Citizen Centric Stakeholder Theory: Sentiment and Behavior Analyses in Social Media

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Abstract of the Dissertation

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In a relatively short period of time, social media has gained significant importance as a mass communication and public engagement tool. Rapid dissemination of information through social media platforms such as Facebook and Twitter, provides individuals and organizations with the ability to broadcast their message to a wide audience instantly and directly. Hence, we now witness almost all public and private organizations with a presence on popular social networks. However, unlike conventional media, social media allows users to wield tremendous influence over popular discussion topics and events. While in traditional media, the narrative is built by a group of established influencers, discussions remain fluid and decentralized on social networks. Although some users do wield more sway than others, all citizens utilizing the platform are stakeholders who have to be recognized and managed if any entity wishes to use these platforms to carry out their mission. The primary goal of this research is to perform analysis of the social media data to gain insights and to better understand the nature of the discourse taking place on popular social media platforms and how sentiment, keywords and users impact these discussions. Such understanding is important to enable prime movers of social media to accurately identify and engage their stakeholders, enabling them to foster more meaningful communication with online social network users.

Towards this end, this dissertation has made the following contributions: First, it has developed a framework to analyze social media usage by adopting the time tested stakeholder theory for social media. It has proposed a Citizen Centric Stakeholder Theory for Social Media, where all users of social media platforms are treated as stakeholders. Second, it has utilized the above framework to investigate the nature and characteristics of social media usage by citizens from around the world. It has evaluated this participation through sentiment and user behavior analysis. As a case study, this dissertation has applied this citizen centric stakeholder theory to analyze Twitter data gathered during US Presidential Elections of November 2016 and UK General Elections of June 2017. Third, it has evaluated the social media communication of public sector organizations operating in the Northeast US to understand their communication strategy in terms of sentiment and message content. Fourth, it has studied the subjectivity and polarity of Twitter data with respect to the location of Tweets. Finally, a web-based system for geospatial visualization of current sentiments associated with a hashtag or word in Twitter messages has been developed.

Preface

Dissertation Committee Members

- Dr. Vijayalakshmi Atluri, Rutgers University
- Dr. Jaideep Vaidya, Rutgers University
- Dr. Soon Ae Chun, City University New York
- Dr. Basit Shafiq, Lahore University of Management Sciences

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Chapter 1

Introduction

We are now living in an era of momentous technological disruptions, which are transforming businesses, industries and overall society at a breakneck pace. One such disruptor is social media. Use of social media has increased exponentially over the last few years. Platforms such as Facebook and Twitter have not only changed the way we interact with one another but also how we share news and comment on world events at almost real time. These networks have provided their users with the power to decide which news event is more interesting or relevant for them. The potential of users to start trends and make some news more popular than others has remarkably changed how events are reported. People are now increasingly relying on them not only to interact with one another but also to read and share news, discuss important events and engage in political conversations. Additionally, proliferation of smart phones has further facilitated the use of this medium, allowing users to communicate without any limitation on time or location.

Facebook and Twitter are two of the largest social media networks in terms of the users. Facebook is the most popular social network and as of the 4th quarter of 2016, has 1.86 billion monthly active users [85]. Twitter on the other hand, averaged 328 million monthly active users as of 1st quarter of 2017 with as many as 500 million messages a day [87].

This massive number of people utilizing social media for information gathering and expressing their views has provided a unique opportunity for e-government initiatives, specifically with regards to communication between government institutions and citizens [61]. Over the years, governments around the world have worked to increase openness and transparency into the working of their institutions [11]. Social media in particular can play a constructive role in this regard. From civic services to police department, information sharing through Facebook and Twitter has provided organizations with the opportunity to increase institutional responsiveness and enhance citizen engagement [61, 28]. Recently there has also been an increase in interest in the use of social media during disaster communication. A wide range of studies suggest that information sharing networks, such as Twitter, can be very useful in times of crisis by quickly and effectively disseminating relevant news [78, 6, 75, 95, 48]. This can be especially beneficial for developing countries where state institutions have a relatively weak mechanism of public engagement and information dissemination.

Usage of social media has also increased during elections. The opportunity presented to engage with millions of online users has been recognized by politicians and political parties globally [77]. The potential role of social media in elections was first highlighted during the US Presidential elections of 2008. During those elections, the campaign of Barak Obama aggressively used Twitter to post campaign updates and inform followers with opportunities to volunteer [10]. Since then, use of social media has been growing globally for political campaigning during general elections. In the recently concluded US Presidential Elections of 2016, and the general elections of United Kingdom of 2017, Twitter played a very important role in the dissemination of information regarding various policy points for candidates and their respective political parties.

1.1 Motivation: Why Social Media Analyses?

The use of social media for advertising, publicity, campaigning and news will only continue to grow in the foreseeable future. One example of this growing importance of social media is by Forrester report [2], according to which internet marketing spending in United States alone will reach $103 billion by year 2019, surpassing broadcast and cable television advertising combined. Thus use of social media to engage users and to create an effective viral message will be of prime importance in the future. Governments, politicians, businesses and non-profit sector, now maintain a presence on social media to ensure they fully capitalize on this new medium of communication. Hence understanding social media users sentiment, their characteristics and behavior can greatly help any mover of online social networks to create a cogent and effective message.

This global rise in usage of social media has expanded the emerging field of techno-social systems, which aims to comprehend and predict behavior of users utilizing these networks [13]. Research in Twitter analytics concerning election prediction and candidate popularity have grown tremendously over the years as where some studies have even gone so far as to state that sentiment analysis of tweets can potentially be used as a substitute for traditional polls monitoring consumer confidence and political approval ratings [72].

Although this area of study is still evolving and a debate on the efficacy of using Twitter sentiment analysis to predict elections and other real world events still continues, this area is nonetheless generating a lot of enthusiasm [60]. Social media provides researchers access to large amounts of user data cheaply and quickly for analysis. Hence we are now witnessing an increased research in the area of social media analyses. From evaluation of marketing campaign success to predicting elections, the role of social media analytics will grow in the future as organizations move towards data driven decision making.

1.2 Problem Statements

In this dissertation we tackle the following four problems associated with social media analysis.

Firstly, due to the relatively decentralized nature of these networks, it becomes important to categorize social media users based on their online traits. Doing this will enable us to analyze these individuals based on their online attributes and better target them with our message.

To solve this problem of user categorization on social media, we develop a framework by adopting the time tested stakeholder holder theory. Stakeholder theory was developed in the 1980s to help managers understand and deal with various stakeholders of the organization. Adapting the stakeholder theory for social media will allow us to better identify users on social media. This framework will also help us understand behavior and sentiment of users during online conversations.

Secondly, research in social media data analytics concerning election prediction and candidate popularity have grown tremendously over the years. Various approaches and methodologies have been proposed to gauge public sentiment during elections.

In this dissertation, we applied citizen centric stakeholder theory framework to evaluate user sentiment and retweeting behavior on Twitter data gathered during US elections of 2016 and UK elections of 2017.

Thirdly, social media creates a tremendous opportunity for these public sector organizations to use established platforms such as Facebook and Twitter for bi-directional communication with citizens. Although most public sector organizations now maintain presence on social media, they are yet to exploit all the potential offered by this new medium of communication.

In this dissertation, we gather social data posts made by the official accounts of these organizations to gauge their communication strategy in terms of sentiment and message content.

Finally, there is rich user meta-data available with each message that is downloaded from Twitter. So far only few variables of from this data are being used in data analyses.

We utilized Twitter user location data to examine user subjectivity and polarity. We used data collected during the US Elections 2016 for this analyses, by mapping sentiment for each presidential candidate according to states. A web-based application was developed for this purpose, which allows for visualization of sentiments associated with a hashtag or word in Twitter messages by plotting them on a map.

1.3 Contributions of this Dissertation

The key contributions made by this dissertation are following:

- Performed data mining on Twitter data gathered during US Presidential Elections of 2016 to gauge sentiment and behavior of users commenting during the elections.
- Created a theoretical framework which using stakeholder theory which can be used to evaluate social media discussions.
- Applied this framework on Twitter election data gathered during US Presidential Elections 2016 and UK General Elections of 2017 to study user sentiment and retweets.
- Evaluated social media communication, in terms of sentiment and message content, of organizations operating in various areas of public service in the Northeast US.
- Analyzed Twitter sentiment in terms of location by examining the subjectivity and polarity of Twitter data with respect to location of tweets.
- Finally, we developed a web-based application that allows for visualization of current sentiments associated with a hashtag or keyword in Twitter messages by plotting them on a map.

Fig. 1.1 shows all the studies conducted in this dissertation along with the proposed future work.

1.4 Organization of the Dissertation

This dissertation is organized as follows. In the second chapter we will define our methodology for data gathering and cleaning along with describing the tools and methodology for sentiment analysis and data analysis. Chapter 3 presents a study of Twitter mining for user sentiment and behavior analysis. In chapter 4 we provide background on the popular Stakeholder Theory and explain its adaptation for social media while in chapter 5 we discuss the applications of this theory on Twitter discourse during the US Elections of 2016 and UK General Elections of 2017. In chapter 6 we analyze social media communication of public sector organizations in terms of sentiment and message content while in chapter 7 of the dissertation we perform location based analysis of Twitter election data. In chapter 8 we present our web-based application, developed for the purpose of location based Twitter subjectivity and polarity analyses while in the final chapter we present our contributions and future work.

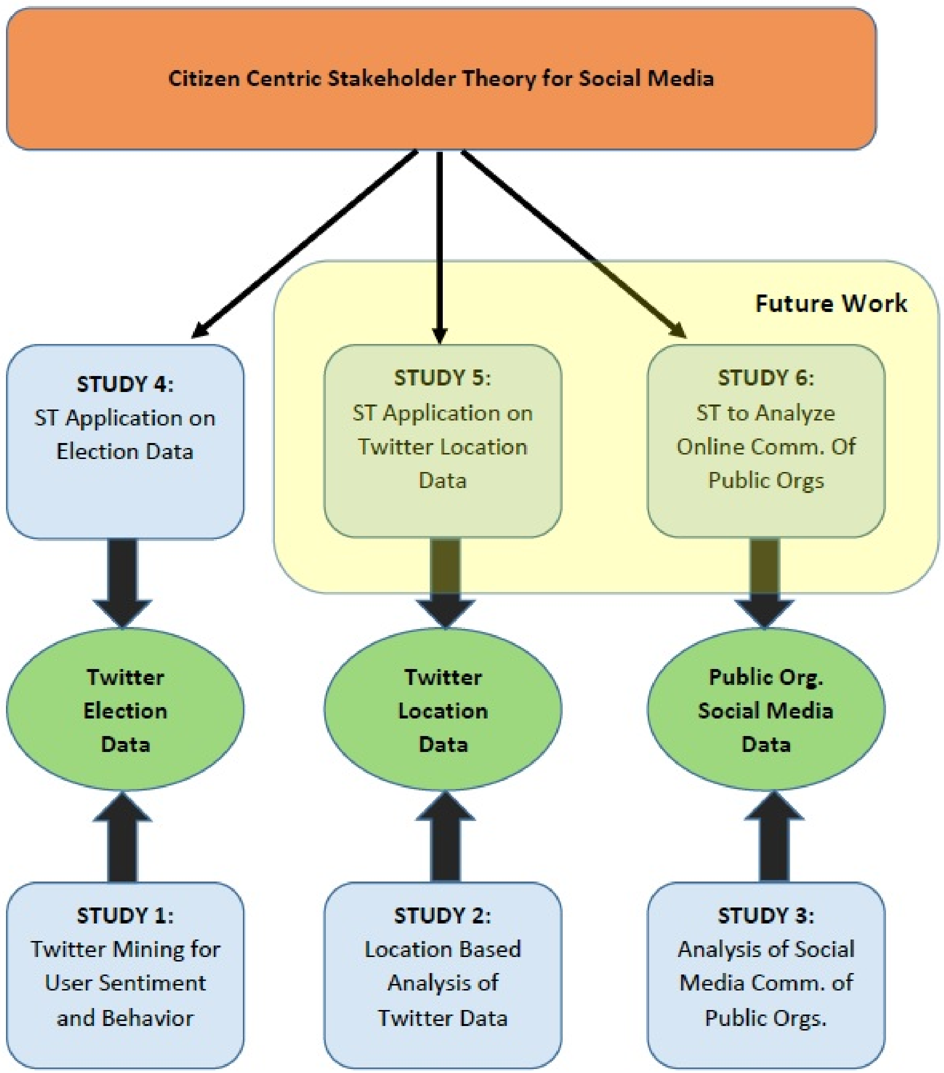

Figure 1.1: Dissertation overview. Four studies completed in this dissertation, along with the 2 planned as future work.

Chapter 2

Data Preparation Methodology

The role of Internet and communication technologies (ICT) in modern society cannot be understated. Individuals and institutions around the world are trying to increase public engagement by utilizing Web 2.0 [11, 61]. This provides a quick and cost effective platform to political actors and state institutions to communicate quickly and directly with public [43]. For example, Twitter is now being used by city governments to benefit their populations by raising information awareness in a simple, low cost fashion. The idea is to enhance the responsiveness of different branches of local governments that deal primarily in performing tasks on behalf of the citizens and interacting with them [61].

Along with governance, Twitter sentiment analysis is also used in vast array of areas related with governance and public trust ranging from predicting resentment against government policies to predicting general election results [20, 93]. Various models have been developed that try to understand the user behavior and retweeting on Twitter [99].

In light of this important role played by Twitter in the general elections, our aim was to utilize user and candidate generated data to understand the nature and behavior of the online discussion. Our approach relied on data gathered from Twitter and performing data analytics to understand the nature of discussions and user behavior on the micro-blogging site. Our methodology comprised of the following steps:

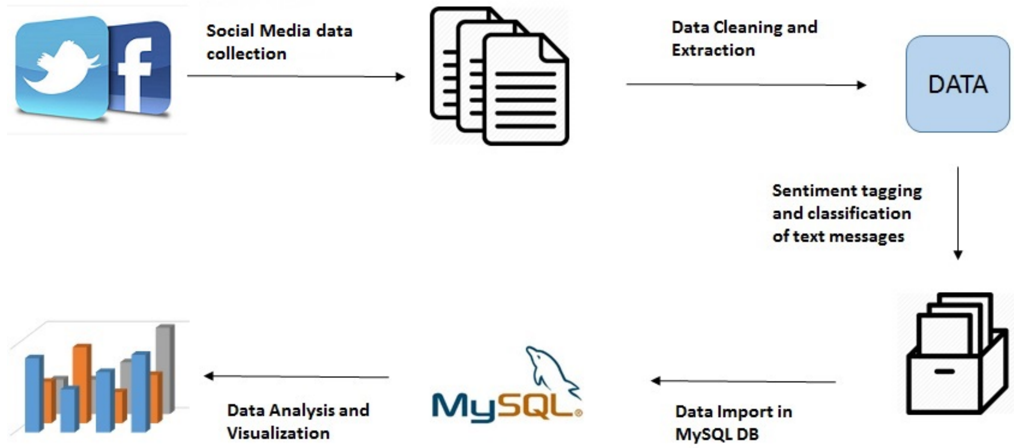

Figure 2.1: Methodology steps involved in Twitter Data Analysis.

- Use of search terms, location co-ordinates, Facebook and Twitter pages to gather user data.
- Data cleaning and extraction.
- Sentiment tagging and classification of text messages.
- Importing data in MySQL database to perform data analysis.
- Development and formulation of hypotheses and derive findings through data analysis, proving or disproving the hypotheses.

We employed Python to gather and clean Twitter and Facebook data. SentiStrength [86], an open source software, was used to identify message sentiment while data analysis was performed using the MySQL database. Fig.2.1 displays the above mentioned steps.

2.1 Data Gathering

We utilized Twitter streaming API for data collection [7]. The streaming API allows near real time access to global stream of Twitter data. For this dissertation we collected Twitter data for the US Presidential Elections November 2016 and UK General Elections of June 2017. We have also gathered data from Twitter and Facebook of public sector organizations that utilize these social media platforms for public engagement and communication.

The US presidential elections were held on 8th November 2016. The dataset for these elections was downloaded for 12 days starting from 29th October until 9th November. Scientific studies use hashtag or keywords to download messages as presence of keywords indicate message relevance to the given topic. In our case, we use the keywords 'Trump', 'Clinton' and 'Election2016' to download tweets. Here we have the two major candidate names along with an impartial term to capture neutral sentiment.

Voting for UK general elections was held on 8th June 2017. Here we downloaded data for 15 days starting from 26th May 2017 to 9th June 2017. The tweets were downloaded containing the keywords, 'Jeremy Corbyn', 'Theresa May', 'Tories', 'Labour' and 'GE2017'. Here we used names of the two major political parties and their heads along with the neutral terms of 'GE2017'.

Scientific studies using Twitter messages either employ hashtags or specific keywords to collect relevant data. Both approaches follow the same principle that hashtags or keywords indicate messages' relevance to a given topic [77].

Using search terms to download data makes these datasets partial for election studies and are biased in such a way some members of the population are less likely to be included. Hence the results of this study regarding social media stakeholder theory will be applicable to the use of social media during general elections only.

Along with keywords, we have also used location parameters to download Twitter data using the streaming API. Here we created a bounded box along a geographical location and all location tagged tweets emanating from that bounded area are captured. However a very small percentage of tweets are location tagged (between 1 to 2%). For each tweet downloaded, we extracted metadata details such as tweet time and date, its id, creator id and user name, location, etc.

Facepager application was used to download Facebook data for analysis [31]. Facepager allows users to fetch public available data from Facebook by using JSON based API. We used Facepager to download posts and comments from Facebook pages of public organizations and famous individuals. The comments and posts also contained metadata such as likes, shares etc.

2.2 Sentiment Analysis Process

With data cleaned and relevant tweet fields extracted, the text messages are then analyzed and tagged with sentiments using SentiStrength [86]. SentiStrength is a freely available software that has been used to perform sentiment analysis in various studies utilizing Twitter data [33, 20, 32]. One of the advantages of using SentiStrength is that the tool has been specifically developed to capture sentiment of short, informal texts [92]. Studies conducted on short texts have shown this tool to be able to capture positive sentiment with 60.6% accuracy and negative sentiment with 72.8% accuracy [91]. Hence, this makes SentiStrength an ideal tool for our exploratory analysis. SentiStrength operates by assigning two scores to each text message it analyzes. It assigns a negative and a positive score, with the scores ranging between [-1, -5] and [1, 5], respectively. A score of -1 or 1 indicates a somewhat neutral text sentiment while a score of -5 or 5 indicates a very high negative or positive sentiment respectively. In-order to classify a tweet as overall positive or negative, we assigned a total sentiment score to each tweet. To do this, we have added both the positive and negative sentiment scores for each tweet as a total sentiment.

$Sentiment(total) = Sentiment(positive) + Sentiment(negative)$

Thus, a total sentiment score of 4 (or -4) indicates a strong positive (or negative) sentiment for the tweet respectively while if the total score adds to 0 then the tweet can be classified as neutral. Finally, the sentiment tagged text messages and the associated metadata are stored in MySQL database for further analysis.

2.3 Data Cleaning

To increase accuracy of our analysis, the next step is to remove noise from our dataset. Presence of spam on Twitter is a well-known phenomenon. Although Twitter tries hard to identify and remove automated accounts, not all bots are easily identifiable as social bots are designed specifically to impersonate human behavior. Much research has been conducted to identify automated non-human activity on Twitter. It has been found that up to 10.5% of Twitter accounts might be bots [24]. Studies have also concluded that as high as 9% of tweets are generated by automated accounts [42]. In order to identify and remove spam present in our dataset in the form of automated activity, we have removed tweets belonging to accounts having abnormally high tweet rates. Through literature review of various studies, we have discovered that users tweeting over 150 times a day can be safely classified as bots [89]. We have found this to be a safe assumption and decided to remove all tweets from our dataset where the associated account had an average of over 150 tweets a day. We have also removed from our dataset, tweets associated with accounts having names such as iPhone giveaways etc. as these tweets are not intended to add towards the political discussion but are rather promotional in nature.

2.4 Data Classification

We performed quantitative analysis of our data set. For this purpose, we utilized following proxies for our Twitter dataset:

- Tweets that are not original and are retweeted by the user contain **RT** string at the beginning of the message. Original tweets do not contain this string. Furthermore, in our dataset, retweets have their original creation date and tweet id. These fields are NULL for new tweets.
- Hashtags (**#**) make user tweets searchable, enabling them to become part of Twitter

trends.

- When a user tweets directly to another twitter user, the message begins with @ character. Hence, tweets beginning without @ are broadcast intended for all audiences while tweets starting with @ are direct messages.

These proxies help us to perform analysis regarding citizen-to-citizen interaction, popular messages and frequent discussion topics.

Chapter 3

Twitter Mining for User Sentiment and Behavior

3.1 Related Work

The potential role social media can play in political events was first highlighted during the US Presidential elections of 2008. Twitter played an important part in the campaign of Barack Obama. The Obama campaign made effective use of Twitter to post campaign updates along with informing followers of opportunities to volunteer [10]. During the 17 months of the election campaign starting from April 2007 to Election Day November 5th 2008, the Obama campaign posted 262 twitter messages and gained approximately 118,000 new followers [38]. In light of this successful Twitter campaign, all major candidates and political parties now have some form of presence on social media.

Furthermore, with an average of 328 million monthly active users as of 1st quarter of 2017 [87], Twitters massive user base has provided political actors with the opportunity to share their message across quickly and cheaply without going through the traditional media briefings and news conferences [77] and to receive the number of opinions without going through formal opinion surveys or polls.

The emerging field of techno-social systems aims to comprehend and predict this behavior. Research in Twitter analytics concerning election prediction and candidate popularity have grown tremendously over the years as well [93, 99, 55, 103, 79]. Some studies have even gone so far as to state that sentiment analysis of tweets can potentially be used as a substitute for traditional polls monitoring consumer confidence and political approval ratings [72]. Although this area of study is still evolving and generating a lot of enthusiasm, nonetheless, a debate on the efficacy of using Twitter sentiment analysis to predict elections and other real world events still continues [37, 65, 54]. Important questions such as how representative Twitter users are of general population remain to be answered. These issues become acute when these analyses are conducted on data obtained from developing countries where a relatively small percentage of population has access to internet.

Another aspect is the varying levels of user activity. Some users are far more active online than others online thus having a greater ”weight” to their opinions when compared with the low activity users. There also exists much noise on Twitter in the form of automated activity and spam, which exploit trending topics to advertise various unrelated products or content. Different solutions have been proposed to differentiate between human activity and that generated by bots [24].

Other studies have looked at how the information spreads on social networks and what role sentiment plays in diffusion [33]. Most agree that sentiment does play an important role in information diffusion on twitter. Some have gone as far as saying that there exists a positivity bias in information spread and that positive tweets are retweeted more and reach a wider audience than negative tweets [32, 33].

With regards to the use of Twitter in politics, researchers have examined the ways in which Twitter influences communication of mainstream news and journalism. Recent research shows that social media in general and twitter in particular are playing an important role for mainstream media as a news source. This can be in form of a quote, background information or policy issues outlined through Twitter messages by politicians or other political actors such as news commentators and observers [73]. Twitter is now ever more used as news agenda building tool for mainstream media [96, 50]. This was a very commonly observed phenomenon during the recently concluded US elections of 2016. Utilization of Twitter by politicians and their campaigns is a popular subject of study. Usage of Twitter during the campaign cycle of 2008 in USA by Barack Obama generated interest in understanding Twitter's role in political campaigns [5, 10]. Similar research was also conducted in analyzing Twitter activity of US Congress members during their election campaigns. Studies showed that congress members frequently posted information on Twitter regarding their political positions on various issues along with details of issues relating with their constituencies [38, 39].

Social media user behavior analysis has also been conducted from the knowledge creation and sharing perspective in e-government context. Studies have been conducted on evaluating knowledge creation and sharing behaviors depending on the level of activity of individual Twitter users [84]. User tweeting behavior in-terms of reusing existing content vis-a-vis new content creation can be dependent upon how frequently they tweet.

In the recent US Presidential Elections of 2016, Twitter played a very important role in the dissemination of information regarding various policy points for both major Presidential contenders, Hillary Clinton and Donald Trump. Both candidates had millions of followers on Twitter and had their tweets closely monitored by public and by the mainstream media. A similar trend was observed in the General Elections held in the United Kingdom on 8th June 2017.

Although it is hard to quantify the role Twitter played in the 2016 elections, majority agree that it was significant. The role of on-line fake news became a hot topic after the surprising result of the US Presidential Elections [3, 4]. The impact of was so significant that prior to the United Kingdom General Elections of June 2017, Facebook advertised full-page print ads in British national dailies featuring tips for spotting fake news. This realization of the importance of social media means that political players cannot ignore it's role during elections. The power of social media as a communication channel, does not lie only in its ability to share their political agenda but also as a real-time two-way channel to continuously monitor and measure public reactions. Overall, social media presents an exciting avenue of opportunity for politicians, campaigners and political activists to not only broadcast their message but also to engage in dialogue with proponents of competing political ideas and ideologies.

In this chapter of our dissertation, we investigate the citizen engagement in the political discourse that took place on Twitter during the US Presidential Elections of 2016 by analyzing the citizen's sentiments and behavior. Our goal is to answer the following research questions:

- Topic and sentiment analysis of Twitter elections dataset: The aim here is to detect if there is a significant correlation between the sentiment and topics discussed on Twitter with the actual citizen opinion and real world events and breaking news of the period. This relationship between sentiment and popular trends on Twitter with the real-life events shows the citizen engaged Tweets can be used as a good predictor of the importance of certain topics and the opinion of public regarding the two primary Presidential candidates and the elections in general.

- Sentiment and impact analysis of tweets by the presidential candidates: The purpose of this analysis was to utilize candidate tweets to evaluate the sentiment of messages posted by both candidates in the last days of their campaign. This allowed us to assess the overall message propagated by each candidate. We also assessed the impact of candidate tweets on the sentiment of the overall discussions taking place on Twitter during this period.

- Analysis of social media user's behavior: The social media usage behavior analyses aims to identify how much Twitter users were using the online forum to speak their minds and engage with one another. The usage behaviors of social media users includes whether there was diversity of opinions and open interaction between users, or whether Twitter was used as an echo chamber, where few opinions were repeated over and over again as retweets with little one-to-one interaction between users.

We performed data analytics on Twitter data to answer these research questions. Over 3.1 million tweets were gathered for 21 days consecutively, starting from 29th of October, up until 18th of November 2016. We collected 150,000 tweets per day on average, which were then used to analyze user behavior and sentiment during this period. In addition, we also analyzed tweets posted by the two major Presidential Candidates, Hillary Clinton and Donald Trump, both of whom used Twitter actively for electioneering. We considered all messages of both candidates leading up to Election Day (8th of November).

3.2 Data

United States of America has the highest number of Twitter users in the world. As of May 2016, there are approximately 67.5 million active users of the microblogging site in the country [87]. This large user base combined with a significant event such as the elections makes Twitter data an ideal case study of social media usage in political discourse. Furthermore, both presidential candidates made extensive use of social media for campaigning. Twitter was used for various purposes: from outlining policies on issues such as security, economy and healthcare to promoting slogans. Twitter was one of the favorite communications tool for Donald Trump, who utilized it regularly to react to news concerning his candidacy and other issues of importance as they rose before and after a hotly contested election.

The data preparation methodology is explained in detail in chapter 2 of the dissertation. In total, 3,108,058 user tweets were used for this study.

A total of 209,370 tweets were identified as having generated by abnormally high activity accounts or by accounts that had names or descriptions that can be classified as spam.

Table 3.1: Dataset Statistics

Tweets per User	Total Tweets	Total Users	% all users	% of all tweets
1	781,575	781,575	69.09%	26.96%
2	309,675	154,964	13.70%	10.68%
3	178,293	59,487	5.26%	6.15%
4	127,424	31,896	2.82%	4.40%
5 or more	1,501,726	103,310	9.13%	51.81%
Total	2,898,693	1,131,232	100%	100%

After excluding the spam tweets, we were left with 2,898,688 tweets for 21 days generated by 1,131,232 unique users. It is interesting to note here that while the average tweet per user in our data set was 2.56, the top 9% of the users were responsible for almost 52% of the tweets while around 69% of users have only 1 associated tweet. Table 3.1 below has the dataset details.

3.3 Research Questions

As discussed earlier, aim of this Twitter mining study was three-fold. Firstly, we wanted to perform sentiment and topic analysis of user tweets to see their correlation with the real world events and breaking news in context of the elections. Secondly, we aimed to assess the impact of political candidate's tweets on the sentiment and discussions of the political discourse taking place on Twitter during this period. Finally, we wanted to evaluate the Twitter as a platform for political discussions with respect to exchanging original thoughts and ideas and interaction between citizens. We now hypothesized these three areas of Twitter research and then tested those hypotheses through data analysis.

3.3.1 Topic and Sentiment Analysis of Twitter Messages

Our first objective was to comprehend political discourse on Twitter by the users. Here we wanted to study the popular topics of discussions along with the sentiment of the Twitter messages and discover their correlation with the real world events and opinions. The purpose of this analysis was to measure how accurately Twitter reflected the public mood and concerns regarding the elections.

Due to the instant nature of communication on Twitter, the microblogging site can be used as a real time latest news identification tool. Several studies have been conducted in this regard, which attempt to identify real world events by analyzing Twitter streaming data [63]. Studies have claimed that based on trending topics based on active time period of tweets showed that as many as 85% of topics are headlines or persistent real world news [22]. Studies have also claimed that Twitter allows users to engage in real-time discussion of live televised broadcasting. Hence during major sports, entertainment and political events, Twitter is used to provide running commentary of real-time world events as they unfold on live television [44]. Thus, we can state that analysis of daily tweets can provide us with the current news events taking place in the real world. We analyzed our Twitter dataset to search for most high frequency daily terms. We then matched these terms with the most important election related news items of the day.

Similarly, Twitter sentiment has also been used in various studies ranging from predicting elections to calculating approval ratings. Studies have been conducted for example to discover correlation between tweets sentiment and public opinion polls. A high correlation of 80% was claimed by one study between the Index of Consumer Sentiment (ICS), conducted by Reuters, and Twitter sentiment [72]. The study also found high correlation between Gallups daily tracking poll for job approval rating of President Barack Obama and Twitter sentiment over the course of 2009. According to the authors this high correlation between Twitter sentiment analysis and public survey data indicated potential of tweets as a substitute for the traditional polls [72].

We used our Twitter dataset to evaluate the sentiment associated with both candidates. We examined which candidate had better sentiment in the online Twitter discussions prior to the Election Day. The result was compared with the polls conducted during this period in time, majority of which had declared Hillary Clinton ahead of Donald Trump.

Hence, in light of the above discussion, we proposed the following hypothesis:

Hypothesis 1 (H1): *Frequency of popular terms in Twitter discussions and Sentiment of Twitter messages are correlated with real world events of significance and with public opinions of the citizens regarding the elections.*

The above hypothesis helped us in identifying the association between Twitter and real world events and opinions during the elections. In order to test this hypothesis, we performed the following data analytical steps:

- Sentiment analysis of the entire Twitter dataset, and of tweets mentioning both candidates, calculating average daily sentiment from Oct 29th Nov 18th 2016.

- Analysis of the most frequently appearing terms in the Twitter conversations during the elections, comparing these with the significant real world events and breaking news.

We believe that our large dataset allowed us to accurately identify public sentiment towards the elections and both of the candidates along with detecting the important events that took place during this period.

3.3.2 Sentiment and Impact Analysis of Candidate Twitter Messages

The second component of our study was to analyze Twitter messages of both candidates, Donald Trump and Hillary Clinton. The objective of this analysis was to evaluate the nature and sentiment of the messages conveyed by each candidate along with assessing the impact of those tweets on the overall political discourse on Twitter.

The first step in this regard was to perform sentiment analysis of tweets by both candidates during the last days of election campaign. Twitter sentiment analysis has been used in the past to understand message and profile of political candidates. Tumasjan et al [93] used sentiment of Twitter messages to understand the political positions of various candidates during the German federal elections. The authors discovered that Twitter sentiment does indeed correspond to the offline political landscape and similar sentiment profiles for example of Angela Merkel and Frank-Walter Steinmeier did indeed reflect their consensus building political style.

We too performed sentiment analysis of the Twitter messages posted by both candidates during the last 10 days of election campaign. This helped us evaluate sentiment of the campaign tweets propagated by both camps enabling us to discern which candidate had a more positive message. However, we also wanted to assess the impact, if any, of these messages posted by each candidate on the overall political sentiment expressed towards on Twitter during this period. We believe that in context of general elections, Twitter messages by the political candidates have an impact on the overall online discussion taking place online.

Hence we propose the following hypothesis: **Hypothesis 2 (H2):** *Sentiment of messages by political candidates during the election campaign has an impact on the sentiment of the overall political discourse taking place on Twitter.*

In order to test the above hypothesis, we performed the following data analytical steps:

- Analysis of Twitter messages by both Presidential candidates during the last 10 days of election campaign, from Oct 29th Nov 7th 2016.
- Evaluate impact of candidate tweets in terms of sentiment on all election related discourse taking place on Twitter during this period.

3.3.3 Analysis of User Behavior

Along with the sentiment analysis, we also wanted to observe the behavior of ordinary users who engaged in Twitter conversations during the course of the Presidential Elections 2016. In this case, we wanted to discern how actively Twitter users were participating in election related discussions. We were particularly interested in understanding the role of Twitter in context of discussion concerning candidates and elections. There remain questions regarding social medias ability to act as a platform encouraging diversity of opinion, interaction between users and conception of original thoughts and ideas. There has been research which suggests contrary to this view with regards to online political discussions, suggesting that Twitter can work as an echo-chamber, where few established opinions are restated again and again [26].

The objective of our behavioral analysis was to establish whether Twitter users were using the online forum to speak their minds and engage with one another. In this regard we looked at two areas in our dataset: content creation and message targeting.

Content creation on social media remains a very interesting subject of study. Researchers have looked at the question of why some content becomes popular and is retweeted thousands of times while many other tweets are never retweeted [14]. The relationship between social ties and the similar types of content that users create and share online along with the motivation to create new content is also an important issue to understand in this regard [102]. Furthermore, for political online social media content, researchers have observed a high rate of reusability [63].

In terms of message dissemination, Twitter allows users to broadcast their message to multiple people with one single tweet. However, Twitter also lets its users interact one-to-one by addressing a person directly. This enables them to respond to other user's tweets paving way for a dialogue. Various studies regarding conversations on Twitter during elections have stated that people do not only use Twitter to post their political opinions but also engage in interactive discussions [93]. Nonetheless, direct messaging also creates complexities for users in having to handle multiplicity and one-to-one conversations at the same time [62]. Management of audience especially becomes challenging as the number of followers of a user grows.

Based on the above discussion, we assumed similar behavior amongst users of our dataset and believed that there were a high number of retweets. We also thought that there would be less one-to-one messages in our dataset. In light of the above discussion, regarding content and user interaction, we proposed the following hypothesis:

Hypothesis 3 (H3): *Majority of users commenting on the elections were not creating new content in the form of original tweets nor were they engaging in interactive discussions with one another but were rather acting passively, rebroadcasting the already available information and ideas with other people in their network.*

We performed the following data analysis steps to test the above hypothesis:

- Analysis of all tweets in the dataset for retweets and original tweets.
- Analysis of Twitter dataset for direct messages between users.

If the above data analyses supported our hypothesis, it would mean that most of the users utilizing Twitter for elections were mostly passive and reusing content or thoughts other users created by simply retweeting them. Fig.3.1 displays the three hypotheses and the related data analyses that will be performed for their testing.

3.4 Data Analysis

We now present the results of our data analysis and test the hypotheses that we developed in the previous section.

3.4.1 Topic and Sentiment Analysis of Twitter Messages

The question of this study was the topic and sentiment analysis of the Twitter messages by users during the elections 2016. Here we performed sentiment analysis of user tweets to observe their correlation with public opinion regarding the two candidates and the elections. We also looked at the most frequent keywords and topics under discussion during this time

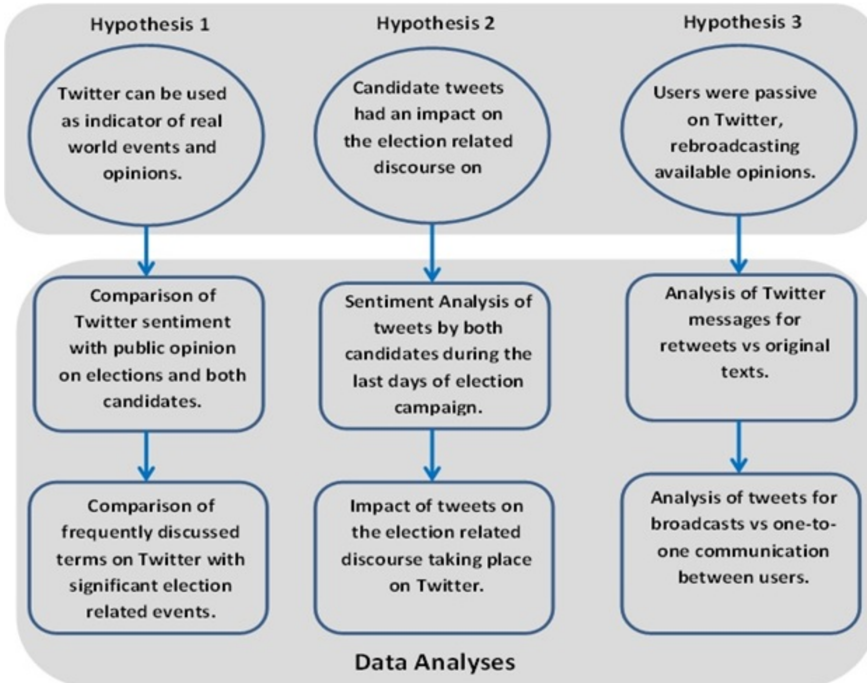

Figure 3.1: Hypotheses and related data analysis.

period to evaluate how interrelated popular Twitter topics are with the real world events and breaking news. The objective of our analysis was to test hypothesis 1 **(H1)** in assessing how accurately Twitter conveyed real world public opinion and key events. We took sentiment as a proxy for public opinion while frequent keywords as important events taking place during this time period. Following are the results of our analysis regard.

Dataset and Candidate Sentiment: Our preliminary data analysis involved analyzing the overall sentiment of entire dataset and of both candidates individually. With all tweets tagged with sentiment scores, we calculated the average daily sentiment of the entire dataset along with tweets mentioning only Trump or Clinton in-order to create a comparison among them. We plotted this daily sentiment in the form of a timeline show in Fig.3.2.

The purpose of this analysis was to identify the overall sentiment of the Twitter conversations related with elections 2016 along with the sentiment of discussions involving both presidential candidates. In our opinion, the candidate having a better sentiment in Twitter conversations would enjoy a better opinion among the general public.

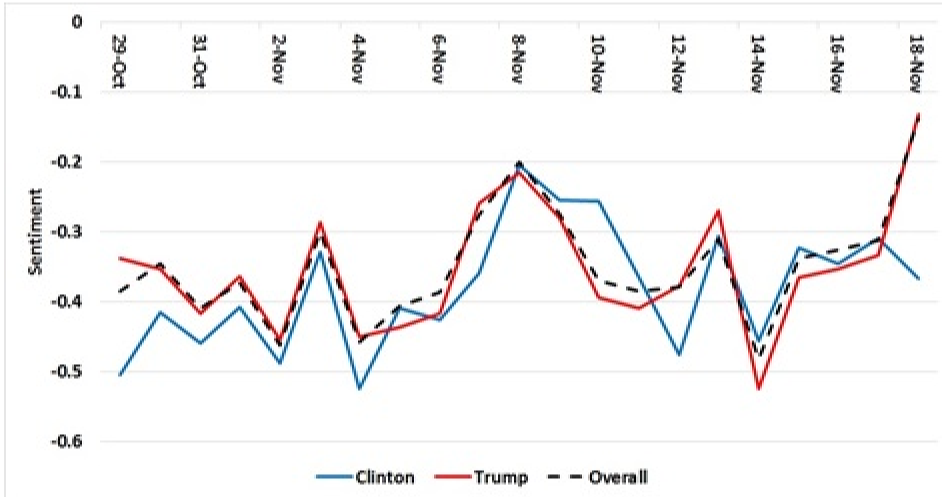

Figure 3.2: Average daily sentiment of tweets containing terms "Trump" and "Clinton".

We discovered that the average daily sentiment was negative for all 21 days of messages. Not only was it negative overall, but also for both candidates. Fig.3.2 shows the average daily sentiment of all tweets in the database along with average daily sentiment of tweets containing the terms Clinton or Trump.

We believe that this finding coincides accurately with the ground reality. The campaign of both Presidential candidates has been declared as one of the most negative in the history of US Presidential elections [18]. The bitter nature of this negative campaign is reflected in the user tweets made during this period regarding both candidates and the elections in general.

Positive, Negative and Neutral Sentiment Tweets: While the daily average sentiment was negative for all days, the number of neutral tweets in the database was higher than the negative and positive tweets. However, neutral tweets have a zero assigned sentiment score and thus have little effect on the daily average sentiment value. Fig.3.3 exhibits the percentage of neutral, negative and positive tweets in our dataset for each day.

We also observed that there were more tweets with negative sentiment than positive. This finding was different from other studies that have been conducted using SentiStrength to perform sentiment analysis of Twitter messages [33, 20, 32]. These overall negative

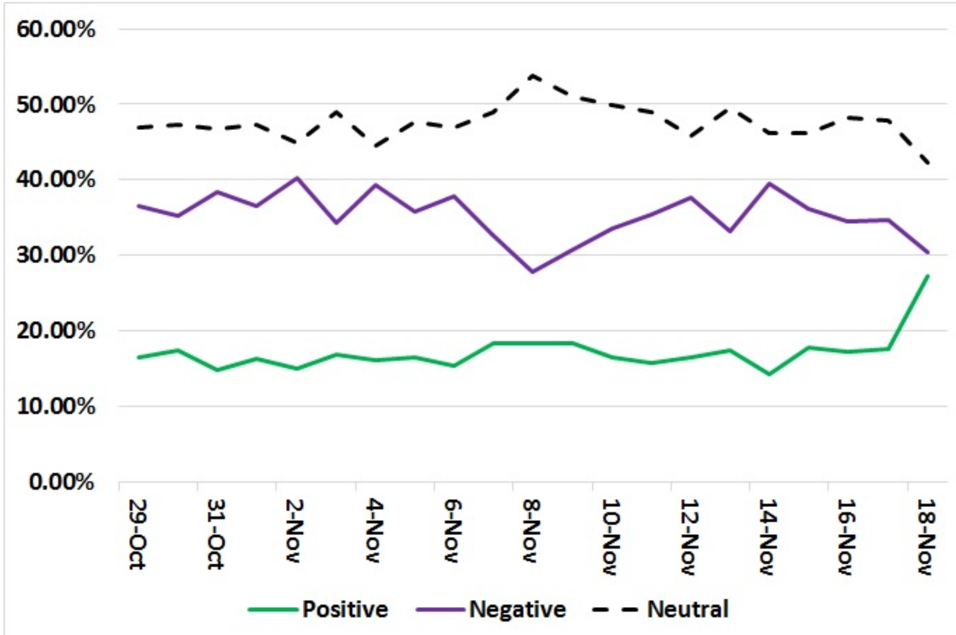

Figure 3.3: Daily percentage of negative, positive and neutral tweets.

scores might indicate the bitter nature of the political campaign associated with Elections 2016. The negative score might also be due to the fact that almost 90% of tweets in our dataset contained either or both candidate names (Clinton or Trump) and the negative sentiment thus indicates strong negative feeling exhibited towards these two candidates by their opponents.

Candidate Popularity: Prior to the elections, most polls conducted by various organizations showed Hillary Clinton leading Donald Trump [1]. Table 3.2 shows the result of most well-known polls conducted between 29th of October to 7th November. We wanted to contrast these poll results with the sentiment trend from our dataset. By creating daily sentiment average of tweets associated with terms "Clinton" and "Trump", we wanted to determine which candidate had the better sentiment score and thus favorable opinion among Twitter users.

In the subsequent sentiment analysis of our data, we discovered that Donald Trump was leading Hillary Clinton. Using first 10 days of pre-election day data, from Oct 29th to Nov 7th, we observed that tweets containing only the keyword Trump had a lower average

Table 3.2: Polls results for elections

Date	Poll	Clinton	Trump
6-Nov	Economist/YouGov	49	45
5-Nov	Fox News	48	44
5-Nov	Bloomberg	46	43
5-Nov	ABC News/Wash Post	49	46
5-Nov	NBC News/SM	51	44
5-Nov	CBS News	47	43
5-Nov	IBD/TIPP	43	42
5-Nov	Monmouth	50	44
5-Nov	LA Times/USC	43	48
4-Nov	NBC News/WSJ	48	43
3-Nov	Reuters/Ipsos	44	40
31-Oct	CBS News/NYT	47	44

negative sentiment than tweets containing only Clinton. Fig.3.4 depicts this sentiment trend in the form of a timeline. As the sentiment was fluctuating for both candidates during these ten days, we created a polynomial trend line of degree 2 in-order to make this sentiment difference more observable. We can establish here that the sentiment trend associated with Donald Trump was consistently less negative than Hillary Clinton.

To further reinforce this finding, we performed t-test on the daily sentiment average shown in Fig.3.4. Following were our null and alternate hypothesis:

$H_0 -> Clinton_{Sentiment} >= Trump_{Sentiment}$

$H_1 -> Clinton_{Sentiment} < Trump_{Sentiment}$

We used F test for sample variance and t-test for hypothesis testing. Test results are shown below:

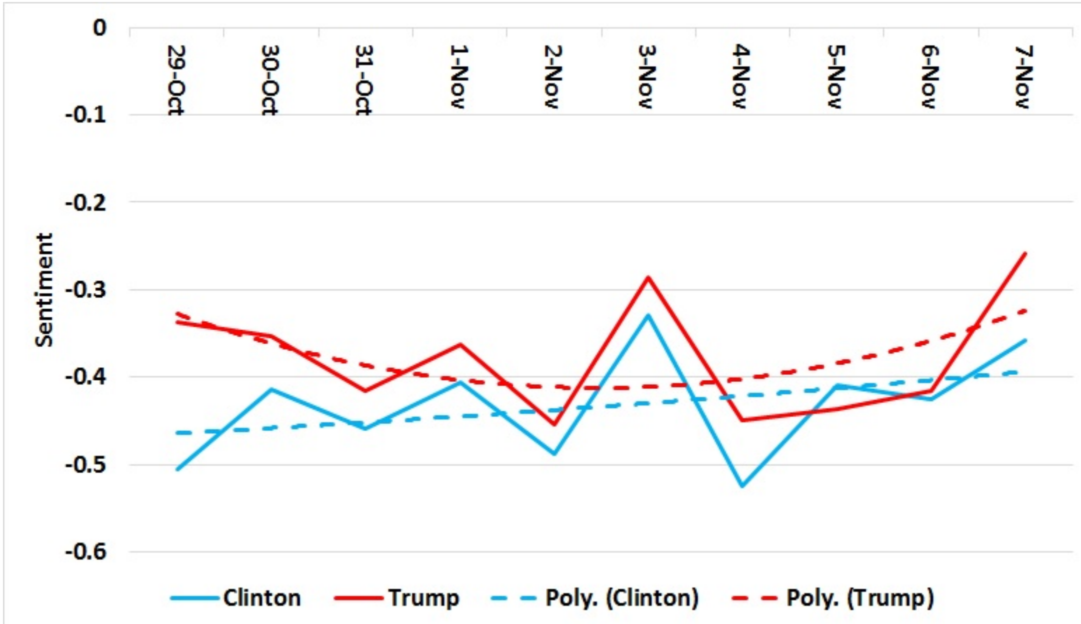

Figure 3.4: Average daily sentiment of user tweets for both candidates and polynomial trend lines of degree 2.

t-stat	1.87
P(T¡=t) one tail	0.038
t critical one tail	1.73

As the t-stat value was higher than the t critical value, we rejected the null hypothesis and accepted the alternate hypothesis, stating that the sentiment of tweets mentioning Donald Trump was indeed more positive than Hillary Clinton. This finding was contrary to majority of the pre-election polls predicting a Hillary Clinton victory. This result however, does reflect the general public opinion as Donald Trump was eventual victor in the elections performing surprisingly better than the polls had indicated.

Twitter for reflection of current news: Finally for hypothesis 1, we wanted to test whether popular Twitter discussion topics reflected significant election related events.

In order to test for this assumption, we created a word cloud of the most popular terms used in our dataset. We found that different terms were popular before and after the elec-

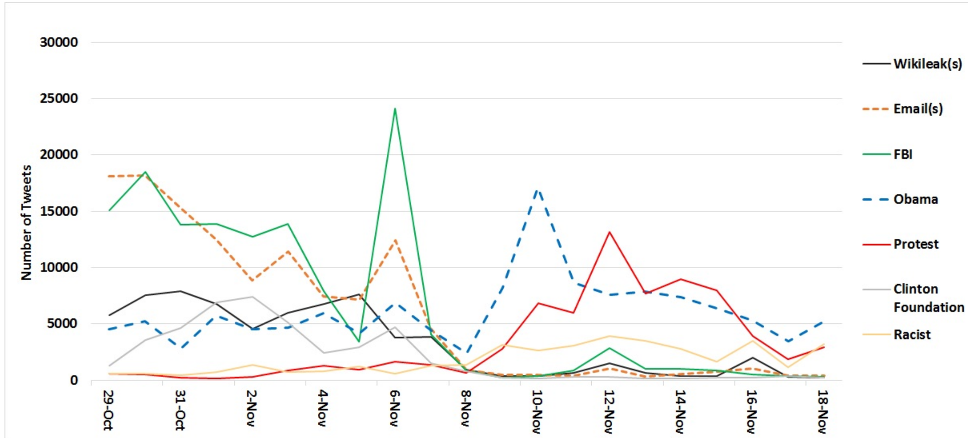

Figure 3.5: Frequency diagram of popular discussion topics.

tions. Fig.3.5 shows popular terms and their occurrence on each day. Here we observed that some terms were popular prior to the Election Day and became relatively obscure post elections. For example *WikiLeaks*, *Emails* and *FBI* were popular discussion topics before 8th of November but became irrelevant later on as the candidate associated with them lost the elections. On the other hand, term such as *Protest* was infrequent prior to the Election Day but becomes popular later on due to the street protests that ensued post elections. Finally, terms like *Obama* remained relatively frequent during this entire period. This was due to President Obamas presence in the news for campaigning before elections and helping president elect in transition post elections.

These popular terms in Twitter conversations indicated election related events, discussions and news as they occurred in real time. We can also detect this by closely observing the peaks of frequent terms in Fig.3.5. For example, *FBI* and *Email* both peak sharply on 6th of November. This was the very same day on which FBI made the announcement that they have completed their review of emails and do not recommend any action against Hillary Clinton.

Likewise, we can spot the term *Obama* abruptly peaking on 10th November, which is the day President Barack Obama met President-Elect Donald Trump in the white house, 2 days after his election victory. This was the most important news item for that day and we

Table 3.3: Three most frequent daily terms.

	1st	2nd	3rd
29-Oct	Email(s)	FBI	Wikileaks
30-Oct	FBI	Email(s)	Wikileaks
31-Oct	Email(s)	FBI	Wikileaks
1-Nov	FBI	Email(s)	Clinton Foundation
2-Nov	FBI	Email(s)	Clinton Foundation
3-Nov	FBI	Email(s)	Wikileaks
4-Nov	FBI	Email(s)	Wikileaks
5-Nov	Wikileaks	Email(s)	Obama
6-Nov	FBI	Email(s)	Obama
7-Nov	Email(s)	Obama	FBI
8-Nov	Obama	Email(s)	Wikileaks
9-Nov	Obama	Racist	Protest
10-Nov	Obama	Protest	Racist
11-Nov	Obama	Protest	Racist
12-Nov	Protest	Obama	Racist
13-Nov	Obama	Protest	Racist
14-Nov	Protest	Obama	Racist
15-Nov	Protest	Obama	Racist
16-Nov	Obama	Protest	Racist
17-Nov	Obama	Protest	Racist
18-Nov	Obama	Racist	Protest

can see it reflected on the Twitter conversations occurring that day.

Finally, the term *Protest* peaked on 12th of November. By this time post-election protests were being held against the electoral results in many major cities of the United States and remained daily headline news item. Table 3.3 displays the top 3 most popular terms for each day from 29th October to 18th of November.

Another interesting observation regarding this phenomenon can be witnessed in trend of the term *Melania*. Melania Trump gave her first major campaign speech in Pennsylvania on 3rd of November 2016. She was one of the most mentioned terms on Twitter that day, remaining relatively obscure before and after that event. Fig.3.6 plots this trend.

Hence we can state that our initial assumption of popular Twitter keywords reflecting important news events of the time is supported by our data analysis and we can state that frequency of popular terms in Twitter discussions can indeed be utilized to identify signifi-

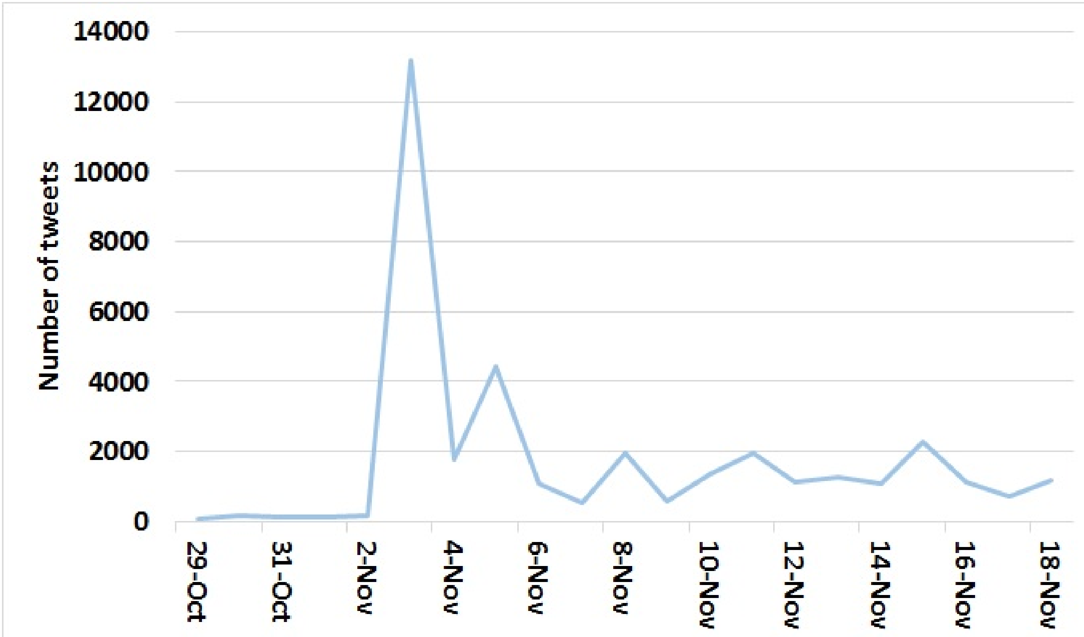

Figure 3.6: Daily frequency chart for tweets mentioning "Melania".

cant real world events and news that were taking place during the elections 2016.

In light of our data analysis above, we can claim that there exists sufficient evidence for us to claim support for Hypothesis 1. The overall negative sentiment of the entire election related dataset for all days, points towards a historical negative and bitter campaign that was fought during the elections 2016 [18]. Both of the candidates, on average, had negative associated sentiment. However, sentiment for Donald Trump was less negative than Hillary Clinton and he did manage to win the elections against the predictions of all major polls (Fig.3.2). Finally we have seen that the most frequently appearing terms on Twitter were the most important election related events taking place during that day. Hence we can claim that Twitter does accurately reflect the public opinion and important topics of concern regarding the elections.

3.4.2 Sentiment and Impact Analysis of Candidate Twitter Messages

In the second phase of our data analyses, we wanted to test hypothesis 2 **(H2)**. Here we wanted to evaluate the sentiment of candidate tweets before the voting day and assess their

Table 3.4: Candidate tweets and their average sentiment

-	Average_Sentiment	Tweets
Donald Trump	0.3925	110
Hillary Clinton	-0.0125	320

impact on the election related discourse on Twitter.

Sentiment analysis of candidate tweets: During the election campaign, both Presidential candidates used Twitter extensively for communication. They did not use it only for interaction with their followers but also to reaffirm policy positions, promote slogans and to attack their opponent.

In the previous section, we evaluated the sentiment on Twitter for both candidates for 10 days prior to the Election Day. In this section, we analyze the sentiment of the tweets generated by Hillary Clinton and Donald Trump Twitter accounts. As was the case with the user tweets, we utilized SentiStrength to calculate the sentiment of candidate tweets. We wanted to evaluate the sentiment of messages conveyed by both candidates on Twitter. We then evaluated the impact of these messages on the overall Twitter discourse. We can observe from Table 3.4 that Donald Trump sent a total of 110 tweets with an average sentiment of 0.3925, while Hillary Clinton tweeted 320 times with her messages having a slightly negative average sentiment of -0.0125. Fig.3.7 plots the daily sentiment trends for tweets by both candidates.

Here we can detect that the average sentiment of tweets originating from Donald Trump's account had a higher positive sentiment when compared with Hillary Clinton's tweets. To create a smoother trend, we utilized a polynomial trend of degree 2 for both candidates. With this we were able to clearly observe that the daily average sentiment of Trump tweets was more positive than Clinton.

To further reinforce this claim, we performed t-test on the average daily sentiment of tweets by both candidates. Following were our null and alternate hypothesis:

$$H_0 -> SentimentofTweets_{Clinton} >= SentimentofTweets_{Trump}$$

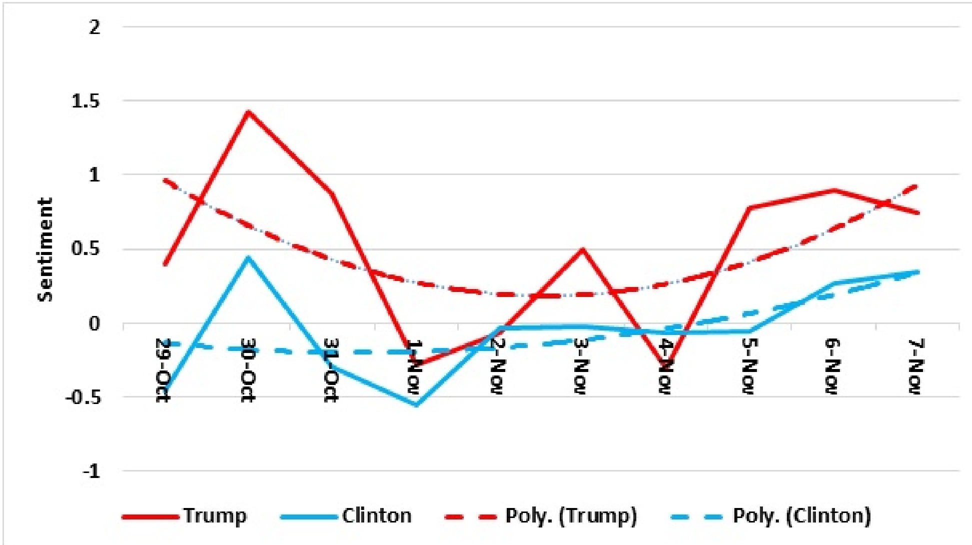

Figure 3.7: Daily average sentiment of tweets by both candidates from 29th Oct – 7th Nov.

$H_1 -> SentimentofTweets_{Clinton} < SentimentofTweets_{Trump}$

We used F test for sample variance and t-test for hypothesis test. Following are the test results:

t-stat	2.59
P(T¡=t) one tail	0.00916
t critical one tail	1.73

As the t-stat value was higher than the t critical value, we rejected the null hypothesis and accepted the alternate hypothesis, stating that sentiment of tweets by Donald Trump was indeed more positive than tweets by Hillary Clinton. We also analyzed tweets by both candidates for frequently used terms. The idea here was to discover the most often used terms in-order to better understand the message conveyed by both candidates. Tables 3.5 and 3.6 show the most frequently used words in tweets along with the average sentiment of those messages.

Table 3.5: Hillary Clinton Tweets

	Total Tweets
Hillary Clinton	**320**

Term	**Num of Tweets**	**% of Total**	**Avg. Sent**
Hillary	**122**	**38.13%**	**0.1475**
Donald/Trump	**71**	**22.19%**	**-0.4225**
Vote	**59**	**18.44%**	**0.2373**

Table 3.6: Donald Trump Tweets

	Total Tweets
Donald Trump	**110**

Term	**Num of Tweets**	**% of Total**	**Avg. Sent**
Thank(s)	**31**	**28.18%**	**1.2903**
Hillary/Clinton	**30**	**27.27%**	**-0.3333**
Great	**18**	**16.36%**	**1.4444**

We can observe from Table3.5 that the most frequently used word by Hillary Clinton was **Hillary** which appeared in over 38% of her tweets with an average positive sentiment of 0.14. This was followed by the terms **Donald** and **Trump** appearing together or separately in over 22% of her tweets. The average sentiment of messages mentioning Donald Trump was highly negative, with a score of -0.4225. We can assume that most of these messages were highly critical of her opponent. Finally, the third most tweeted term was **vote** appearing in over 18% of her tweets with an average positive sentiment of 0.237. It appears that Hillary campaign was eager to encourage people to go out and vote and believed that a high voter turnout would be to their advantage.

From Table3.6 we can observe that the most frequently used word in Donald Trumps tweets was **Thank(s)** appearing in 31% of his tweets with a highly positive average sentiment of 1.29. The second most used term was **Hillary/Clinton**, which appears in 30% his tweets and has an average negative sentiment of -0.33. This again shows that, just like Hillary Clintons messages, these tweets were very critical of his opponent. Both candidates used Twitter to attack each other and a significant percentage of their tweets had a negative sentiment because of this behavior. Finally, the third most frequently used term by Donald Trump was **Great**, which appear in over 16% of his tweets with a very positive sentiment of 1.44.

Impact of candidate sentiment on Twitter discussion: We stated in the previous section that for 10 days prior to the elections, tweets mentioning Donald Trump had a less

Table 3.7: Dataset Statistics

Date	Trump Tweets	Sent Trump	Clinton Tweets	Sent Clinton
29-Oct	57,598	-0.2812	41,630	-0.4866
30-Oct	55,200	-0.3374	47,246	-0.4084
31-Oct	58,468	-0.3862	40,778	-0.4136
1-Nov	54,165	-0.3754	41,663	-0.4294
2-Nov	59,310	-0.4899	37,823	-0.5596
3-Nov	61,644	-0.3034	37,474	-0.3794
4-Nov	64,362	-0.4691	37,024	-0.5889
5-Nov	62,721	-0.4743	38,499	-0.45
6-Nov	63,837	-0.4064	41,627	-0.4042
7-Nov	76,795	-0.2311	25,851	-0.3493
Total	614,100	-0.373	389,615	-0.448

negative sentiment than those mentioning Hillary Clinton. We also observed that tweets created by candidate Trump had a higher positive sentiment than candidate Clinton. Now we wanted to gauge the effect of candidate tweets on the overall sentiment displayed towards them on Twitter during this time period. The purpose of this analysis was to evaluate how much of an impact candidate tweets had on the overall political discourse related with election and regarding both of the candidates. In the previous section, we calculated the daily sentiment of tweets mentioning Trump and Clinton only, without any overlap. In order to gauge the effect of Tweets by the two candidates on their own sentiment, we removed retweets of messages by both candidates from our dataset in-order to measure the impact of sentiment of their own messages on discussions regarding them.

Table 3.7 shows us that the tweets mentioning Trump only amounted to a total of 614,100 while tweets mentioning Clinton numbered 389,615. As these tweets mention only one term, either Trump or Clinton, and do not contain both keywords, hence the retweets of opposing candidate were already removed. Removing Hillary Clinton retweets from tweets mentioning Clinton and Donald Trumps retweets from tweets mentioning Trump,

Table 3.8: Retweets of candidate tweets

	Tweets	Average Sentiment	% of Total
Hillary Clinton	983	-0.4425	0.24%
Donald Trump	1897	1.7559	0.31%

Table 3.9: Most popular tweets of each candidate.

Candidate	Tweet	Sentiment	Retweets
Hillary Clinton	RT @HillaryClinton: It's time for Trump to answer serious questions about his ties to Russia. https://t.co/D8oSmyVAR4	-1	2481
Donald Trump	RT @realDonaldTrump: So nice - great Americans outside Trump Tower right now. Thank you! https://t.co/34ATTgICTz	2	1145

we discover that 983 retweets in the Clinton dataset were her own tweets while for Donald trump this number was 1897. Table 3.8 shows the sentiment and percentage of total for these messages.

The share of retweets that are part of subsets used to calculate sentiment for each candidate was less than 1%. Hence we can safely state that the retweets of the two candidates make up a very small part of our overall dataset used to calculate sentiment of both candidates and had negligible effect on the sentiment of discussion taking place on Twitter. Thus hypothesis 2 **(H2)** is not supported by our data analysis. However, we can notice that Donald Trump retweets had a very high positive sentiment while the average sentiment of Hillary Clinton retweets was negative. This is also reflected from the most retweeted tweet by the two candidates in our Twitter corpus prior to November 8th. The most retweeted Hillary Clinton tweet had a sentiment of -1 while the most retweeted Trump tweet had a sentiment of 2. Table 3.9 shows the most frequently retweeted messages of both candidates:

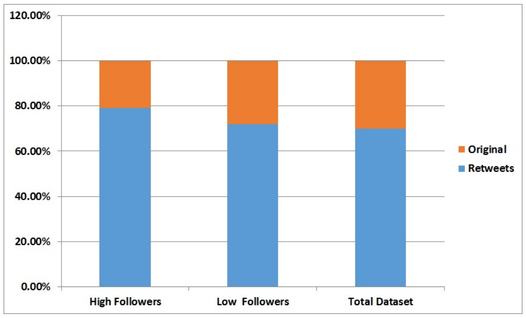

Figure 3.8: Tweeting behavior of users.

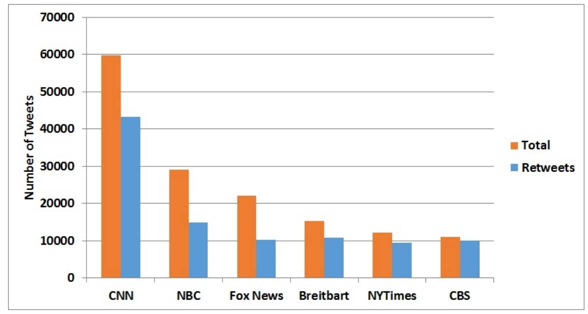

Figure 3.9: Popular news outlets mentioned.

3.4.3 Analysis of User Behavior

We now present the results obtained through analysis of our data that helped us refute or verify our initially developed hypothesis (hypothesis 3) regarding user behavior.

Content Creation: Studies have shown that number of retweets on Twitter usually ranged from 1.44% to 19.1% of all messages [93]. Majority of the tweets created on Twitter are never retweeted. However, this was contrary to our finding where in our dataset number of retweets was as high as 70%. Majority of the users in our dataset, commenting on the elections were not creating any new content but rather reusing the information already present. Furthermore, 100 most retweeted tweets appeared 7081 times in our dataset at an average of almost 71 times each. This behavior of high retweets was present amongst all user groups regardless of the number of followers they had or the frequency with which they tweeted. For top 100 users with followers and friends greater than 10,000, 79% of their tweets were retweets while for the bottom 100 users with 1 follower and 1 friend this number was 72%. The statistics are shown in Fig.3.8. This reusing of the information corroborates the study conducted by McKenna et al. [63] who discovered that 87% of political bloggers provide links to news articles and other blogs in their blog posts. Fig.3.9 shows the most popular news outlets mentioned in the tweets.

Message Targeting: In order to test our message targeting assumption, we looked at all the tweets in our database that started with the expression @. Other studies have also utilized a similar approach to gauge interactive discussions on Twitter [93]. We discovered

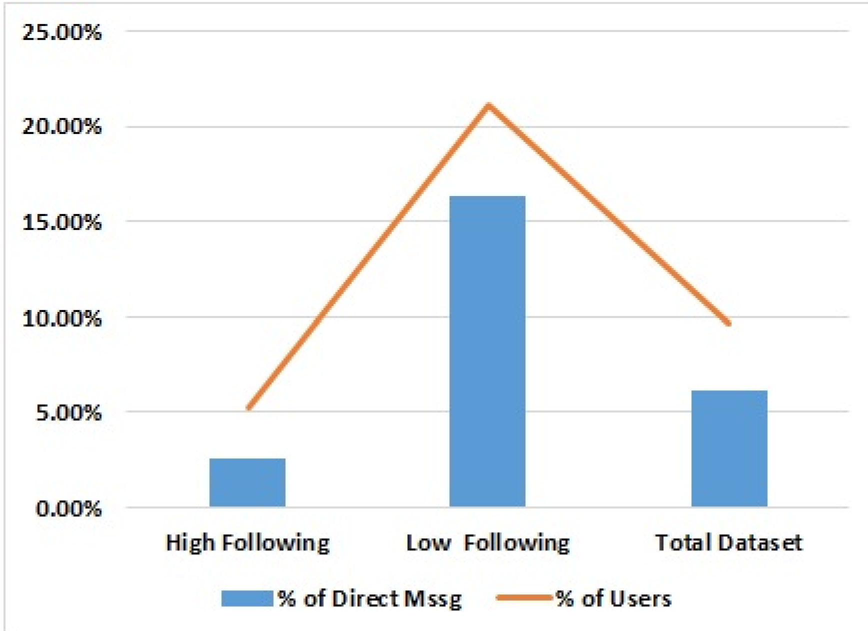

Figure 3.10: The line graph displays percentage of users with high and low followers engaging with other Twitter users through direct messages. The bar graph shows percentage of messages that were direct.

that few tweets were targeted to other users directly and this low one-to-one interaction with other users was significantly less for users who had a large number of followers. For the entire dataset, users engaged in direct messaging formed only 9.66% of all users while direct messages accounted for only 6.17% of all tweets. This number is lower than that of 10% claimed by other studies analyzing political discussions on Twitter in context of elections [93]. Fig.3.10 shows the percentage of direct messages created by users with high and low number of followers while fig.3.11 shows the sentiment of direct messages according to user followers. We can observe from these two diagrams that users with high following engage less in direct one-to-one communication with other users. We can also see that direct messages of these users have less negative sentiment. Hence hypothesis 3 **(H3)** was supported by our dataset: majority of Twitter users were not creating new content but retweeting information amongst their network. They also did not engage in one-to-one discussions with other users and primarily use the platform to simply rebroadcast already present opinions.

Figure 3.11: Sentiment of direct messages by users according to their number of followers. Users with large following on average have less negative sentiment when interacting with other Twitter users.

3.5 Findings

We now present the findings of our data analyses.

3.5.1 Twitter as Indicator of Real World Events and Opinion

We found ample support for Hypothesis 1 in our data analysis. As discussed, many studies have claimed the effectiveness of Twitter to gauge public opinion and to predict real world events including elections [72], [93], [20]. Our research concurs with these findings. We found a negative overall sentiment for all election related tweets which resembles the historically bitter and negative election campaign for US Presidential elections 2016 [18]. Similarly, although both candidates had negative sentiment overall, tweets mentioning Trump had a comparatively better sentiment than those mentioning Clinton (Fig.3.4). This finding is in contrast with most polls conducted during this period that showed Hillary Clinton leading Donald Trump, predicting a Hillary Clinton win. However, the election results were contrary to the polls and Twitter sentiment was a better measure is this regard.

We also observed that in context of Elections 2016, Twitter remained a good proxy to identify the most significant daily events that are taking place. Several studies have looked at Twitter streaming data as a source for identifying current news and real world events [91], [17]. They have concluded that Twitter trends are usually the most important events of the day and can be used to predict headline news. There has been much debate on the usability of Twitter sentiment to gauge public opinion and various studies have claimed that Twitter sentiment analysis is indeed a good measure of public opinion [99]. We believe that by finding support for hypothesis 1, we can state that in case of US Elections 2016, Twitter proved to be an accurate indicator of public opinion and of important election related events.

While most polls sample a couple of thousands of users to gauge candidate popularity, analysis of data from social media outlets such as Twitter allow for a much larger sample size. In our study, we analyzed around 2.9 million tweets made by over 1.1 million users. This large sample size allows us to make an accurate assessment of general public sentiment and topics of importance.

3.5.2 Sentiment of Twitter messages by Candidates during Elections 2016

In sentiment analysis of candidate tweets for 10 days prior to elections, we observed that Twitter messages of Donald Trump had a significantly higher positive sentiment than Hillary Clintons tweets. We detected a similar pattern in the frequently used terms by both candidates shown in Tables 3.5 and 3.6. Two of the three most frequently used words in tweets by Donald Trump were Thank(s) and Great. These words gave his tweets a higher positive sentiment. However, as we can see from Table 3.8 that candidate tweets formed a very small portion of our dataset in the form of retweets. Hence, they had negligible effect on the overall sentiment exhibited towards these candidates on Twitter. Thus we do not find support for hypothesis 2 in our data analysis and state that candidate tweets had no impact on the sentiment of overall political discourse that took place in Twitter.

Nonetheless, we can state here that, Donald Trump ran a more positive campaign on Twitter compared to Hillary Clinton. His messages had more positive words and generated a greater positive sentiment around his campaign.

We also observe that both candidates mentioned each other frequently in their tweets and employed a very negative tone. This is evident from Tables 3.5 and 3.6, where tweets from both candidates mentioning other candidate's name had a highly negative sentiment.

3.5.3 User Behavior on Twitter during Elections 2016

According to our data analysis, we believe that although Twitter is a popular tool for political discussions and debate, a very small number of users dominate this platform. Table 1 displays this dominance, where almost 52% of all tweets in our dataset originate from around 9% of the users while over 69% users accounted for only 26% of total tweets. Support for hypothesis 3, further solidifies this conclusion as 70% of tweets in our dataset were retweets. Hence, majority of users were passively following trends and discussions through retweets and did not actively participate in conversations by expressing their original thoughts.

Support for **(H3)** also indicates that in context of US elections 2016, Twitter was primarily used to spread political opinion and not to discuss these opinions with other users. Only 6.17% of messages in our sample were direct messages. This finding of using Twitter for broadcasting rather than engagement for political conversations is in contrast with other Twitter studies conducted during elections that claim people use the social media platform to engage in interactive discussions [93].

These results answer our initial question regarding political discourse on Twitter in context of US elections 2016. Little diverse and original opinions existed on the social media platform while few users interacted with each other. Twitter acted primarily as an echo chamber, where users re-broadcasted few stated opinions.

3.6 Discussion

For this Twitter mining of election, we analyzed approximately 2.9 million Twitter messages related with the US Presidential elections of 2016. These tweets were collected over a period of 21 days, before and after the elections that were held on November 8th. The tweets were filtered based on their text mentioning either the two major Presidential candidates (Clinton and Trump) or the term Election 2016.

One purpose of this study was to gauge if there existed a significant correlation between the sentiment and the topics discussed on Twitter with the citizen's opinions and real world events and breaking news related with the elections. Our data analysis affirmed this correlation, by supporting hypothesis 1. We discovered an overall negative public sentiment towards the election and both candidates. This is in line with the bitter election campaign executed by both major candidates (Table 3.5 and 3.6) [18]. We also learned that in context of the elections 2016, a timeline of Twitter trends and frequently used words could be utilized to identify events of significant importance as they happened.

We discovered that Donald Trump had a more positive campaign message than Hillary Clinton. He used more positive words and created a positive sentiment around his campaign. However, we found little evidence supporting hypothesis 2, and believe that these messages did not have a significant impact on the overall sentiment of the political discourse taking place on Twitter.

In terms of user behavior, it was observed that little original content was created by users during discussions and most were rather retweeting. We also saw that a very small percentage of messages were direct and contrary to findings by some other studies, majority of the users did not engage in direct one to one conversations with each other. These findings support hypothesis 3 and points to the use of Twitter as a broadcasting platform where users simply restated opinions and not as a stage to engage in interactive conversations with other users or to create original thoughts and ideas.

Chapter 4

Citizen Centric Stakeholder Theory

In this chapter of the dissertation, we will discuss role of social media for organizational communication along with providing background into stakeholder theory which was developed during the 1980s in the area of organizational management. Stakeholder theory has been the topic of discussion in thousands of research articles. We will discuss some of the important ones here that are most pertinent to our research.

4.1 Background

Social media data analysis has become a very important topic of study in recent years. Platforms such as Facebook and Twitter have not only changed the way we interact with one another but also on how we share news and comment on world events at almost real time. The power of users to start trends and make some news more popular than others has remarkably changed how events are reported. One example of this growing importance of social media is by Forrester report [2], according to which internet marketing spending in US will reach $103 billion by year 2019, surpassing broadcast and cable television advertising combined. This high level of advertisement spend on internet is an indication of the realization of the importance of online user presence and activity.

Not only commercial but public organizations are also using social media to their advantage. High level of public connectedness through social media has changed the way local and national government institutions interact with public. For example, almost all police departments of large US cities have presence on multiple social media platforms including Facebook and Twitter [16]. This enables them to quickly engage an get citizen help on any impending emergency. Local governments providing civic services such as garbage collection and infrastructure maintenance are also using social media to get feedback from citizens on priority of public works.

Recently, the idea of e-governance and smart city has also taken hold globally. Internet has provided policy makers with the opportunity to increase government awareness and institutional responsiveness while enhancing citizen engagement. It has been indicated that efforts by government to increase public participation in the affairs of government and taking greater input into decision making can improve public trust in government [52].

Social media has also enabled policy makers to collect data created by citizens for analysis. The hope is that this data deluge in the form of big data will provide policy makers with a more sophisticated, wider-scale, finer-grained and real-time understanding of their constituents [53]. Facebook too has become a popular tool with regards to communication between government institutions and citizens [45]. Majority of public sector organizations now manage Facebook pages thorough which they communicate with the community in which they operate.

4.2 Stakeholder Theory

Stakeholder Theory was developed in the area of organizational management during the 1980s as a tool for the managers to identify relevant stakeholders of the organization [35]. The theory stated that while obligation of an organization towards its stockholders have long been emphasized, the modern corporate should also take its stakeholders into consideration. Stakeholders are groups to which an organization is responsible in addition to stockholders. These include not only organization shareholders but also employees, customers, suppliers, lenders and society in general. The theory argues that by identifying stakeholders and their relationship with the organizations, managers can better operate in their working environment. Stakeholder theory has gained prominence over the years and has been applied not only in business ethics but also in areas like corporate social responsibility, human resource, management and law [49, 76]. Recently, it has also been adapted for application in the context of e-government [34]. It is reasoned that application of stakeholder theory for e-governance does not cause a conceptual mismatch, as the government objective of providing services to citizens is similar to an organization looking after its stakeholders.

The stakeholder theory utilizes the notion of stakeholder salience to categorize/prioritize different types of stakeholders. This salience theory identifies different types of stakeholders using three measures: power, legitimacy and urgency [66] as shown in Fig. 4.1. Below we have a brief definition of these three stakeholder traits:

- Power: Stakeholder power is defined as the ability to influence the firm. Stakeholders possessing power are in a position to carry out their will on the organization.
- Legitimacy: Stakeholder legitimacy is defined as validity of relationship with the firm. This relationship can be contractual or in the form of a legal or moral claim.
- Urgency: Stakeholder urgency is defined as criticality of stakeholder‘s claim on the firm. Thus urgency defines the intensity to which a stakeholder‘s claim calls for immediate action.

The study states that managers give priority to stakeholders based upon these features. Furthermore, there can be stakeholders who possess more than one salience, i.e., a group of people might have both power and legitimacy attributes. Priority of such stakeholders is higher than those who possess only one attribute. Hence, stakeholders who possess

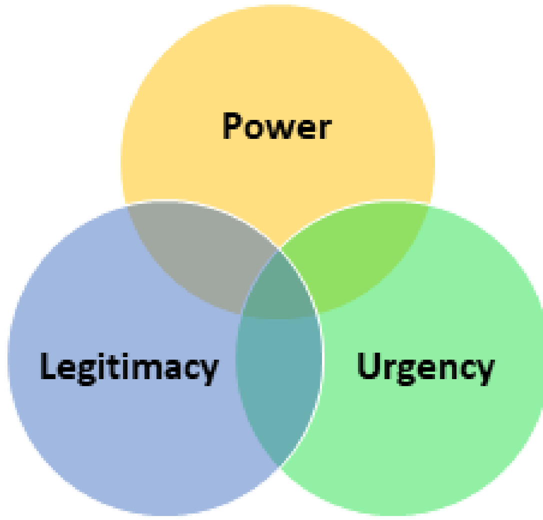

Figure 4.1: Stakeholder saliences of $power$, $legitimacy$ and $urgency$. A definitive stakeholder is defined as one who possesses all three features.

all three salience attributes – power, legitimacy and urgency – are described as *definitive stakeholders* and managers are required to attend to their needs immediately.

There have been past attempts to adopt stakeholder theory for social media [81]. On social media, stakeholder saliences will change to reflect the nature of the platform, as here salience needs to be evaluated based on their influence and content shared on social media. Sedereviciute et al. [81], for instance, adapted stakeholder theory for social media where stakeholder saliences are based on the characteristics of online networking sites, where using social network analysis , power is defined as the central position of user in a social network while both legitimacy and urgency are defined as the content shared by the users. However, this model defines legitimacy and urgency in terms of the content shared by users. We believe that both legitimacy and urgency cannot be defined only in terms of content shared by a user but rather indicate distinct online user behaviors. In the following section of the paper, we present our own adaptation of stakeholder salience theory for social media.

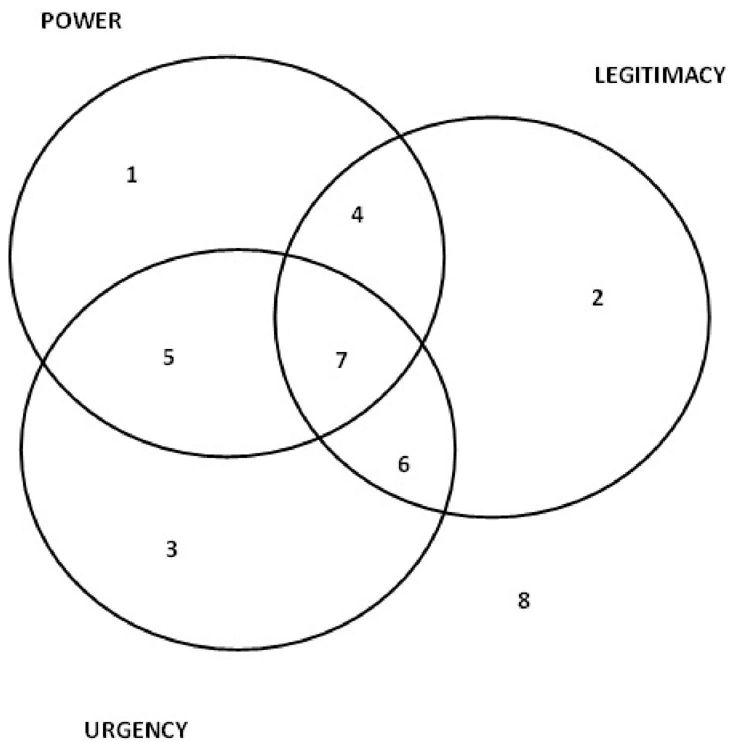

Figure 4.2: Stakeholder classification based on attributes.

4.2.1 Stakeholder Theory Salience

One important aspect of stakeholder theory development is the notion of stakeholder salience [66]. Developed in 1997, Stakeholder salience is evaluated using three measures: power, legitimacy and urgency. The study states that managers give priority to stakeholders based upon these features.

Furthermore, there can be stakeholders who possess more than one salience i.e. a group of people might have both power and legitimacy attributes. Priority of such people is thus higher than those who possess only one attribute. Hence, users who possess all three salience attributes, power, legitimacy and urgency are described by the paper as *definitive stakeholders* and managers are required to attend to their needs immediately.

Fig.4.2 displays the 8 types of stakeholders based on the number of attributes present. Following is an explanation of these stakeholder types:

1. **Dormant stakeholders:** these stakeholders possess power and hence can impose

their will on the organization. However, they neither possess the legitimacy nor the urgency in relationship with the firm. Hence is argued that their power remains dormant.

2. **Discretionary stakeholders:** these stakeholders possess the legitimacy, however, they do not have the power nor the urgency.

3. **Demanding stakeholders:** these stakeholders have urgent claims on the firm. However, they do not possess the power nor legitimacy. Hence these are demanding stakeholders.

4. **Dominant Stakeholders:** these stakeholders possess both power and legitimacy and hence have a confirmed dominance over the organization. Hence these stakeholders are called dominant as they not only have legitimate claims over the organization but also keep the power to act upon them.

5. **Dangerous Stakeholders:** these stakeholders have power and urgency; however, their claims lack legitimacy. The study classifies them as dangerous as due to the urgency of their claims along with the power they yield, these stakeholders can attempt to coerce the firm into illegitimate activity to in-order fulfill their claims.

6. **Dependent Stakeholders:** these stakeholders have legitimacy over the firm and also have urgency to their claims. However, as they do not possess any power, they are dependent upon others to fulfill their claims. Hence they are termed as dependent stakeholders.

7. **Definitive Stakeholders:** these stakeholders have all three attributes. They have legitimate claims, their claims are urgent and they also possess the power over the firm to act upon them. Managers of the firm are required to attend to these stakeholders immediately.

8. **Non-stakeholders:** these entities lie outside the stakeholder salience model. They dont possess any power, nor have any legitimate or urgent claims over the firm. Hence for the organization, these entities are classified as non-stakeholders.

The stakeholder salience study was an attempt to further explain the original stakeholder theory put forward in the 1980s. It tries to explain why some stakeholder claims are worthy of higher priority than others for an organization. The paper develops on the original theory where each stakeholder is evaluated based solely on the legitimacy of their status. The salience study expands into other attributes such as power and urgency in order to better understand which stakeholders really count for the managers of a firm.

4.2.2 Stakeholder Theory Adoption for Social Media

There have been attempts to adopt stakeholder theory for social media. As discussed in the previous section, stakeholder saliences were developed to identify the significance and importance of different stakeholders with respect to the organization. These, salience are defined as Power, Legitimacy and Urgency where many stakeholders might possess more than one salience.

On social media, these stakeholder attributes will change to reflect the nature of the platform. Sedereviciute et al. [81] adapted stakeholder theory for social media. Here stakeholder saliences are based on the characteristics of online networking sites. They utilize social network analysis to describe the stakeholder features. Thus power is defined as the central position of user while the legitimacy and urgency as defined through content shared. A user who shares a lot of content relevant to the organization becomes a legitimate stakeholder while someone who shares a lot of content online has the urgency salience. Hence stakeholders' power relates to his or her central position in the online community. A user with a large number of followers on Twitter has high power due to her ability to reach a large audience with a message.

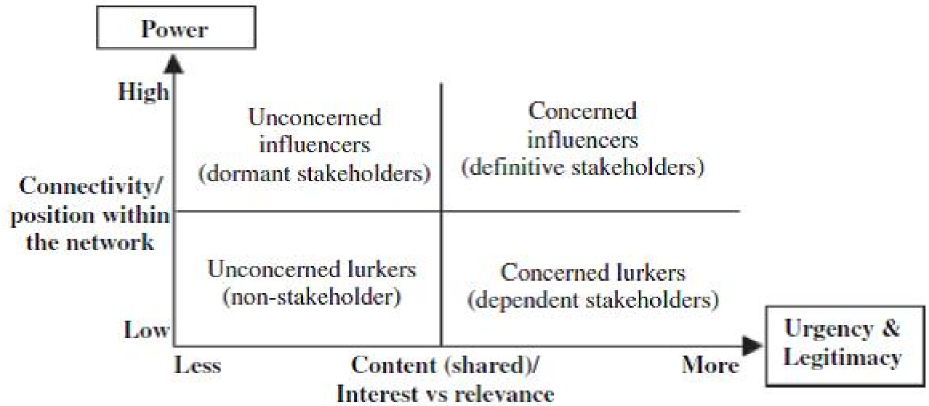

Figure 4.3: Stakeholder groups as a function of their salience in social media [81].

Legitimacy relates with the relevance of the topic under discussion. A social media user discussing and sharing a lot of news regarding police departments online will become a legitimate social media stakeholder of police departments. Finally, urgency is defined by the frequency of discussions under a particular topic. As, Urgency and Legitimacy, both relate with content creation, hence according to Sedereviciute et al. [81] these two dimensions can be treated as one. Fig 4.3 describes these stakeholder salience in context of social media.

We believe however, that the approach used by this model does not define stakeholder saliences adequately with regards to social media. Both legitimacy and urgency cannot be defined only in terms of content shared by a user but rather indicate distinct online user behaviors. In the following section of the paper, we present our own adaptation of stakeholder salience theory for social media.

4.3 Citizen Centric Stakeholder Theory for Social Media

In this dissertation we perform social media data analysis to evaluate its usage for communication with citizens. This communication can be between organizations and citizens or by political leaders during general elections. One method of performing such an analysis is by understanding the behavior and sentiment of social media users. We can evaluate this through analyzing popular retweets, sentiment expressed towards individuals and organizations of importance, content creation, direct messages, popular trends and keywords etc.

In-order to achieve this goal of developing a thorough understanding of social media usage, we want to be able to better identify social media users. To accomplish this, we attempt to develop a framework for social media users. We will be utilizing popular, time tested Stakeholder Theory for development of this framework. Specifically, we want to be able to create a citizen centric stakeholder theory, which treats all social media users as stakeholders.

Development of such a framework can help enable organizations and individuals, who utilize the web to engage with citizens on a mass scale, to better identify their target audience. A framework developed using stakeholder theory as a foundation can help these employers of social media to distinguish between various social media users. Such a distinction can enable them to identify the users they want to target specifically in order to create a better communication and reception for their message online, getting their message clearly to social media users.

Adoption of stakeholder theory for social media is a challenging task as there are millions of users online and thus millions of possible stakeholders to identify and engage. Nonetheless, we believe that positive identification of these stakeholders can enables social media users to target the ones most critical to their message and hence enable effective communication or message propagation online.

Our approach is to create a stakeholder theory for social media that is citizen centric. As all organizations or political leaders utilize social media to engage with users, social media stakeholder theory attempts to identify for them, social media users, based on the saliences of Power, Legitimacy and Urgency. However, application of stakeholder theory on social media is different in its dynamics than from an organizational setting as in this case we are trying to identify and categorize millions of users as stakeholders. Following are the characteristics of these stakeholders on social media that will determine their saliences:

- Power: Power (which can also be viewed as influence) of stakeholders on a social media platform is determined by their importance in the social network [81]. It is observed that even large networks are usually driven by very few individuals who act as hubs around whom most of the activity is organized [88]. Hence actors who have a central position in the network have a greater potential to influence conversations. This network factor remains vital in social media as well, since online social networks resemble an enormous network where stakeholders create and share information [88]. For example, a stakeholder with large following has the potential to propagate her message to a large audience. Celebrities and influential people have millions of followers on Facebook and Twitter and any statement for or against any cause or political candidate has the potential to become major news. Similarly, celebrity endorsements on social media can generate positive publicity for a candidate. Hence stakeholder power can be defined as the following equation:

  $$power = number\ of\ followers$$

  In context of social media, users with a large following possess the power salience and have the potential to impact online discourse in terms of setting specific agenda by directing conversation and by framing the discussion topics.

- Legitimacy: Legitimacy of social media stakeholders relates with their status and reputation on social media.

  A study by Chu et al. [24] on detection of automation on Twitter created a parameter of user reputation to discriminate between human and automated activity. The study examined 500,000 Twitter users for this purpose. It stated among other findings that a measure of account reputation can be used to distinguish human activity from bot. The study formulates that humans have a near equal number of followers and friends. This is not true for bots as in-order for bots to create a bigger network, the common strategy is to follow a large number of users in hope that some of these users will follow them back. The study defined account reputation using the following equation:

$$Account\ Reputation = \frac{num\ of\ followers}{num\ of\ followers\ +\ num\ of\ friends}$$

The above equation assigns an account reputation value between 0 and 1, with accounts having value close to 1 being highly reputed. The study concluded that majority of bots or automated accounts had a reputation of less than 0.5.

Stakeholder theory defines legitimacy as validity of stakeholder relationship with the firm [66]. On Twitter a valid account is one which is operated by a human user and is not an automated account. Hence in Twitter setting, we define legitimacy as account reputation.

However, in context of our citizen centric stakeholder theory, legitimacy differentiates not only between automated and human Twitter users but also between different human users. Hence some users have a higher reputation by having more followers than friends. Celebrity accounts on Twitter for example have millions of followers while they in turn follow a very small number of other users. This high ratio of followers compared to friends gives their Twitter accounts high reputation and assigns their online content more legitimacy than other users with a lower number of followers compared to friends. On the other hand, a stakeholder who follows more users than is followed by will have a negative legitimacy value. A stakeholder who follows a large number of other users, but is followed by few users cannot be considered to possess high legitimacy as few users are interested in hearing what that person has to say. Hence stakeholder legitimacy can be calculated using the following equation:

$$legitimacy = log\left(\frac{followers}{follows}\right)$$

Here followers are those users who follow the stakeholder on Twitter while follows is the number of other Twitter users whom the stakeholder follows. We are taking log of the followers and follows ratio in-order to keep the legitimacy variable value in a manageable range. Hence this enables us to objectively evaluate stakeholders legitimacy who have followers and friends ranging from millions to few dozens. Taking the example of Katy Perry, who as of October 2017, has over 105 million followers on Twitter but is only following 2014 other users. By the above formula her legitimacy value will be 5.71. This will be one of the highest legitimacy values for a Twitter user as a large audience is interested in hearing her message

- Urgency: Urgency on social media is defined in terms of the overall online activity of a stakeholder. Thus the amount of content posted, shared and liked by a stakeholder will determine the level of urgency. The more intense and frequent stakeholders participation in discussions on particular topics, the higher will be their urgency. Stakeholders gain this salience by actively participating in online discussion along with frequently sharing relevant content on social media. A stakeholder can gain urgency by not only actively posting messages and content online but by also sharing and liking posts created by other stakeholders. Hence both active and passive forms of propagation can be included in defining urgency. However the weights could be assigned to these activities reflecting their level of engagement. For example, the following equation can describe the urgency of a stakeholder on Twitter:

$$Urgency = \big((0.75 * numberoftweets) + (0.25 * numberoffavorites)\big)$$

Here we assigned a higher weight to tweets and lower to favorites as online tweeting is a more engaging activity than liking messages of other users. Thus a stakeholder tweeting and favoring messages of other Twitter users frequently has a higher urgency compared with a stakeholder rarely tweets to likes tweets of other users. The above saliences defined in stakeholders in terms of citizen centric stakeholder theory for social media where online users of social media are the central figures. These saliences can change over time based on changing activity and online influence of stakeholder. As we have discussed earlier, possessing a combination of two or more saliences increases the importance of a single or group of stakeholders.

The above saliences defined in terms of citizen centric stakeholder theory, in this application of stakeholder theory, we have kept the social media users as the central figures. As discussed earlier, a combination of two or more saliences increases the urgency of engaging a single or group of stakeholders. Fig 4.4 graphically shows the three dimensions of the stakeholder theory in terms of characteristics of social media users.

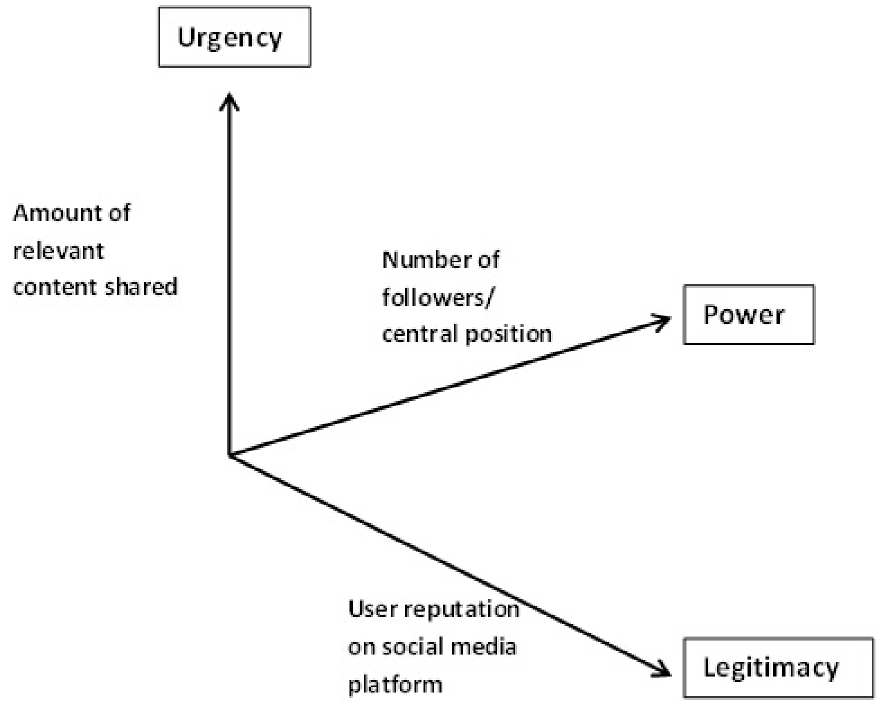

Figure 4.4: User saliences as defined by the Citizen Centric Stakeholder Theory.

4.4 Citizen Centric Stakeholder Theory Applications

We believe that citizen centric stakeholder theory can be applied in broad areas of social media research. It can be used to categorize social media users resulting in identification of key participants in an online discussion. These users would have a high degree of influence on the sentiment of topics of discussion. Analyses of these key participants can help explain the prevalent sentiment and opinions on social media discourse. Identification of key participants can also help gauge how effective an organization or individual is in their social media communication in terms of targeting the right individuals with their message and allaying their concerns through direct communication.

This theory can also be used to evaluate social media communication of users to understand sentiment and message propagation. Traits such as power, legitimacy and urgency can help explain why tweets of certain users are retweeted more than others [88, 36]. Similarly it is observed that users with a large following usually maintain a positive sentiment and avoid contentious topics and debates as they do not know which of their followers might be offended by their statement [62].

Furthermore, rather than analyzing sentiment of tweets, we believe that focus should be made on analyzing sentiment of users. For example, One of the well documented phenomenon on Twitter is the fact that a very small number of users monopolize political discussions on Twitter [14, 99]. Thus with participation being lopsided, utilizing sentiment of tweets or evaluating volume of tweets or terms mentioning a particular candidate or political party as an indicator of popularity become dubious. Hence we believe that in order to accurately gauge public opinion using Twitter sentiment, researchers should take sentiment of individual users in consideration.

In the next chapter, we will apply our citizen centric stakeholder theory to analyze Twitter data collected during US elections of 2016 and UK elections of 2017. Using stakeholder salience described above, we will evaluate the impact of these attributes on message sentiment and propagation as retweets.

Chapter 5

Citizen Centric Stakeholder Theory Application on Twitter Election Data

We will now utilize the citizen centric stakeholder theory, proposed in chapter 4 to analyze social media data. Here we will use two case studies. The first involves the use of Twitter data gathered during the US Presidential Elections of 2016 and the UK General Elections of 2017. We will use the stakeholder theory to analyze user behavior and sentiment, particularly in terms of retweets and message propagation. Stakeholder theory will allow us to identify whether reputation and following plays a vital role on why some tweets are retweeted more than others.

5.1 Background and Motivation

The advent of social media networks has dramatically transformed the way people communicate and share information with each other. These networks have provided their users with the power to decide which news event is more interesting or relevant for them. Therefore network effect in terms of views of a video or number of followers of a celebrity play a huge part in determining the content that goes viral [36, 74]. Thus, unlike conventional media, social media allows users direct influence over popular discussion topics. While in traditional mainstream media, narrative is built by a group of established influencers, discussions remain fluid and decentralized on social networks. Hence, in order to fully benefit from all the bidirectional features of social media platform, organizations and individuals employing social media for marketing or communication must actively observe and participate in the information sharing processes taking place online. However, although all users can influence the Twitter discussions, some users have more influence than others when it comes to message propagation and the ability to influence opinions of other users. One of the well documented phenomenon on Twitter is the fact that a very small number of users monopolize the entire discussion [99, 15]. Hence although Twitter allows researchers to evaluate tens of millions of tweets generated by millions of distinct users, the resulting conclusions are unconvincing due to the bias of a very small group of users accounting for majority of tweets. Thus it becomes crucial for employers of Twitter to identify influential users on the social media platform in-order to focus more attention towards the segment of users who have the biggest impact on online discussions. In this section of the dissertation, we apply the citizen centric stakeholder theory, developed in the previous chapter, to analyze message propagation and sentiment on Twitter. By evaluating stakeholders based on salience, we analyze the impact of these features can have on retweets and message sentiment. Furthermore, we also assess the impact of stakeholder sentiment on their retweets. Some studies have claimed that tweets with positive sentiment reach more users than tweets with negative sentiment [33]. Hence along with stakeholder salience, we also assess impact of stakeholder sentiment on message retweets. However, rather than using sentiment of individual tweets, we create a stakeholder sentiment parameter, where sentiment of all tweets created by a stakeholder are averaged to assign a stakeholder sentiment. We use stakeholder sentiment variable to determine its impact on message propagation.

In the recently concluded US Presidential Elections of November 2016, and UK General Elections of June 2017, Twitter played a very important role in election campaigning. As of 2017, USA has approximately 69 million while UK has 16.4 million monthly active users of the microblogging site [87]. Thus candidates and political parties involved in both elections had millions of followers on Twitter and used the social media platform to frequently communicate their stance on important policy points such as immigration, economy, security etc. As multiple studies analyzing Twitter election data have observed that a large number of tweets in election related Twitter datasets are retweets [100], understanding why some tweets are retweeted millions of times while most are never retweeted remains an important research topic.

Thus we attempt to understand the role of stakeholder salience on message retweet and sentiment during political discourse that took place on Twitter during the US and UK elections. By utilizing data from two elections that took place a year apart in two different countries, our findings will be compelling if we get similar results in both datasets. Our study makes the following key contributions:

- Development of a theoretical framework of social media stakeholder theory that can be used to categorize social media users based on stakeholder theory saliences.
- Evaluating the role of stakeholder saliences on retweets and sentiment of tweets.
- Finally, appraising the impact of stakeholder sentiment on retweets.

Findings from this study will enable employers of social media to better understand online users and dynamics of conversation taking place on social networks. Using our categorization of stakeholders, they will be able to segment their target audience based on tangible attributes, enabling them to effectively target them with their message, as the goal of any social media campaign is to reach a large online audience.

As a test case for our citizen centric social media stakeholder theory, we apply it on Twitter data to test our hypotheses of whether the salience factors play a role in explaining message sharing and sentiment. We will examine these questions using data gathered during the US and UK elections of November 2016 and June 2017.

5.2 Hypothesis Development

We now develop our research hypotheses using the social media stakeholder theory. We describe the impact of stakeholder salience on message propagation and sentiment on Twitter.

5.2.1 Stakeholder Retweets on Twitter

Various studies have looked at the dynamics of message propagation on Twitter. Especially with regards to political discourse, it has been observed that the number of retweets in discussions remain very high [99, 93]. We discover a similar pattern in US and UK elections datasets. Almost 72% of the tweets of US dataset were retweets while for the UK dataset, number of retweets was more than 75% of messages. Hence understanding why some tweets are retweeted millions of times while most are never retweeted remains an important research topic.

In this paper, we look at the dynamics of message propagation. We assess the impact of stakeholder salience, and sentiment on the number of their retweets. To calculate retweets of a stakeholder, we need to first identify all stakeholders who have created at-least one original message (not a retweet). Retweets of all original messages by a stakeholder will then be added to create a stakeholder retweets variable. The following equation is used to calculate the average number of retweets for all tweets of a stakeholder, denoted as variable *SR*:

$$SR = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{m} RT_{i,j} \tag{5.1}$$

Here n is the total number of original tweets by a stakeholder while m is the total number of retweets. Each original tweet is represented as i while each retweet is shown as j. Here $i \in$ set of original tweets by the stakeholder defined as $I = \{i_1, i_2, i_3..., i_n\}$. A higher SR value will indicate higher retweet rates for a stakeholder tweets.

5.2.2 Stakeholder Sentiment on Twitter

In this section, we hypothesize if the salience factors also influence the sentiment of tweets by stakeholders. Rather than calculating individual sentiment of each tweet, we investigate the sentiment of each stakeholder to understand the impact of salience factors on stakeholders, but not on the individual tweets. Specifically, we are calculating sentiment of each stakeholder instead of individual tweets for two reasons. Firstly, one of the well documented phenomenon on twitter is the fact that a very small number of users monopolize discussion on Twitter [14]. We detect a similar pattern in both of our datasets. Only 3.25% users were responsible for almost 57% of all tweets in our US Twitter corpus. Similarly for the UK dataset, 2.25% users were responsible for over 50% of all tweets.

Hence with participation being so lopsided, techniques utilizing sentiment of tweets or evaluating volume of tweets mentioning a particular candidate or political party as an indicator of popularity become dubious [15, 19, 93]. We believe that in order to accurately gauge the popularity of a candidate on Twitter, researchers should look at the sentiment and behavior of individual users rather than the number of tweets mentioning a particular candidate or political party. In this way, we would be able to cater for the bias in the data.

Secondly, as we are treating all social media users as stakeholders and are evaluating them based on their attributes such as power, legitimacy and urgency. Hence we will also evaluate message propagation based on sentiment profile of stakeholders by creating a sentiment values for each Twitter user and then observe the number of retweets that user has. This stakeholder sentiment SS is defined as an average sentiment of all the tweets in the following equation:

$$SS = \frac{1}{n}\sum_{i=1}^{n} ST_{i,j} \tag{5.2}$$

Here ST is the sentiment of each individual stakeholder tweet while n is the total number of stakeholder tweets.

5.3 Role of Stakeholder Salience on Message Propagation and Sentiment

In this section, we use the stakeholder saliences of power, urgency and legitimacy, defined in the previous section, and examine their impact on message propagation and sentiment on Twitter. We now develop several hypotheses to evaluate the role of each salience on message propagation and sentiment.

5.3.1 Role of Stakeholder Power in Retweets and Sentiment

Our first set of hypotheses evaluates the role of stakeholder power on message propagation and sentiment. On Twitter, power translates into number of followers of a stakeholder while the message propagates in the form of retweets. Message propagation on Twitter remains one of the most active areas of academic research. While some tweets are retweeted thousands of times, most tweets are never retweeted. Message content such as hashtags and URL have a strong relationship with retweeting [88]. Similarly studies have also discovered a strong linear relationship between retweets and the number of followers a user has on Twitter [88]. We expect that a similar pattern may be discovered in our election datasets, where stakeholder with larger number of followers will have more retweets of their messages.

In terms of sentiment, it is observed that Twitter stakeholders with a large following usually maintain a positive sentiment and try to avoid contentious topics and debates [62]. This self-censorship of avoiding divisive topics and issues stems from the fact that having a large following, a stakeholder might not know which of their followers they might end up offending with their remarks [62]. As in our model, stakeholder power is directly correlated with the number of followers, we expect a similar behavior. Hence we propose the following hypotheses with regards to the impact of stakeholder power on retweets and sentiment:

Hypothesis 1 (H1): *Stakeholders with high Power have a higher number of retweets.*

Hypothesis 2 (H2): *Stakeholders with high power have higher positive sentiment.*

5.3.2 Role of Stakeholder Legitimacy in Retweets and Sentiment

We earlier defined legitimacy in terms of the stakeholder reputation on social media. We defined status of a stakeholder as the log ratio between the number of Twitter users who are followers of the stakeholder and the number of Twitter users who the stakeholder follows.

These celebrities who are active on Twitter and have a large following and high reputation are retweeted far often than ordinary users. Studies have discovered that celebrities with large following are retweeted extensively [36]. Similarly, a strong positive linear correlation exists between the number of followers of users and the number of retweets of their messages [88].

Studies have also discovered that human users on Twitter, usually follow and are followed by almost an equal number of users [24]. This is not true for Twitter bots as to create a bigger network, the common bot strategy is to follow a large number of users in hope that some of these users will follow them back. Thus automated accounts results in high negative legitimacy values, which indicates the low legitimacy.

To determine if stakeholder legitimacy has any impact on retweets and sentiment, we propose the following hypotheses:

Hypothesis 3 (H3): *Higher legitimacy results in higher number of retweets for a stakeholder.*

Hypothesis 4 (H4): *High legitimacy positively influences sentiment of a stakeholder.*

5.3.3 Role of Stakeholder Urgency in Retweets and Sentiment

We have expressed stakeholders' urgency in terms of the overall activity on a social media platform. On Twitter, stakeholders gain urgency through tweeting and by liking tweets of other users. Hence, along with number of tweets posted, we will also take into consideration the number of tweets a user marks as favorite.

While measures such as followers, retweets etc. have been looked at intensively, utility features such as favorites have mostly been overlooked in Twitter research [97]. In this study, we consider both the number of tweets a user is creating and the number of tweets a user marks as favorites in the definition of urgency, as an overall indicator of the level of online activity. However as marking tweets as favorites is a passive form of activity when compared with posting messages, we assign favorites of a stakeholder lesser weightage than number of tweets as discussed in chapter 4. Hence in terms of determining the impact of urgency on stakeholder retweets and sentiment, we propose the following hypothesis:

Hypothesis 5 (H5): *Higher urgency influences higher number of retweets for a stakeholder.*

Hypothesis 6 (H6): *Higher urgency influences stakeholder sentiment more positively.*

5.3.4 Role of Stakeholder Sentiment in Message Propagation

Finally, we want to evaluate the impact of stakeholder sentiment on stakeholder retweets. Role of sentiment in message propagation on Twitter remains a popular topic of research. Some studies have claimed that tweets with positive sentiment reach a wider audience than those with negative sentiment [33]. Contrary to these findings, our preliminary analysis, as shown in Figs 5.2 and 5.3, indicate that a large number of negative tweets have been retweets in both US and UK datasets. In addition, both datasets show that the retweet rates of negative sentiment tweets is higher than tweets with positive sentiment (Fig 5.14). Hence we question if negative sentiment tends to generate higher retweets than positive when it comes to election related discourse. Thus, along with analyzing the role of stakeholder salience in message propagation, we pose the following hypothesis to investigate if the stakeholder sentiment SS impacts on the number of stakeholder retweets SR:

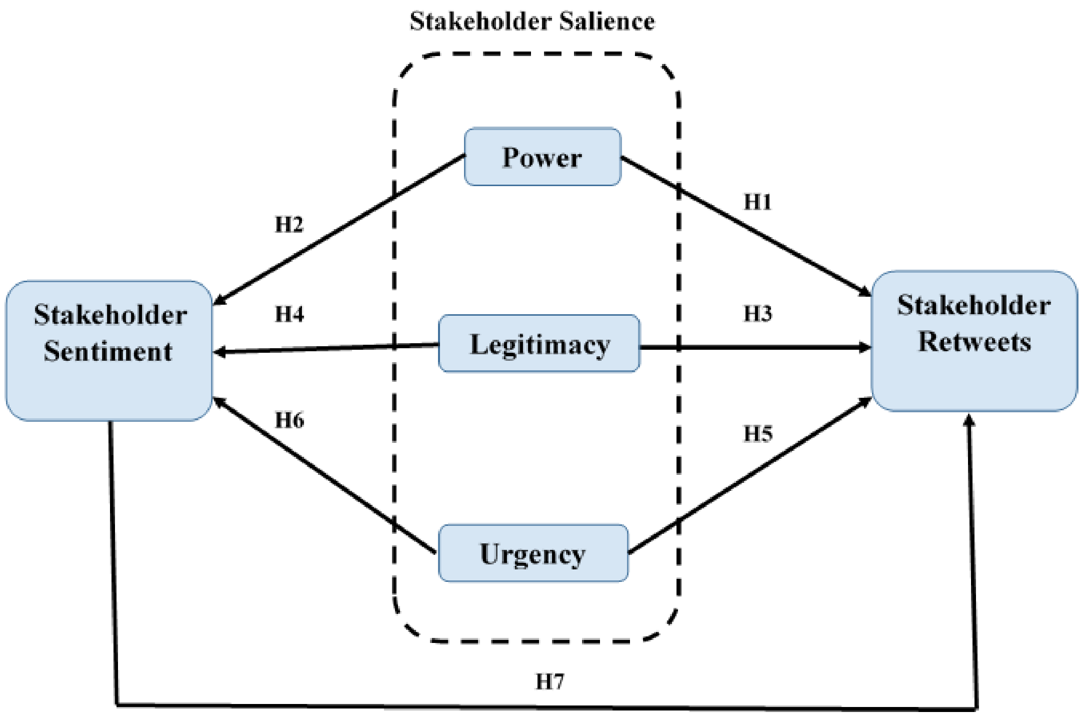

Figure 5.1: Hypothesis model for evaluating the impact of stakeholder salience and sentiment on message retweets on Twitter.

Hypothesis 7 (H7): *Higher negative sentiment SS of a stakeholder will result in a higher retweets SR.*

The above seven hypotheses can be represented in the form of the social media stakeholder model shown in Fig 5.1.

5.4 Data Preparation Methodology

Our data collection and cleaning methodology is explained in chapter 2 of this dissertation in detail. For this study we utilized data gathered during US and UK elections of 2016 and 2017 respectively. In total, we used around 30 million tweets gathered during the US elections and 10 million tweets during elections in the UK. Table 5.1 provides an overview of both datasets.

Table 5.1: Statistics of US and UK Twitter datasets collected during 2016 and 2017 elections respectively. Majority of tweets in both datasets are retweets.

Tweets	Total Tweets	Total Users	Original Tweets	Retweets	Retweets %
US Elections	29,098,834	5,708,690	8,153,615	20,945,219	71.98%
UK Elections	9,910,453	1,321,392	2,475,075	7,435,378	75.03%

5.4.1 Sentiment Analysis

Using SentiStrength, we assigned sentiment scores to all tweets. The process of assigning sentiment scores to text messages is explained in chapter 2 in detail. Our preliminary sentiment analysis of both datasets reveal that there are more negative sentiment tweets than positive. This finding is different from other studies that have used SentiStrength to evaluate sentiment of tweets [33]. Figs 5.2 and 5.3 show the distribution of tweets for in terms of their sentiment values.

We observe similar distribution pattern of tweets for both US and UK election datasets where negative sentiment tweets are higher in number than the positive sentiment tweets. Although the highest number of tweets for any sentiment value are neutral with 0 sentiment, tweets with negative sentiment far outnumber tweets with positive sentiment. Thus both datasets are skewed to the left with a skewness coefficient of -0.36 for US and -0.38 for UK datasets respectively.

After our initial data exploration, in the next section, we proceed to in-depth analyses of data in-order to test our hypothesis.

5.5 Descriptive Analyses

We now discuss the results of our data analysis. Like most election related Twitter studies, we discovered that a small number of users and tweets accounted for majority of retweets during both US and UK elections. The dataset collected during the US elections of Nov 2016, only 100,000 tweets were retweeted 15.2 million times while only 8% users in the

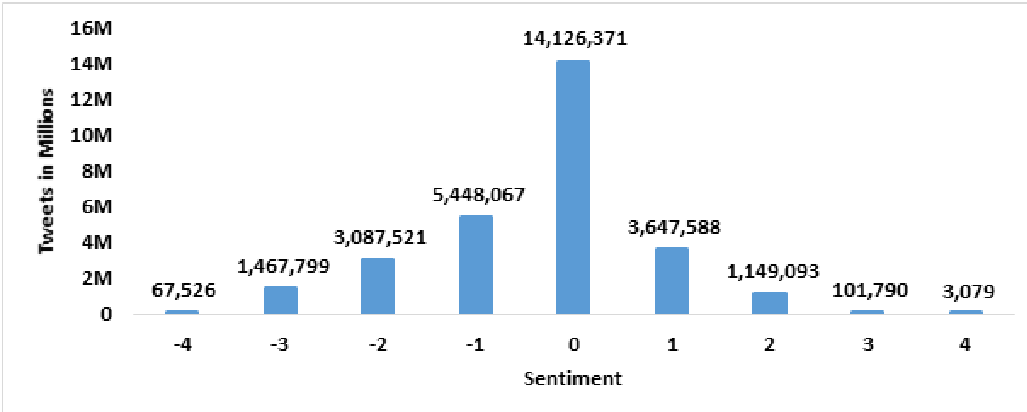

Figure 5.2: Distribution of tweets in US elections 2016 dataset in terms of sentiment polarity. We can observe that roughly half of the tweets are neutral $(sentiment = 0)$. However, the number of negative tweets is 10,070,913 and is more than double that of positive sentiment tweets which amount to 4,901,550 making the distribution skewed to the left with a skewness coefficient of -0.36.

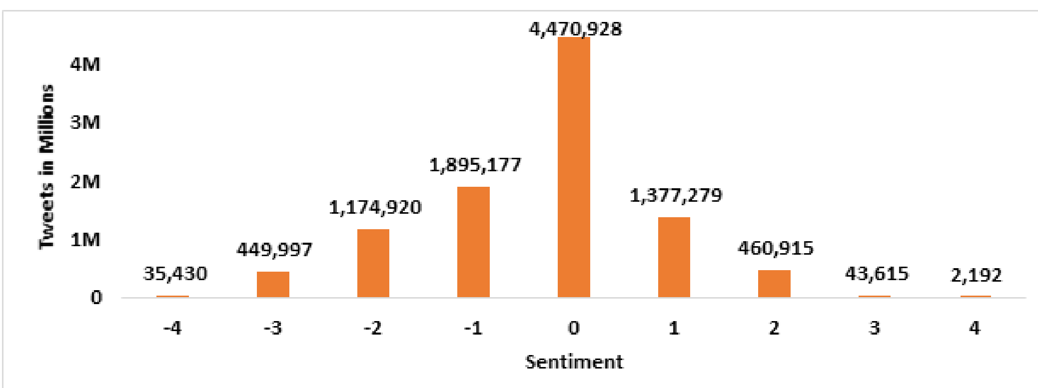

Figure 5.3: Distribution of tweets for UK elections 2017 dataset in terms of sentiment polarity. Highest number of tweets have neutral $(sentiment = 0)$. However, we can observe that just like US Election 2016 dataset, number of negative sentiment tweets is much higher 3,555,524 than positive sentiment tweets which number at 1,884,001 making the distribution skewed to the left with a skewness coefficient of -0.38.

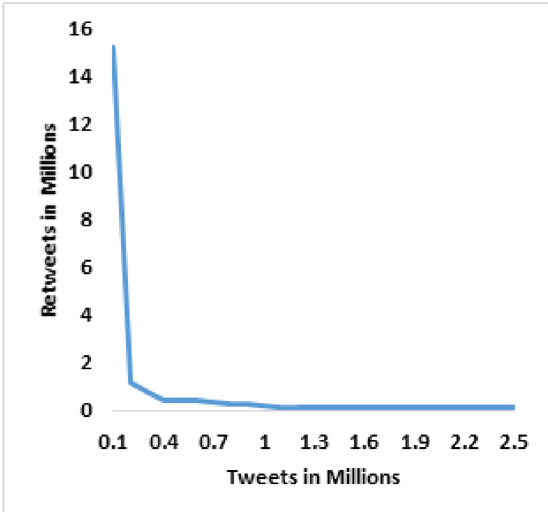

Figure 5.4: Displays the relationship between tweets and retweets during the US elections. Only 100,000 tweets account for over 15.2 million or 72% of all retweets.

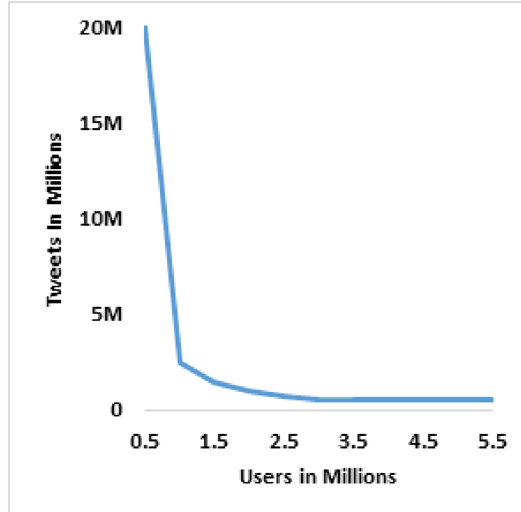

Figure 5.5: Shows the relationship between users and number of tweets during the US elections. Only 500,000 or 8% users are responsible for over 20 million or 69% of all tweets.

dataset accounted for 69% of all tweets. Fig 5.4 and 5.5 display this dominance where a small number of tweets and users account for a very large percentage of retweets and tweets respectively. We discover a similar pattern for the UK elections of 2017 where only 100,000 tweets were retweeted over 6.2 million times while top 100,000 tweeters, had 6.8 million messages in our dataset accounting for almost 70% of all tweets in the gathered. Figs 5.6 and 5.7 show this dominance.

In order to test our hypothesis of stakeholder salience and sentiment, we identified over 2 million users in the US dataset and over 479,000 users in the UK dataset who created at-least one original tweet. We then looked at all the retweets these tweets created in our dataset. Table 5.2 provides details of users from these two datasets.

We calculated the stakeholder retweet SR and sentiment SS variable for each of the stakeholders shown in table 5.2 by utilizing the methodology described in the hypothesis development section. Both of these variables are used as dependent variables in our data analysis for hypothesis testing related with stakeholder salience.

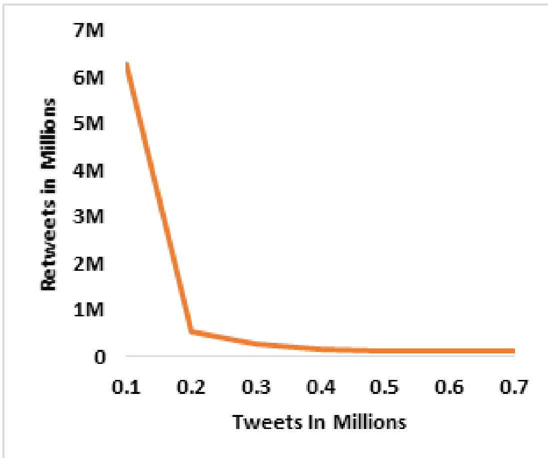

Figure 5.6: Displays the relationship between tweets and retweets during the UK elections. Only 100,000 tweets account for 6.2 million retweets or over 83% of all retweets.

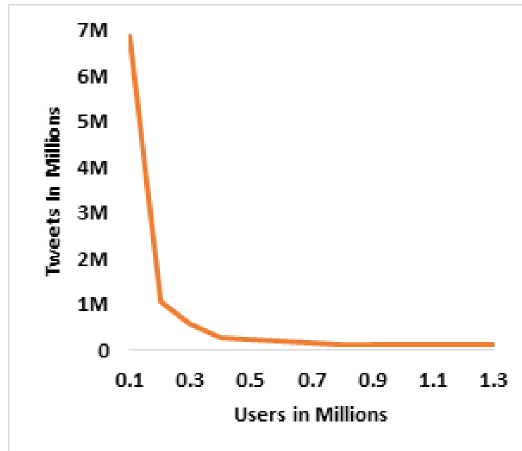

Figure 5.7: Shows the relationship between users and number of tweets during the UK elections. Only 100,000 or 7% users are responsible for over 6.8 million or 69% of all tweets.

Table 5.2: Stakeholders with one or more original tweets and retweets of all their original tweets in our datasets.

Tweets	Stakeholders with at least one original tweet	Stakeholder retweets	Retweets per stakeholder
US Elections	2,007,169	9,555,757	2.32
UK Elections	479,171	4,908,180	4.55

5.6 Stakeholder Salience Impact on Retweets and Sentiment

We can see from table 5.2 that majority of tweets in both US and UK dataset are retweets. We have also observed that majority of tweets in both datasets have negative sentiment (Figs 5.2 and 5.3). This is consistent with our previous studies in US elections where we discovered a larger number of negative sentiment messages than positive [100].

To evaluate how stakeholder salience impact retweets and sentiment, we developed the hypotheses shown in Fig 5.1. The first six hypotheses relate with stakeholder salience. We hypothesized in H1, H3 and H5 that higher stakeholder salience of power, legitimacy and urgency will lead to higher number of stakeholder retweets. For each individual salience, we grouped stakeholders in increasing order based on their salience values and calculated average number of retweets for each group. We now test our hypothesis using the data.

5.6.1 Power

Stakeholders of both datasets were divided into groups based on power. We get an R^2 value of 0.57 and 0.86 for retweets and sentiment for power respectively for the US dataset. Fig 5.8 shows the stakeholder power relationship with retweets and sentiment for US dataset. We discovered correlation coefficients of power both as positive and statistically significantly for both derived variables (0.99, $p < 0.01$ and 0.91, $p < 0.01$ for SR and SS respectively).

For the UK elections dataset, we have an R^2 of 0.66 and 0.79 for retweets and sentiment respectively. Fig 5.9 displays the stakeholder power relationship with retweets and sentiment. We discovered a significant and positive correlation between power and stakeholder retweets SR (0.98, $p < 0.01$). However, surprisingly the relationship between stakeholder power and sentiment was negative (-0.24, $p > 0.05$). This negative correlation was insignificant however as the p value was greater than 0.05.

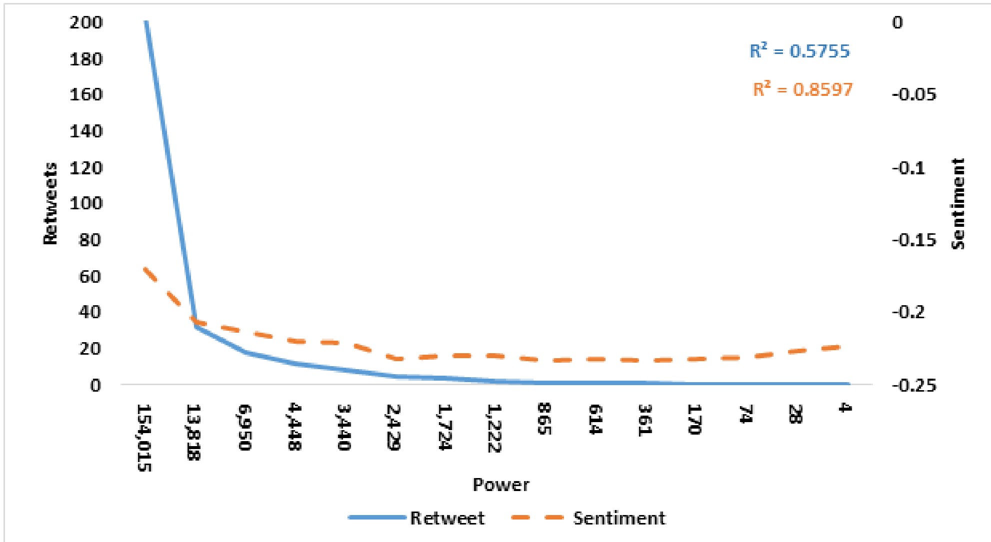

Figure 5.8: Stakeholder power in relation with stakeholder retweets and sentiment during US elections.

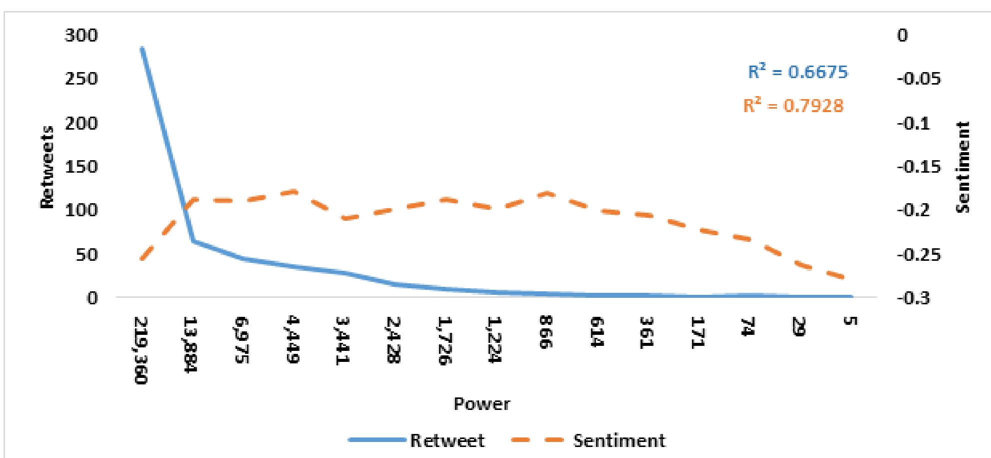

Figure 5.9: Stakeholder power in relation with stakeholder retweets and sentiment during UK elections.

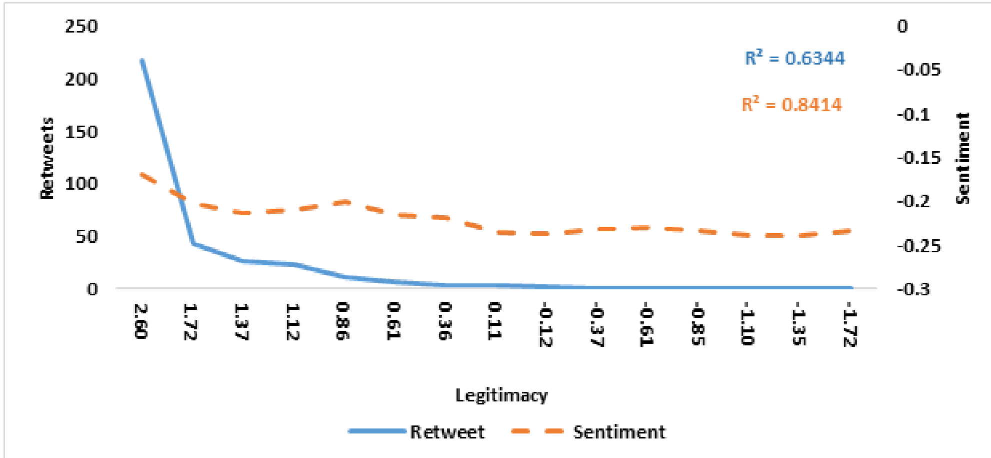

Figure 5.10: Impact of stakeholder legitimacy on retweets and sentiment during US elections.

Hence we can state that with our data analysis, we find support for hypothesis 1 in both US and UK elections datasets and conclude that stakeholder power does indeed impact message retweets. However we did not find sufficient support for hypothesis 2, as while in the US dataset, we found a significant positive relationship between sentiment and power, this relationship was negative and insignificant in the UK dataset.

5.6.2 Legitimacy

Legitimacy was the second stakeholder salience that we tested on our datasets in terms of its impact on stakeholder retweets and sentiment. We have explained the calculation of legitimacy salience in the hypothesis section. We organized our stakeholders based on legitimacy values ranging from greater than 2 to less than -1.5.

We discovered an R^2 value of 0.63 and 0.84 for retweets and sentiment respectively for the US elections dataset. Fig 5.10 shows the relationship of stakeholder legitimacy with retweets and sentiment. We discovered a significant and positive correlation between stakeholder legitimacy with SR and SS (0.69, p <0.01 and 0.88, p <0.01 respectively).

For the UK elections dataset, we got an R^2 of 0.85 for stakeholder retweets SR and 0.36 for stakeholder sentiment SS. Fig 5.11 shows the impact of stakeholder legitimacy

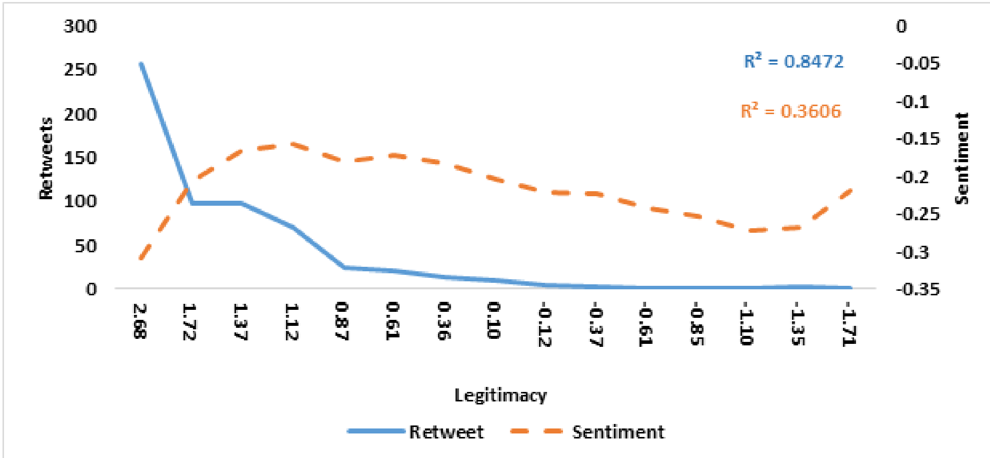

Figure 5.11: Impact of stakeholder legitimacy on stakeholder retweets and sentiment during the UK elections.

on retweets and sentiment during UK elections. We discovered a significant and positive correlation between legitimacy and stakeholder retweets (0.89, p $<$0.01). In case of stakeholder sentiment however, although the correlation between legitimacy and SS was positive, it was statistically insignificant (0.23, p $>$0.05).

We found support for hypothesis 3 in both US and UK elections datasets in our data analysis and can state that stakeholder legitimacy has a significant positive impact on message retweets. However, we did not find sufficient support for hypothesis 4, as while in the US dataset, we found a significant positive relationship between sentiment and legitimacy, this relationship was insignificant in the UK dataset.

5.6.3 Urgency

Finally, we analyze the impact of stakeholder urgency on retweets and sentiment. We calculate urgency of a stakeholder as defined in the hypothesis section of the paper. We then plot stakeholder retweets and sentiment against these values.

Fig 5.12 shows urgency impact on stakeholder retweets and sentiment during the US elections. We get an R^2 of 0.92 and 0.83 for retweets and sentiment respectively. We found a significant positive relationship between urgency and stakeholder retweet SR (0.97, p

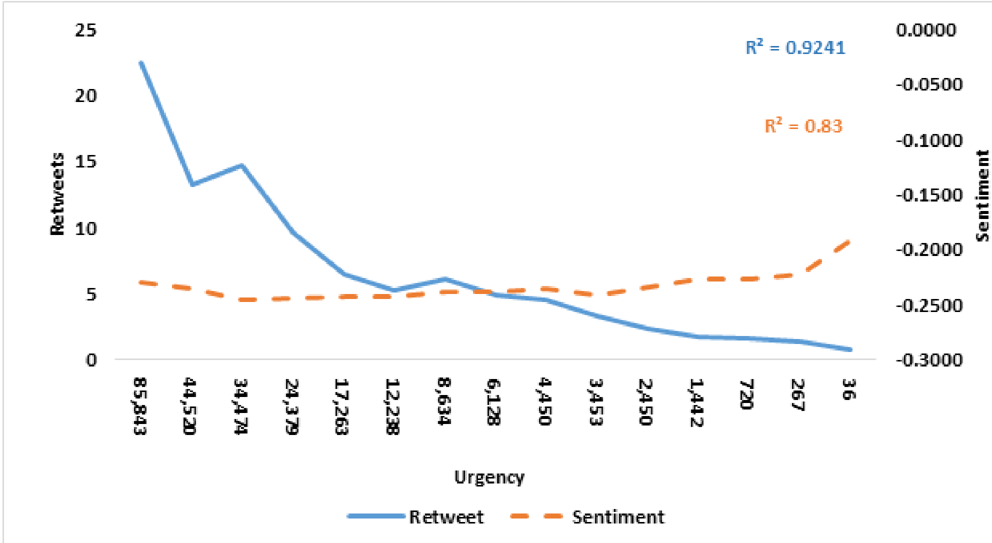

Figure 5.12: Impact of stakeholder urgency on stakeholder retweets and sentiment during the US elections.

<0.01). However, we discovered a negative correlation between urgency and stakeholder sentiment SS (-0.2, p >0.05).

For the UK elections dataset, we had a R^2 of 0.93 and 0.84 for retweets and sentiment. Fig 5.13 displays the stakeholder power relationship with retweets and sentiment for UK dataset. We discovered positive correlation between urgency and stakeholder retweet SR and negative for stakeholder sentiment SS. In both cases however, the correlation was statistically significant (0.97, p <0.01 and -0.90, p <0.01 for retweets and sentiment respectively).

We found support for hypothesis 5 in both US and UK elections datasets in our data analysis and can state that stakeholder urgency has a significant positive impact on message retweets. However, we did not find sufficient support for hypothesis 6, as while we discovered a negative correlation between urgency and sentiment in both datasets, the relationship was insignificant in the US dataset.

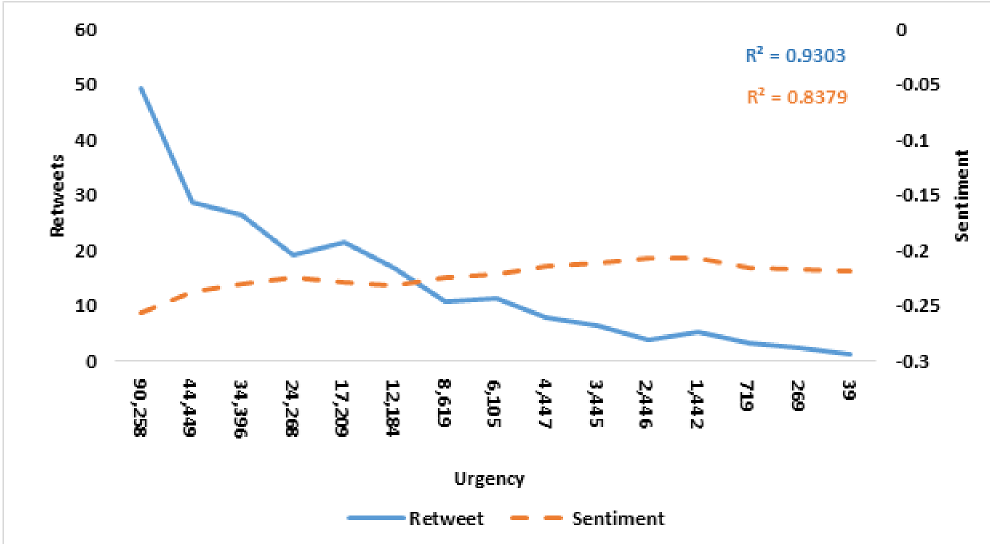

Figure 5.13: Impact of stakeholder urgency on stakeholder retweets and sentiment during the UK elections.

5.6.4 Role of Stakeholder Sentiment in Message Propagation

Along with stakeholder salience, we also evaluate the role of stakeholder sentiment SS in Twitter message propagation. Some studies have claimed that positive sentiment reaches more audience than negative. It is claimed that positive sentiment retweets reach a larger audience than negative [33]. As we can observe from Figs 5.2 and 5.3, majority of the tweets in our datasets have a negative sentiment. We observed a similar trend for retweets in both datasets where a larger proportion of retweets had a negative sentiment than positive.

Fig 5.14 shows the percentage of retweets in both US and UK datasets in terms of sentiment. We can observe here that retweets of negative sentiment are in a higher percentage than positive.

Here we can observe that both datasets exhibit similar behavior in terms of sentiment and retweets. Tweets with positive sentiment are retweeted lesser than negative retweets, and the lowest number of retweets are for the most positive value +4. Plotting a polynomial line of degree 2 and executing polynomial regression on them, we get an R^2 of 0.82 and 0.86 for UK and US datasets respectively.

However, in order to categorize stakeholder retweets by sentiment, we calculated the

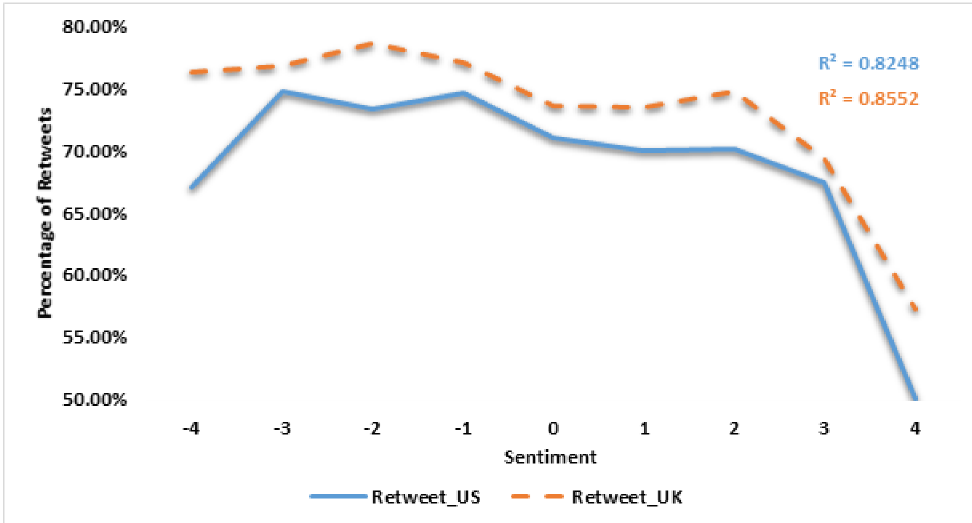

Figure 5.14: Percentage of retweets for each sentiment value in the US and UK datasets.

stakeholder retweet SR and stakeholder sentiment SS by taking an average of and of all of stakeholder's original tweets. Fig 5.15 shows the relationship between these two variables. We used SS as independent and SR as the dependent variable. We can observe a very similar pattern for both US and UK election datasets where highest number of retweets per stakeholder are for those stakeholders who had a slightly negative overall sentiment.

For both datasets we discovered a negative correlation between sentiment and retweets, indicating that stakeholders with negative sentiment have a higher number of retweets. However, the correlation was insignificant for both datasets ($p > 0.05$) and hence hypothesis 7 is not supported by our data analysis.

5.7 Hypotheses Testing Results

Table 5.3 provides a summary of the stakeholder salience correlation with retweets and sentiment for US and UK election datasets.

We can observe from table 5.3 that stakeholder salience of power, legitimacy and urgency have a significant positive correlation with higher retweets per stakeholder in both US and UK datasets. Hence hypotheses 1, 3 and 5 are supported by our data analyses.

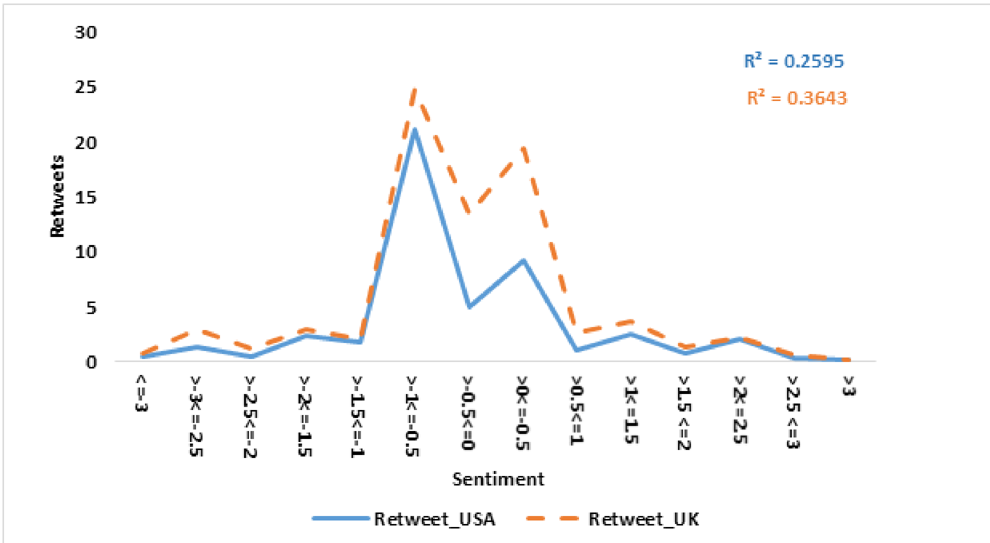

Figure 5.15: Impact of stakeholder sentiment on retweet rates for USA and UK election. Stakeholders with sentiment between -1 and -0.5 have the highest retweet rates in both datasets.

Table 5.3: Correlation matrix of stakeholder salience of power, legitimacy and urgency with stakeholder retweets SR and stakeholder sentiment SS for US and UK election datasets. Last table row shows the impact of stakeholder sentiment SS on stakeholder retweets SR. Values with * indicate statistically significant correlation with p <0.01.

	SR(US)	**SR(UK)**	**SS(US)**	**SS(UK)**
Power	0.99*	0.98*	0.91*	-0.24
Legitimacy	0.69*	0.89*	0.88*	0.23
Urgency	0.97*	0.97*	-0.20	-0.90*
SS	-0.12	-0.13	-	-

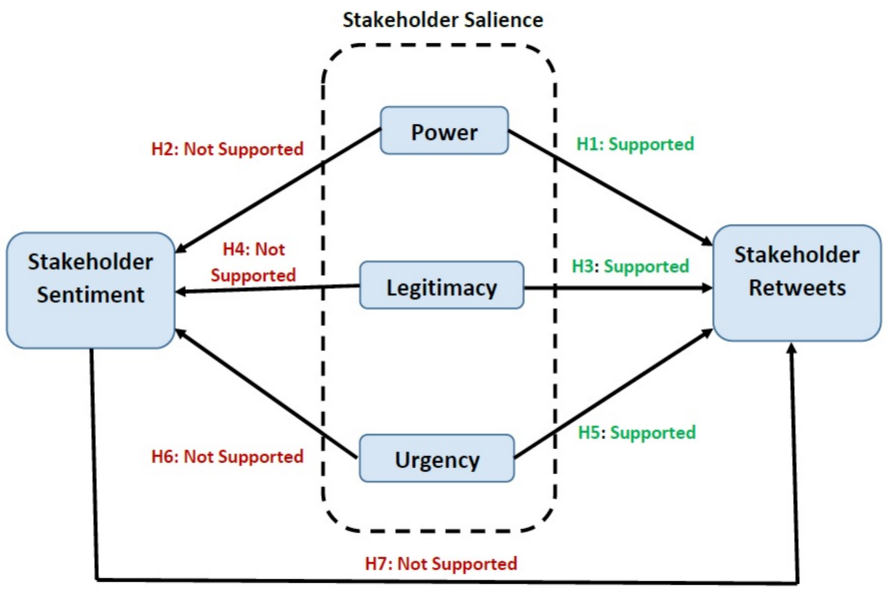

Figure 5.16: Model with hypotheses results.

On the other hand, power and legitimacy have a positive correlation with sentiment in both datasets, however this correlation is insignificant for the UK dataset. For urgency, the correlation with sentiment is negative in both datasets, however for the US dataset, this correlation is insignificant. Thus hypotheses 2, 4 and 6 are not supported by our data analyses.

Finally, we observe from table 5.3 that correlation between stakeholder sentiment SS and stakeholder retweets SR is negative for both datasets. However, the relationship is insignificant and hence hypothesis 7 is not supported by our analysis. Table 5.4 briefly describes the hypotheses result. Fig5.16 shows which hypotheses from our model are supported and not supported by the data analyses.

5.8 Discussion

5.8.1 Impact of Salience on Stakeholder Retweets

Support for hypotheses 1, 3 and 5 in both US and UK datasets suggests that stakeholder salience does indeed play a significant role in message propagation on Twitter during gen-

Table 5.4: Results of hypotheses test. 3 out of 7 hypotheses are supported by our test result.

Hypothesis	**Explanation**	**Result**
H1	Stakeholder power was positively and significantly correlated with stakeholder retweets during US and UK elections (0.99, $p < 0.01$ and 0.98, $p < 0.01$).	Supported
H2	Stakeholder power had both positive and negative correlation with stakeholder sentiment during US and UK elections respectively (0.91, $p < 0.01$ and -0.24, $p > 0.05$).	Unsupported
H3	Stakeholder legitimacy was positively and significantly correlated with stakeholder retweets during US and UK elections (0.69, $p < 0.01$ and 0.89, $p < 0.01$).	Supported
H4	Stakeholder legitimacy was positively correlated with stakeholder sentiment during US and UK elections. However in case of UK the correlation is insignificant (0.88, $p < 0.01$ and 0.23, $p > 0.05$).	Unsupported
H5	Stakeholder urgency was positively and significantly correlated with stakeholder retweets during US and UK elections (0.97, $p < 0.01$ and 0.97, $p < 0.01$).	Supported
H6	Stakeholder urgency was negatively correlated with stakeholder sentiment during US and UK elections. However for US dataset the correlation is insignificant (-0.20, $p > 0.05$ and -0.90, $p < 0.01$).	Unsupported
H7	Stakeholder sentiment is negatively correlated with stakeholder retweets during US and UK elections. However the correlation is insignificant for both datasets (-0.12, $p > 0.05$ and -0.13, $p > 0.05$).	Unsupported

eral elections. Validation of hypothesis 1 suggests that more followers of a stakeholder leads to more retweets while support for hypothesis 3 affirms that legitimacy, calculated as a log ratio between followers of stakeholders and users she follows, also has a significant positive impact on message retweets. These finding are similar to results of other studies that have looked into the relationship between user followers and retweets [88]. It is not surprising to observe that during elections, stakeholders behaved as any large social network driven by very few individuals around which everything is organized [9]. Thus actors who have a central position in the network have a greater potential to influence conversations and this network factor remains vital in our election datasets as well.

Finally, support for hypothesis 5 indicates that users with high urgency have more retweets. As urgency is measured by the number of messages created and liked by a stakeholder on Twitter, it indicates a high level of activity and this activity translates into a large number of retweets. This too appears to reaffirm some of the results shown by other studies looking into Twitter retweets stating that a user has more influence by having an active audience who retweet [21]

Overall, stakeholder salience of power, legitimacy and urgency do a good job of explaining retweets during elections on Twitter, with our hypotheses validated on both US and UK election datasets. Thus we can state that our stakeholder salience model can be utilized to understand retweets during election related discussions on Twitter. This can be beneficial for candidates and political parties, who use Twitter for political campaigning. By targeting stakeholders that rank high on power, legitimacy and urgency, they can create a bigger impact and reach a larger audience with their message on Twitter.

5.8.2 Impact of Salience on Stakeholder Sentiment

In terms of the impact of stakeholder salience on sentiment, we did not find sufficient support for hypotheses 2, 4 and 6. For hypothesis 2, although stakeholder power had a significant positive correlation with sentiment in the US election dataset, this relationship was negative for the UK dataset. This negative relationship is contrary to other studies that have looked at Twitter sentiment stating that users with a large following usually maintain a positive sentiment and try to avoid contentious topics as they might not know which of their followers they might end up offending [62]. This was not true during UK elections where we can observe from Fig 5.9 that stakeholders with the highest following exhibited a high negative sentiment in their messages. However, this negative correlation was insignificant with p $>$0.05 and hence we do not find significant support for hypothesis 2 in our data analysis.

Legitimacy had a positive correlation with SS and although we discovered a significant positive relationship between legitimacy and SS during US elections, the correlation was insignificant during the UK elections. Hence hypothesis 4 was not supported by our data analysis in both datasets.

Finally, hypothesis 6 was not validated by our data analysis and we discovered a negative correlation between stakeholder urgency and sentiment. This shows that majority of the stakeholders who were tweeting frequently and liking tweets had a negative sentiment. A large number of negative sentiment tweets and retweets in both election datasets indicate that majority of the activity originated from users who exhibited a negative sentiment.

5.8.3 Impact of Stakeholder Sentiment on Retweets

Along with salience, we also tried to evaluate the impact of stakeholder sentiment SS on stakeholder retweets SR during elections. We discovered that stakeholder with negative sentiment SS had higher retweets SR on average than stakeholder with positive sentiment for both US and UK datasets (Fig 5.15). We also discovered that tweets with higher negative sentiment are retweeted more than tweets with positive sentiment. Fig 5.14 shows this relationship where increase in positive sentiment leads to decrease in retweet percentage.

However, although stakeholder with -1 sentiment had the highest number of retweets in both datasets (Fig 5.15), and we discovered a negative correlation between stakeholder sentiment SS and retweets SR, we could not find significant support for hypothesis 7. Hence our hypothesis of negative stakeholder sentiment leading to a higher number of retweets is not supported.

A negative overall sentiment seen in both datasets does however indicates the unpleasant nature of modern elections. The US elections 2016 saw one of the most historically bitter and negative presidential election campaigns [18]. The UK elections too saw an increased use of social media for negative campaigning. Hence negative sentiment on Twitter reflects this overall negativity witnessed during the US and UK elections.

Chapter 6

Analyses of Social Media communication of Public Sector Organization

Along with analysis of election data, we also evaluate the social media communication strategy of public sector organizations. For this study, we collected data from both official Facebook and Twitter pages of various organizations operating in the area of public service. Analysis of this data will help us determine how these organizations are utilizing social media in terms of message sentiment and content. We will also evaluate how nature of organizational work affects this communication. Findings from this study will help these organizations foster better communication with the citizens.

6.1 Motivation

The global population continues to increase at a rapid pace while the resources at disposal of government institutions remain finite. With the turn of the century governments around the world are facing new challenges such as mass urbanization and growth in the cities. Large cities bring their own set of challenges such as law and order and providing effective civic services. To meet these new challenges, governments around the world are moving towards new technologies.

Over the last couple of years, the idea of smart cities has emerged globally where digital governance with the help of information and communication technologies (ICT) enable an effective and efficient governance [70]. One aspect of this effort is the use of social media for communication with the citizens by public sector organizations. The proliferation in use of social media has created new possibilities for public organizations to engage citizens in government work. These efforts are now being made at the national level such as the Open Government Directive in the U.S. which emphasized core principals of open governance by encouraging government agencies to benefit from these new platforms [25]. Since then, government agencies have come a long way in using social media for communication with citizens. For example, according to a survey by the International Association of Chiefs of Police (IACP), approximately 96.4% of 553 U.S. law enforcement agencies use social media [47]. In this chapter of the dissertation, we investigate the nature and sentiment of communication by public sector organizations on Facebook and Twitter. For this purpose we collect posts and tweets of these organizations and analyze them for sentiment and content. The goal of our research is to answer the following questions:

- How usage of social media differs for various organizations depending on the nature of their operations? The goal here is to evaluate the sentiment of messages posted by these organizations online along with the content and frequency of these messages in-order to evaluate organization's online communication strategy.

6.2 Related Work

By using already available social media platforms, public organizations can save funds that would be required to develop and maintain customized solutions to interact with citizens. It also allows government institutions to have candid communication with their citizens. One such attempt was the creation of social media platform to facilitate bidirectional communication between local government and citizens where the system allows Newark City

Government to connect with residents, enabling them to request several public services [61]. The platform's primary method of communication is through the Twitter social network allowing its users to send and receive short messages.

Social media also help in increasing openness and transparency into the working of public organizations [11]. Studies have shown that from civic services to police departments, information sharing and public engagement through Twitter can lead to greater transparency and more confidence of citizens on their state and local institutions [43].

Law enforcement agencies are actively using social media platform as this enables them to handle crimes more effectively while promoting a harmonious relationship between police and community. One such example is the use of Twitter by the London Metropolitan Police (MET) and Greater Manchester Police (GMP) during the British riots of 2011 [29]. Studies have also indicated that by using social media. Police forces can increase their perceived legitimacy by enabling transparency and participation [40].

Researchers have also looked at the potential role of social media in public transit services. For example, studies have looked at how Twitter can be used to gauge transit rider satisfaction [27]. Sentiment analysis is performed on tweets shared by transit riders. Similarly, researchers have also looked at the role Twitter can play in development of transport policy and planning along with effective operations of transport system [80]. The benefit of using social media for this purpose in comparison to using traditional surveys to measure riders' satisfaction and creating policies is that the cost of data collection is minimal. Furthermore, data can be gathered in real time from a large segment of users, providing policy makers and operation managers access to a large quantity of user data in a relatively short amount of time.

6.3 Analysis of Social Media Communication

As discussed earlier, the aim of this research is to understand the characteristics of communication by public sector organizations that takes place on Facebook and Twitter. In this section, we discuss the hypothesis development which will be tested by our data analysis.

6.3.1 Sentiment Analysis of Organizational Communication

Sentiment analysis of social media communication is being used in vast array of areas related with governance and public trust. These analysis range from predicting resentment against government policies to forecasting general election results [20, 93]. Similarly, role of sentiment in online message propagation remains a popular topic of research. For example, some studies have claimed that tweets with positive sentiment reach a wider audience than those with negative sentiment [33]. Hence in-order to reach a wider audience, organizations should create a positive message.

However, we also believe that the nature of organization‘s work plays an important role in determining the sentiment of organizational communication. For example, law enforcement agencies primarily use social media to disseminate information and alerts regarding crimes, traffic alerts, safety notices to citizens on an urgent basis [47]. This would be different from alerts by a public transport authority such as MTA (New York City) or SEPTA (Philadelphia) where most messages pertain with train and bus schedules and delays.

Research Question 1: *How nature of organization’s work affects sentiment of organization‘s social media messages?*

6.3.2 Frequency Analysis of Organizational Communication

In this research, we examine social media communication of public sector organizations on two different platforms, Facebook and Twitter. Organizations have various goals when engaging on social media. These goals could be disseminating information or creating a call for action. Hou and Lampe [46] create a framework to evaluate the social media communication of non-profit organizations. They divide the communication into 3 categories, information, community and action. Using our Facebook and Twitter data, we evaluate how frequently organizations are communicating with citizen.

Research Question 2: *How frequently these organizations are using social media for communication?*

6.3.3 Message Framing by Organizations in Twitter Communication

Message framing on Twitter is an important area of research. For example, adding hashtags (#) to keywords in Twitter and Facebook by message posters makes them searchable by other online users and now play an important role in the context of coverage and discussion of news [84]. The use of hashtag allows users to become part of trends and also enables them to reach a large audience by making their messages searchable.

We believe that a similar trend will be observed in the organizational communication on Twitter and Facebook. As these organizations use social media to inform public and broadcast critical alerts, they will be more concerned about making their tweets and posts more searchable than ordinary users having fewer followers and lesser number of messages. By framing their messages using hashtags, organizations are able to reach a broader audience, making their messages more searchable. Thus we will answer the following research question:

Research Question 3: *How organizations use # to make their tweets more searchable for users?*

6.3.4 Direct Communication by Organizations in Twitter Communication

Twitter not only allows it‘s users to broadcast their message to many people but also lets them interact one-to-one by addressing a person directly. Using“@”before a particular user name, is an effective way for users to interact with each other [90]. This enables them to respond to other user‘s tweets paving way for a dialogue and bi-directional communication. Various studies regarding conversations on Twitter have stated that people do not only use Twitter to post opinions but also engage in interactive discussions [93]. Nonetheless, direct messaging creates complexities for users in terms of target audience, especially for users with a large following in having to handle multiplicity and one-to-one conversations at the same time [62]. Management of audience becomes challenging as the number of followers of a user grows. Almost all Facebook and Twitter accounts of the organizations used in this study have followers ranging from tens of thousands to millions of users. Examining tweets of the public organization for direct messages can help us understand agencies‘ social media practices in the context of engaging public users for building community relationship along with addressing citizens‘ needs.

Research Question 4: *What is the nature of communication of the organizations? How much do they engage in direct messaging with other users, creating a conversation and answering user queries directly?*

6.4 Methodology

For this study, we used Facebook and Twitter posts of public sector organizations. Our approach relied on performing data analytics to understand the nature and sentiment of the posted by these organizations on the social media sites. We performed sentiment analysis using SentiStrength software. Details of this process are provided in chapter 2 of the dissertation.

Table 6.1: 3,200 tweets and 1,561 Facebook posts were collected for each organization. This table displays the daily average of tweets and posts made by each organization.

Organization	Facebook Posts per day	Tweets per day
Boston Police	1.85	4.8
Philadelphia Police	1.73	4.93
NY Police Dept.	1.12	10.22
NY Dept. of Motor Veh.	0.9	2.5
Penn Dept. of Motor Veh.	1.76	4.48
NY Energy	1.82	4.33
PPL Electric	1.76	4.13
NY Metro	0.9	228.57
SEPTA	1.26	103.23

6.4.1 Dataset

Public organizations that have official presence on both Facebook and Twitter are selected for this study. This data is downloaded from the official Facebook pages and Twitter handles of the organizations. Facepager application is used for this purpose [31]. Twitter on the other hand provides access to past 3,200 tweets for any account. Fig 2.1 in chapter 2 of the dissertation shows the methodology steps involved in data gathering, preparation, sentiment classification and final analysis.

In total we downloaded Facebook and Twitter posts of 9 public organizations on 9th April 2018. These agencies operated in the areas of law enforcement, transportation, transit and electricity providers. We selected at least 2 public organizations from each of these 4 areas and collected the last 3,200 tweets and 1,561 posts for each organizations. Table 6.1 shows the organizations and the number of days it took for each organization to make these posts and tweets.

6.5 Data Analyses Results

We now present the results of our data analyses.

Table 6.2: Example of a typical tweet by New York Police Department, Boston Police Department and Philadelphia Police Department.

Organization	Tweet
New York Police	”WANTED: Six male teens for assaulting a 14-year-old boy in front of 1251 Stebbins Ave #Bronx at 10:30pm on Sunday”
Boston Police	”UPDATE: Victim Identified in Death Investigation in the Area of 1 Costello Circle in South Boston https://t.co/ArUIcVZ2vo”
Philadelphia Police	”Wanted: Suspect for Commercial Robbery in the 17th District [VIDEO] https://t.co/4LLV4aAoiH”

6.5.1 Sentiment Analysis of Organizational Communication

The first research question relates with the sentiment analysis of the organizational communication on social media. Fig 6.1 displays the sentiment on Twitter and Facebook for all organizations under study. We notice similar sentiment intensity for all organizations on both platforms.

We also observe that police departments have a much more negative sentiment overall than other organizations. This is due to the fact that majority of their messages are crime alerts or other broadcasts related with public safety. Table 6.2 shows some of the tweets by the three police departments we have used in this study

Hence in answering **RQ1**, we can state that the nature of organizational work does indeed play an important role in the sentiment of their messages.

6.5.2 Frequency Analysis of Organizational Communication

The second research question looks at how frequently public organizations utilized Facebook and Twitter to communicate with citizens. Fig. 6.2 shows the number of daily Facebook posts and tweets made by each organization under study.

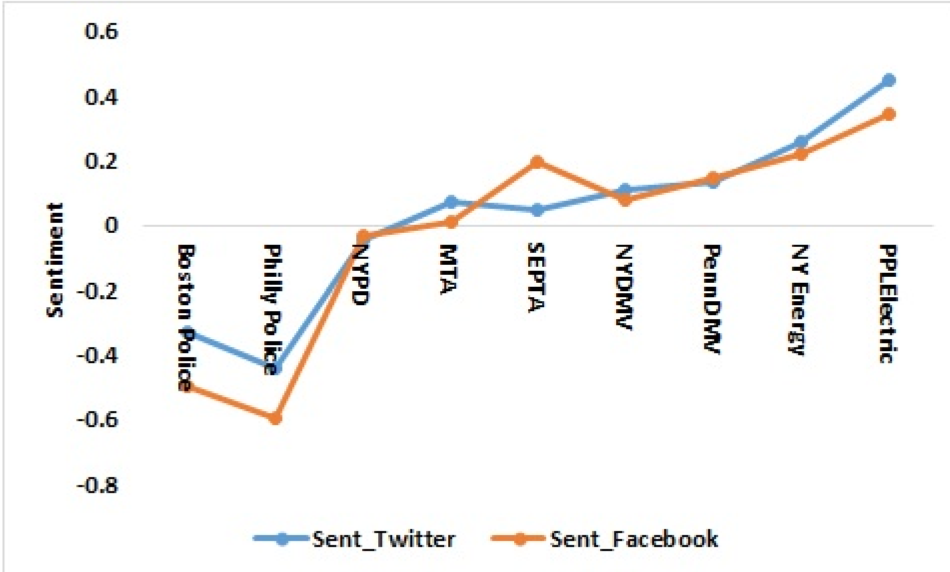

Figure 6.1: Sentiment of tweets and Facebook posts of public organizations under study. We can observe similar sentiment for both Twitter and Facebook for each organization.

Table 6.3: Example of a typical tweet by MTA and SEPTA.

Organization	Tweet
SEPTA	”Norristown: Train #8266 going to Elm St is operating 10 minutes late. Last at Queen Lane.”
MTA	”Northbound 6 trains are running with delays because of an unruly passenger at Grand Central-42 St.”

Here we can observe that on Facebook, almost all organizations had a similar rate of postings as shown in table 6.1. However, on Twitter, we observe a very large number of daily tweets for SEPTA and MTA, both public transportation providers in Philadelphia and New York City respectively. These organizations have to communicate regularly with their riders, keeping them up-to-date with any delays with the trains. Table 6.3 provides an example of SEPTA and MTA tweet, hundreds of which are made everyday to inform riders of any delays in operations of trains and buses.

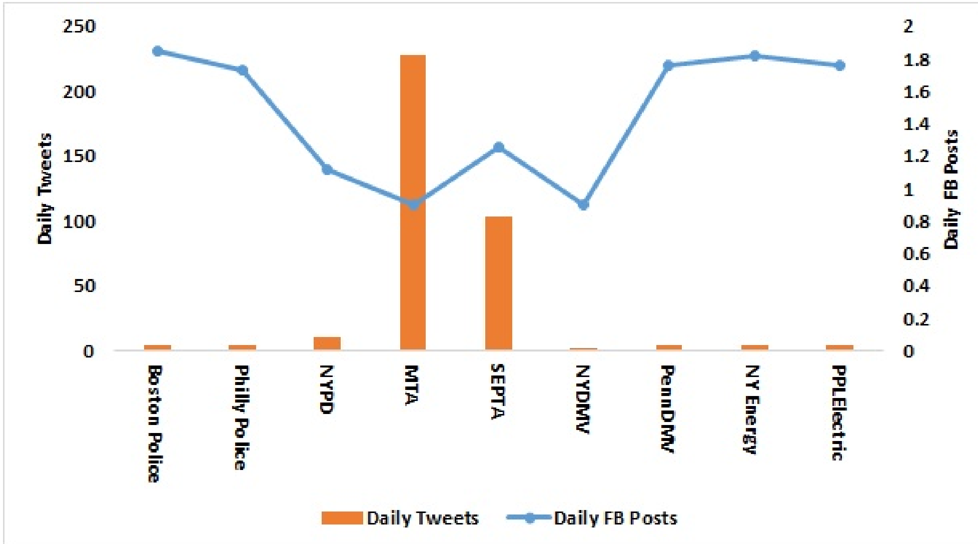

Figure 6.2: Average number of tweets and Facebook posts of organizations in a day.

6.5.3 Message Framing by Organizations in Online Communication

The third research question looks at how messages are framed by public organizations on Twitter. As discussed earlier, using hashtags to make tweets more popular is one way to achieve this. Fig. 6.3 shows the percentage of hashtags in Facebook posts and tweets made by each organization.

There is no clear pattern in terms of utilization of hashtags by the organizations. We discovered few hashtags in the tweets made by MTA while in SEPTA tweets a high percentage contained hashtags although both organizations operate in the area of public transport.

6.5.4 Direct Communication by Organizations in Twitter Communication

Along with framing, we also looked at Twitter messages of these organizations for direct communication, evaluating whether they are fully utilizing bi-directional nature of the platform. We wanted to quantify the degree of these organizations‘ engagement in direct conversations with their users. As discussed, Twitter allows users to broadcast their message to multiple people along with letting them interact one-to-one by addressing a person

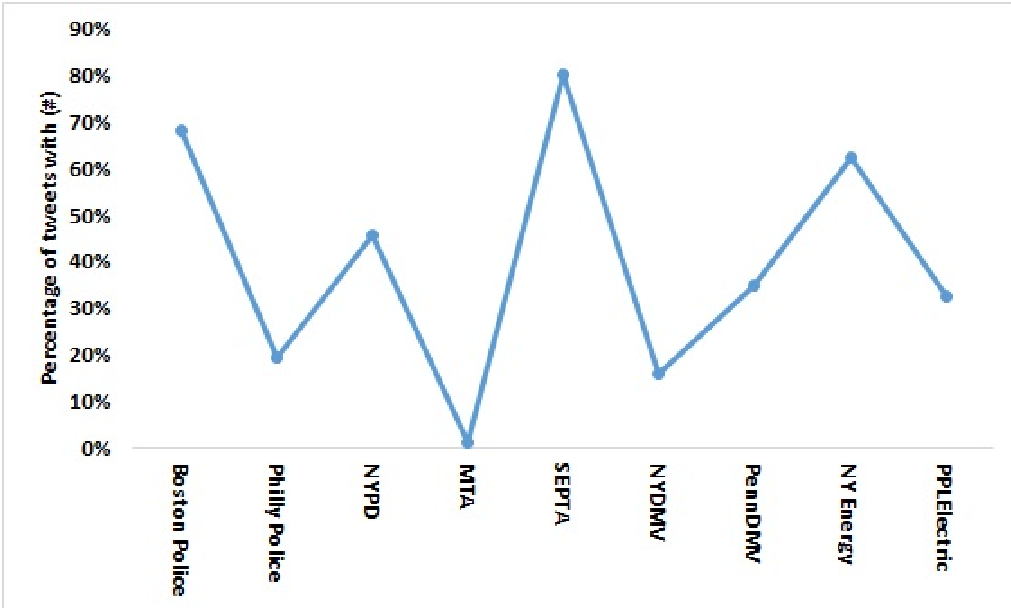

Figure 6.3: Percentage of tweets by public organizations containing hashtags. Hashtags makes it easier for Twitter users to identify important trends allowing for tweets to become more popular.

Table 6.4: Correlation matrix between direct message tweets and tweets containing hashtag(#)

-	Direct Messages	Tweets with #
Direct Messages	1	
Tweets with #	-0.8137	1

directly, enabling online dialogue.

We evaluated organizational communication for dialogue by looking at all the tweets in our database that start with the expression "@". Other studies have also utilized a similar approach to gauge interactive discussions on Twitter [93]. Fig 6.4 shows the percentage of tweets that are direct messages.

We observe that usage of hashtags and direct messages are in inverse correlation for most of the organizations. We can see this from Fig 6.5. Table 6.4 displays this negative correlation which is statistically significant ($p < 0.01$).

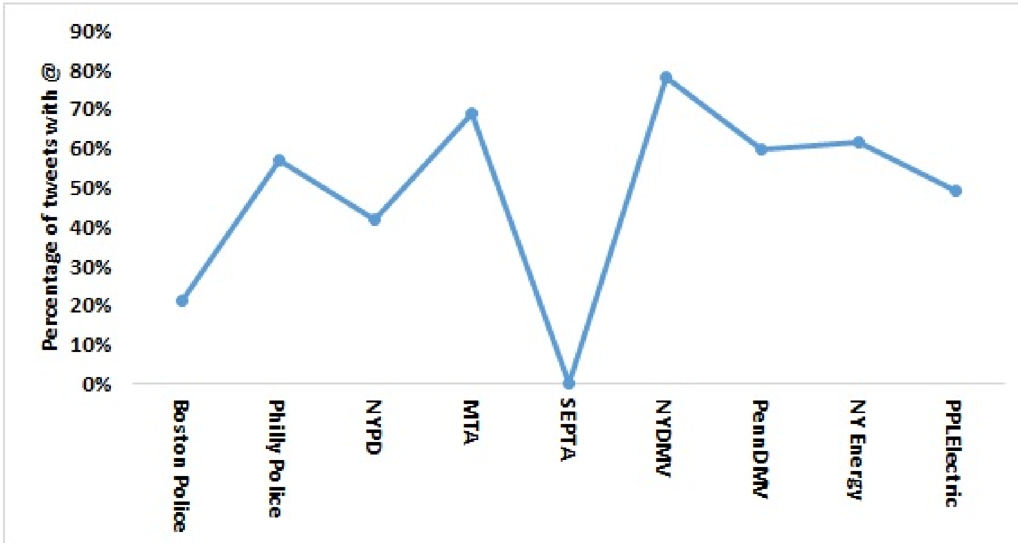

Figure 6.4: Percentage of twitter messages direct messages by public organizations.

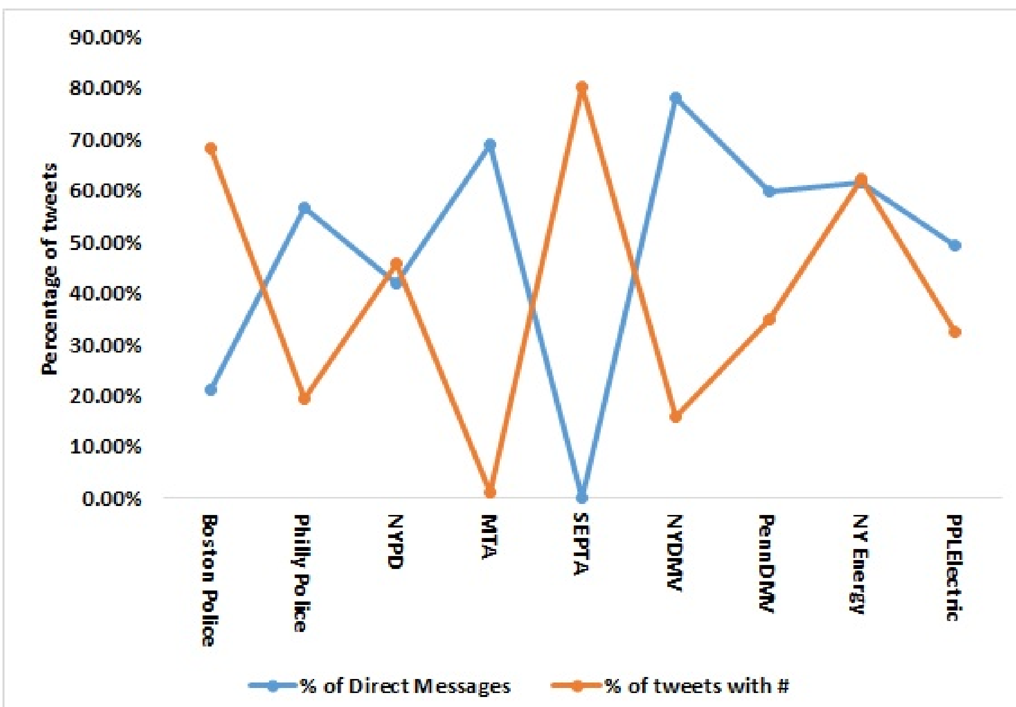

Figure 6.5: Percentage of twitter messages that are direct messages and have hashtags for all organizations under study.

6.6 Discussion

The purpose of this data analyses was to evaluate social media communication of organizations operating in various areas of public service in Northeast US. We wanted to understand how sentiment and content of messages by organizations is affected by their area of operations. We will now discuss the results of our data analyses.

6.6.1 Difference in Usage of Social Media by Public Organization

The foremost question under discussion is how the message sentiment, content and frequency changes for various organizations utilizing social media for public engagement depending on the nature of their operations.

For example, in terms of sentiment, we discovered a correlation between message sentiment and organization's field of work. Fig 6.1 shows sentiment of Facebook and Twitter messages of all organizations under study. We discover that sentiment of all organizations is similar on Facebook and Twitter. This is due to the fact that important messages are broadcast simultaneously on both platforms, resulting in uniformity of sentiment. We also observed that police organizations generally have a negative sentiment messages due to their nature of communication with the citizens, appraising them on crime alerts and public safety messages. Table 6.2 provides examples of broadcast messages by the three police departments.

In frequency analysis, we discovered that almost all organizations used Twitter more frequently than Facebook. The number of daily Facebook posts for all organizations was somewhat similar as shown in table 6.1. However, on Twitter, there was a huge variance in terms of number of daily tweets. Here we observe that New York Metro and SEPTA (transportation authority of Philadelphia) are far more active on Twitter. These two organizations tweeted over 228 and 103 times a day on average respectively. This indicates the use of Twitter as a tactical tool by these organizations, where train and bus delays or other transport related disruptions were broadcast regularly to the users.

Finally for message framing and direct communication, we observe an inverse correlation between the two (table 6.4). This shows us that either an organization is focused on using social media for broadcasting or for direct one-to-one communication.

The above analyses helps us discern the different ways in which organizations utilize social media depending on the nature of their operations.

Chapter 7

Location Based Twitter Analysis

High level of public connectedness through social media has changed the way local and national public institutions interact with citizens. For example, almost all police departments of large US cities have presence on multiple social media platforms including Facebook and Twitter [16]. This presence enables them to quickly engage and get citizen help on any impending emergency. Local governments providing civic services such as garbage collection and infrastructure maintenance are also using social media to get feedback from citizens on priority of public works [61]. The idea of e-governance and smart city is taking hold globally and Internet has provided policy makers with the opportunity to increase government awareness and institutional responsiveness through citizen engagement. It has been indicated that efforts by government to increase public participation in the affairs of government and taking greater input into decision making can improve public trust in government [52].

One area that has also witnessed an increase in use of Twitter is that of electoral campaigning. With the growing importance of Twitter as a communication tool, politicians and political parties now maintain a significant presence on the micro-blogging platform. This surge in Twitter usage for political campaigning during elections has also increased interest of researchers of data analysis. Election prediction using Twitter data is becoming a popular research area [83, 93] where citizen sentiment is utilized to estimate candidate performance in general elections [100].

However there is still supplementary Twitter meta-data that has not been used in data analysis. For example, while measures such as followers, re-tweets etc. have been looked at intensively in Twitter data analysis, utility features have mostly been overlooked [97]. One such feature is that of location. Twitter allows user to enter their location information in their profile. Although this attribute is optional, a significant number of users still choose to provide their city/state and country information voluntarily which is downloaded with each tweet as metadata. While a large number of election related studies have utilized Twitter data, from terms frequency to sentiment analysis, in-order to predict elections and evaluate candidate popularity, none have used Twitter location parameters. We believe that by utilizing location information, we can get a more accurate understanding of the on-ground public opinion. For example, recently in some elections around the world, a strong political divide is observed between urban and rural areas or between services based and manufacturing based zones where economic policies have unequal impact on the regions within a country. By utilizing location data, we can accurately gauge support levels for candidates and policies on each region or part of the country, giving us a more detailed picture of public opinion.

Sentiment analysis of Twitter messages, can be defined as a host of activities centered on text mining. Through sentiment analysis, researchers try to understand the attitudes, opinions, views and emotions from text using Natural Language Processing (NLP). Thus although sentiment analysis is primarily associated with classifying opinions in text into categories such as ”positive”, ”negative” or ”neutral”, it also involves subjectivity analysis, where parts of speech such as adjectives, adverbs and some group of verbs and nouns are taken as indicators of a subjective opinion [51].

In this study, we make the following two contributions. First, we study the subjective and polarity of Twitter data with respect to the location of Tweets. Findings from this research will enable further fine grained sentiment analysis of Twitter data by using the location variable, allowing for more accurate results of user sentiment and behavior analysis [101]. Second, we present a web-based application that enables collection and analysis of Twitter data [82]. Here the user inputs a keyword and from there on, the application fetches live tweets, extracts their text, calculates user location, performs data analysis and creates a map allowing us to visualize the current trend associated with the user input term. This analysis platform also facilitates researchers to analyze tweets that were gathered in the past during a particular event. The motivation behind building this application is to provide a single automated platform, which serves as a complete end-to-end system for sentiment analysis and visualization of Twitter location data.

We use Twitter data gathered during the US Elections of 2016 as a case study. In this section of the dissertation, we will utilize this web-application to perform subjectivity and polarity analyses of Twitter location data making the following contributions:

- Subjectivity analysis of location data, allowing us to gauge effectiveness of the platform in plotting subjectivity of tweets on a map for visualization.

- Polarity analysis of location data, evaluating accuracy of the platform in plotting sentiment and opinion of Twitter users on a map.

7.1 Related Work

Large number of Twitter users, coupled with the APIs made available by the micro-blogging site, has allowed researchers from all over the world to engage in Twitter data analysis. This interest has led to the emerging field of techno-social systems which aims to comprehend and predict future events [8, 94].

Twitter sentiment analysis is one such area where research ranges from predicting resentment against government policies to predicting general election results [20, 15]. Increase in use of Twitter by politicians during general elections has resulted in increased research of understanding role of Twitter during electoral campaigns [5]. Similar research was also conducted in analyzing Twitter activity of US Congress members during their election campaigns where these candidates frequently posted information on Twitter regarding their political positions on various issues [38, 39].

Several measures have been proposed in research to predict comparative strength of political candidates on Twitter. One such measure is that of ‘relative support‘ used during the analysis of Spanish Presidential Elections of 2011 and Italian parliamentary elections of 2013 [15, 19]. The relative support measure utilizes time series slope of accumulated Twitter messages mentioning each candidate to compute their support on Twitter.

However, while there has been an exponential growth in the research pertaining with public opinion and sentiment prediction using Twitter, a debate still exists on the efficacy of the methods employed [37, 65]. As Twitter data does not contain important demographic information such as age,sex, income, education etc. doubts exist over how representative data sample is of general population.

Researchers have also examined the ways in which Twitter chatter can potentially influence mainstream media. It is shown that twitter is now playing an important role as a news source for mainstream news [73]. Twitter is now ever more used as news agenda building tool for mainstream media [30, 31]. This was a very commonly observed phenomenon during the recently concluded US elections of 2016.

Social media has also enabled policy makers to collect data created by citizens for analysis. Data deluge in the form of big data allows policy makers to develop a more sophisticated, wider-scale, finer-grained and real-time understanding of their constituents [53]. Facebook too has become a popular tool with regards to communication between government institutions and citizens [45]. Majority of public sector organizations now manage Facebook pages thorough which they communicate with the community in which they operate.

7.2 Subjectivity and polarity analysis

Sentiment analysis of Twitter messages involves a host of activities which includes understanding the attitudes, opinions, views and emotions from text using Natural Language Processing (NLP). Other terms used for sentiment analysis are subjectivity analysis, opinion mining, and appraisal extraction. The words sentiment, opinion and polarity are used interchangeably but there are differences between them.

In this paper we are performing two message level classifications. These are:

- Subjectivity Classification: e.g. how subjective or objective is a particular message.
- Polarity Classification: e.g. how positive or negative is a particular message.

Various sets of features can be considered when evaluating any text for subjectivity and polarity analysis. For example, vocabulary features such as unigrams and bigrams can help detect domain specific opinionated expressions [23].

7.2.1 Subjectivity

Subjectivity analysis of the text is a part of sentiment analysis, where using Natural Language Processing (NLP) researchers classify a text as opinionated or not opinionated [51]. Presence of certain terms such as adjectives, adverbs and some group of verbs and nouns are taken as indicators of a subjective opinion. Thus subjectivity analysis is the classification of sentences as subjective opinions or objective facts. Hence for a set of messages in a dataset, through subjectivity analysis, we identify sentences that are subjective from those that are objective. Speech patterns such as use of adjectives along with nouns are used as an indicator for subjectivity of a statement [51].

We have utilized Python TextBlob for the Natural Language Processing (NLP) to perform subjectivity analysis on our dataset. Python TextBlob is a popular NLP tool available for free which can be used to perform text subjectivity analysis. Subjectivity of every tweet was calculated with the help of the textblob library which uses a built-in model to calculate the subjectivity value. Table 7.1 shows the range of subjectivity values. A value close to 0 indicates an objective text while a value close to 1 indicates a highly subjective text. Details on the working of Python NLP in are provided in Bird, Klein and Loper 2009 [12].

7.2.2 Polarity

Once through subjectivity analysis we determine whether a sentence is opinionated or not, we perform polarity analysis of the text to ascertain whether it expresses a positive or negative opinion [51]. The purpose of polarity analysis, is to determine the emotional attitude of text writer with respect to the topic under discussion [58]. With Twitter gaining popularity as a communication tool, interest in analyzing it‘s data to determine public mood or opinion towards a topic or a popular personality has also grown [93, 72]. Polarity analysis enables us to gain that insight, by quantifying the sentiment of text. The text can thus be classified as negative, positive or neutral. Several tools are available for sentiment analysis of short text. In this case, just as with subjectivity analysis, we have utilized Python TextBlob package for the polarity analysis on our dataset.

Polarity analysis using Python Textblob, words in the lexicon are assigned scores for negative and positive polarity. These polarity scores range from -1 to 1, where -1 represents extremely negative sentiment while 1 represents extremely positive sentiment respectively. A polarity score of 0 suggests a neutral sentiment.

Using the python Textblob, polarity scores were assigned to tweets for both candidates. Textblob uses a built-in model to calculate the polarity values. These tweets were organized based on the states from which they originated. In order to get a distinguishable polarity score, the original polarity scores for both candidates were scaled by a factor of 100. Table 7.1 briefly describes the polarity metrics.

We will use a tweet by Donald Trump made during the election campaign and captured in our dataset to further explain the concept of subjectivity i.e. opinion and polarity:

Table 7.1: Subjectivity and polarity calculation.

Metric	Explanation	Scale
Subjectivity	Measure of text as fact or opinion	0 to 1
Polarity	Text sentiment	-1 to +1

- **Message:** @realDonaldTrump: So nice —great Americans outside Trump Tower right now. Thank you!
- **Subjectivity:** nice, great.
- **Polarity:** positive.

The above tweet ranks high in subjectivity and expresses a highly positive sentiment. Following is another example from literature showing subjectivity and polarity in a sentence [51]:

- **Message:** The story of the movie was weak and boring!
- **Subjectivity** weak, boring.
- **Polarity:** negative.

7.3 Analysis of US Election Tweets

In this study, we try to understand the characteristics of Twitter discussion based on their location. For this purpose we utilized Twitter data collected during the US Presidential Elections 2016. In this section, we discuss the research questions that we developed to test on this data.

7.3.1 Subjectivity Analysis

The first research question relates with the analysis of Twitter location data to evaluate the subjectivity of user messages during the elections. There has been several studies on user behavior on Twitter during elections. Some of the research studies have suggested users as less than factual with their online comments and that they use Twitter as an echo-chamber, where few opinions are restated repeatedly [26]. High level of recycling tweets is also a well documented phenomenon. Many recent studies into Twitter analysis during general elections have observed that little original content was created by users during discussions and most engage in re-tweeting [15, 99]. Similarly, a high level of heterogeneous user behavior was also discovered on Twitter during the Venezuelan protests of 2010 [68].

Our purpose of analyzing user subjectivity is to evaluate whether Twitter users were tweeting or re-tweeting facts during political debate or whether most of their messages were emotional subjective opinions. Furthermore, Twitter content creation remains an interesting area of study as researchers analyze why some tweets becomes popular and are re-tweeted more than other messages [102]. This phenomenon is also detectable in political discussions where researchers have observed a high rate of content reuse [63].

Based on the above discussion, we wanted to analyze user content in terms of subjectivity. Hence we propose the following research question:

Research Question 1: *How subjectivity scores for each candidate varied across states and who was mentioned in more subjective tweets?*

To answer this question, we performed the following data analysis:

- Subjectivity analysis of the Twitter dataset using location attribute. Average subjectivity score for each candidate is calculated.

- Comparing the state-wise subjectivity scores for both candidates, to gauge which contestant was mentioned in more subjective tweets.

7.3.2 Polarity Analysis

Polarity analysis, also known as the emotion or sentiment calculation of a text, has gained a lot of popularity in the domain of text mining. The purpose of polarity analysis is to determine the attitude of text writer with respect to the topic under discussion [58]. People are increasingly using Twitter to comment on various topics or share their opinion about an event or a popular personality. Hence polarity analysis can help in measuring public attitudes and perception towards important events and developments. Examples of research studies utilizing Twitter sentiment range from election prediction to stock price forecast [67, 99]. Similarly, in terms of approval ratings, studies have discovered a strong correlation between Twitter sentiment and public opinion polls with some claiming as high as 80% correlation between the two [72]. This high correlation can be taken as an indication of the potential of Twitter for public polls.

However, while there has been an abundance of research in the area of Twitter sentiment analysis, little research has been performed evaluating Twitter sentiment in context of location. We believe that analysis taking location into consideration can help during elections by allowing candidates to focus on their areas of strength and weakness by allocating resources more efficiently and according to the geographical needs. Furthermore, metadata associated with each tweet is rich in detail and amongst other variables also includes user location. In our study, we use this location attribute to evaluate the sentiment of both presidential candidates across the 10 most populous states of US. We then compare these sentiment scores of the two candidates with the election results. This will allow us to evaluate how indicative Twitter location data is of public opinion in these states. Hence we have the following research question:

Research Question 2: *How sentiment of Twitter messages based on state location correlates with the real world sentiment of the public towards the two candidates?*

To answer this research question, we performed the following data analytical steps:

- Polarity analysis of the Twitter dataset organized into US states using location attribute. Average sentiment for both candidates is calculated for each state.

- Comparing this state-wise sentiment with the actual election result to test the accuracy of Twitter sentiment analysis based on location.

7.3.3 Case Selection

As it is not mandatory for Twitter users to share their location information, many tweets contain null or some arbitrary value for location variable. This greatly reduced the number of tweets used in our data analysis. In total 3,341,324 tweets with valid user location values were gathered from all 50 states of the US for this study.

Although we use tweets from all states to construct US sentiment maps for both candidates shown in Fig. 7.3 and 7.4, for our two research questions, we utilized tweets from only the 10 most populous states of the US. These 10 states contain almost 54% of US population and accounted for over 60% of all tweets in our dataset. With a large population and thus a large Twitter user base, we were able to consistently gather a sizeable number of daily tweets from each of these states for both candidates. This allowed us to better determine average sentiment values for users tweeting from these states as a small number of tweets could result in error due to an atypical sample. Table 7.2 shows the number of tweets collected from these 10 states of the US, which were used for state-wise subjectivity and polarity analysis.

We can observe an instance of this anomaly in the Fig. 7.3 where along with democratic strongholds of California, New York, Washington, Illinois etc. Hillary Clinton enjoys a high positive sentiment in South Carolina as well, which is a strong Republican state. This aberration is down to the fact that very few location tweets were collected from South Carolina and further still, very few of those tweets mentioned Hillary Clinton. Hence this sentiment is not an accurate representation of the ground reality. In future to cater for this inconsistency, we will gather data for a longer period of time, ensuring that a sufficiently large, representative sample is collected from all states.

Table 7.2: Number of tweets collected from each of the 10 states that were utilized for subjectivity and polarity calculations.

State	Tweets	% of all tweets
California	471,501	14.11%
Florida	312,364	9.35%
Georgia	103,426	3.10%
Illinois	106,893	3.20%
Michigan	80,994	2.42%
New York	316,114	9.46%
North Carolina	103,421	3.10%
Ohio	98,593	2.95%
Pennsylvania	106,849	3.20%
Texas	314,021	9.40%
Total	2,014,176	60.28%

7.4 Data Preparation Methodology

Our data gathering and cleaning process is explained in chapter 2 of the dissertation. Twitter data collected consisted of numerous fields and metadata. We were interested in extracting only a few of the fields from this data. Fields such as tweet text, location, followers count, friends count, and time of tweet were extracted. A dictionary was also created to map most popular cities in the USA to their respective states if state information was missing. Although we downloaded over 15 million user tweets from Nov 1st to Nov 8th, we were able to correctly extract 3,341,324 tweets using our location dictionary. However while all 50 states were represented in our dataset, we decided to utilize the 10 largest states by population for our analysis. We used these 10 states as they were well represented in our data and accounted for over 60% of all tweets in our dataset. Table 7.2 provides details of tweets from these states.

7.5 Results

We now present the results of our data analysis. These results will be utilized to corroborate hypotheses that we developed in the previous section.

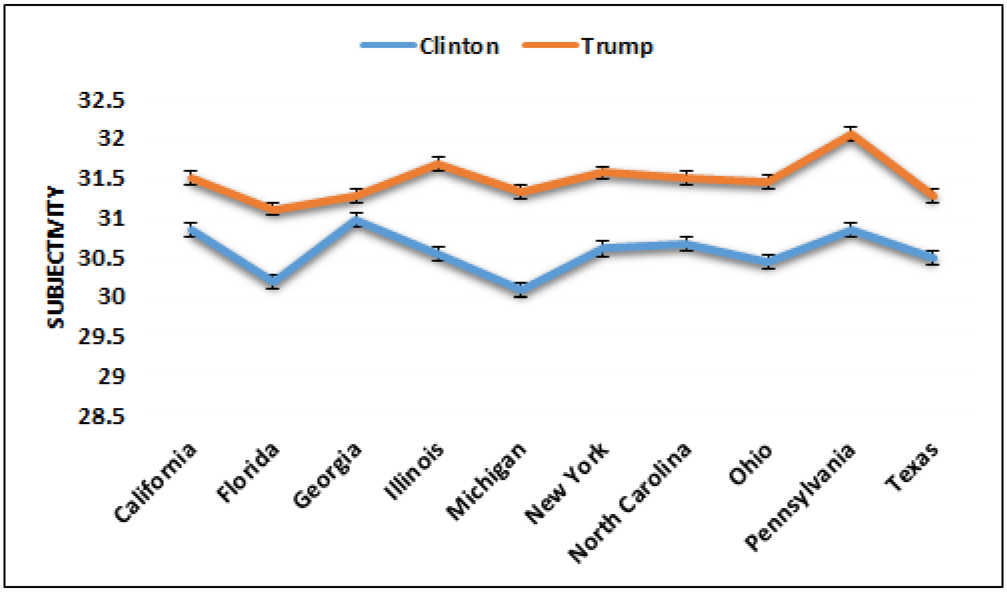

Figure 7.1: Subjectivity scores of each candidate across the 10 most populous states of the US.

7.5.1 Subjectivity Analysis

We performed subjectivity analysis of tweets for both candidates using the Twitter location data. The subjectivity analysis involves trying to determine how emotion, speculation, opinion, sentiment are expressed in natural language [98]. While message polarity determines the positive or negative connotation of a text, subjectivity analysis tries to discern whether the text is subjective in the form of an opinion, belief, emotion or speculation or objective as a fact [59].

We evaluate tweets from 10 states of the US during the elections 2016 in terms of their subjectivity. We wanted to gauge which of the two candidate had a higher subjectivity in the tweets mentioning them. Fig. 7.1 displays the subjectivity scores of the tweets mentioning both candidates in the 10 most populous states of the US.

We can observe from Fig. 7.1 that tweets mentioning Donald Trump have a higher subjectivity score for all 10 states compared with those mentioning Hillary Clinton. To further distinguish the divergence between subjectivity scores of the two candidates, we perform t-test on their subjectivity values. Following are our null and alternate hypotheses:

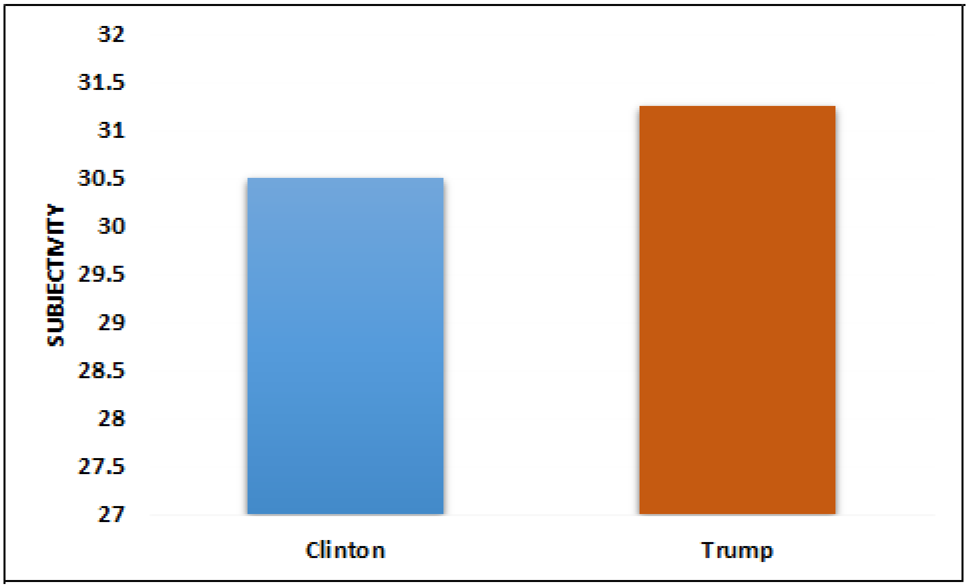

Figure 7.2: Overall subjectivity score of each candidate across all states of US.

$H_0 -> Clinton_{Subjectivity} = Trump_{Subjectivity}$

$H_1 -> Clinton_{Subjectivity} \neq Trump_{Subjectivity}$

We used F test for sample variance and t-test for hypothesis testing. Test results are shown below:

t-stat	7.35
P(T <=t) two tail	7.96629E-07
t critical two tail	2.10

As the t-stat value is higher than t critical, we can reject the null hypothesis and accept the alternate hypothesis stating that tweets mentioning Donald Trump were more subjective than those mentioning Hillary Clinton. This phenomenon of high subjectivity of tweets mentioning Donald Trump was observed for all states of the US. Fig. 7.2 shows overall subjectivity for both candidates across all states.

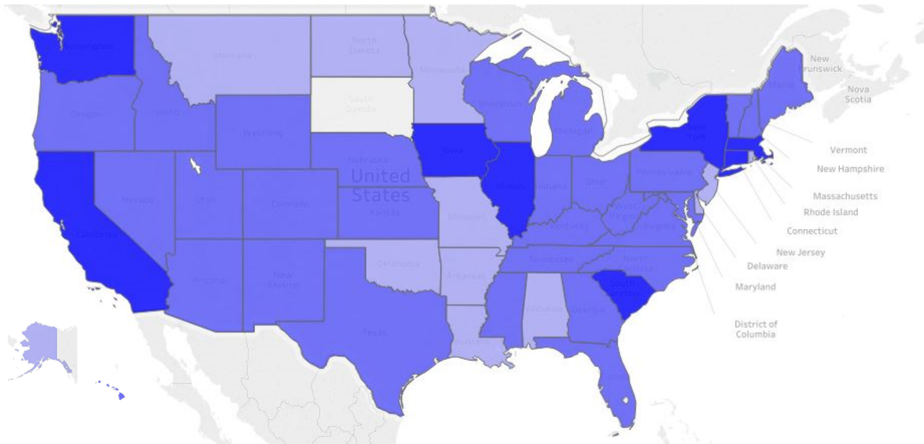

Figure 7.3: Overall sentiment of Tweets mentioning Hillary Clinton across all states of the US. Darker shades indicate higher positive sentiment.

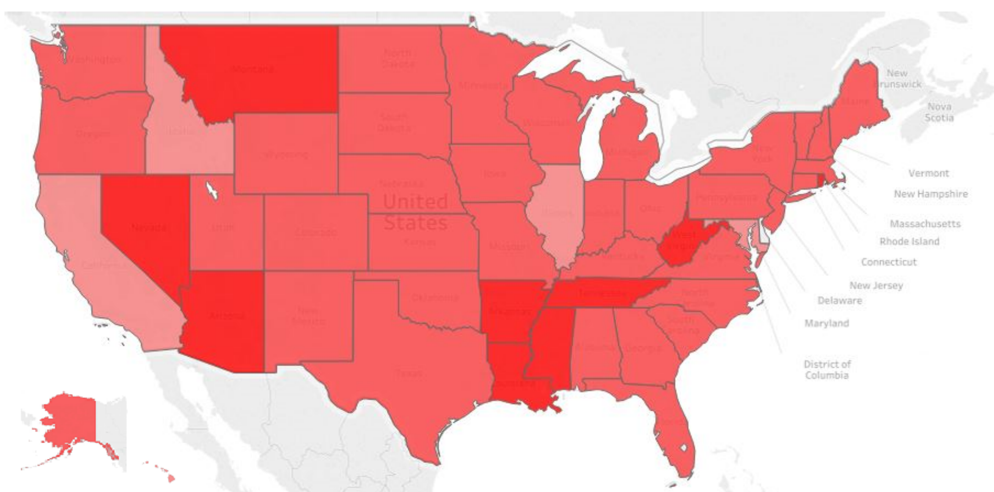

Figure 7.4: Overall sentiment of Tweets mentioning Donald Trump across all states of the US. Darker shades indicate higher positive sentiment.

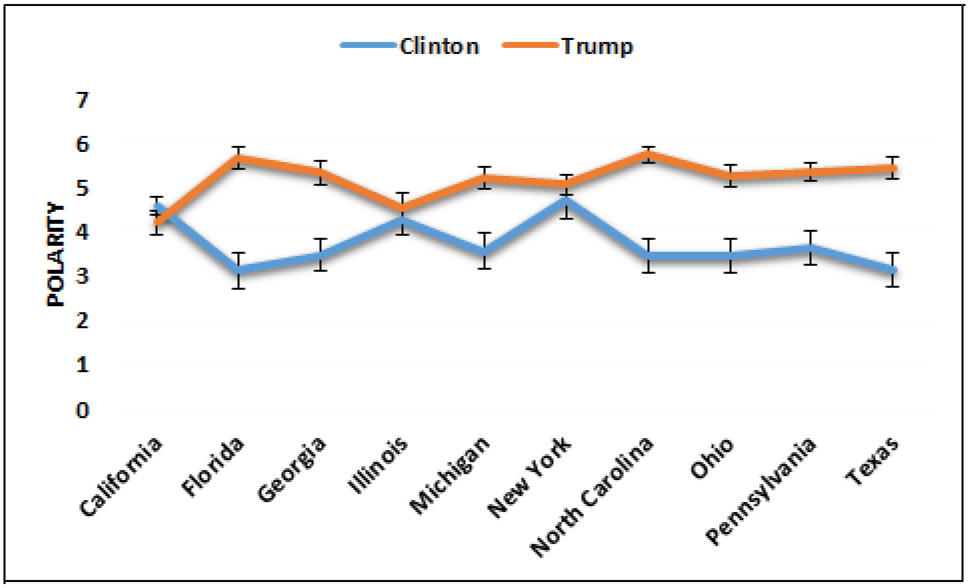

Figure 7.5: Polarity scores for each candidate across the 10 most populous states of the US.

7.5.2 Polarity Analysis

Along with subjectivity analysis, we have also used location data to perform polarity analysis of tweets mentioning Hillary Clinton and Donald Trump in 50 sates of US during elections 2016. With all tweets tagged with polarity scores, we calculate average polarity of each state using Tweets location. Fig. 7.3 and 7.4 show the polarity map of US for both Hillary Clinton and Donald Trump respectively. Dark color indicates higher polarity and hence more positive sentiment for the candidate.

To closely examine and compare polarity of the two candidates, just like subjectivity analysis, we utilize data from the 10 most populous states of the US shown in table 7.2. The purpose of this analysis is to identify the overall sentiment of each state towards these candidates in the Twitter conversations during the elections. We wanted to evaluate how this polarity score compares with the actual results of the elections 2016. Out of these 10 states Donald Trump won 7 while Hillary Clinton was victorious in 3. Fig. 7.5 shows the polarity scores.

Here we can observe that Hillary Clinton has a higher polarity score than Donald Trump in only California. However, Illinois and New York States, are within the margin of error

Table 7.3: Polarity scores and standard errors of tweets mentioning Hillary Clinton and Donald Trump created by users in the 10 most populous states of the US. Higher polarity score indicates higher positive sentiment. Last column indicates the eventual winner of the State in 2016 Presidential Elections.

State	Clinton Polarity	Trump Polarity	Error Clinton	Error Trump	Election Winner
California	4.59	4.19	0.20	0.27	Clinton
Florida	3.12	5.65	0.40	0.25	Trump
Georgia	3.45	5.34	0.36	0.28	Trump
Illinois	4.26	4.55	0.35	0.32	Clinton
Michigan	3.55	5.20	0.41	0.23	Trump
New York	4.71	5.07	0.40	0.23	Clinton
North Carolina	3.46	5.74	0.37	0.19	Trump
Ohio	3.44	5.27	0.38	0.25	Trump
Pennsylvania	3.64	5.34	0.37	0.19	Trump
Texas	3.13	5.42	0.36	0.24	Trump

for both candidates. Hillary Clinton won both of these states. Table 7.3 shows the polarity scores and error terms along with the eventual winner of these states in the elections.

It has been reported that Donald Trump enjoyed better sentiment on social media than Hillary Clinton [100]. He had more followers than Hillary Clinton and used Twitter more frequently with his tweets generating greater media attention. We can observe similar results in our location analysis where he enjoys better polarity score in 9 out of 10 states.

7.6 Discussion

We will now discuss the results of our data analysis.

7.6.1 Subjectivity Analysis

For our first research question, we performed subjectivity analysis of Twitter messages during US elections 2016. Here again we used Twitter location data to analyze which candidate was mentioned in more subjective tweets. Results of subjectivity analysis are shown in Fig. 7.1. We can observe that tweets mentioning Donald Trump were more subjective than those mentioning Hillary Clinton. This phenomenon was observed across the board in all 10 states under study. We discovered a similar result for all states shown in Fig. 7.2.

Much research has been conducted regarding user behavior on Twitter. It is observed that a small number of users drive discourse on Twitter with a lack of debate and divergence of opinion [15, 68]. In our subjectivity analysis, we have observed that tweets mentioning Donald Trump were more emotional and opinionated than factual. This high subjectivity was apparent during the election campaign where a bitter and negative campaign was fought by both candidates with Donald Trump creating much controversy through his tweets [30].

A high subjectivity score does not indicate a higher propensity for a voter to vote. What it does indicate however is that Twitter users mentioning Donald Trump in their tweets were more opinionated.

7.6.2 Polarity Analysis

For our second research question, we performed polarity analysis for both presidential candidates in terms of Twitter location data. Polarity scores of both candidates for all 50 states are shown in Fig. 7.3 and 7.4. To perform a comparative analysis for both candidates, we calculated polarity for 10 most populous states of the US.

Results of polarity analysis for these states are shown in Fig. 7.5 and in table 7.3. Our polarity analysis was able to correctly gauge public sentiment in 8 out of the 10 states under study. However for two states, Illinois and New York, where Hillary Clinton was victorious, our dataset shows Trump as having better sentiment among the Twitter users from those states. However, it should be noted that for both of these states the difference between the polarity scores of the candidates is within the margin of error. Non-the-less, we state that our polarity analysis of Twitter location data remains inconclusive.

Twitter data analysis for election prediction has become an popular area of research. Many studies have claimed to effectively predict elections by determining public opinion utilizing Twitter data analysis [93, 72]. On the other hand, doubt has also been expressed by highlighting the limitations of utilizing Twitter data for election prediction [37, 65]. Our result using Twitter location data to gauge public sentiment towards candidates using Twitter is somewhat inconclusive. Out of the 10 states used for data analysis, sentiment of 8 was correctly predicted. Two states were predicted incorrectly, however for both of these states the polarity scores of the two candidates were within the margin of error. We believe that further analysis of Twitter location data, where location is looked in more detail including city and county level can generate interesting results for understanding public opinion towards political candidates.

7.7 Conclusion and Future Work

In this research study, we have presented a web-based application that can be used to perform subjectivity and polarity analysis of Twitter location data. This analysis can be performed real time by fetching live tweets or on historical data fetched in the past. The application can also extract user location data from tweets and use it to plot subjectivity and polarity on a map allowing us to perform user sentiment and behavioral analysis based on their location. We believe that this ability to map user sentiment and objectivity provides tremendous benefit over traditional Twitter sentiment analysis. Rather than of evaluating all users as a whole we are able to distinguish their opinions based on geographical location.

We tested our research questions by using Twitter location data collected during the US Presidential Elections 2016 as a case study. We analyzed over 3.3 million Twitter messages gathered from all 50 states of the US. Almost 60% of these messages were generated in the 10 most populous states and these states were utilized to answer our three research questions. Data was accumulated for 8 days, from Nov 1st to Nov 8th 2016 and messages were filtered based on their containing the keywords Clinton and Trump. Although many research studies have utilized Twitter data for election sentiment and user behavior analysis during general elections, no study so far has utilized the location attribute of tweets. The primary purpose of this study was to utilize this location information, contained in the message metadata to create a more sophisticated and detailed analysis of user subjectivity and polarity during the elections. It was observed that tweets mentioning Donald Trump were more subjective in nature than those mention Hillary Clinton. This was observed in all 10 states under study and was verified by the data analyses conducted to answer the research questions. In terms of polarity, we had mixed results, where Clinton had higher polarity than Trump in only California. However for the other states that she won in the elections but had lower polarity in our data analysis, the scores were within margin of error.

In future, we would like to expand this study by performing analysis of more detailed location information. By dividing US states into rural and urban areas we can further refine our location sentiment analysis as rural urban divide plays a very important role in elections. With exact location analysis, sentiment and behavior of users towards political candidates can be understood with greater accuracy.

We would also like to expand this study to other countries of the world. Rather than using geo-location, we created a dictionary to map location information provided by users. By expanding this dictionary to states and regions of other countries of the world, we can create a similar detailed sentiment map.

Chapter 8

Twitter Analyses and Visualization System

In this dissertation, we also present a web-based system which can be used for collection of Twitter data, extraction of the metadata, analyze the data based on the extracted metadata parameter (which can be location) and finally visualize the subjectivity and polarity associated with a keyword in Twitter messages. The keyword can be present in the message in the form of a hashtag, phrase or it can simply be a word. As the user enters the keyword, the application is able to fetch live tweets, extracting text from each tweet, mapping user location, while calculating subjectivity and polarity of each tweet. We then plot these scores on a map allowing us to visualizes the trend associated with selected keyword.

During past few years, we have witnessed a flurry of research activity in the area of Twitter sentiment analysis [20, 99, 33]. These analysis are applied to a variety of fields like analyzing reviews and responses for serving customers efficiently. Our system also facilitates a researcher to analyze tweets that were fetched from past. The motivation behind building this system was to provide a single automated platform, which serves as a complete end-to-end system for sentiment analysis and visualization.

Along with real-time Twitter data analysis, we can also use the platform to calculate and visualize subjectivity and polarity of tweets that are downloaded previously and are present in the form of a dataset. In our study of Twitter location data, we have utilized this application for the case study involving data collected during US elections 2016 for analysis and visualization.

8.1 Motivation

As discussed throughout this dissertation, Twitter sentiment analyses is now used in various areas related with governance. However, data collection and analyses of sentiment and location visualization are not straight forward, delaying governments or researcher in utilizing Twitter to gauge public opinion on various topics and issues related with governance, elections, protests etc.

The primary goal behind development of the web platform for data collection, analysis & visualization is to enable researchers and policy makers to quickly and accurately map sentiment of any topic under discussion on Twitter. The application can perform real-time sentiment analyses based on keyword provided by the user, mapping that sentiment on the map allowing for easy visualization. This enables researchers and policy makers to perform quick analysis of any breaking news or current event. In short the goals of the application are following:

- To provide researchers with a tool that enables them to perform sentiment analysis on tweets in real-time based on a keyword.
- To gain insights in location and temporal variations of citizen sentiments
- To identify the locations of citizens dissatisfaction regions

Furthermore, the data-dictionary developed for the application can retrieve a large number of location based tweets which is not possible using geo-tagged tweets only. State and city names in both long and short forms along with cities with same name but present in different states of the US are mapped in the correct state. This allows researchers and other users of the application to collect a large sample of location tweets enabling them to perform meaningful analyses of citizen's subjectivity and polarity.

8.2 System Design

The system is built using flask framework and Python as a platform. The application has a static web form, which allows a user to enter the search string (hashtag, a phrase or a word) and select the number of tweets that are to be visualized. Once the form is submitted, a script executing at the back-end of the system will fetch live tweets and calculate subjectivity and polarity of user tweeting to be plotted on graphs.

Figure 8.1 shows the system architecture, displaying it's major operations. The process begins with input query from user in the form of a search string and the desired number of tweets for processing. The Flask framework processes this request while Twitter API is used to fetch live tweets. The system then performs data cleaning and location extraction along with subjectivity and polarity calculations. JSON and javascript is then used to plot the final results. Figure 8.2 displays the execution process of the application.

8.3 Location Parsing

One of the function performed by this application is that of extracting the location of a user from tweet metadata. For this purpose, a string parser was created to extract user location provided in the *location* field from the tweet meta-data. The location variable is parsed and extracted by comparing and mapping the location text with a dictionary containing all interesting locations.

The challenge of location data however is the fact that it is present in various different forms. For example, location for some users has text only. For example, our location study of US elections 2016 described in 7, location columns of most contained prominent US

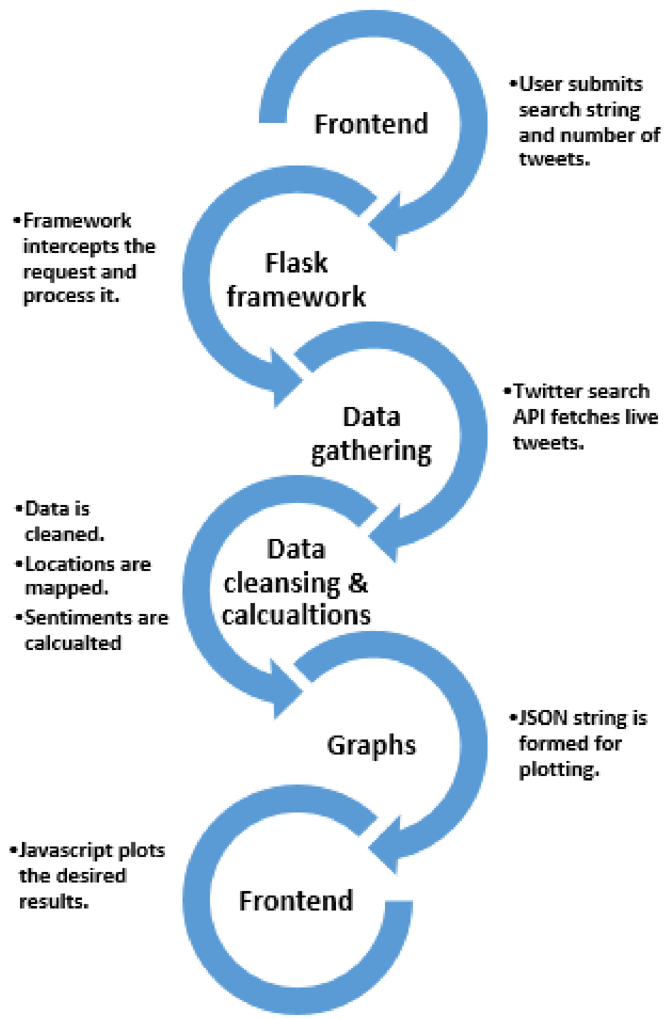

Figure 8.1: Application architecture.

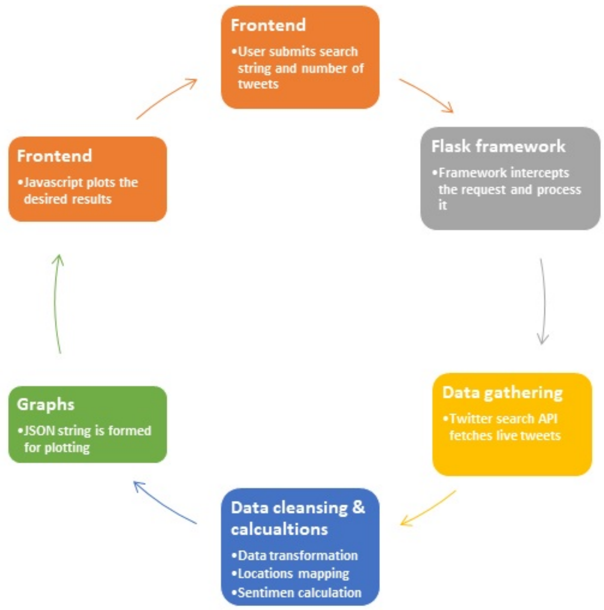

Figure 8.2: System execution process.

cities along with country name. Hence some location parameters were set as Los Angeles, USA; NYC, USA; Chicago, USA; San Francisco, USA; etc. Moreover, some location text had state short form and country name such as TX, USA; CA, USA; IL, USA; NV, USA; etc. To extract precise states from such location definitions, we created a dictionary to map prominent cities against state names. Here we also created and mapped state names versus the short form of state represented by two letters. Pseudo code for the location extraction is given in algorithm 1.

8.4 Subjectivity & Polarity Analysis

The application can be used for subjectivity and polarity analysis of user texts. Subjectivity analysis is defined as the classification of sentences as subjective opinions or objective facts. Hence for a set of messages in a dataset, through subjectivity analysis, we identify sentences that are subjective from those that are objective. Speech patterns such as use of adjectives along with nouns are used as an indicator for subjectivity of a statement [51].

Polarity analysis is the sentiment analysis of text. Just as with subjectivity analysis,

Algorithm 1 Parse the state name from user location

```
Parsing state name for user location

states_list = "list of states"
temp_list = []
while index in "length of dataframe" do
   location = "user location"
   while state in states_list do
      if re.search(state,location): then
         temp_list.append(state)
         break

         dataframe['State_User'] = temp_list
      end if
   end while
end while
```

we utilized Python TextBlob package for polarity analysis on our dataset. Polarity analysis using Python Textblob, words in the lexicon are assigned scores for negative and positive polarity. These polarity scores range from -1 to 1, where -1 represents extremely negative sentiment while 1 represents extremely positive sentiment respectively. A polarity score of 0 suggests a neutral sentiment. Using the python Textblob, polarity scores are assigned to user texts. Pseudo code for subjectivity and polarity calculation are is given in algorithm 2.

Algorithm 2 Calculate subjectivity and polarity of each user.

```
subjectivity = []
polarity = []

while index in "length of cleansed_dataframe" do
   wiki = TextBlob("tweet_text")
   subjectivity.append(wiki.sentiment.subjectivity)
   polarity.append(wiki.sentiment.polarity)
end while

cleansed_dataframe ['Subjectivity'] = subjectivity
cleansed_dataframe ['Polarity'] = polarity
```

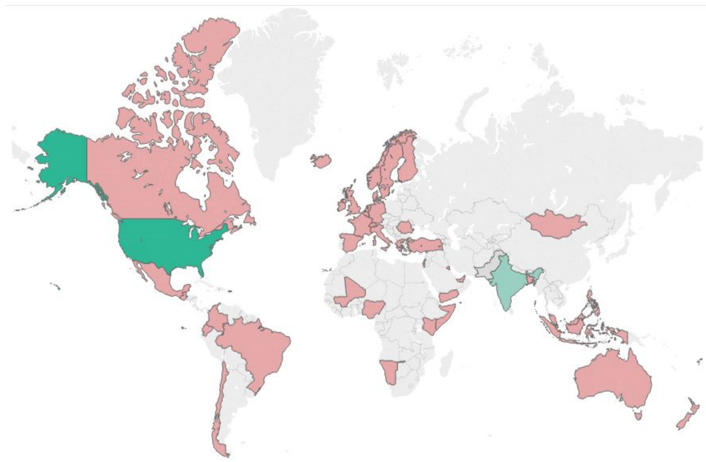

Figure 8.3: Sentiments of term ‘#WaterCrisis‘ from around the world. Shades of green represent positive sentiment while pink represents negative sentiment.

8.5 Data Visualization

The application can be used to create visual aides, representing the data as scatter plots, bar graphs and map plots. To create these visualizations, a JSON string is created using *plotly* library which is rich in methods to plot various types of graphs. For each graph, a JSON is created and provided to the front-end of the application for creating the required visualizations. A plotly JavaScript file is imported in the static web page which takes information from JSON string and plots the various graphs.

8.6 Experimental Results

This section showcases the application results with search string ‘#Watercrisis‘. Water shortage around the world is a major concern and we wanted to gauge the public sentiment around this important public issue. By utilizing the Twitter search API, the application fetched 1,164 tweets from around the world. Sentiment from these tweets are plotted on the map shown in Fig. 8.3.

8.7 Benefits of Web-application

Although there are several online applications available for Twitter sentiment analysis [71] our platform provides several advantages. First, not only does it fetch tweets real time using the Twitter streaming API but it can also be used to analyze tweets that we have collected in the past and are present in an external database. This allows us to rerun our analysis on old data and on a larger dataset. The US election data utilized in this paper was collected during the US elections in November 2016, however using our application we were able to analyze over 15 million tweets collected during this time period and were able to identify 3.3 million tweets with user provided location that were used to calculate polarity and subjectivity of the two presidential candidates, Hillary Clinton and Donald Trump.

The second advantage of our platform is the data dictionary that we created to identify user location. Most of the Twitter location analysis are performed on geo-location data collected from user device. This has to be explicitly enabled by the user and only 1-2% of tweets contain user geo-location data as part of metadata [57, 41]. Furthermore, the streaming API, used to download Twitter data allows users to retrieve at most 1% sample of all tweets on Twitter [69]. Thus utilizing streaming API to download tweets based on geo-location parameters severely restricts the number of messages that can be retrieved.

In our application platform, we utilize the location provided by Twitter user. This enables us to use a larger number of tweets for our analysis. The challenge of location data however is the fact that it is present in various different forms. For example, our location study of US elections 2016 presented in this paper, user locations were presented in several different formats. As discussed in chapter 7, location columns of some users contained location information in varying formats where some locations would contain city and state while others would share state and country. Even state and city names could be in both long and short forms such as TX, USA or NYC, NY etc. Furthermore, many cities with same name occur in different states of the US. Our location dictionary maps prominent cities against state names while also mapping state names versus the short form of state represented by two letters. Pseudo code for the location extraction is given in 1.

8.8 System Limitations

A drawback of our approach is that unlike geo-tagged tweets, where location is very precise and accurate, user provided location can be imprecise or inaccurate. Non-the-less this approach enabled us to gather over 3.3 million location based tweets for 8 days of November 2016 (1st - 8th November) using the streaming API. By updating our dictionary with states and cities of other regions of the world, we can perform our location analysis of subjectivity and polarity of tweets for other countries as well.

Another limitation of the system is that we have not conducted any study gathering feedback of researchers and policy makers in terms of their preferences and requirements in such a system. So far only we have utilized the web-based application for location based sentiment analysis. Furthermore no empirical study has been conducted as yet where user evaluations of the system are gathered. Hence it is hard to determine right now, how effective the system is in helping end users achieve their intended goals while utilizing this tool.

Chapter 9

Contribution and Future Work

9.1 Contributions

In this dissertation we presented a framework to analyze social media usage by adopting stakeholder theory for social media. We proposed a Citizen Centric Stakeholder Theory for Social Media, where all users of social media platforms are treated as stakeholders. This framework was used to investigate the nature and characteristics of social media usage by citizens from around the world. We evaluated this participation through analyses of stakeholder sentiment and online behavior.

Using the citizen centric stakeholder theory, we analyzed social media data collected during various events. We analyzed Twitter data collected during the US Presidential Election of 2016 and during the UK General Elections of 2017. We discovered that stakeholder salience such as power, legitimacy and urgency do indeed played a significant role in message propagation on Twitter.

This dissertation also presented Twitter mining study into the US elections and discovered an overall negative public sentiment towards the election and both major Presidential candidates. We learned that in context of the elections 2016, a time-line of Twitter trends and frequently used words could be utilized to identify events of significant importance as they happened. In terms of user behavior, it was observed that little original content was created by users during discussions and most were rather retweeting. We also saw that a very small percentage of messages were direct and contrary to findings by some other studies, majority of the users did not engage in direct one to one conversations with each other.

Taking the sentiment analyses forward, we utilized location data to map Twitter user sentiment according to states during the 2016 US Presidential elections. We analyzed over 3.3 million Twitter messages gathered from all 50 states of the US. Primary purpose of this study was to utilize this location information, contained in the message metadata to create a more sophisticated and detailed analysis of user subjectivity and polarity during the elections. It was observed that tweets mentioning Donald Trump were more subjective in nature than those mention Hillary Clinton. This was observed in all 10 states under study and was verified by the data analyses conducted to answer the research questions. In terms of polarity, we had mixed results, where Clinton had higher polarity than Trump in only California. However for the other states that she won in the elections but had lower polarity in our data analysis, the scores were within margin of error indicating that further research into this area can yield a more detailed and accurate picture of public opinion.

In this dissertation, we also presented a web-based system which can be used for collection of Twitter data, extraction of the metadata, analyze the data based on the extracted metadata parameter (which can be location) and finally visualize the subjectivity and polarity associated with a keyword in Twitter messages. The subjectivity and polarity analysis of 2016 US Presidential elections were performed using this tool.

Finally, we gathered Facebook and Twitter data for various public sector organizations, evaluating their messages in terms of sentiment and content. It was observed that nature of organization's operations have an impact on the sentiment of the messages. For example, police organizations generally had a negative sentiment of messages due to their nature of communication with the citizens, appraising them on crime alerts and public safety messages. Similarly, some organizations used Twitter as a tactical tool, tweeting hundreds of messages everyday appraising their users of current situation. Transportation organizations such as MTA and SEPTA (Philadelphia public transit)frequently updated their riders of any delays in buses or trains. We also observed an overall negative correlation between message framing, such as using hashtags (#) and direct one-to-one communication, indicating that most organizations either use Twitter for broadcasting or for direct communication with their customers.

Insights from this research will allow us to better understand the nature of discourse taking place on popular social media platforms and how sentiment, keywords and users behavior impacts these discussions. It will also enable us to perform more detailed sentiment analyses, especially in terms of location. In future we can evaluate the spatial aspect of social media sentiment in more detail, where county or even city level sentiment can be calculated. This will allow policy makers to find out exactly not only the general public sentiment but also it's degree across various geographical locations. The web-based application in will facilitate in this research, by providing a single automated platform, which serves as a complete end-to-end system for sentiment analysis of Twitter messages along with their visualization based on location on the map.

Furthermore, citizen centric stakeholder theory, provides a framework to analyze users of social media based on attributes such as power, legitimacy and urgency. Social media allows users to directly influence discussion topics. This effectively turns citizens utilizing social media into stakeholders who have to be recognized and managed. Citizen centric stakeholder theory can thus become an effective tool to evaluate popular online discussions. This will allow movers of social media for marketing, political campaigning or for other causes to create a more effective and robust message, targeted to the right stakeholder.

	Organization Communication on Social Media	User Sentiment on Social Media
Police		
NYPD		
Philadelphia Police		
Boston Police		
Transportation		
MTA		
SEPTA		
Utilities		
NY Power Authority		
PPL Electric		
Dept. of Motor Vehicle		
NY Dept. of Motor Veh.		
Penn Dept. of Motor Veh.		

Figure 9.1: Framework for analyses of public sector organizations on social media. Here we evaluate the sentiment and characteristics of social media messages by public sector organizations. We also gauge sentiment and behavior of users discussing these organizations on social networks.

9.2 Future Work

9.2.1 Analyses of Social Media communication of Public Sector Organizations

In future we will expand the scope of public organization study described in 6. In expanding the scope of the study, we will not only evaluate sentiment and content of organizations' messages on social media but also perform sentiment analyses of tweets by the citizens discussing these organizations. This will allow us to not only evaluate the impact of their social media communication on behavior and sentiment of social media users enabling us to evaluate the effectiveness of communication strategy utilized by these organizations. We can observe a schematic of the framework that will be used to evaluate organization and user messages shown in Fig 9.1.

We will also utilize the social media framework to categorize messages of the organizations into various categories. This categorization will help us gain understanding of the communication strategy of the organizations. Social media framework was developed to identify the communication strategies of organizations using social media for communication. Broadly speaking, the communication tactics of the organizations are divided into three categories. These are described as push, pull and networking strategies utilized by organizations for interaction [47, 64]. Table 9.1 displays these strategies along with the mechanisms used to implement them. This study will try to answer the following questions:

- **How public sector organizations use Push, Pull and Networking strategies on social media?** This study will help us understand how different organizations based on their nature of work and area of operation, are able to utilize the strategy best suited to their purpose. Most of the organizations simply use Facebook and Twitter due to the presence of a large number of users on the platform. However, both social media platforms allow for rich bi-directional communication which can be very beneficial to many organizations that are right now using them as a broadcasting tool.

- **How message sentiment and characteristics differ for organizations utilizing social media for public engagement?** We will analyze Facebook posts and Twitter messages of the organizations based on their target audience and nature of service provided. Hence for example a local electricity provider might utilize online social networks differently than a police department.

- **What are difference and similarities in user sentiment and behavior on social media with respect to organizations under study?** Here we want to observe the changing user behavior with a change in the organization being discussed. Hence sentiment and message content discussing a police department would be different than the sentiment and behavior when discussing public transit service.

By answering these questions, we hope to achieve the following objectives:

Table 9.1: Framework for measuring social media strategies of public sector organizations.

Tactic	Description	Mechanism
One-way push	Inform and educate through broadcast and announcement.	Number of followers. Number of likes. Number of daily Messages.
Two-way pull	Engagement through bi-directional communication.	Retweets. Hashtags. Information requests from public.
Networking	Two way interaction for community building.	Direct messages, replies. Tips to improve public safety, health. Following citizens.

- Identifying the intended audience of public organizations online by using stakeholder theory.
- Identifying the online communication strategy of the organizations by using the social media framework and by evaluating the message sentiment.
- Evaluate reputation of various government organizations on social media and how, if any, improvement in this reputation is due to their social media communication strategy.

Findings from this analyses will help these organizations foster better communication with the citizens. It will also enable them to get feedback on their operations, allowing them to further improve their processes.

9.2.2 Stakeholder Theory Application on Twitter Location Data

In future we would also like to apply the citizen centric stakeholder theory for social media on Twitter location data. By applying stakeholder theory on location data, we would be able to better identify stakeholders in-terms of their relevance to the organizations. For example a Twitter user residing in a certain city, his tweets about the police department or any other public service organization of that city should carry more weightage than users who do not live in the area.

The location aspect also gains importance because of the fact that services provided by any public organization, or any candidate contesting elections from a particular constituency are bound to a certain physical geographic location. These organizations and individuals face challenges of managing relationships within ever-growing users of social networks, as social media allow all kinds of users to interact with them directly. However many of these users are outside of the local communities being served by these organizations or are not constituents of the individual candidate. Hence priority of these stakeholders will be less than those who reside in the local community and provide feedback using social networks.

In chapter 4 we introduce a stakeholder with saliences such as power, legitimacy and urgency, defining these traits in terms of social media. For this study, we will define stakeholder legitimacy in-terms of location. Hence any social media user residing in the community served by an organization will have higher legitimacy as a stakeholder and will require closer attention than non-local stakeholders.

Studies have discovered that local users, participate on social media by providing more supportive and positive messages along with requests that are more actionable. On the other hand, it is reported that messages from non-local users are driven more by the national trend of sentiment towards an organization, such as police brutality, rather than actual concerns about issues such as public safety [47].

In this study we will try to answer the following research questions:

- **How online user sentiment differs according to location?** Here we will gauage sentiment of online users according to location in an effort to determine how sentiment of users, residing in a local community of an organization or a political candidate changes compared to those users who are non-local, commenting from a national or international perspective.

- **How user sentiment differs in different parts of the world?** Here we will observe sentiment of people tweeting in one location is different from other parts of the world. We will evaluate sentiment, content generation etc. to discover particular traits. This will also help us understand whether people residing in a certain country/region are generally more skeptic or optimistic online and does this behavior also extends towards government, its institutions and individuals.

- **How organizations interact with stakeholders based on their location?** Here we will analyze the message of the organization based on the salience of their audience. We will evaluate the sentiment and nature of the tweets by the organization and how caters to its audience in terms of their location. Hence we will try to determine whether local stakeholders are treated differently than non-local.

9.2.3 ICT for Closer Public Interaction and Trust

Motivation

The role of Internet and communication technologies ICT in modern society cannot be understated. This can be seen by the Digital Agenda for Europe (2010-2020) put forth by the European Commission in 2010. Governments and institutions around the world are trying to increase transparency into their working[11]. Furthermore, the movement to increase public participation in government through social media has also gained momentum with time. Web 2.0 provides a quick and cost effective platform to political actors and state institutions to communicate directly with public, disseminating information without going through the traditional media channels[43, 56]. Close and direct public interaction is intended to increase public trust on the public institutions.

Twitter as tool for communication and gauge for public trust evaluation

In this study we would like to understand the impact of social media communication by government institutions with public and how effective this method is enabling public participation and increasing trust. We will try to understand whether the ICT enabled initiatives help build public trust in the institutions. Our approach will utilize social media data analytics performed on data generated on microblogging platforms such as twitter. Here we will perform sentiment analysis of this data and evaluate trust as a measure of sentiment.

Pakistan perspective

We will be conducting this study from Pakistan's perspective, following the tweets of various state actors and institutions and how effective they are in generating public trust by directly communicating with them. Pakistan has a total population of over 200 million with a relatively low internet penetration. However a large segment of the population is young and utilizes social media to engage in discussions and express political opinions.

Over the last couple of years, important institutions of state such as the armed forces now actively engage in tweeting in-order to convey policy statements directly to the masses. The purpose is to directly interact with the public without going through traditional media channels. We will evaluate whether this approach has resulted in generating greater public trust or otherwise.

Approach

We will be performing quantitative research methods collecting data for analysis using surveys and tweets. The objective is to understand how effective twitter is in increasing public awareness and trust on the state institutions. Surveys can be conducted online while several tools are available to gather and perform sentiment analysis of twitter data.

Through exploratory analysis of sentiment of twitter data, our aim is to track the effectiveness of social media as a communication channel between state institutions leading to greater trust. We will be hypothesizing that an increase in positive sentiment signals increasing public trust in state institutions and vice-versa.

Bibliography

[1] Bbc news. http://www.bbc.com/news/election-us-2016-37450667. Accessed: 2016-11-30.

[2] Forrester report. https://www.forrester.com/report. Accessed: 2017-05-09.

[3] Npr. http://www.npr.org/sections/alltechconsidered/2017/04/03/522503844/how-russian-twitter-bots-pumped-out-fake-news-during-the-2016-election. Accessed: 2017-06-15.

[4] Nytimes. https://www.nytimes.com/2016/11/14/technology/facebook-is-said-to-question-its-influence-in-election.html. Accessed: 2017-06-15.

[5] L. C. Abroms and R. Craig Lefebvre. Obama's wired campaign: Lessons for public health communication. *Journal of health communication*, 14(5):415–423, 2009.

[6] A. Acar and Y. Muraki. Twitter for crisis communication: lessons learned from japan's tsunami disaster. *International Journal of Web Based Communities*, 7(3):392–402, 2011.

[7] T. API. Streamingapi, 2018. Accessed: 2018-04-01.

[8] S. Asur and B. A. Huberman. Predicting the future with social media. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on*, volume 1, pages 492–499. IEEE, 2010.

[9] A.-L. Barabási and J. Frangos. *Linked: the new science of networks science of networks*. Basic Books, 2014.

[10] J. C. Baumgartner, J. B. Mackay, J. S. Morris, E. E. Otenyo, L. Powell, M. M. Smith, N. Snow, F. I. Solop, and B. C. Waite. *Communicator-in-chief: How Barack Obama used new media technology to win the White House*. Lexington Books, 2010.

[11] J. C. Bertot, P. T. Jaeger, and J. M. Grimes. Using icts to create a culture of transparency: E-government and social media as openness and anti-corruption tools for societies. *Government information quarterly*, 27(3):264–271, 2010.

[12] S. Bird, E. Klein, and E. Loper. *Natural language processing with Python: analyzing text with the natural language toolkit*. " O'Reilly Media, Inc.", 2009.

[13] J. Bollen, H. Mao, and A. Pepe. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. *Icwsm*, 11:450–453, 2011.

[14] J. Borondo, A. Morales, R. Benito, and J. Losada. Mapping the online communication patterns of political conversations. *Physica A: Statistical Mechanics and its Applications*, 414:403–413, 2014.

[15] J. Borondo, A. Morales, J. C. Losada, and R. M. Benito. Characterizing and modeling an electoral campaign in the context of twitter: 2011 spanish presidential election as a case study. *Chaos: an interdisciplinary journal of nonlinear science*, 22(2):023138, 2012.

[16] L. Brainard and M. Edlins. Top 10 us municipal police departments and their social media usage. *The American Review of Public Administration*, 45(6):728–745, 2015.

[17] M. Broersma and T. Graham. Social media as beat: Tweets as a news source during the 2010 british and dutch elections. *Journalism Practice*, 6(3):403–419, 2012.

[18] Brookings. The brookings institution, 2016. Accessed: 2018-04-15.

[19] G. Caldarelli, A. Chessa, F. Pammolli, G. Pompa, M. Puliga, M. Riccaboni, and G. Riotta. A multi-level geographical study of italian political elections from twitter data. *PloS one*, 9(5):e95809, 2014.

[20] N. A. Calderon, B. Fisher, J. Hemsley, B. Ceskavich, G. Jansen, R. Marciano, and V. L. Lemieux. Mixed-initiative social media analytics at the world bank: Observations of citizen sentiment in twitter data to explore" trust" of political actors and state institutions and its relationship to social protest. In *Big Data (Big Data), 2015 IEEE International Conference on*, pages 1678–1687. IEEE, 2015.

[21] M. Cha, H. Haddadi, F. Benevenuto, and P. K. Gummadi. Measuring user influence in twitter: The million follower fallacy. *Icwsm*, 10(10-17):30, 2010.

[22] J. Cheng, L. Adamic, P. A. Dow, J. M. Kleinberg, and J. Leskovec. Can cascades be predicted? In *Proceedings of the 23rd international conference on World wide web*, pages 925–936. ACM, 2014.

[23] J. M. Chenlo and D. E. Losada. An empirical study of sentence features for subjectivity and polarity classification. *Information Sciences*, 280:275–288, 2014.

[24] Z. Chu, S. Gianvecchio, H. Wang, and S. Jajodia. Detecting automation of twitter accounts: Are you a human, bot, or cyborg? *IEEE Transactions on Dependable and Secure Computing*, 9(6):811–824, 2012.

[25] C. Coglianese. The transparency president? the obama administration and open government. *Governance*, 22(4):529–544, 2009.

[26] E. Colleoni, A. Rozza, and A. Arvidsson. Echo chamber or public sphere? predicting political orientation and measuring political homophily in twitter using big data. *Journal of Communication*, 64(2):317–332, 2014.

[27] C. Collins, S. Hasan, and S. V. Ukkusuri. A novel transit rider satisfaction metric: Rider sentiments measured from online social media data. *Journal of Public Transportation*, 16(2):2, 2013.

[28] A. Culotta. Towards detecting influenza epidemics by analyzing twitter messages. In *Proceedings of the first workshop on social media analytics*, pages 115–122. ACM, 2010.

[29] S. Denef, P. S. Bayerl, and N. A. Kaptein. Social media and the police: tweeting practices of british police forces during the august 2011 riots. In *proceedings of the SIGCHI conference on human factors in computing systems*, pages 3471–3480. ACM, 2013.

[30] B. Edkin. Forbes, 2016. Accessed: 2016-12-13.

[31] Facepager. Facepager, 2018. Accessed: 2018-04-01.

[32] E. Ferrara and Z. Yang. Measuring emotional contagion in social media. *PloS one*, 10(11):e0142390, 2015.

[33] E. Ferrara and Z. Yang. Quantifying the effect of sentiment on information diffusion in social media. *PeerJ Computer Science*, 1:e26, 2015.

[34] L. S. Flak and J. Rose. Stakeholder governance: Adapting stakeholder theory to e-government. *Communications of the Association for Information Systems*, 16(1):31, 2005.

[35] R. E. Freeman and D. L. Reed. Stockholders and stakeholders: A new perspective on corporate governance. *California management review*, 25(3):88–106, 1983.

[36] L. Gandy and L. Hemphill. Will this celebrity tweet go viral? an investigation of retweets. 2014.

[37] D. Gayo Avello, P. T. Metaxas, and E. Mustafaraj. Limits of electoral predictions using twitter. In *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*. Association for the Advancement of Artificial Intelligence, 2011.

[38] M. Glassman, J. R. Straus, and C. J. Shogan. Social networking and constituent communication: member use of twitter during a two-week period in the 111th congress. Congressional Research Service, Library of Congress, 2009.

[39] J. Golbeck, J. M. Grimes, and A. Rogers. Twitter use by the us congress. *Journal of the American Society for Information Science and Technology*, 61(8):1612–1621, 2010.

[40] S. G. Grimmelikhuijsen and A. J. Meijer. Does twitter increase perceived police legitimacy? *Public Administration Review*, 75(4):598–607, 2015.

[41] S. Hahmann, R. S. Purves, and D. Burghardt. Twitter location (sometimes) matters: Exploring the relationship between georeferenced tweet content and nearby feature classes. *Journal of Spatial Information Science*, 2014(9):1–36, 2014.

[42] S. Haustein, T. D. Bowman, K. Holmberg, A. Tsou, C. R. Sugimoto, and V. Larivière. Tweets as impact indicators: Examining the implications of automated "bot" accounts on twitter. *Journal of the Association for Information Science and Technology*, 67(1):232–238, 2016.

[43] T. Heverin and L. Zach. Twitter for city police department information sharing. *Proceedings of the Association for Information Science and Technology*, 47(1):1–7, 2010.

[44] T. Highfield, S. Harrington, and A. Bruns. Twitter as a technology for audiencing and fandom: The# eurovision phenomenon. *Information, Communication & Society*, 16(3):315–339, 2013.

[45] S. Hofmann, M. Räckers, D. Beverungen, and J. Becker. Old blunders in new media? how local governments communicate with citizens in online social networks. In *System Sciences (HICSS), 2013 46th Hawaii International Conference on*, pages 2023–2032. IEEE, 2013.

[46] Y. Hou and C. Lampe. Social media effectiveness for public engagement: Example of small nonprofits. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pages 3107–3116. ACM, 2015.

[47] Y. Huang, Q. Wu, and Y. Hou. Examining twitter mentions between police agencies and public users through the lens of stakeholder theory. In *Proceedings of the 18th Annual International Conference on Digital Government Research*, pages 30–38. ACM, 2017.

[48] A. L. Hughes, L. A. St Denis, L. Palen, and K. M. Anderson. Online public communications by police & fire services during the 2012 hurricane sandy. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 1505–1514. ACM, 2014.

[49] T. M. Jones. Instrumental stakeholder theory: A synthesis of ethics and economics. *Academy of management review*, 20(2):404–437, 1995.

[50] A. Jungherr. Twitter in politics: a comprehensive literature review. *Browser Download This Paper*, 2014.

[51] V. Kharde, P. Sonawane, et al. Sentiment analysis of twitter data: A survey of techniques. *arXiv preprint arXiv:1601.06971*, 2016.

[52] S. Kim and J. Lee. E-participation, transparency, and trust in local government. *Public Administration Review*, 72(6):819–828, 2012.

[53] R. Kitchin. The real-time city? big data and smart urbanism. *GeoJournal*, 79(1):1–14, 2014.

[54] E. Kouloumpis, T. Wilson, and J. D. Moore. Twitter sentiment analysis: The good the bad and the omg! *Icwsm*, 11(538-541):164, 2011.

[55] A. O. Larsson and H. Moe. Studying political microblogging: Twitter users in the 2010 swedish election campaign. *New Media & Society*, 14(5):729–747, 2012.

[56] G. Lee and Y. H. Kwak. An open government maturity model for social media-based public engagement. *Government Information Quarterly*, 29(4):492–503, 2012.

[57] K. Leetaru, S. Wang, G. Cao, A. Padmanabhan, and E. Shook. Mapping the global twitter heartbeat: The geography of twitter. *First Monday*, 18(5), 2013.

[58] N. Li and D. D. Wu. Using text mining and sentiment analysis for online forums hotspot detection and forecast. *Decision support systems*, 48(2):354–368, 2010.

[59] A. C. E. Lima, L. N. de Castro, and J. M. Corchado. A polarity analysis framework for twitter messages. *Applied Mathematics and Computation*, 270:756–767, 2015.

[60] B. Liu. Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, 5(1):1–167, 2012.

[61] D. Lorenzi, J. Vaidya, B. Shafiq, S. Chun, N. Vegesna, Z. Alzamil, N. Adam, S. Wainer, and V. Atluri. Utilizing social media to improve local government responsiveness. In *Proceedings of the 15th Annual International Conference on Digital Government Research*, pages 236–244. ACM, 2014.

[62] A. E. Marwick and D. Boyd. I tweet honestly, i tweet passionately: Twitter users, context collapse, and the imagined audience. *New media & society*, 13(1):114–133, 2011.

[63] L. McKenna and A. Pole. What do bloggers do: an average day on an average political blog. *Public Choice*, 134(1):97–108, 2008.

[64] I. Mergel. A framework for interpreting social media interactions in the public sector. *Government Information Quarterly*, 30(4):327–334, 2013.

[65] P. T. Metaxas, E. Mustafaraj, and D. Gayo-Avello. How (not) to predict elections. In *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on*, pages 165–171. IEEE, 2011.

[66] R. K. Mitchell, B. R. Agle, and D. J. Wood. Toward a theory of stakeholder identification and salience: Defining the principle of who and what really counts. *Academy of management review*, 22(4):853–886, 1997.

[67] A. Mittal and A. Goel. Stock prediction using twitter sentiment analysis. *Standford University, CS229 (2011 http://cs229. stanford. edu/proj2011/GoelMittal-StockMarketPredictionUsingTwitterSentimentAnalysis. pdf)*, 15, 2012.

[68] A. Morales, J. Losada, and R. Benito. Users structure and behavior on an online social network during a political protest. *Physica A: Statistical Mechanics and its Applications*, 391(21):5244–5253, 2012.

[69] F. Morstatter, J. Pfeffer, H. Liu, and K. M. Carley. Is the sample good enough? comparing data from twitter's streaming api with twitter's firehose. In *ICWSM*, 2013.

[70] T. Nam and T. A. Pardo. Conceptualizing smart city with dimensions of technology, people, and institutions. In *Proceedings of the 12th annual international digital government research conference: digital government innovation in challenging times*, pages 282–291. ACM, 2011.

[71] NCSU. Sentiment viz, 2018. Accessed: 2018-04-04.

[72] B. O'Connor, R. Balasubramanyan, B. R. Routledge, and N. A. Smith. From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*, 11(122-129):1–2, 2010.

[73] J. H. Parmelee. Political journalists and twitter: Influences on norms and practices. *Journal of Media Practice*, 14(4):291–305, 2013.

[74] L. Qiu, Q. Tang, and A. B. Whinston. Two formulas for success in social media: Learning and network effects. *Journal of Management Information Systems*, 32(4):78–108, 2015.

[75] Y. Qu, C. Huang, P. Zhang, and J. Zhang. Microblogging after a major disaster in china: a case study of the 2010 yushu earthquake. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, pages 25–34. ACM, 2011.

[76] R. W. Roberts. Determinants of corporate social responsibility disclosure: An application of stakeholder theory. *Accounting, organizations and society*, 17(6):595–612, 1992.

[77] D. M. Romero, B. Meeder, and J. Kleinberg. Differences in the mechanics of information diffusion across topics: idioms, political hashtags, and complex contagion on twitter. In *Proceedings of the 20th international conference on World wide web*, pages 695–704. ACM, 2011.

[78] T. Sakaki, M. Okazaki, and Y. Matsuo. Tweet analysis for real-time event detection and earthquake reporting system development. *IEEE Transactions on Knowledge and Data Engineering*, 25(4):919–931, 2013.

[79] E. T. K. Sang and J. Bos. Predicting the 2011 dutch senate election results with twitter. In *Proceedings of the workshop on semantic analysis in social media*, pages 53–60. Association for Computational Linguistics, 2012.

[80] L. Schweitzer. Planning and social media: a case study of public transit and stigma on twitter. *Journal of the American Planning Association*, 80(3):218–238, 2014.

[81] K. Sedereviciute and C. Valentini. Towards a more holistic stakeholder analysis approach. mapping known and undiscovered stakeholders from social media. *International Journal of Strategic Communication*, 5(4):221–239, 2011.

[82] N. Sharma, R. Pabreja, U. Yaqub, V. Atluri, S. Chun, and J. Vaidya. Web-based application for sentiment analysis of live tweets. In *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age*, page 120. ACM, 2018.

[83] L. Shi, N. Agarwal, A. Agrawal, R. Garg, and J. Spoelstra. Predicting us primary elections with twitter. *URL: http://snap. stanford. edu/social2012/papers/shi. pdf*, 2012.

[84] D. Shwartz-Asher, S. Chun, and N. R. Adam. Social media user behavior analysis in e-government context. In *Proceedings of the 17th International Digital Government Research Conference on Digital Government Research*, pages 39–48. ACM, 2016.

[85] F. Stats. Facebook statistics, 2018. Accessed: 2018-04-01.

[86] I. L. Stats. Sentistrength, 2017. Accessed: 2017-12-13.

[87] I. L. Stats. Twitter statistics, 2017. Accessed: 2017-12-13.

[88] B. Suh, L. Hong, P. Pirolli, and E. H. Chi. Want to be retweeted? large scale analytics on factors impacting retweet in twitter network. In *Social computing (socialcom), 2010 ieee second international conference on*, pages 177–184. IEEE, 2010.

[89] Sysomos. Sysomos report, 2016. Accessed: 2016-10-09.

[90] L. Tang, Z. Ni, H. Xiong, and H. Zhu. Locating targets through mention in twitter. *World Wide Web*, 18(4):1019–1049, 2015.

[91] M. Thelwall, K. Buckley, and G. Paltoglou. Sentiment in twitter events. *Journal of the Association for Information Science and Technology*, 62(2):406–418, 2011.

[92] M. Thelwall, K. Buckley, G. Paltoglou, D. Cai, and A. Kappas. Sentiment strength detection in short informal text. *Journal of the Association for Information Science and Technology*, 61(12):2544–2558, 2010.

[93] A. Tumasjan, T. O. Sprenger, P. G. Sandner, and I. M. Welpe. Predicting elections with twitter: What 140 characters reveal about political sentiment. *ICWSM*, 10(1):178–185, 2010.

[94] A. Vespignani. Predicting the behavior of techno-social systems. *Science*, 325(5939):425–428, 2009.

[95] S. Vieweg, A. L. Hughes, K. Starbird, and L. Palen. Microblogging during two natural hazards events: what twitter may contribute to situational awareness. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 1079–1088. ACM, 2010.

[96] K. Wallsten. Microblogging and the news: political elites and the ultimate retweet. *Political Campaigning in the Information Age*, pages 128–147, 2014.

[97] K. Weller. Trying to understand social media users and usage: The forgotten features of social media platforms. *Online Information Review*, 40(2):256–264, 2016.

[98] J. Wiebe, T. Wilson, R. Bruce, M. Bell, and M. Martin. Learning subjective language. *Computational linguistics*, 30(3):277–308, 2004.

[99] U. Yaqub, S. Chun, V. Atluri, and J. Vaidya. Sentiment based analysis of tweets during the us presidential elections. In *Proceedings of the 18th Annual International Conference on Digital Government Research*, pages 1–10. ACM, 2017.

[100] U. Yaqub, S. A. Chun, V. Atluri, and J. Vaidya. Analysis of political discourse on twitter in the context of the 2016 us presidential elections. *Government Information Quarterly*, 34(4):613–626, 2017.

[101] U. Yaqub, N. Sharma, R. Pabreja, S. Chun, V. Atluri, and J. Vaidya. Analysis and visualization of subjectivity and polarity of twitter location data. In *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age*, page 67. ACM, 2018.

[102] X. Zeng and L. Wei. Social ties and user content generation: Evidence from flickr. *Information Systems Research*, 24(1):71–87, 2013.

[103] X. Zhang, H. Fuehres, and P. A. Gloor. Predicting stock market indicators through twitter i hope it is not as bad as i fear. *Procedia-Social and Behavioral Sciences*, 26:55–62, 2011.