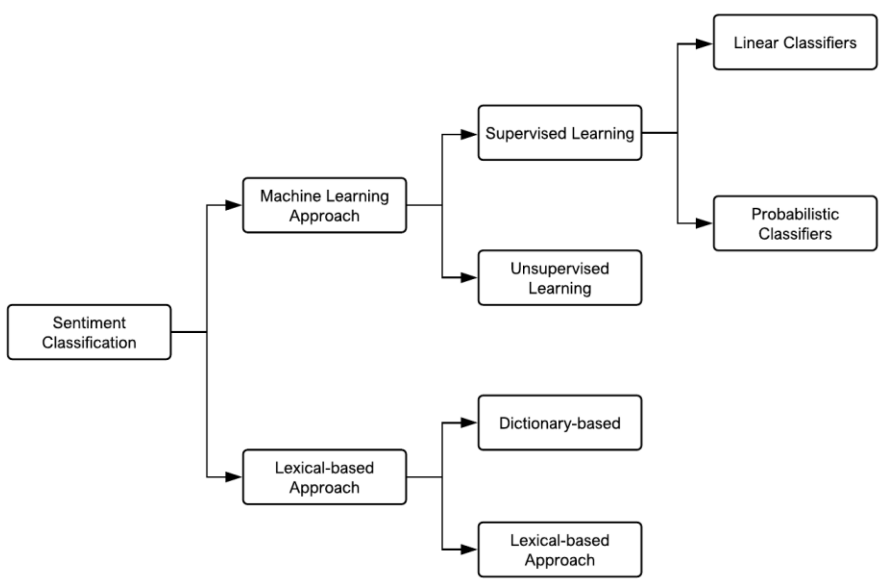

Figure 11 Sentiment classification techniques (Srinivas 2017)

Emotion Model

The goal of sentiment classification is to classify the emotions expressed in these texts along with a polarity spectrum of positive - neutral - negative. A more advanced classification task would be to consider multiple emotional states like “disappointed”, “excited”, or “angry”. In CHAPTER II, we reviewed Social-mediated Crisis

Communication (SMCC) model, that categorizes emotions into attribution-independent emotions (anxiety, apprehension, and fear), attribution-dependent emotions (disgust, contempt, and anger), and self-attributed emotions (embarrassment, guilt, and shame).

However, these emotions can be implications of different feelings. We propose an emotion model to follow while annotating or labeling our documents. The proposed emotion model (see Figure 12) identifies emotions and their opposites in relevant feelings experienced during disasters. The proposed model is based on the psychoevolutionary theory of emotions (Plutchik 1982). The emotions labeled in red color are negative, while positive emotions are colored as green.

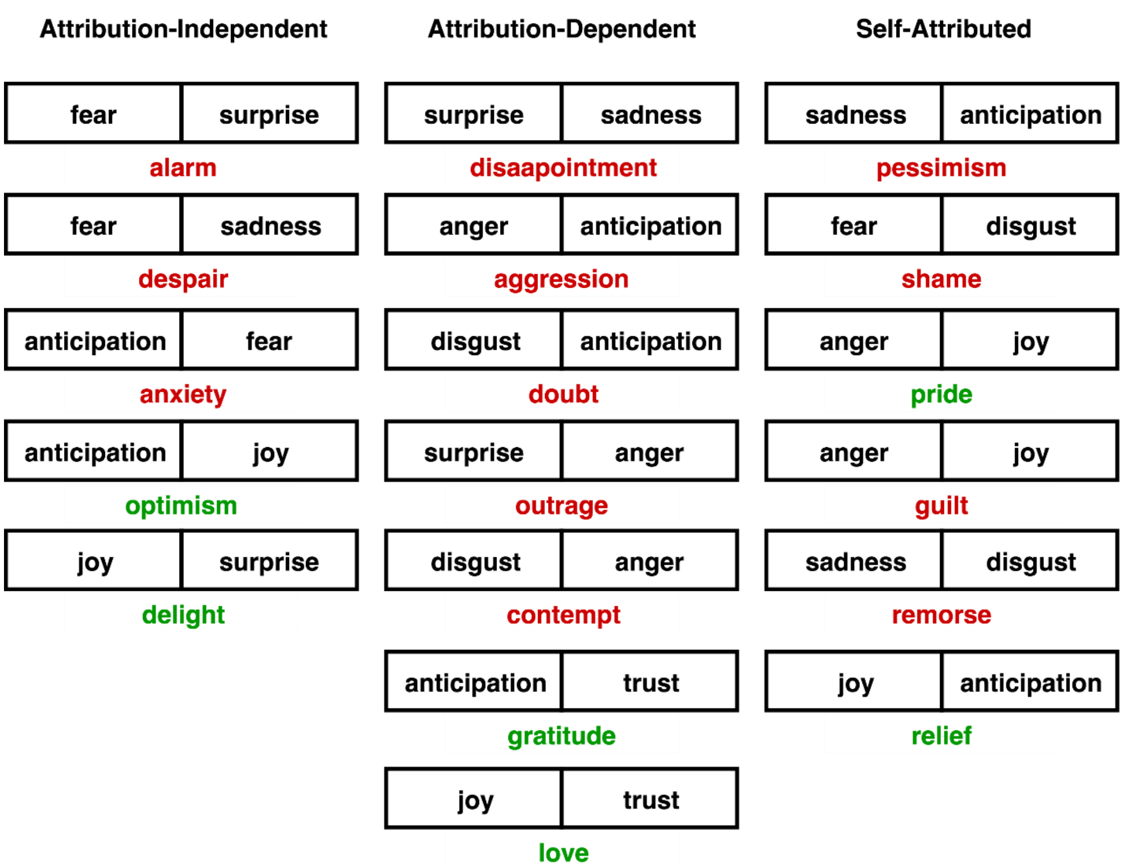

Figure 12 Emotion Model adapted from (Plutchik 1982)

Such emotion models serve multiple purposes, (i) it allows us to formalize and document emotions, their polarities related to a particular domain, (ii) it helps minimize the ambiguity in the interpretation of emotions while annotating documents with labels, (iii) it can be utilized to annotate or classify documents with complex emotions using models that only can only classify basic emotions.

Sentiment Granularity

The sentiment for the corpus can be observed at the different granularity of lexical units within a corpus that are annotated. These levels of granularity are word, phrase, sentence, paragraph, and document. The choice of sentiment annotation level is based on the way the emotional markers appear in the corpus. Though words contain essential information about emotion. However, the full range of feelings can be observed accurately with combined or higher-level lexical units such as phrases and sentences. We review these different granularity levels in following sections.

Document Level

The document level sentiment refers to a general sentiment assigned to a whole document. In this case, every word, sentence, and a paragraph of the document is assigned the same sentiment or emotion. Document-level sentiment annotation is the most popular sentiment granularity and is commonly used in various applications such as online product and services reviews or political commentaries. Annotating or labeling sentiments at document level generally reduces the complexity as it does not try to describe intricate emotions expressed in the text. Document-level annotation also reduces the amount of effort and time required to manually label the corpora. In fact, document level annotation is quite effective at generalizing sentiment labels for the whole document, depending on how sentiment polarity and emotion model has been defined. For example, documents that consist of texts expressing multiple and conflicting emotions are difficult to classify if the sentiment polarity is modeled in multiple tiers. For example, in case of movie reviews, classifying 1-star reviews as Negative and 5-star reviews as Positive is the most efficient as they both tend to be farthest from the decision boundary of a machine learning model. However, overlooking the presence of mixed and other emotions can cause misclassification of 2, 3, and 4-star reviews. Therefore, researchers such as Pang et al. (Dave et al. n.d.; Pang et al. 2002; Pang and Lee 2008) has traditionally opted for flattened or simplified sentiment polarity classes. Similarly, in this thesis, I prefer to use simplify proposed emotional model to a binary classification model for document-level sentiment classification.

Paragraph Level – Paragraph level annotation does not differ from document level annotation, except for a single document or corpus divided into its paragraphs. Paragraph level sentiment annotation can be effective and useful while analyzing documents of exceptionally large sizes, such as news articles or research articles where ideas are articulated in an organized manner in form of paragraphs.

Sentence Level

Sentence level sentiment annotation is performed for each individual sentence. Sentence level sentiment analysis is not fundamentally different from document level sentiment analysis if sentences are represented as bag-of-words tokens. However, it allows distributing sentiment values to each individual sentence in a document. It is useful if research involves examining the distribution of users’ positive and negative sentiment in each document, or positions and sequence of these sentiments. This approach of annotating and analyzing sentiments at sentence level can be useful to determine better strategies to frame effective and efficient communication messages during disasters.

Sentence level sentiment annotation is also heavily related to subjectivity classification which classifies sentences that express factual information from sentences that express subjective views and opinions (Wiebe 1994). However, sentence-level sentiment analysis annotation is not useful when sentiment has to be generalized for the whole document. It is difficult to assign the whole document a sentiment by aggregating sentence-level sentiment values. Aggregating these sentiments in a meaningful way is nearly impossible without knowing relations between sentences.

Word Level

In word level sentiment annotation each word of a document is labeled with its emotional connotation. Word level sentiment annotation is often used with lexicon-based sentiment analysis. SentiWordNet and WordNet are two popular examples of word-level annotation lexicons (Baccianella et al. 2004; Esuli and Sebastiani 2006; "WordNet: A Lexical Database for English George A. Miller" 1995). Word level sentiment annotation and analysis are commonly used for linguistics and communication studies.

Phrase-Level – Phrase level sentiment analysis is fundamentally similar to that of word-level sentiment annotation. It allows to effectively capture unique sequences of words that express an emotion, where each individual word taken out of the phrase will not provide the same information. Text representation techniques such as n-grams are used to detect and capture phrases in the document.

Meaningful Sentiment Aggregation and Granularity

Words, phrases, sentences, documents are all language constructs while understanding sentiment on each level of granularity is helpful to describe, illustrate or explain general sentiments and their distribution; many research questions can only be answered when sentiment is analyzed at a meaningful level that corresponds to a real-world application. For example, the sentiment expressed toward a particular characteristic of a product, service, or an organization. Liu et al. describe this sentiment granularity as Aspect Level sentiment. (Liu 2012).

Aspect Level

Aspect level sentiment annotation and analysis are one of the fine-grained levels of sentiment analysis as it tries to annotate and classify sentiments expressed towards a particular subject. The aspect level sentiment analysis is a challenging problem in the current state of text classification and opinion mining research. A structured summary of sentiments about subjects and their aspects can be produced, which turns unstructured text to structured data and can be used for all kinds of qualitative and quantitative analyses. Instead of looking at language constructs such as documents, sentences, or words aspect level annotation focuses on the sentiment itself and target of the sentiment. For example, in the sentence "I highly appreciate quick response by the evacuation team.", the Positive sentiment is associated with "Evacuation team" as an aspect, rather than being assigned to the sentence itself. These sentiments can be aggregated per aspect to present an overview of sentiments towards each aspect of a product. Aspect level granularity can be repurposed to describe and analyze sentiments expressed in disaster communication in a meaningful manner.

In disaster management aspect level sentiments can describe sentiments towards services provided by different disaster response and management organizations. At increased granularity, sentiments can also be observed and analyzed for common issues for each service. A high-level overview of these sentiments can allow organizations such as FEMA to find service bottlenecks and improve public relations.

Social Media Content

How do you define a document? There is no formal definition for a document. In most applications, the document may refer to a single corpus, such as a news article, scientific paper, or an online review. In case of social media, most researchers prefer to refer a single social media post as a document (Agarwal et al. 2011; Pak and Paroubek 2010; Pang et al. 2002; Wang et al. 2012). However, when we consider the document to be a single corpus, i.e. a collection of written texts by a particular author, a Twitter or Facebook post may not be a suitable equivalent.

Social media such as Twitter and Facebook are apt for conversations and interactions, unlike Blogging platforms that are more suited for long written texts focused on a single topic. Social media texts are often organized in “threads”, threads are sequential combinations of posts and comments contributed by multiple users. Figure 13 illustrates an example of a common thread and its structure.

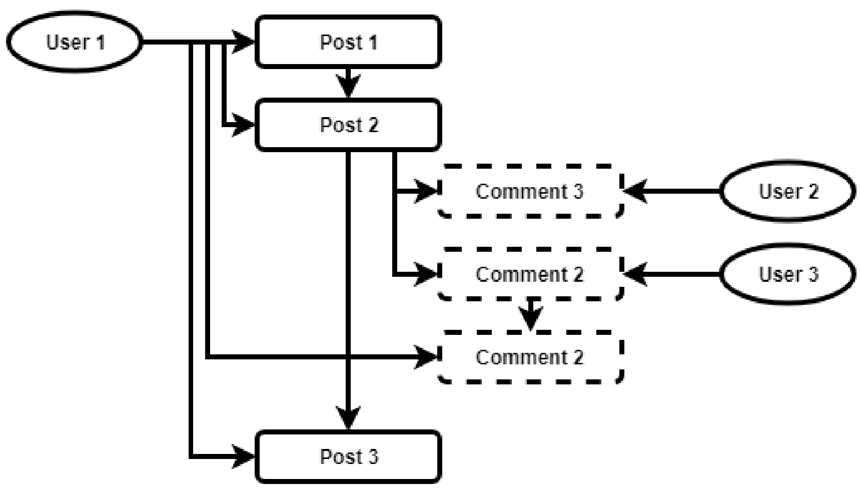

Figure 13 Example of a thread

Microblogging platforms such as Twitter, often have character limitation per post. Twitter allows 280 characters per Tweet and 140 characters per Tweet prior to November 2017. This character limitation often forces users to write multiple Tweets in a thread to express a single idea. Treating single Tweet as a document in these cases delinks the Tweet from its related Tweets and lose its context. Threads on social media can vary in length and complexity. Popular or viral social media posts can amass thousands of nested comments. Fragmented user texts and responses are required to be collected and combined to form a meaningful set of documents.

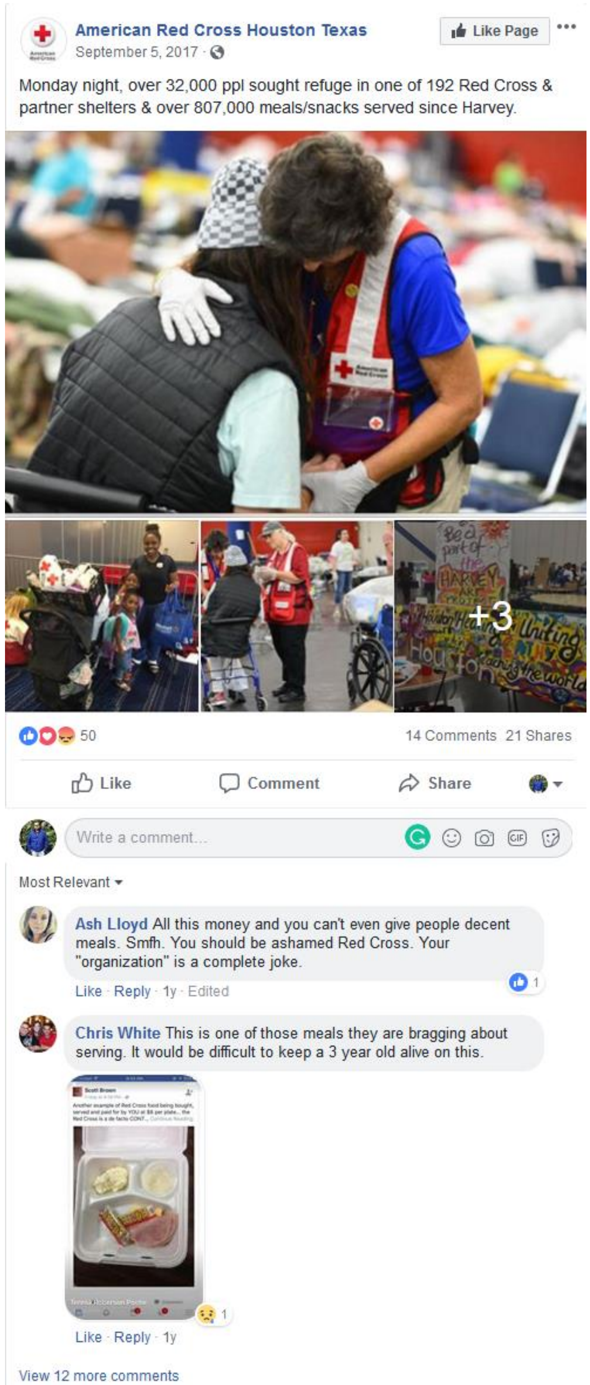

Figure 14 Example of Thread of FEMA Facebook Post

Texts can be collected by user or topics. Either approach allows answering different questions. Collection of related texts can be based on information such as posts or comments per user occurring in a single thread. For topic or issue-based aggregation, classification of texts can be achieved either using either supervised machine learning techniques or unsupervised topic modeling techniques.

Sentiment Subjectivity and Classification

Sentiment subjectivity analysis is often done after sentence-level sentiment analysis. Researchers have previously tested similar approaches (Hatzivassiloglou and Wiebe 2000; Riloff et al. 2006; Wiebe 2000; Wilson et al. 2005). Sentence level sentiment subjectivity analysis often consists of two sub-tasks.

Given a sentence *s*.

1. *Subjectivity classification*: Determine whether *s* is a subjective sentence or an objective sentence.
2. *Sentence-level sentiment classification*: If s is subjective, determine whether it expresses a positive or negative opinion.

This approach assumes that a single sentence *s* has sentiment information expressed towards a single subject.

In most applications, one needs to know what object or features of the object the opinions are on. However, the two sub-tasks of the sentence-level classification are still very important because (1) it filters out those sentences which contain no opinion, and (2) after we know what objects and features of the objects are talked about in a sentence, this step helps to determine whether the opinions on the objects and their features are positive or negative.

Most existing researches study both problems, although some of them only focus on one. Both problems are classification problems. Thus, traditional supervised learning methods are again applicable. One of the bottlenecks in applying supervised learning is the manual effort involved in annotating a large number of training examples. To save the manual labeling effort, a bootstrapping approach to label training data automatically.

Machine Learning for Classification

In recent years, machine learning and deep learning techniques have been proven to be highly effective for natural language processing and sentiment analysis. In machine learning approach, documents are converted into feature vectors using various data representation techniques. Labeled sets of these documents are used to train classification models using machine learning algorithms.

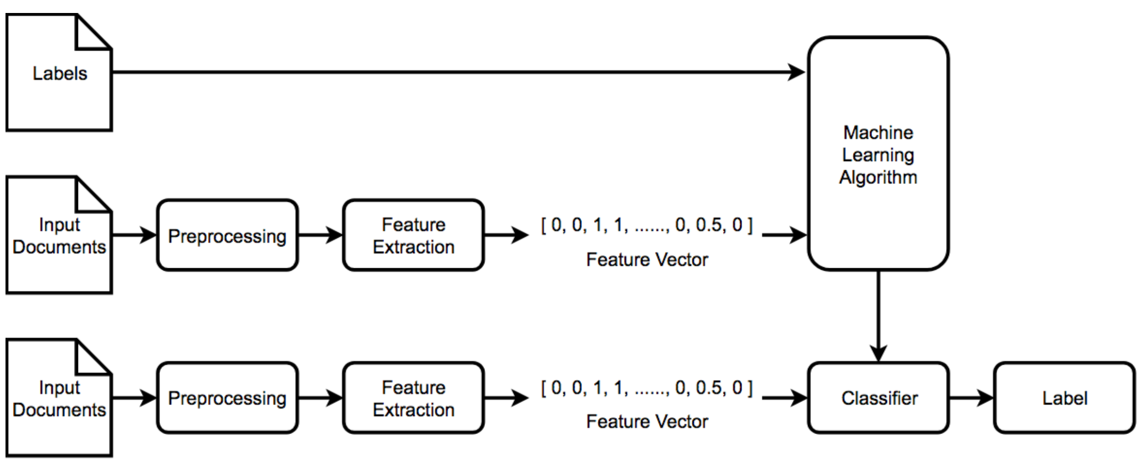

Figure 15 Supervised Text Classification Process (Bird et al. 2009)

These classifiers can learn from the training data to create a decision criterion for sentiment classification, then they are used to conduct classification of the document based on sentiments (Ghiassi et al. 2013; Pang and Lee 2008; Singh et al. 2013). These machine learning approach for sentiment analysis is a supervised learning paradigm, where a large number of labeled training data are required to train the classifier before it is used for classifying the new data (Pang et al. 2002). The process of classification of texts using machine learning can be generalized as shown in Figure 15. Machine learning algorithms such as Naïve Bayes, Support Vector Machines (SVM), and Maximum Entropy are some of the commonly used algorithms for text classification (Liu 2010). However, recently some researchers have opted for deep learning based techniques for text classification (Ghiassi et al. 2013; LeCun et al. 2015; Rios and Kavuluru 2015; Zhang et al. 2015). Stanford's CoreNLP also uses deep learning for sentiment classification (Manning et al. 2014). There is a need to explore these techniques further for document-level sentiment classification. Moreover, many of the neural network algorithms require substantial amounts of high-quality labeled data for training. These algorithms are also more complex and resource intensive. Therefore, these techniques were not opted for this research, at this stage. However, we explore the possible adoption of neural networks and deep learning in future studies.

Alternate methods for sentiment analysis use natural language processing (NLP) based techniques. These techniques are often paired with lexical analysis tools to provide sentiment information. NLP driven techniques are often better at describing deeper aspects of sentiment such as subjectivity of the sentiment (Jin and Liu 2010; Taboada et al. 2011). However, they are computationally expensive, in most cases, they are only effective and efficient while parsing smaller corpus at a time, such as sentences. However, some aspects of NLP, such as part of speech tagging and named entity recognition can be paired with text mining and classification techniques. Most named entity recognition applications require character level annotated label data. Therefore, we do not consider these techniques in our study.

CHAPTER VI:

DATA PREPROCESSING

Data Labeling

As we discussed earlier, data labeling is the most labor-intensive and lengthy process in this study. Labeling of the data was done in stages, in chunks of 2000 social media posts at a time. We used sampled validation sets to verify the quality of labeling. The labeling of the data set is highly susceptible to human interpretation, judgment and error, while proposed emotion model tries to reduce these errors, such errors can still occur while manual labeling of the dataset.

Table 6 Labeled Dataset

Dataset	**Labeled**
Twitter	8,821
FEMA - Facebook	5,976
FEMA - Twitter	15,393
Red Cross – Facebook	8,630
Red Cross - Twitter	8,670
Total	**47,490**

Some studies consider labeling to be done automatically, using existing sentiment classification models, in order to reduce labeling effort or costs. However, even the best sentiment classification models are not perfect. There are some toolkits such as SentiWordNet, NLTK, Stanford CoreNLP, or Vader (Bird et al. 2009; Esuli and Sebastiani 2006; Manning et al. 2014), and some services such as AWS Comprehend, GCP Natural Language or Azure Text Analytics (Amazon Web Services 2018; Google Cloud Platform 2018; Microsoft Azure 2018) that can offer out-of-the-box sentiment classification. These products and services differ greatly from each other. NLTK and SentiWordNET provide lexical analytics-based sentiment classification, while CoreNLP is a deep learning-based model that provides sentence-level sentiment polarity scores.

Moreover, their effectiveness while dealing with short and noisy texts also varies. For example, if a model performs well with IMDb movie reviews, it does not mean it will perform the same with disaster-related Twitter data. However, a combination of these tools can be used to aid the verification process.

Text Cleaning

Machine learning methods usually fail to achieve the desired accuracy due to the data sparseness caused by noisy data. For example, word "people" and its often-misspelled variant on social media "ppl" represent the same concept for the human readers. However, they are two separate features in the bag-of-words representation of data. We identify such features as noisy textual features. To handle perform classification of these texts with reliability, noisy textual features need to be generalized. Such generalization can be achieved using lexical analysis, feature compression, and dimensionality reduction techniques as well as incorporating hidden topic discoveries from large-scale data collections.

Data Cleaning Pipeline

Before data is represented as bag-of-words and moving to feature selection, we need to clean text data, it involves reducing possible variations of words that may be necessary, fixing spelling errors, removing non-English documents. In this section, we present our lexical preprocessing pipeline.

Removing whitespaces

We are being with removing trailing and leading whitespaces, as it can cause the addition of empty text tokens depending on text tokenization algorithms used.

Removing and handling punctuation

At the second stage in the pipeline, we remove punctuation from the text. Punctuation is usually handled by many tokenizations and stop word removal implementation. Tokenizers that tokenize text based on word boundaries often split tokens by whitespace between them. This causes words followed by punctuation to be counted as an entirely different word.

For example, word ‘relieved’ and ‘relieved.’ (with a period in the end) is considered as two different words or tokens. To handle these variations, some implementations of tokenization algorithms separate punctuation from word or simply drop them.

While periods, commas, and semicolons do not carry much meaning as tokens, the same cannot be said about an exclamation mark. For example, word ‘help’ appearing in a sentence does not exactly have the same usage as ‘help!’, it indicates urgency and is a sentiment marker to consider. However, the occurrence of ‘help’ and ‘help!’ are not disjunct. By separating ‘help’ and ‘!’ we allow both to be tokenized.

Removing URLs

We remove URLs from the texts as they carry little to no information about sentiment. We can identify if the document contains media, by looking at URL if it is shared from platforms such as Instagram or YouTube. However, since we record media presence and type in social media post while scraping or collecting data, we can drop URLs entirely from our texts.

Splitting Attached Words

After removal of punctuation or white spaces, words can be attached. This happens especially when deleting the periods at the end of the sentences. The corpus might look like: “the brown dog is lostEverybody is looking for him”. So, there is a need to split “lostEverybody” into two separate words.

Correcting Misspelled Words

Social media posts are infamous for their misspelled words and grammatical mistakes. It is not uncommon to see people misspelling words, for example, ‘adres’ instead of ‘address’ or ‘the’ as ‘hte’. These misspelled words end up as independent features in bag-of-words, increasing dimensionality and sparsity of feature vectors.

There are two methods of fixing incorrectly spelled words, using spellcheck dictionaries and word similarity, or using probabilistic learned autocorrection models. We opt for well tested open-source spell check dictionaries such as HunSpell.

Normalizing Text to Lowercase

Finally, we convert all text to lowercase to avoid considering the same words as unique features, such as ‘HELP, ‘Help’, or ‘help’.

Removing Stopwords

Optionally, we remove stop words using stop word dictionaries. Stop words are basically a set of commonly used words in any language: mainly determiners, prepositions, and coordinating conjunctions. By removing the words – such as ‘the’, ‘and’, ‘a’, ‘or’ – that is very commonly used in a given language we can focus only on the important words instead and improve the accuracy of the text processing.

Stemming and Lemmatization

For grammatical reasons, we observe different forms of a word, such as organize, organizes, and organizing used in a document. There are also derivationally related words with similar meanings, such as democracy, democratic, and democratization. In many situations, it seems as if it would be useful for a search for one of these words to return documents that contain another word in the set.

The goal of both stemming and lemmatization is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form. For instance:

am, are, is → be

car, cars, car's, cars' → car

For English language, Porter's algorithm is the most commonly used algorithm for stemming (Porter 1980)

Once the texts are cleaned, processed, and tokenized, they are ready to be converted into feature vectors. In the next chapter, we review text representation and feature selection techniques required for representing data in mathematical constructs.

Text Representation & Feature Selection

As described in the previous chapter, sentiment polarity classification is one of the primary tasks in sentiment analysis. Use of machine learning methods for classification of texts over sentiments is increasingly popular and proven approach (Abirami and Gayathri 2016; Hu, J. Tang, et al. 2013; Rothfels and Tibshirani 2010; Silva et al. 2016; Srinivas 2017). This task requires building a 'model' of sentiment polarity classes using labeled/annotated training data. The training data must be processed and expressed as a set of numerical features prior to using the machine learning algorithm to build the model. This conversion of text data into numerical values is called data or text representation. These numerical values capture some form of information about components of texts such as a word, letter, or a symbol. We call these components of texts as features. There is an extensive research on various text representation techniques, their advantages (Goldberg et al. 2014; Mikolov et al. 2013; Pennington et al. 2014; Salton et al. 1975; Zhang et al. 2008). However, the effectiveness of these text representation techniques is highly dependent on data quality, the domain of application and machine learning techniques in use. There are two primary modeling techniques to represent text data, a vector space model, and a statistical language model. Secondly, these modeling techniques are augmented using weighting techniques to represent documents more accurately. Thirdly, feature generalization techniques can be used to further enrich text representation with part-of-speech (POS) tags derived from natural language processing (NLP) techniques. The number of features in a vector, the sparsity of vectors, and their effectiveness depend on various techniques explained below.

Bag of Words Model

The **s**entence can be represented in many different ways. First, we can always represent a sentence as a string of characters. However, the downside of this representation is that it does not allow meaningful analysis since it is not even able to recognize words. A solution to this problem is to perform word segmentation to obtain sequences of words. This is the most common technique to represent text and is often referred to as the Bag-Of-Words model. Each word represents a feature. This process is also referred to as "Tokenization" since the document is broken down into tokens (individual words). Simply put, in bag-of-words model presence of a word is treated as a feature in a vector. Bag of words model is often used with lexical analytical techniques and natural language processing. It is often augmented by various cleaning techniques to make text representation effective. For example, a common bag of words representation of standard English text usually contains words like "I, a, an, the, if, for", at the highest frequency and make up most of the text. These are called "stop words". These stop words are removed from a corpus using prebuilt lexicons of stop-words.

There are more lexical processing techniques such as stemming, negation, chunking, and thinking to better refine the representation of text for various linguistic and semantic analytical purposes.

Stemming is the process for reducing inflected (or sometimes derived) words to their stem, base, or root form generally a written word form. For example, ran, running, runs are all derived from the word “run”. A commonly used stemming algorithm for the English language is the “Porter's Algorithm”. Stemming is effective when it is consistent and used on large text documents. It is not a suitable technique for natural language processing, as it can cause severe information loss.

Chunking and chinking are processes that are used with part-of-speech tagging of text to group words into meaningful chunks that pan multiple words, such as ‘noun phrases. The idea is to group the nouns with the words related to them.

Negations such as not and never are often included in stop-word lists and hence are removed from the text analysis. Combined with other words, though, negations reverse the polarity of words. Because polarity classification may be affected by negations, SA researchers have tried incorporating them into the feature vector. We take the approach of who use a heuristic to identify negated words and create a new feature by appending NOT- to the words (for example, a phrase “don’t like” results in feature NOT-like).

Vector Space Model

Vector Space Model (VSM) is the oldest and better-known model for text representation for text classification problems. VSM is largely adopted from information retrieval and document ranking research, originally being developed for finding related documents based on similarities. VSM is based on simple linear algebraic computation where the entire document is represented as one vector with presence or frequency of each word representing a dimension. Text can be represented in VSM using various representations methods.

Bit Vectors

The bit vector is a simple representation based on word presence. It is the simplest form of VSM representation where a vector is constructed filled with binary values. The length of the vector is the vocabulary of the entire corpora. With each value in the vector representing the presence of the word in a given document (with 1 indicating that the term occurred in the document, and 0 indicating that it did not). However, this representation can be misleading if one word is more important than other words. Presence of frequently-used words, stop-words also poses hinderance. Bit vectors are relatively more effective when text is preprocessed by removing stop-words.

Term Frequency Vector (TF)

TF refers to the Term Frequency of a word, i.e. the total count of the number of occurrences of a particular word in a document. Higher the value of TF, higher the weight for the feature. The term frequency vector is defined as follows.

$$x_i = \text{count of word } W_i \text{ in document } \mathrm{d_i}$$

$$d_i = (x_1, x_2, x_3, \dots, x_n)$$

But TF by itself has some shortcomings. For example, if the documents were all about “FEMA aid application”, the term “FEMA” is highly likely to occur multiple times. The emphasis of the document was not about the FEMA but the aid application. This is also true for stop-words such as the word 'The'. In general context, the word 'The' may not be the most important one, maybe with the exception of Wikipedia page for the word 'The'.

Term Frequency-Inverse Document Frequency

In representing a document as a vector, a weight must be assigned to each term that represents the value of the corresponding component of the vector. Researchers have developed, utilized, and evaluated many formulae for assigning weights. With few exceptions, these formulae may be characterized as belonging to the general category as TF-IDF weights.

TF-IDF was originally developed to improve the accuracy of ranking functions. However, in text representation for machine learning, it also serves as a method to remove stop words and reoccurring patterns that do not have significant meaning.

TF-IDF is obtained by multiplying term frequency for word W_i by inverse document frequency for the word $W_i, IDF(W_i)$.

$$d_i = c(W_i, d) * IDF(W_i)$$

$$IDF(W) = \log\left[\frac{(M+1)}{k}\right]$$

$M = total\ number\ of\ docs\ in\ collection$

$k = total\ number\ of\ docs\ containing\ W$ (doc frequency)

TF-IDF representations can be used by using variants of the $IDF(W)$ functions that apply scaling. Since it is unlikely that ten occurrences of a term in a document actually carry ten times the significance of a single occurrence. A common medication is a sublinear term frequency scaling (Manning et al. 2008).

Pivoted Length Normalization

Generally, longer documents will as a result of containing more terms have higher term frequency values. Secondly, longer documents also contain more unique terms that may not be significant to the topic. This leads to larger documents having more features that skew the decision boundary on text classification. Longer documents can broadly be lumped into two categories: (i) verbose documents that essentially repeat the same content - in these, the length of the document does not alter the relative weights of different terms; (ii) documents covering multiple different topics, in which the search terms probably match small segments of the document but not all of it - in this case, the relative weights of terms are quite different from a single short document that matches the query terms. Compensating for this phenomenon is a form of document length normalization that is independent of term and document frequencies. In pivoted length normalization, the idea is to use average document length as a pivot, as a reference point. So, for the average document length, the normalizer will be 1, for longer documents, there will be some penalization.

$$normalizer = 1 - b + b\frac{|\,d\,|}{avg\ dl}$$

$$b \in [0,1]$$

Where, d is the length of the document, and $avg\ dl$ is the average length of documents in the whole corpora. Average document length is used as the ‘pivot’.

Statistical Language Model (SLM)

The problem of Modeling Language Formal languages, like programming languages, can be fully specified. All the reserved and special words can be defined and the valid ways to use them can be precisely defined. Natural language does not conform to such rules. Natural languages are not designed, they emerge, and are ever changing. Natural languages involve a vast number of terms that can be used in ways that introduce all kinds of ambiguities yet can still be understood by other people (Sparck Jones et al. 2000).

The vector space model largely depends on the bag-of-words representation of the text. Which considers each word to be an independent term or a feature. The problem with this model is that it often loses information based on context and phrases. Statistical Language Modeling or Language Modeling is the development of probabilistic models that are able to predict the next word in the sequence given the words that precede it. This allows us to effectively quantify uncertainties in natural language. Unigrams and N-grams are common ways SLM is implemented.

Unigram Language Model

Unigram language model is generated by calculating the probability of each word occurring in a document. Where, $p(w_i)$ is the probability of a word w_i occurring, and N is the vocabulary size. Total of all probabilities in vocabulary N is 1.

$$\{p(w_i)\} \;\; p(w_1) + \cdots + p(w_N) = 1$$

The probability of a sequence of words is a product of the probability of each word.

$$p(w_1, w_2, \dots w_n) = p(w_1)\, p(w_2) \; \dots p(w_n)$$

SLM can also be used for topic representation, which can be used to verify the results of the classification of text based on topics or unsupervised topic modeling techniques. Probabilities of words specific to a domain appearing in a general collection are lower but are higher for a collection that is domain specific. This allows us to detect topics in the text.

Where,

B is a collection of probabilities of words in the English language.

C is a collection of probabilities of words in a domain.

d is a collection of probabilities of words in a specific topic.

We can calculate

Background LM: $p(\, w \mid B \,)$

Collection LM: $p(\, w \mid C \,)$

Document LM: $p(\, w \mid d \,)$

To retrieve words that represent topics and get rid of the frequently-used words we need to normalize the Topic Language Model.

$$Nomralized\ Topic\ LM\ = \frac{p(w \mid \text{"Rescue"})}{p(w \mid B)}$$

N-grams

Using n-grams over unigrams serves the benefit of being able to capture some dependencies and relations between the words and the importance of individual phrases. Significant improvement in polarity classification task using high n (up to 6) can be found in some applications (Cui and Google 2006). The effectiveness of n-grams, when used with corpora with low average document length, is unclear, where reoccurring patterns may not carry significant information. However, N-gram terms can also be used along with unigram representation of its own components to overcome this issue.

Part-of-Speech (POS)

Part of speech. The part-of-speech (POS) of each word can be important too. Words of distinct parts of speech (POS) may be treated differently. For example, it was shown that adjectives are important indicators of opinions. Thus, some researchers treated adjectives as distinctive features. However, one can also use all POS tags and their n-grams as features. These features can be used to avoid the problem of data sparsity by generalizing the phrases/n-grams by replacing some of the words in each phrase with their POS. The most drastic generalization would be replacing all words with POS tags, at the cost of heavy information loss. Adjectives, verbs, and nouns and their sequences may be indicative of sentiment polarity. POS tags, individually and in combination can be used to help classification performance.

CHAPTER VII:
FEATURE EXTRACTION

In this chapter, we explore the data to study and verify potential features that define the sentiment of the document. In CHAPTER V, we reviewed techniques that represent data in mathematical models. These data representation techniques are capable to capture features that directly appear as text. However, we also discussed other explicit and implicit network features that may carry information about the sentiment expressed in the document or the collection of the documents.

Topic Modeling

In CHAPTER V, we reviewed how textual data can be represented and how relevant features can be selected for training machine learning models. However, in the case of short and noisy social media text data, even the most sophisticated and elaborate feature selection techniques can fall short, as there are not enough features, to begin with. In CHAPTER III, we also proposed to incorporate implicit network data as features in the sentiment classification task. While #-hashtags and @-mentions allow us to form networks of conversations and discussion topics, they often do not describe nature or different opinions in those discussion topics. Topic modeling is a suitable tool for this purpose, as it allows the discovery of abstract topics that occur in texts, which is achieved by finding hidden semantic structures in the text. The produced topics are clusters of similar words that can be used to group similar texts together. Every topic modeling method tries to capture this intuition. However, they are fundamentally different and have their strengths and weaknesses.

Latent Dirichlet Allocation (LDA)

LDA is a probabilistic generative model that can be used to estimate the multinomial observations by unsupervised learning (Blei et al. 2003). With respect to topic modeling, LDA is a method to perform so-called latent semantic analysis (LSA). The intuition behind LSA is to find the latent structure of “topics” or “concepts” in a text corpus. LDA is a generative graphical model. It can be used to model and discover underlying topic structures of any kind of discrete data in which text is a typical example. In LDA, a document is generated by first picking a distribution over topics from a Dirichlet distribution, which determines a topic assignment for words in that document. Then the topic assignment for each word placeholder is performed by sampling a particular topic from a multinomial distribution. And finally, a particular word is generated for the word placeholder by sampling from a multinomial distribution.

Latent Semantic Analysis (LSA)

LSA is a computational text analysis tool that builds a semantic space from a corpus of text. This semantic space is then used to compute the similarity between words, sentences, paragraphs, or whole documents for a wide variety of purposes (Deerwester et al. 1997; Foltz et al. 1998; Laham 1998; Landauer 1997). Note that this semantic space is a high-dimensional vector space (typically 300 or more dimensions) with little inspectable value to humans; additional methods are needed to create that inspectable structure. After performing LSA, the results can be compared directly to LDA output or can become input for further algorithmic processing to understand the similarity values in a separate way. LSA has mixed reception due to its inability to match observed data, for example predicting human word associations. This is due to the nature of the spatial representation that is intrinsic to LSA, forcing symmetry in the similarity of words and imposition of the triangle inequality, among others. While these criticisms are valuable, they are at the word-to-word comparison level, which may or may not become trivial with exceptionally large corpora and repository sizes.

Traditionally, LSA has used the Singular Value Decomposition, but Non-negative Matrix Factorization can also be used for LSA, as seen in related research (Kim and Park 2007).

Data Exploration

Initial data exploration helps us to understand the data. Though it may not provide actionable insight, it allows getting a general idea about the data. Data exploration is usually doe using statistical methods and visualization techniques.

The Twitter dataset is a collection of tweets during Hurricane Harvey from Houston, the Texas area. We explored this data to explore use-pattern of hashtags and mentions and distribution of documents by various disaster-related topics.

Table 7 Hashtags and Mentions in Tweets

Total Tweets	22637
Tweets containing Hashtags	10750 (47.49%)
Tweets containing Mentions	2983 (13.18%)
Tweets containing both Hashtags and Mentions	1518 (6.71%)
Tweets containing only Hashtags	9232 (40.78%)
Tweets containing only Mentions	1465 (6.47%)

Exploring Label Distribution

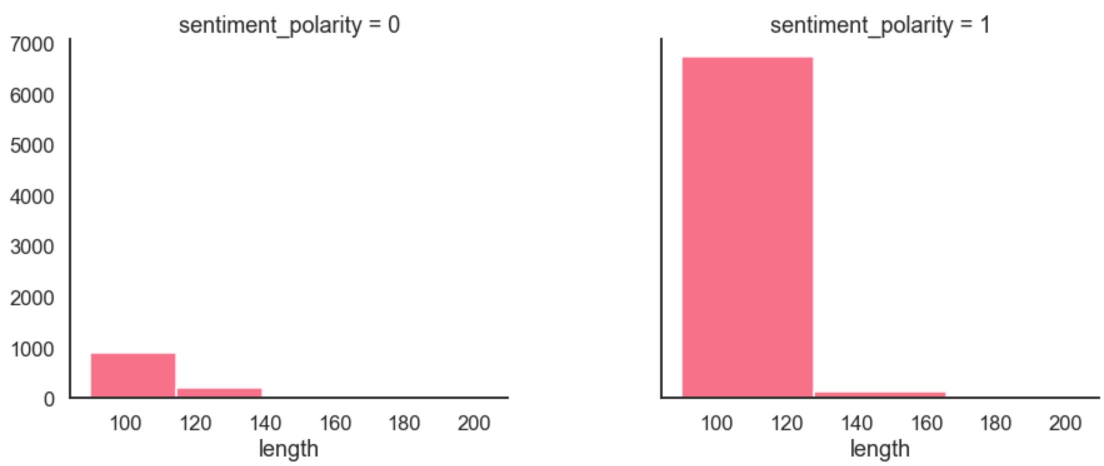

Figure 16 Label distribution on the Twitter dataset

Figure 16 shows the distribution of sentiment polarity by length across two sentiment classes. We observe the highly disproportionate distribution of sentiment classes on the Twitter dataset, with 85% of classes being positive. Looking at Figure 21, we can also observe that most common features in the corpora express optimism and joy post-disaster.

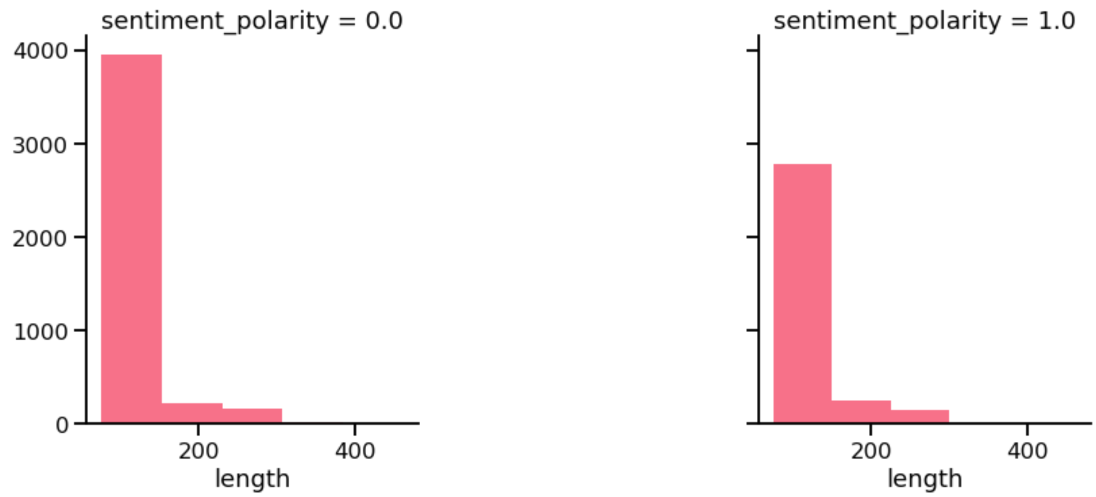

Figure 17 Label distribution on FEMA Twitter dataset

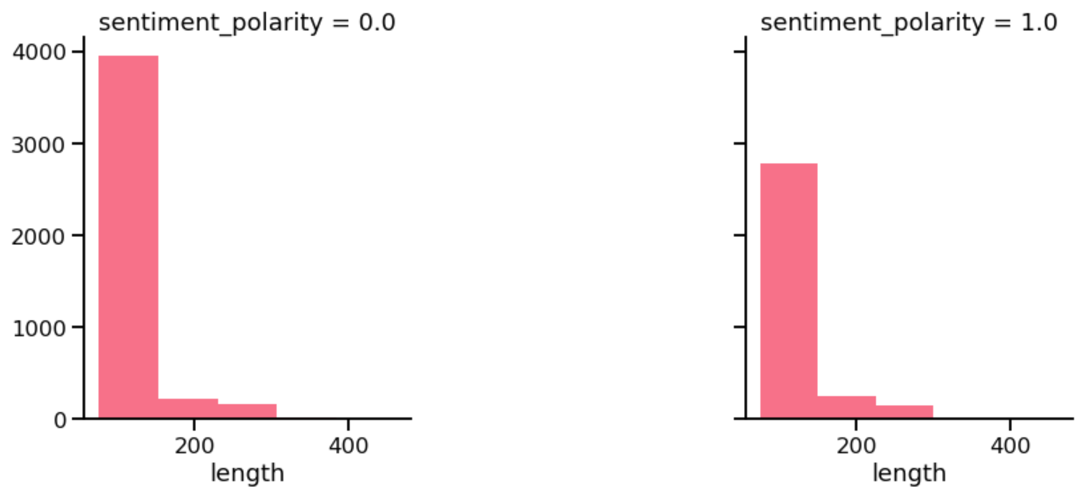

Figure 18 Label distribution on FEMA Facebook dataset

For FEMA datasets Twitter (Figure 17) and Facebook (Figure 18), we observe the more balanced distribution of classes that is slightly skewed towards negative. For both, Facebook, and Twitter the class distribution is 42% positive and 58% negative.

The Red Cross Facebook (Figure 19) documents are similar to FEMA's Facebook (Figure 18) documents with similar cluster heterogeneity and sentiment class distribution.

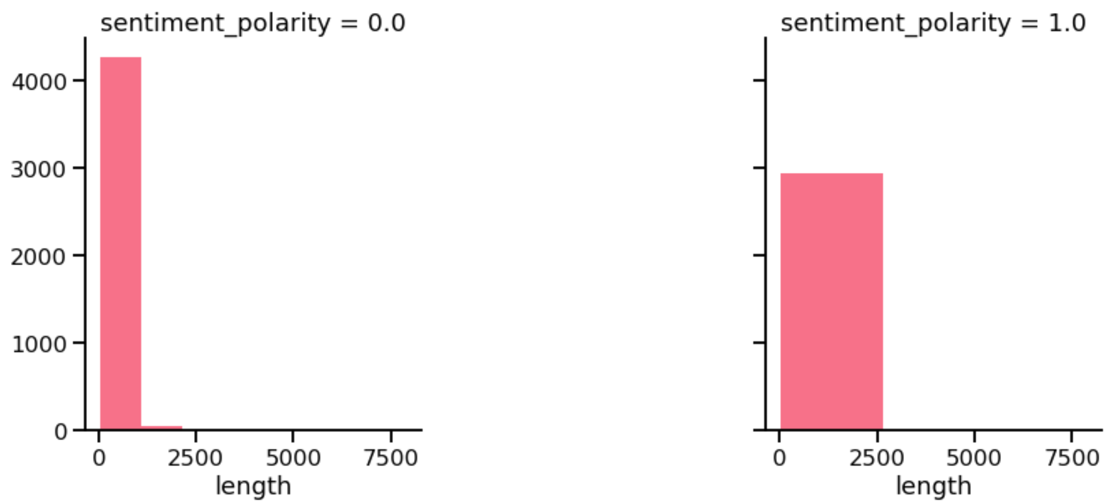

Figure 19 Label distribution on Red Cross Facebook dataset

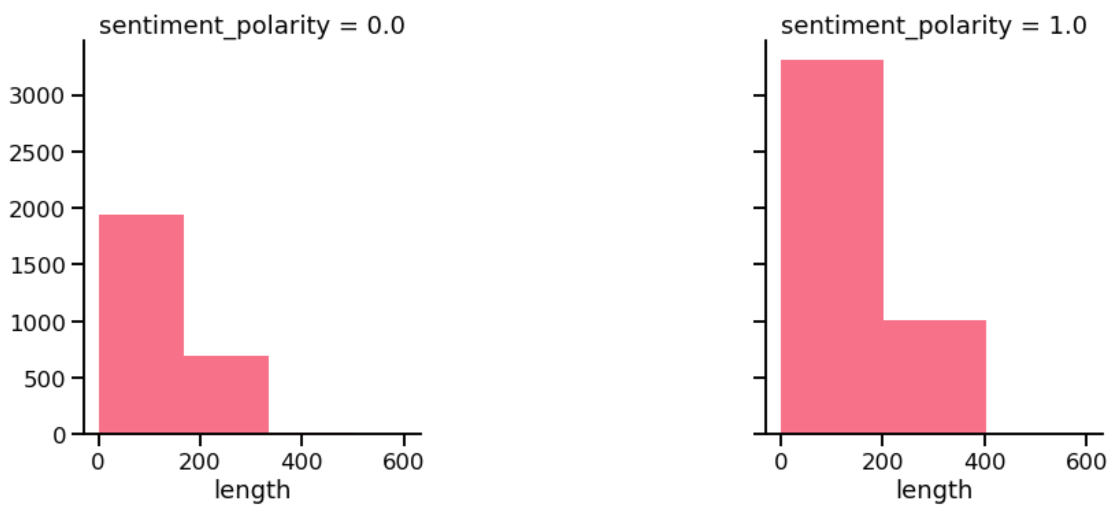

Figure 20 Label distribution on Red Cross Twitter dataset

We see 40% positive samples and 60% negative samples for Red Cross Facebook dataset Figure 19. The Red Cross Twitter dataset stands out from rest of the FEMA and Red Cross datasets. With having sentiment class distribution that is 62% positive and 38% negative (Figure 20). We also observe more heterogeneity and distinctiveness in topics for Red Cross Twitter documents.

Exploring Topics

Word cloud visualization can be used to get a general idea of popular terms in the entire corpora. Figure 21, Figure 22 and Figure 23 display the Word cloud visualization of all datasets. Word cloud visualization makes it easy to interpret term frequencies in the given dataset, hence providing some explanation of possible prominent features in the dataset. They also allow us to spot noisy features, irrelevant words, and out-of-vocabulary words. With Word cloud visualization we can identify trends and patterns that would otherwise be unclear or difficult to see in a tabular format.

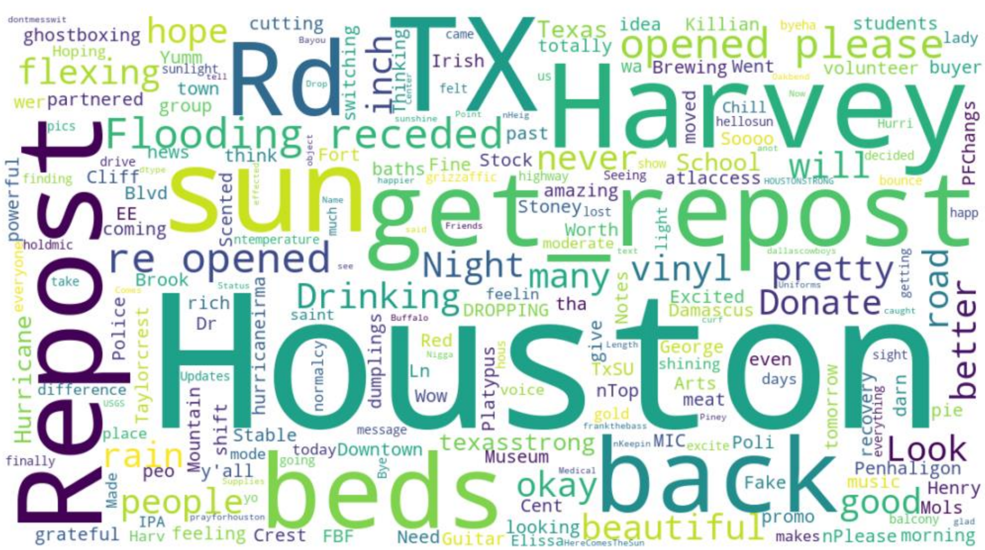

Figure 21 Wordcloud of Hurricane Harvey related Tweets

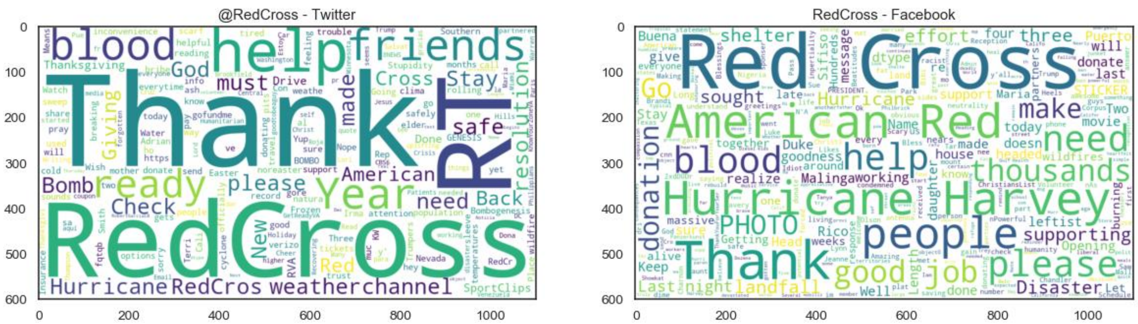

Figure 22 Wordcloud of Red Cross Facebook and Twitter Posts

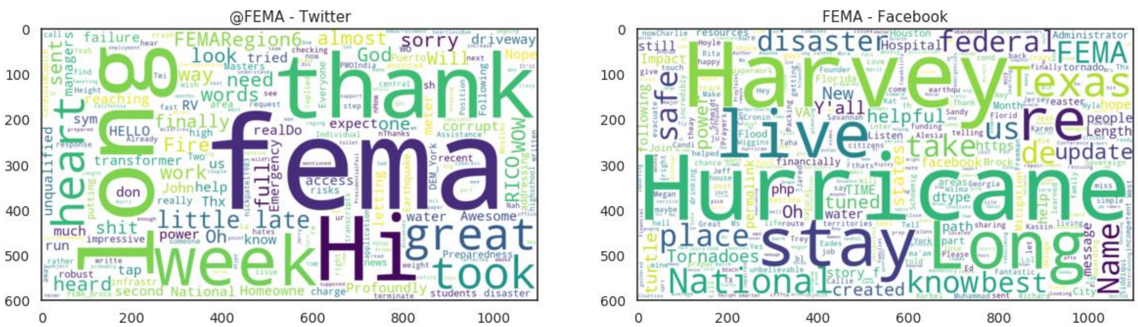

Figure 23 Wordcloud of FEMA Facebook and Twitter posts

Though Wordcloud provides a general idea about the corpora, topic term distribution provides a better understanding of the topic distribution and term significance in the corpora. We can observe that topic modeling effectively captures discussions around particular issues such as flooding or tornados. However, topic modeling is an unsupervised method, and there is no way to accurately guess exactly how many topics are in the collection.

Exploring Sentiment Distribution by Topics

The sentiment class distribution by topics allows us to identify topics where social media posts tend to be more opinionated on one side. Figure 24, Figure 25, Figure 26, Figure 27, and Figure 28 show sentiment class distribution by topics for Twitter, FEMA - Facebook, FEMA Twitter, Red Cross Facebook, and Red Cross Twitter datasets respectively. For Red Cross Facebook dataset (Figure 27), we can observe that most topics have more negative opinions, but some topics are overwhelmingly negative.

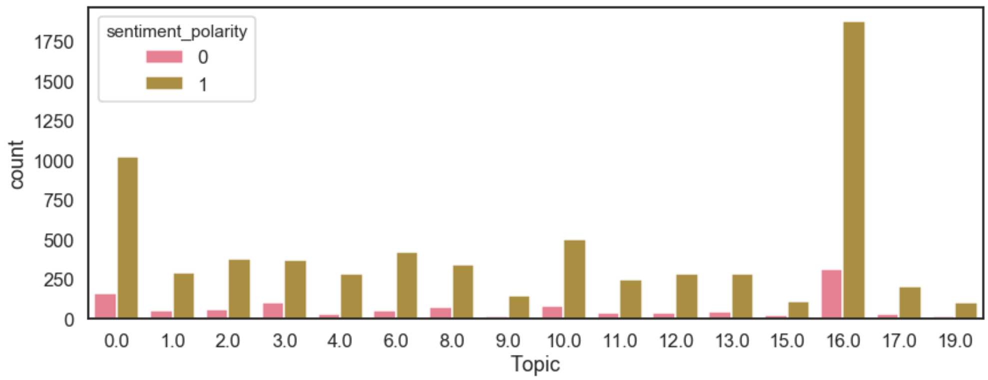

Figure 24 Twitter - sentiment class distribution by topic

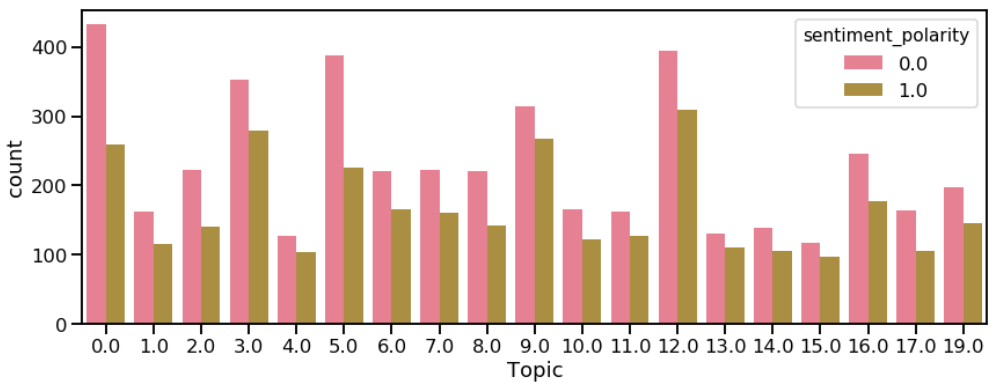

Figure 25 FEMA Facebook - sentiment class distribution by topic

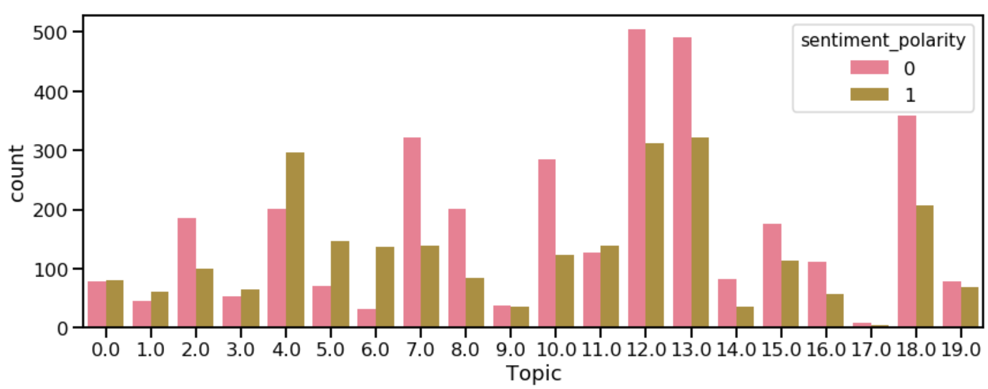

Figure 26 FEMA Twitter - sentiment class distribution by topic

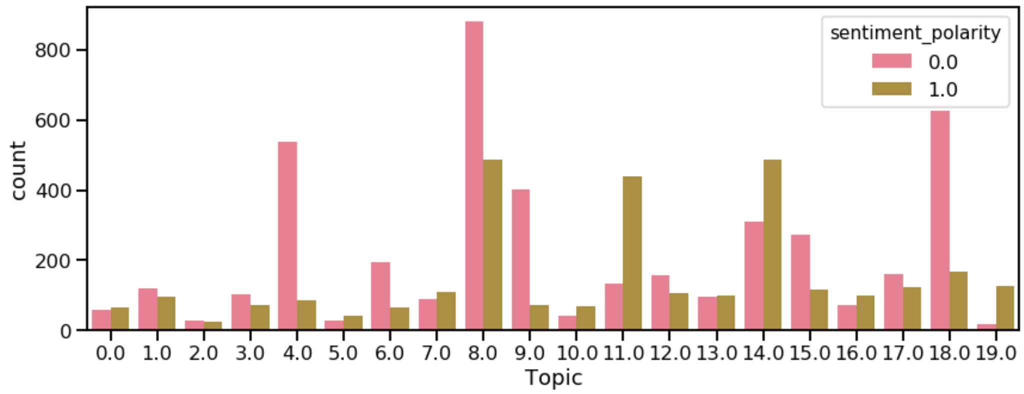

Figure 27 Red Cross Facebook - sentiment class distribution by topic

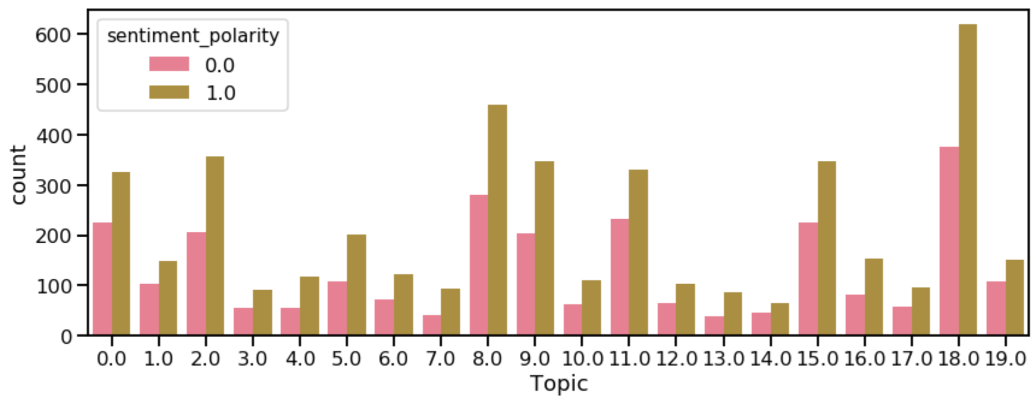

Figure 28 Red Cross Twitter - sentiment class distribution by topic

Finding Optimal Number of Topics

Normally, LDA is used as an exploratory technique that requires human interpretation. However, we can use perplexity to automate our guess of possible topics in a collection. Perplexity is a statistical measure of how well a probability model predicts a sample. As applied to LDA, for a given value of k, you estimate the LDA model. Then given the theoretical word distributions represented by the topics, compare that to the actual topic mixtures, or distribution of words in your documents.

Figure 29 shows Coherence values per number of topics for twitter dataset.

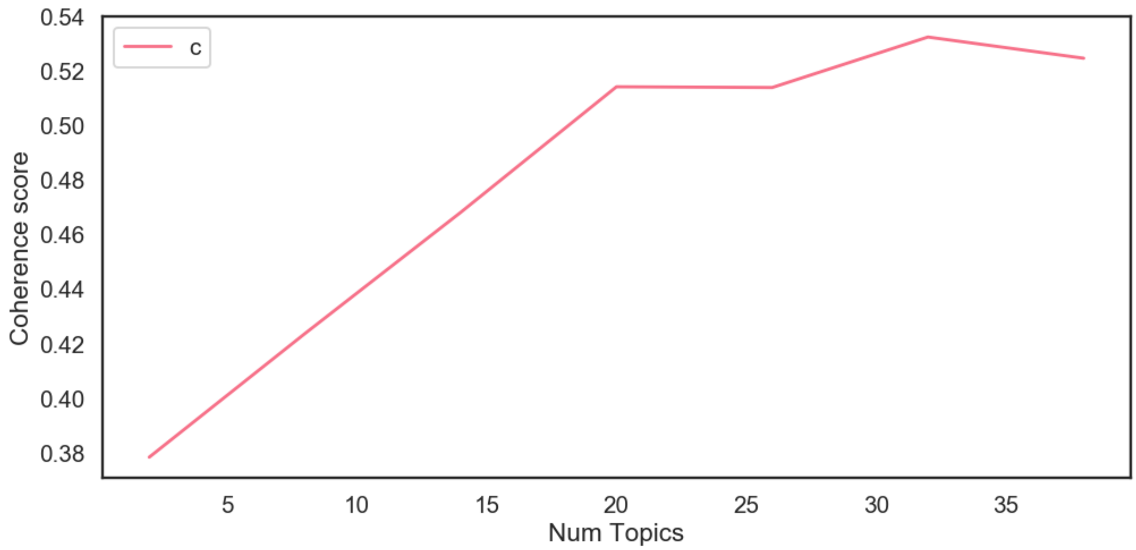

Figure 29 Coherence per number of topics for the Twitter dataset

```
2 topics have Coherence Value of 0.3734
8 topics have Coherence Value of 0.4188
14 topics have Coherence Value of 0.4861
20 topics have Coherence Value of 0.512
26 topics have Coherence Value of 0.5028
32 topics have Coherence Value of 0.5165
38 topics have Coherence Value of 0.5317
```

Following is an example of 20 topics extracted from the dataset.

Topic 0	traffic fwy flooding rd closed lanes westside lp affecting stop
Topic 1	new thank god prayers pray area relief way donations ll
Topic 2	houston texas hurricaneharvey prayforhouston houstonstrong eastside church lol praying
Topic 3	repost get_repost don safe make right share dr check team
Topic 4	mph pasadena wind humidity drinking weather george current clouds temperature
Topic 5	work best rt hard hardy year blue fall like old
Topic 6	day let thanks rescue amazing pearland crazy music labor came
Topic 7	houston tx city time downtown memorial northside trying needed friend
Topic 8	people good stay center ve strong minutes hope man better
Topic 9	harvey hurricane love pm storm tonight st house hr neighborhood
Topic 10	help rain friends donate great doing money able bad gulf
Topic 11	like going greens little week really shelter beautiful things fashion
Topic 12	ft bayou tx usgs flow height buffalo cfs point piney
Topic 13	twitter com pic tx family houston tomorrow ward free think
Topic 14	today need look live ready place volunteers stuck party folks
Topic 15	just posted photo houston texas got frontage video morning meyerland
Topic 16	park come tornado hours business thoughts university youtube white working
Topic 17	know la en del casa affected dannyboy real link el
Topic 18	open happy food community finally birthday support making drive sunday
Topic 19	water high main home flood baytown flooded th looking helping

We calculated the optimal number of topics for all other datasets. Table 8 shows the optimal number of topics based on perplexity and coherence scores for remaining datasets.

Table 8 Optimal number of topics based on perplexity and coherence scores

Dataset	**The optimal number of topics**
Twitter	20
FEMA - Facebook	32
FEMA - Twitter	14
Red Cross – Facebook	20
Red Cross - Twitter	24

We observe more topic-specific discussions involving FEMA, more on Facebook, compared to Twitter. Figure 30 shows the topic clustering of Twitter posts with x and y axis being two t-sne components. The colors denote different topics, extracted using LDA. The clustering is achieved by reducing the dimensionality of the dataset. t-Distributed Stochastic Neighbor Embedding (t-SNE) is used to reduce the dimensionality of the feature space in order to effectively visualize the dataset. The algorithm starts by calculating the probability of similarity of points in high-dimensional space and calculating the probability of similarity of points in the corresponding low-dimensional space. The similarity of points is calculated as the conditional probability that a point A would choose point B as its neighbor if neighbors were picked in proportion to their probability density under a normal distribution centered at A. The positioning of the data points is based on their position in vector space, while color or topics denote documents that share words that are semantically related. It then tries to minimize the difference between these conditional similarities in higher-dimensional and lower-dimensional space for a perfect representation of data points in lower-dimensional space (Van Der Maaten and Hinton 2008).

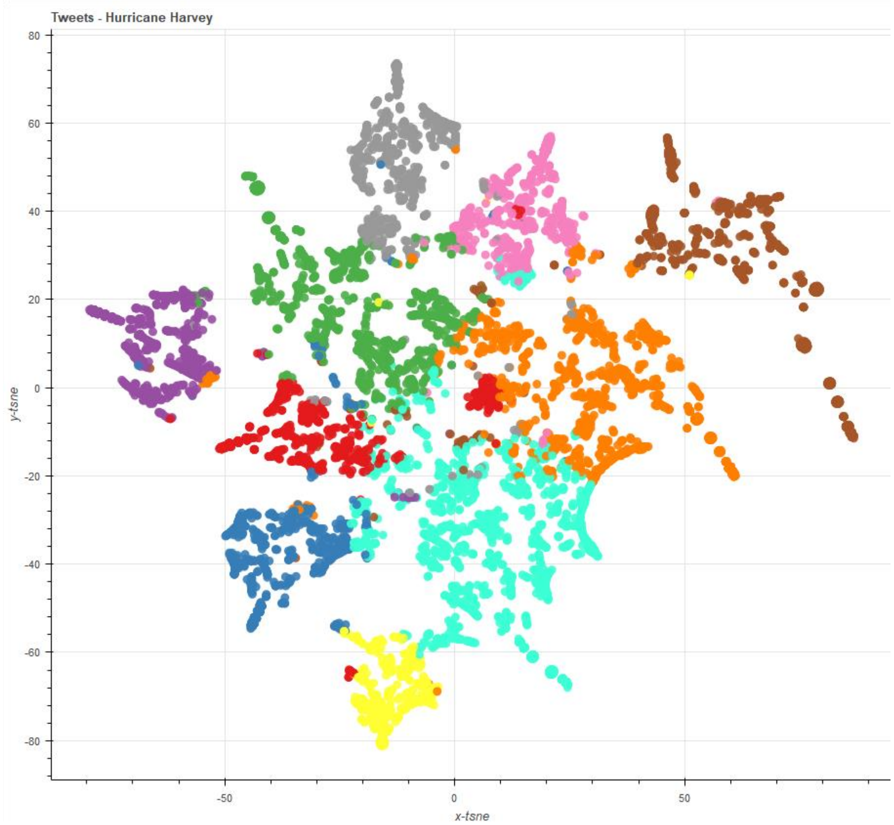

Figure 30 Twitter topic clusters

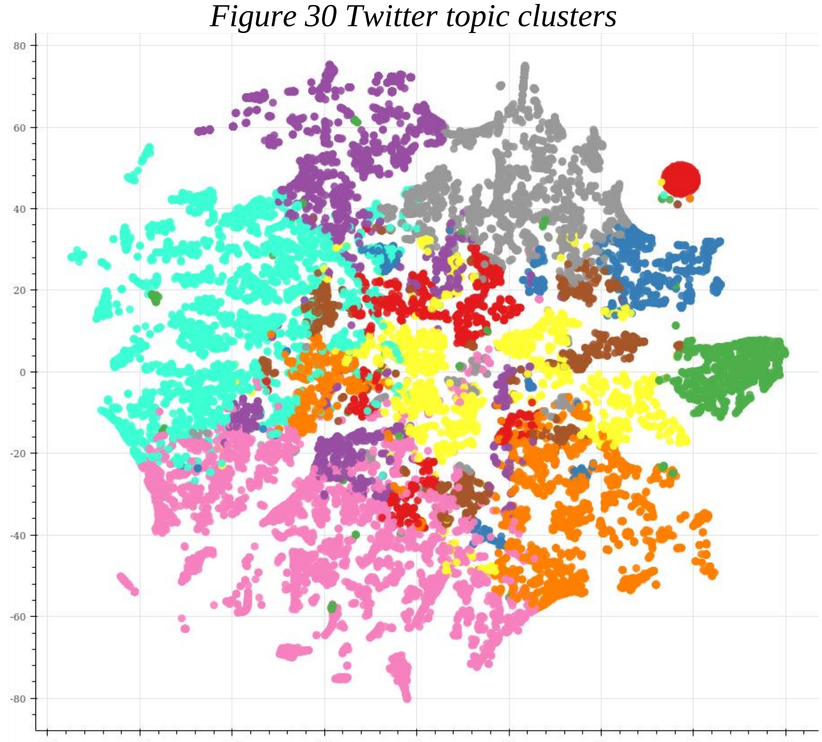

Figure 31 FEMA Twitter topic clusters

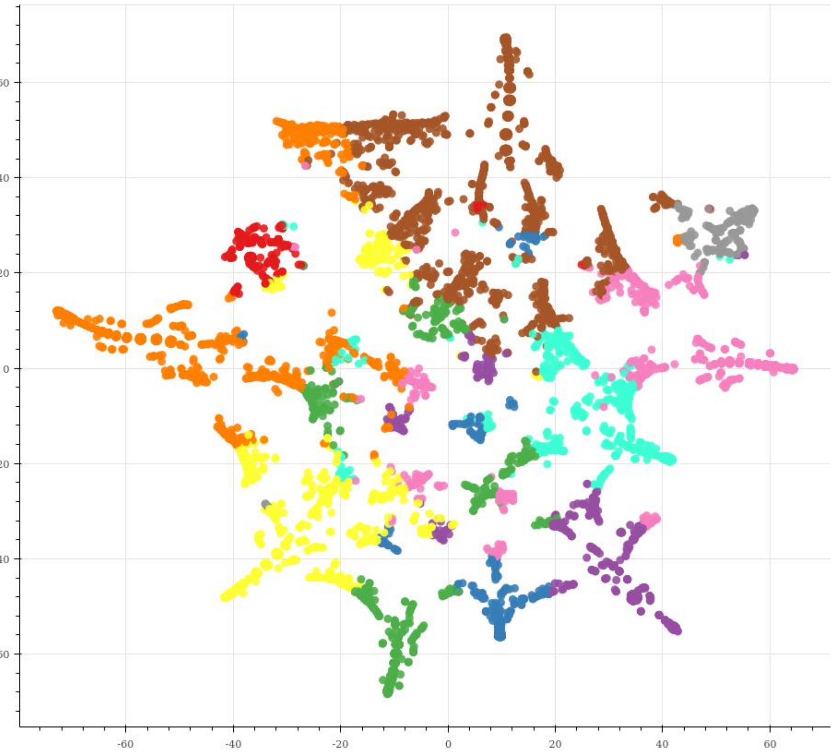

Figure 32 FEMA Facebook topic clusters

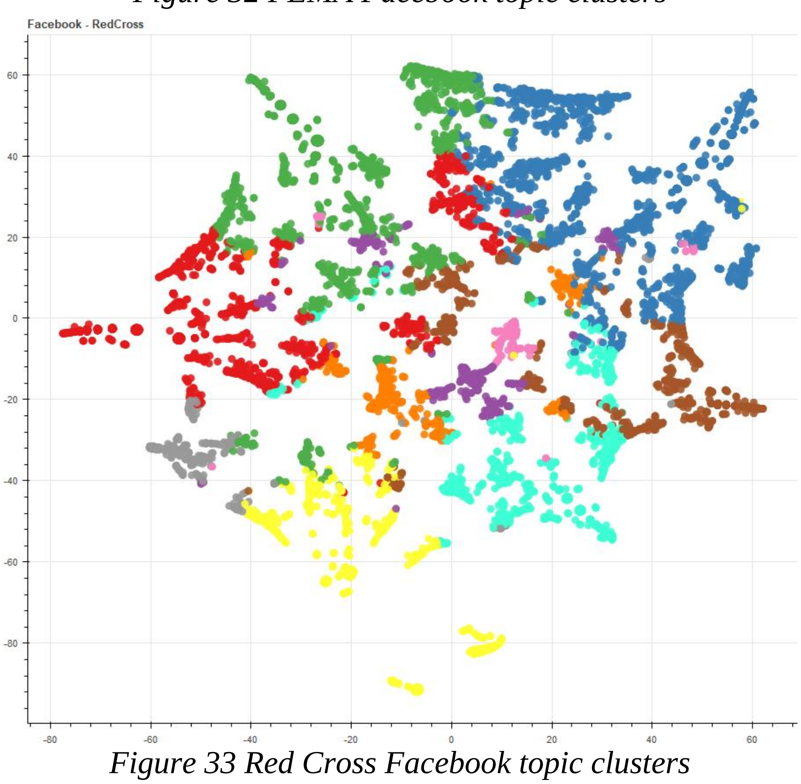

Figure 33 Red Cross Facebook topic clusters

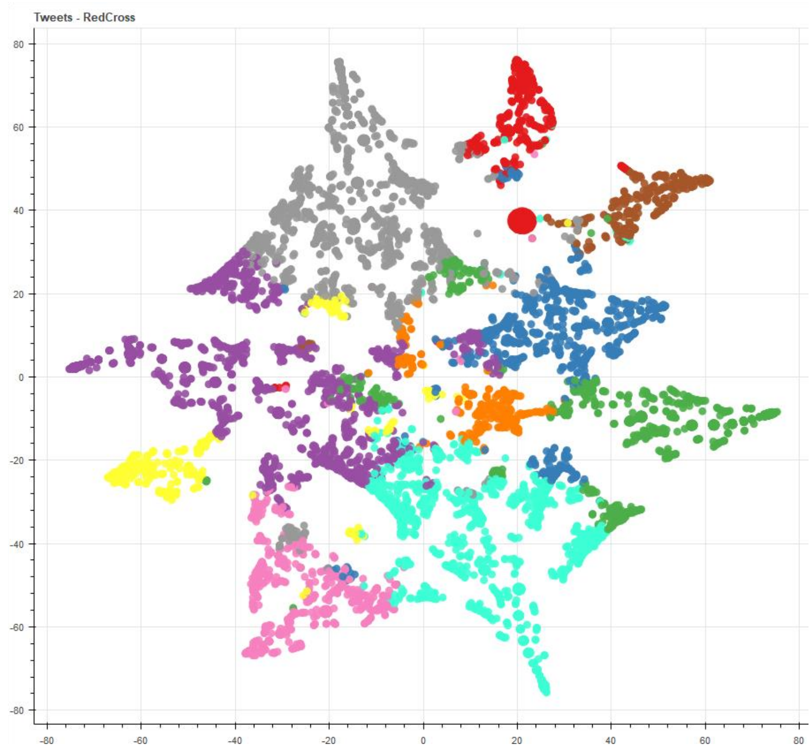

Figure 34 Red Cross Twitter topic clusters

The major difference between FEMA related communication of Twitter and Facebook is noise and variance in samples. Topics found on Facebook are far more heterogeneous in nature than Twitter. We can also observe clearly separated subgroups of texts for most topics on Facebook. For example, texts with complaints and grievances are grouped in a single topic. However, can be further divided into issue-specific subgroups. Though both samples produce similar vocabulary sizes of TF representations as seen in Table 9, feature vectors for Twitter communication are far sparser than of Facebook. The feature vectors become far sparser, with extremely small amount of non-negative occurrences compared to the total size of the sparse matrix while using n-grams for representation of terms. That is 0.1279% non-negative occurrences for TF, and 0.0312% non-negative occurrences for n-grams.

Table 9 Vocabulary length for various feature selection techniques

	Bag of Words (TF)	**N-grams (1-3 range)**	**BoW + POS Tags**
Twitter	13930	96965	23547
FEMA - Facebook	13449	169508	36584
FEMA - Twitter	15958	153151	45758
Red Cross – Facebook	12481	181838	34596
Red Cross - Twitter	17611	130762	43687

CHAPTER VIII:

CLASSIFICATION AND RESULTS

Classification Techniques and Considerations

During our literature review, we identified the most commonly used classification algorithm widely used for text classification problems. Naïve Bayes classifiers, Support Vector Machines (SVM), Maximum Entropy classifiers, and Boosted Decision Trees are some of the most common classification techniques used techniques.

We review these techniques to see if they fit the criteria of our application, i.e. accurately classifying sparse vectors with high dimensionality.

Naïve Bayes Classifier

Naïve Bayes (NB) classifiers are family of classifiers based on popular Bayes theorem. Naïve Bayes classifiers build simple yet well performing linear models, especially for text classification problems. They are also preferred as being computationally inexpensive. The term "Naïve" comes from the assumption that features in a dataset are mutually independent. These classifiers tend to perform well for small sample sizes.

Bayes rule can be applied to documents and classes.

For a document d and a class c.

$$P(c|d) = \frac{P(d|c)P(c)}{P(d)}$$

Naïve Bayes classifier can be defined as

$$Most\ Likely\ Class = argmax\ P(c|d)$$

$$= argmax \frac{P(d|c)P(c)}{P(d)}$$

$$= argmaxP(d|c)P(c)$$

where $c \in C$

$d = (x_1, x_2, x_3, \ldots, x_n|c)P(c)$

NB classifiers generally work better for social media data because they are robust to irrelevant features. They do not suffer from fragmentation, where there are many equally prominent features. NB also performs optimally if features are mutually independent.

However, the assumption of independence does not hold up in our application. These vectors contain many interdependent features due to common phrases and constructs, generally, it does not affect the accuracy negatively due to limited vocabulary in TF/TF-IDF vectors. However, after heavy text cleaning and processing, we still observe extremely high dimensionality or vocabulary sizes for our TF/TF-IDF vectors. This high dimensionality occurs due to a varied range of topics captured in the entire dataset. If NB classifiers are used to classify texts in select few closely related topics, then these independent models perform much better.

In our initial classification tests, we observed 0.585 accuracies for classification on the whole dataset while an average of 0.742 accuracies on independent NB models.

Support Vector Machines (SVM)

Support vector machines are based on the Structural Risk Minimization principle (Vapnik 2000). For two-class, separable training data sets, there are lots of possible linear separators. Intuitively, a decision boundary drawn in the middle of the void between data items of the two classes seems better than one which approaches remarkably close to examples of one or both classes. While some learning methods such as the perceptron algorithm find just any linear separator, others, like Naive Bayes, search for the best linear separator according to some criterion. The SVM, in particular, defines the criterion to be looking for a decision surface that is maximally far away from any data point. This distance from the decision surface to the closest data point determines the margin of the classifier. This method of construction necessarily means that the decision function for an SVM is fully specified by a subset of the data which defines the position of the separator. These points are referred to as the support vectors.

SVMs are very universal learners. Fundamentally, SVM can learn linear threshold function. By using a simple plug-in of an appropriate kernel function, SVM can be repurposed to learn polynomial classifiers. SVMs perform well independently of the dimensionality of the feature space. SVMs work well with text categorization because SVM (i) can work with high dimensionality are resistant to overfitting, (ii) can work with sparse vector space, and (iii) can provide both linear and polynomial classifiers.

In our initial classification tests, we observed 0.751 accuracies for classification on the whole dataset while an average of 0.753 accuracies on independent SVM models.

Since SVMs performed better than NB with the whole dataset, while an only slight improvement over independent SVM models we narrowed down SVM for our final evaluation.

Modeling and Encoding Network Features

Researchers have utilized various methods to model and represent network features that can be used with a machine learning algorithm (Hu, L. Tang, et al. 2013; Tan et al. 2011). The two tried and tested approaches are (i) modeling object-object relations in a matrix, and (ii) indexing network features as numerical values that can be added to the feature vector.

(Hu, L. Tang, et al. 2013) uses the former approach, paired with proposed SANT algorithm that has successfully improved the accuracy of sentiment classification.

However, it is not suitable to use with the sparse network of users and topics. It also posits limitation while changing how relationship strength between objects is determined, by requiring to recompute matrices for all one-to-one relationships. (Tan et al. 2011), on the other hand, opts for a simpler approach of indexing and encoding network features as a numerical value that can be appended to feature vector. This approach can be extended and used with diverse types of social relations of different arities without modifying the classification algorithm. This approach allows us to use these features in multiple ways.

A) Combining Network Features with Textual Features

The network features can directly be combined with text feature vectors. However, doing it directly with sparse TF or TF-IDF representation is ineffective as the produce vectors are of extremely high dimensionality. To effectively combine distinct types of features the dimensionality of VSM representations can be reduced. Singular value decomposition (SVD) and Non-negative matrix factorization (NMF) can be used to reduce the dimensionality of such representations efficiently (Nylen and Wallisch 2017). This makes managing normalization and regularization of encoded features easier.

B) Combining Network Features with Sentiment Scores

Another approach is to use multi-tiered classification model, where different classification models are trained to use distinctive features. First, we train the sentiment classification model to classify documents using only textual features. Then, we use the confidence scores of predicted labels as a feature that represents a sentiment score of the document. Secondly, we train another model with previously predicted sentiment scores and encoded network features

Both of these approaches have their distinct set of advantages and disadvantages. For approach A, the textual features are required to be compressed. However, corpora with high variance as we witness in our samples is difficult to compress without losing a lot of information. Which, in turn, can affect the accuracy of the classification. In order to reduce information loss, we need to increase the components that correspond to latent topics in documents. To determine the number of components for dimensionality reduction using SVD, we need to first explore the number of meaningful topics and subtopics in a sample.

In our study, we opt for the latter approach, the approach B, though it offers more flexibility with selection of suitable machine learning algorithms and training both models separately allowing modification to one without affecting another, requires exceptionally large amount of labeled data as the second model has to be trained only from the results of the first model, avoiding any overlap between testing, verification, and validation sets.

Results & Evaluation

This chapter summarizes the classification results for all five datasets. As a standard in most sentiment analysis studies, we use accuracy as our evaluation metric.

The results of classification models are summarized in following tables, Table 10 for the Twitter dataset, Table 11 and Table 12 for FEMA datasets, and Table 13 and Table 14 for Red Cross datasets. The feature weights are a degree of influence of individual features that influenced the prediction using a model. We can use feature weights to identify prominent features in the classification model and diagnose our models any irrelevant features. Feature weights closer 0 have little to no influence over prediction.

Table 10 Classification: Hurricane Harvey Searches – Twitter

	Textual Features	**With Group-Topic Network Features**
TF	0.892	**0.928**
TF-IDF	0.882	
TF N-grams	**0.906**	
TF-IDF N-grams	0.880	
Feature Weights	**y=Positive** top features **Weight? Feature** +1.528 <BIAS> *… 3225 more positive …* *… 9705 more negative …* -0.951 terrible -0.978 trump -1.016 worst -1.017 not -1.076 didn -1.155 stopped -1.213 bad -1.650 worse -1.775 donate	**y=Positive** top features **Weight? Feature** +2.001 x2 -1.000 <BIAS>

Table 11 Classification: FEMA Official – Facebook

	Textual Features	**With Group-Topic Network Features**
TF	0.702	**0.782**
TF-IDF	**0.761**	
TF N-grams	0.727	
TF-IDF N-grams	0.749	
Feature Weights	**y=Positive** top features **Weight? Feature** +6.038 great +4.902 thank +4.196 our +4.015 thank you +3.380 finally *… 51826 more positive …* *… 47481 more negative …* -3.505 why -4.110 please -4.528 trump -5.871 no -6.096 not	**y=Positive** top features **Weight? Feature** +2.730 x1 -1.667 <BIAS>

Table 12 Classification: FEMA Official – Twitter

	Textual Features	**With Group-Topic Network Features**
TF	0.760	**0.780**
TF-IDF	**0.771**	
TF N-grams	0.762	
TF-IDF N-grams	0.658	
Feature Weights	**y=Positive** top features **Weight?** **Feature** +4.352 employees +4.178 prison +3.988 inmates +3.796 yoruba +3.307 registration +3.264 conditions *… 4024 more positive …* *… 3764 more negative …* -3.188 shame -3.375 bs -3.468 answers -3.503 millions	**y=Positive** top features **Weight?** **Feature** +1.866 x1 -0.025 x0 -0.937 <BIAS>

Table 13 Classification: American Red Cross Official – Facebook

	Textual Features	**With Group-Topic Network Features**
TF	0.724	**0.864**
TF-IDF	0.788	
TF N-grams	0.824	
TF-IDF N-grams	**0.841**	
Feature Weights	**y=Positive** top features **Weight?** **Feature** +4.725 thank +3.934 great +3.460 years +3.048 ready +2.777 amazing +2.772 opinions *… 3462 more positive …* *… 3302 more negative …* -2.670 scam -2.743 doesn -2.820 wrong -5.381 donate	**y=Positive** top features **Weight?** **Feature** +2.235 x6 +0.016 x1 -1.406 <BIAS>

Table 14 Classification: American Red Cross Official – Twitter

	Textual Features	**With Group-Topic Network Features**
TF	0.557	**0.633**
TF-IDF	0.584	
TF N-grams	0.567	
TF-IDF N-grams	**0.612**	
Feature Weights	**y=Positive** top features **Weight?** **Feature** +2.601 got *… 6454 more positive …* *… 5074 more negative …* -2.342 cnn -2.365 dyk -2.373 least -2.413 times -2.416 samaritanspurse -2.495 blooddonor -2.561 stuff -2.642 wonder -3.380 look	**y=Positive** top features **Weight?** **Feature** +1707.210 x2 +66.783 x1 +55.253 x0 +33.539 <BIAS>

We tested different combinations of data representations and feature selections techniques and classification using network features using the results from the previous model. As discussed in an earlier chapter, we trained two separate models to incorporate network features we do not require to test the second model for each data representation technique as we extend upon best results only. We find that using implicit network information improved accuracy by approximately 2% across all datasets.

CHAPTER IX:

CONCLUSIONS

Consisting of nine chapters, this thesis presents a comprehensive and in-depth research work in the field of sentiment analysis for disaster communication that is required to evaluate crisis communication theories and improve disaster communication strategies. Our focus is to improve the sentiment classification of disaster-related communication on social media that often suffers from poor data quality. In order to do that, we proposed incorporating implicit disaster-related social relations to improve sentiment classification of social media documents. Thereby, the problems faced in the real world and the research gaps have been identified in the first two chapters, which also provided the motivation of this research. Additionally, research questions and objectives have been formulated. To recap, the research questions are as follows:

1) *How implicit social relation between emergent citizen groups and issues can be extracted effectively?*
    a. *What data represent the issue discussed in a collection of social media posts?*
    b. *How accurately do topics describe issues discussed during a disaster?*
2) *Can implicit network information be used to improve sentiment classification accuracy?*
    a. *Does group-issues social relation correlate with sentiment labels?*
    b. *How much do implicit network features contribute to model accuracy?*
3) *How network information can be encoded as a feature in a classification problem?*
    a. *What are possible ways to combine numerical or categorical features with textual features?*

   b. *What algorithms or techniques are effective for classification using these techniques?*

4) *How sentiments can be presented at a meaningful level for disaster management?*
   a. *How sentiment classes can effectively be defined to represent disaster-related emotions?*
   b. *How complex sentiment classes can be generalized to binary polarity?*

Aiming to answer these questions we studied and evaluated different approaches and techniques in data representation, feature selection, feature extraction, and sentiment classification. We reviewed studies that employ explicit social relations to improve sentiment classification. We formally defined the research space in the context of disaster management, based on which we propose to extend relevant work in various aspects with the goal to facilitate disaster communication using social media We tested and evaluated our approach using data for different disaster management organizations from different social media platforms and observed that incorporating and using implicit social relation information improved the quality of sentiment classification by various degrees.

Summary of Contributions

- We proposed an emotion model adapted from the psychoevolutionary theory of emotions and attribution theory that breaks down complex emotions into basic emotions allowing us to formally define emotions and sentiments with clarity, eliminating any ambiguity that may occur due to misinterpretation. The proposed emotion model can be used for annotating documents with appropriate sentiments or generalize them at a higher level.

- We demonstrated and used topic modeling techniques to categorize texts based on disaster-related issues successfully and use that information to define the relationship between emergent citizen groups and issues.

- We extensively reviewed the importance of sentiment information in disaster-related information. We believe that sentiment classification on disaster-related sentiment classes can allow disaster managers to:
    - Identify issues with grievances
    - Identify and diagnose bottlenecks in disaster relief processes
    - Identify reputational threats and address the public's negative sentiment

- We reviewed various techniques of data representation, feature selection and encoding to determine suitable set techniques for studies that can be generalized over several types of social media platforms.

- We successfully evaluated the potential and use of implicit network data such as disaster-related social relations for improving sentiment analysis.

Future Work

- The techniques and data explored in this study allow us to explore and compare use patterns of various social media platforms by users and disaster management organizations. Understanding these use patterns can help improve disaster communication strategies for organizations such as FEMA and Red Cross.

- From Twitter datasets, we found that social media data for one platform during one disaster can be comprised of highly varied vocabularies limiting the effectiveness of extracting discussion topics using topic modeling methods by causing fragmentation of extracted topics over different vocabularies. We propose an ensemble of models combined with boosted algorithms for these vocabularies to classify these documents effectively.

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