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Analysis of political discourse on twitter in the context of the 2016 US presidential elections

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A R T I C L E I N F O

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A B S T R A C T

Social media now plays a pivotal role in electoral campaigns. Rapid dissemination of information through platforms such as Twitter has enabled politicians to broadcast their message to a wide audience. In this paper, we investigated the sentiment of tweets by the two main presidential candidates, Hillary Clinton and Donald Trump, along with almost 2.9 million tweets by Twitter users during the 2016 US Presidential Elections. We analyzed these short texts to evaluate how accurately Twitter represented the public opinion and real world events of significance related with the elections. We also analyzed the behavior of over a million distinct Twitter users to identify whether the platform was used to share original opinions and to interact with other users or whether few opinions were repeated over and over again with little inter-user dialogue. Finally, we wanted to assess the sentiment of tweets by both candidates and their impact on the election related discourse on Twitter. Some of our findings included the discovery that little original content was created by users and Twitter was primarily used for rebroadcasting already present opinions in the form of retweets with little communication between users. Also of significance was the finding that sentiment and topics expressed on Twitter can be a good proxy of public opinion and important election related events. Moreover, we found that Donald Trump offered a more optimistic and positive campaign message than Hillary Clinton and enjoyed better sentiment when mentioned in messages by Twitter users.

1. Introduction

Online social media networks, such as Facebook and Twitter, have enabled people to not only use the platform for interaction with one another but also to read and share news, discuss important events and engage in political discussions. Additionally, proliferation of smart phones has further facilitated the use of this medium, allowing citizens to communicate without any limitation on time or location.

This rich medium of communication, presented by social media, has been recognized by politicians and political parties globally (Romero, Meeder, & Kleinberg, 2011). The potential of social media in political campaigns 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 (Baumgartner et al., 2010). In 17 months starting from April 2007 to Election Day November 5th 2008, the Obama campaign posted 262 twitter messages and gained approximately 118,000 new followers (Glassman, Straus, & Shogan, 2009). In light of this successful Twitter campaign, all major candidates and political parties now have some form of presence on social media.

Social media also allows government institutions to have candid communication with their citizens (Lorenzi et al., 2014), potentially increasing openness and transparency into the working of their organizations (Bertot, Jaeger, & Grimes, 2010). 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 (Heverin & Zach, 2010).

As of 1st quarter of 2017 Twitter has an average of 328 million monthly active users (Statista, 2017) providing political actors with a massive user base to share their message quickly and cheaply without going through the traditional media briefings and news conferences (Romero et al., 2011). Thus it is not surprising that in the recently concluded US Presidential Elections of 2016, Twitter played a very important role in the dissemination of information regarding various policy points for both serious presidential contenders, Hillary Clinton and Donald Trump. Both candidates had millions of followers on

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Twitter and their tweets closely monitored by public and mainstream media. Although it is hard to quantify the role Twitter played in the 2016 elections, majority agree that it was significant. This means that political players cannot ignore the role of social media as a communication channel to not only share their own 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.

This increase in political discourse on Twitter has also led to an increase in research of Twitter analytics in terms of election prediction and candidate popularity (Tumasjan, Sprenger, Sandner, & Welpe, 2010; Yaqub, Chun, Atluri, & Vaidya, 2017). Some studies have even suggested that sentiment analysis of tweets can potentially be used as a substitute for traditional polls monitoring consumer confidence and political approval ratings (O'Connor, Balasubramanyan, Routledge, & Smith, 2010).

In this paper, we investigate citizen participation in the political discourse that took place on Twitter during the US Presidential Elections of 2016 by analyzing the citizens' sentiment and behavior. Our goal is to test 1) if the sentiments, and contents expressed in the political discourse on Twitter are indicative of the citizen opinion and the topics reflect the real-life events of importance; 2) gauge the sentiments of each candidate's campaign messages on Twitter and assess their impact on the sentiment of the overall election related discussion on the platform; and 3) if the social media communication behaviors promotes citizen to citizen interactions with abundant exchange of original ideas and opinions.

To test these assumptions we employed data analytics approach. We collected over 3.1 million tweets for 21 days consecutively, starting from 29th of October, up until 18th of November 2016, downloading 150,000 tweets per day on average. This data was then used to analyze citizen behavior and sentiment during this period. Furthermore we also analyzed the tweets posted by Hillary Clinton and Donald Trump, both of whom used Twitter actively for electioneering. All tweets made by both candidates starting from 29th of October until Election Day (8th of November), were considered for this study.

Specifically, we present the following analyses of the Twitter data set:

- Topic and sentiment analysis of Twitter dataset: The aim here was to detect if there existed 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 real-life events suggested that citizen tweets can be used as a good predictor of the importance of certain topics and of public opinion regarding the elections and the two presidential candidates.
- Sentiment and impact analysis of tweets by the two presidential candidates: The purpose of this analysis was to utilize candidate tweets in-order to evaluate sentiment of messages posted by both Hillary Clinton and Donald Trump in the last days of their campaign. We wanted to assess the characteristics of message propagated by each candidate along with evaluation of the impact of candidate tweets on the sentiment of discussions taking place on Twitter during this period.
- Analysis of social media users' behavior: The social media usage behavior analysis aims to identify how actively Twitter users were using the online forum to speak their mind and engage with one another. Usage behavior analysis gauged whether there was diversity of opinions and open interaction between citizens, or were few opinions repeated over and over again as retweets with little one-to-one interaction.

The rest of the paper is structured as follows. In Section 2, we review the related work in the literature while in Section 3 we discuss our methodology and data. In Section 4, we develop hypotheses that are tested through data analysis. Section 5 presents the results of our data analysis and hypothesis testing. In Section 6 we discuss these results while in Section 7, we conclude our paper.

2. Literature review

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 (Bertot et al., 2010; Lorenzi et al., 2014). This provides a quick and cost effective platform to political actors and state institutions to communicate quickly and directly with public (Heverin & Zach, 2010). 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 (Lorenzi et al., 2014).

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 (Calderon et al., 2015; Tumasjan et al., 2010). Various models have been developed that try to understand the user behavior and retweeting on Twitter (Broersma & Graham, 2012). The emerging field of techno-social systems aims to comprehend and predict this behavior. 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 (Avello, Daniel, & Mustafaraj, 2011; Metaxas, Mustafaraj, & Gayo-Avello, 2011). 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 citizen activity. Some users are far more active online than others and thus have a greater 'weight' to their opinions. 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 (Chu, Gianvecchio, Wang, & Jajodia, 2012).

Other studies have looked at how the information spreads on social networks and what role sentiment plays in diffusion (Ferrara & Yang, 2015b). 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 (Ferrara & Yang, 2015a; Ferrara & Yang, 2015b).

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 or policy issue outlined through Twitter messages by politicians or other political actors such as news commentators and observers (Parmelee, 2013). Twitter is now ever more used as news agenda building tool for mainstream media (Jungherr, 2014; Wallsten, 2014). 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 (Abroms & Craig Lefebvre, 2009; Baumgartner et al., 2010). 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 issues relating with their constituencies (Glassman et al., 2009; Golbeck, Grimes, & Rogers, 2010).

Another measure, proposed to predict comparative strength of political parties or political candidates on Twitter, is that of “relative support”. Introduced by Borondo, Morales, Losada, and Benito (2012), this parameter was utilized to analyze the Spanish Presidential Elections of 2011 (Borondo et al., 2012). The method used the slopes of the time series of accumulated tweets mentioning each political party to measure their support on Twitter. The study claimed that user activity on Twitter correlated with the election results. This measure was also applied to gauge support for the four main parties in the 2013 Italian parliamentary elections (Caldarelli et al., 2014).

Social media user behavior analyses have 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 a Twitter users (Shwartz-Asher, Chun, & Adam, 2016). It was discovered that user tweeting behavior in-terms of reusing existing content vis-à-vis new content creation is dependent upon how frequently they tweet.

3. Hypotheses development

The aim of this study was three-fold. Firstly, we wanted to perform sentiment and topic analysis of user tweets to gauge 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 of discourse taking place on Twitter. Finally, we wanted to evaluate Twitter as a platform for political discussions with respect to exchanging original thoughts and ideas and interaction between citizens. In this section, we hypothesized these three areas of research.

3.1. Topic and sentiment analysis of twitter messages

Our first objective was to comprehend political discourse on Twitter. Here we wanted to study popular topics, sentiment of tweets and discover their correlation with the real world events and opinions in-order to measure how accurately Twitter reflected public mood and concerns regarding the elections.

Due to its instant nature of communication, Twitter 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 (McKenna & Pole, 2008). It is claimed that analysis of Twitter data showed that as many as 85% of trending topics were headlines or persistent real world news (Cheng, Adamic, Alex Dow, Kleinberg, & Leskovec, 2014). Studies have also shown 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 (Highfield, Harrington, & Bruns, 2013). 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 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. For example, studies have been conducted to discover correlation between tweet's sentiment and public opinion polls. A high correlation of 80% was reported by one study between the Index of Consumer Sentiment (ICS), conducted by Reuters, and Twitter sentiment (O'Connor et al., 2010). The study also found high correlation between Gallup's 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 (O'Connor et al., 2010).

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. In light of the discussion, we proposed the following hypothesis:

Hypothesis 1. 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.

3.2. Sentiment and impact analysis of candidate twitter messages

The second component of our study was to analyze tweets by Donald Trump and Hillary Clinton, in-order to evaluate nature and sentiment of the messages conveyed by each candidate along with assessing their impact 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. (2010) used sentiment of tweets to determine 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 that 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 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. In addition, we also wanted to assess the impact, if any, of these messages on the overall political sentiment expressed on Twitter during this period. We believe that in general elections, Twitter messages by political candidates can have a significant impact on the overall online discussion. Hence we propose the following hypothesis:

Hypothesis 2. 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.

3.3. Analysis of user behavior

Along with the sentiment analysis, we also wanted to observe the behavior of Twitter users who engaged in conversations during the US elections. We wanted to discern how actively Twitter users were participating in election related discussions. There remain questions regarding social media's 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 (Borondo et al., 2012; Colleoni, Rozza, & Arvidsson, 2014; Morales, Borondo, Losada, & Benito, 2015).

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. For this purpose 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 tweets become popular and is retweeted thousands of times while many other tweets are never retweeted (Tumasjan et al., 2010). 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 (Zeng & Wei, 2013). Furthermore, for political online social media content, researchers have observed a high rate of reusability (Thelwall, Buckley, & Paltoglou, 2011).

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 not only use Twitter to post their political opinions but also engage in interactive discussions (Tumasjan et al., 2010). Nonetheless, direct messaging also creates complexities for users in having to handle multiplicity and one-to-one conversations at the same time (Marwick, 2011). Management of audience especially becomes challenging as the number of followers of a user grows.

Based on the above discussion, we assumed similar behavior among users in our dataset and believed that there were a high number of retweets and that there would be less one-to-one messages. Hence 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.

3.4. Method

In order to verify our hypothesis, we performed quantitative analysis of our data set by utilizing following proxies:

- 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.
- 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.
- Using SentiStrength, each tweet was assigned a sentiment score. These sentiment scores are aggregated and averaged for each day, based on candidate name.

4. Methodology

United States of America has the highest number of Twitter users in the world (Statista, 2017). As of May 2016, there are approximately 67.5 million active users of the microblogging site in the country (Statista, 2017). 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. We utilized citizen and candidate generated data on Twitter to understand the nature and behavior of the online discussion during elections. Our approach relied on performing data analytics to understand the nature of discussions and user behavior on the microblogging site. In this section of the paper, we will briefly discuss some important aspects of our methodology.

4.1. Data set

We utilized Twitter streaming API for data collection (https://dev.twitter.com/streaming/overview). The streaming API allows near real time access to global stream of Twitter data. We collected tweets for a total of 21 days, starting from 29th of October 2016 and ending on 18th of November 2016. We gathered 10 days of data prior to the elections day and 10 days of post-election data. In total, 3,108,058 tweets were used for this study.

Scientific studies using Twitter messages either employ hashtags or specific keywords to collect relevant data. Both approaches follow the same principle that hashtag or keywords indicate a message's relevance to a given topic (Abroms & Craig Lefebvre, 2009). In our case, we used the keywords 'Trump', 'Clinton' and 'Election2016' to download tweets. We used the two major candidate names along with a generic election related term. Using keywords instead of hashtags was primarily motivated by the reasoning that hashtags are utilized by citizens who are somewhat familiar with the concept of trends on Twitter and are hence more experienced than a novice user. By downloading data utilizing keywords, we have attempted to make our data sample more inclusive. For each tweet, we extracted metadata details such as tweet time and date, its id, creator id and user name, location, etc.

We also gathered all tweets posted by Hillary Clinton and Donald Trump for 10 days prior to the voting day (8th of November). These messages were used for sentiment analysis and for comparison with the overall citizen sentiment on Twitter towards both candidates.

4.2. Sentiment analysis

Once the data was cleaned and relevant tweet fields were extracted, all text messages were analyzed and then tagged with sentiment scores using SentiStrength (SentiStrength). SentiStrength is a freely available software that has been used to perform sentiment analysis in various studies utilizing Twitter data (Calderon et al., 2015; Ferrara & Yang, 2015a; Ferrara & Yang, 2015b). One of the advantages of using SentiStrength is that it was developed specifically to capture sentiment of short, informal texts (Thelwall et al., 2010). 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 (Thelwall et al., 2010).

SentiStrength operates by assigning two scores to each text message it analyzes. It assigns a negative and a positive score, with negative scores ranging between $[-1, -5]$ and positive scores between (SentiStrength; SYSOMOS, 2007). 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 add both positive and negative sentiment scores for each tweet as a total sentiment.

$$\text{Sent (total)} = \text{Sent (positive)} + \text{Sent (negative)}$$

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 is classified as neutral.

4.3. Removing noise from data

To increase analyses accuracy, we removed noise from our dataset. Presence of spam on Twitter is a well-known phenomenon. Although the social media platform tries hard to identify and remove automated accounts, not all bots are easily identifiable as social bots are designed specifically to impersonate human behavior. It was discovered that as many as 10.5% of Twitter accounts might be bots (Chu et al., 2012). Studies have also concluded that as high as 9% of all tweets are generated by automated accounts (Haustein et al., 2016).

In order to identify and remove spam present in the form of automated activity, we removed tweets belonging to accounts having abnormally high tweet rates. Through literature review of various studies, we discovered that users tweeting over 150 times a day can be safely classified as bots (SYSOMOS, 2007). We found this to be a safe assumption and removed all tweets from belonging to accounts that

Table 1
Number of tweets by user groups based on tweeting frequency.

Tweet per user	Total Tweets	Total Users	Percent of all users	Percent 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, 10)	363,727	56,826	5.02%	12.55%
[10, 20)	361,330	27,071	2.39%	12.47%
[20, 50)	445,728	15,159	1.34%	15.38%
[50, 100)	225,950	3456	0.31%	7.79%
≥ 100	104,991	798	0.07%	3.62%
Total	2,898,693	1,131,232	100%	100%

averaged more than 150 tweets a day. We also removed tweets originating from accounts having names such as “iPhone giveaways” etc. as these tweets were not intended to add towards the political discussion but were rather promotional in nature.

A total of 209,370 tweets were resultantly identified as having either generated by abnormally high activity accounts or by accounts that had names or descriptions which could be classified as spam. Removal of spam tweets left us with 2,898,688 tweets created by 1,131,232 unique users. It is interesting to note here that the average tweet per user in our data set was 2.56, where the top 9% of the users in terms of frequency of tweets were responsible for almost 52% of all messages while around 69% of users had only 1 associated tweet. Table 1 shows the dataset details.

Fig. 1 displays the cumulative distribution function for users and tweets shown in Table 1. It can be observed from the graph that less than 5% of the users were responsible for almost 40% of all tweets. These users had 10 or more associated tweets in our dataset. Hence we can state that user tweeting behavior was heterogeneous during the elections and few users were responsible for a large number of tweets. These findings are similar to previous Twitter studies that have looked at the tweeting behavior of online users. For example, Morales et al., also discovered a highly heterogeneous user behavior on Twitter during the online Venezuelan protests of 2010 (Morales, Losada, & Benito, 2012).

5. Findings

In this section, we present the results of our data analysis and test the hypotheses that we developed in the previous section.

5.1. Topic and sentiment analysis of twitter messages

The first area of our 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 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.

5.1.1. Sentiment analysis of citizen tweets

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. 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.

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. 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 (The Brookings Institution, 2016; The Forbes, 2016; The Washington Post, 2016). 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.

5.1.2. 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 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 (Calderon et al., 2015; Ferrara & Yang, 2015a;

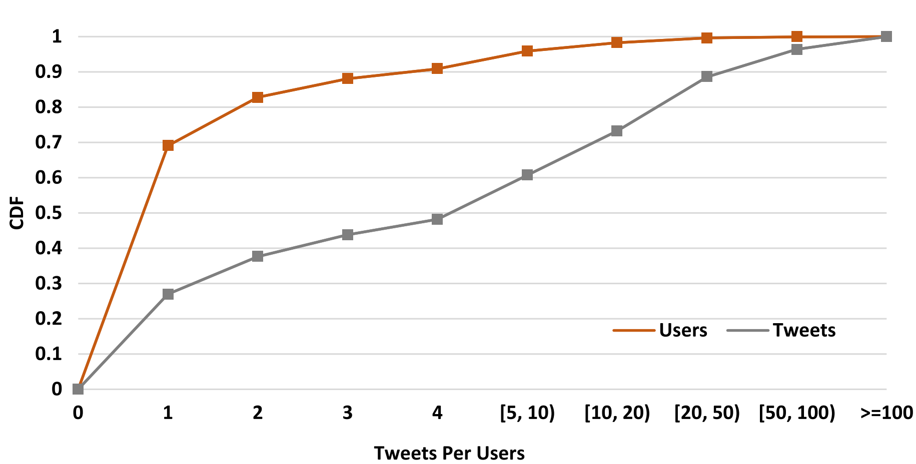

Fig. 1. CDF of tweets and users based on the frequency of tweets by users. Almost 70% of users tweeted only once and account for 27% of all tweets in the dataset, while top 10% users in terms of tweeting frequency account for more than 50% of all tweets.

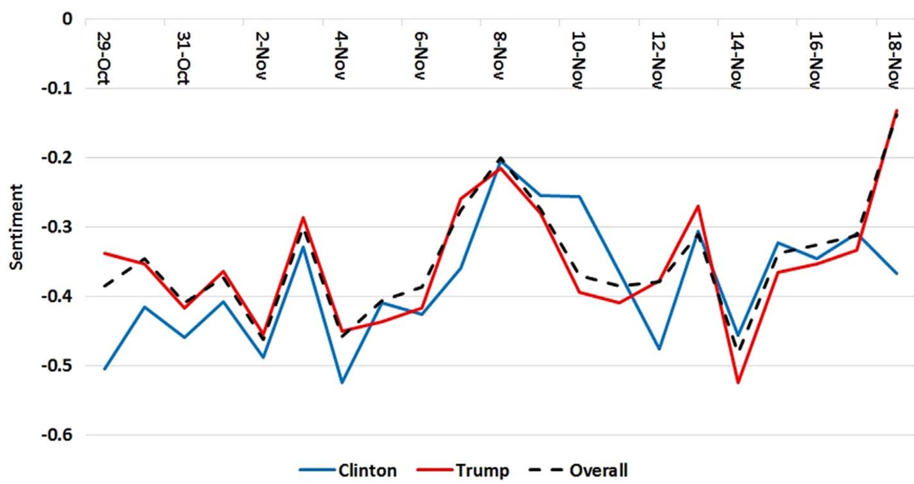

Fig. 2. Average daily sentiment of all tweets in the dataset and of both candidates.

Ferrara & Yang, 2015b). These overall negative 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.

5.1.3. *Candidate popularity*

Prior to the elections, most polls conducted by various organizations showed Hillary Clinton leading Donald Trump (BBC News, 2016). Table 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 negative sentiment than tweets containing only "Clinton". Fig. 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

Table 2
Polls predictions before Election Day. Bold represents leading candidate in the poll. (BBC News, 2016).

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
2-Nov	Fox News	**46**	45
2-Nov	McClatchy/Marist	**46**	44
31-Oct	CBS News/NYT	**47**	44
31-Oct	Economist/YouGov	**48**	45
30-Oct	Gravis	**50**	**50**
29-Oct	NBC News/SM	**51**	44

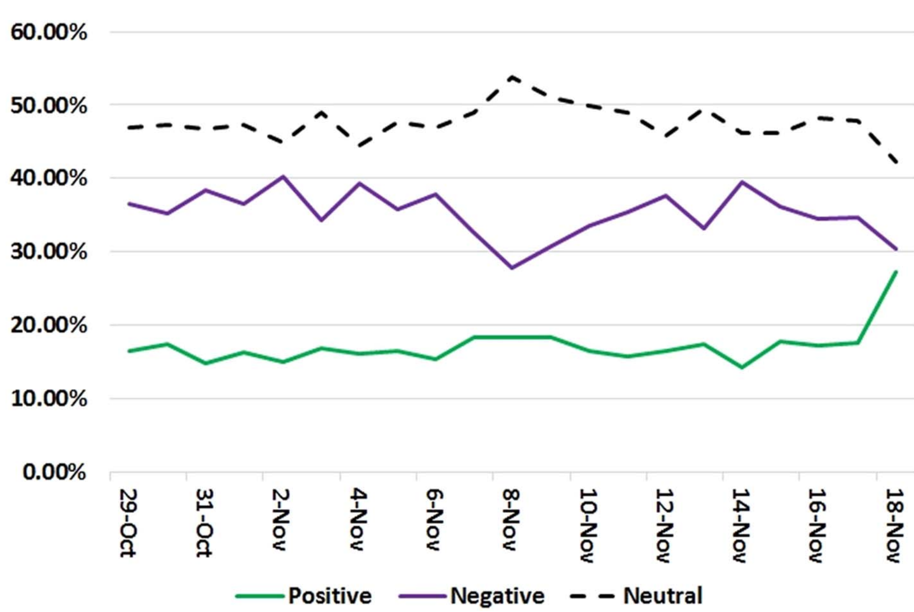

Fig. 3. Daily percentage of negative, positive and neutral tweets.

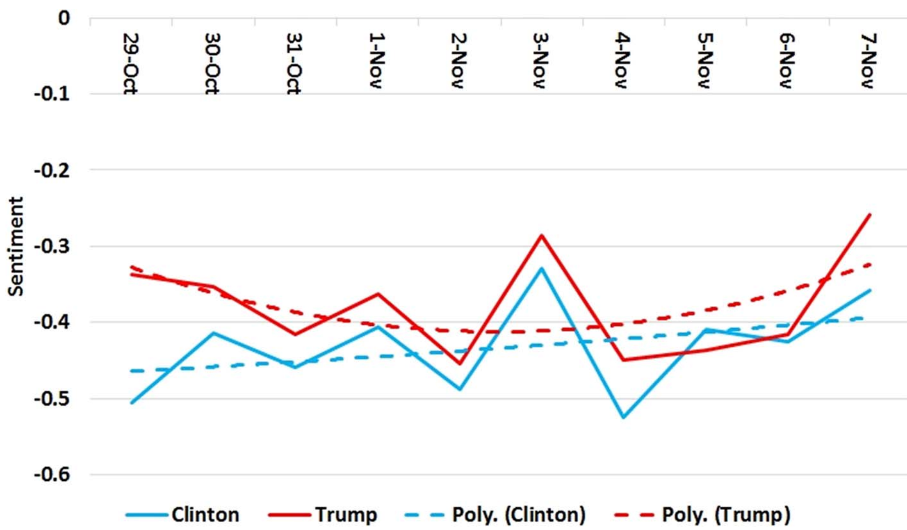

Fig. 4. Daily average sentiment and polynomial sentiment trend for both candidates leading up to the Election Day.

Table 3
Daily Tweets mentioning 'Trump' or 'Clinton' only and their average sentiment.

Date	Trump Tweets	Sent. Trump	Clinton Tweets	Sent. Clinton	Std. Error Trump	Std. Error Clinton
29-Oct	71,908	− 0.338	57,700	− 0.505	0.0047	0.0045
30-Oct	68,031	− 0.353	60,919	− 0.415	0.0046	0.0044
31-Oct	72,371	− 0.416	58,046	− 0.459	0.0043	0.0044
1-Nov	71,524	− 0.363	60,258	− 0.407	0.0048	0.0045
2-Nov	76,612	− 0.454	56,059	− 0.488	0.0045	0.0044
3-Nov	76,998	− 0.286	54,537	− 0.329	0.0043	0.0043
4-Nov	78,914	− 0.449	53,751	− 0.525	0.0046	0.0052
5-Nov	77,809	− 0.436	54,540	− 0.409	0.0045	0.0046
6-Nov	78,018	− 0.416	55,338	− 0.426	0.0041	0.0043
7-Nov	92,534	− 0.259	42,318	− 0.359	0.0036	0.0054

Hillary Clinton. Table 3 displays the number of daily tweets mentioning each candidate along with the average sentiment shown in Fig. 4 and standard error.

To further reinforce this finding, we performed *t*-test on the daily sentiment average shown in Fig. 4. Following were our null and alternate hypothesis:

$H_0 \rightarrow$ Clinton Sentiment $\geq$ Trump Sentiment

$H_1 \rightarrow$ Clinton Sentiment$<$ Trump Sentiment

We used F test for sample variance and discovered F value to be less than F critical. Hence we applied *t*-test for two samples assuming equal variance. Results of the *t*-test are shown below:

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, 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.

5.1.4. *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 elections. Fig. 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

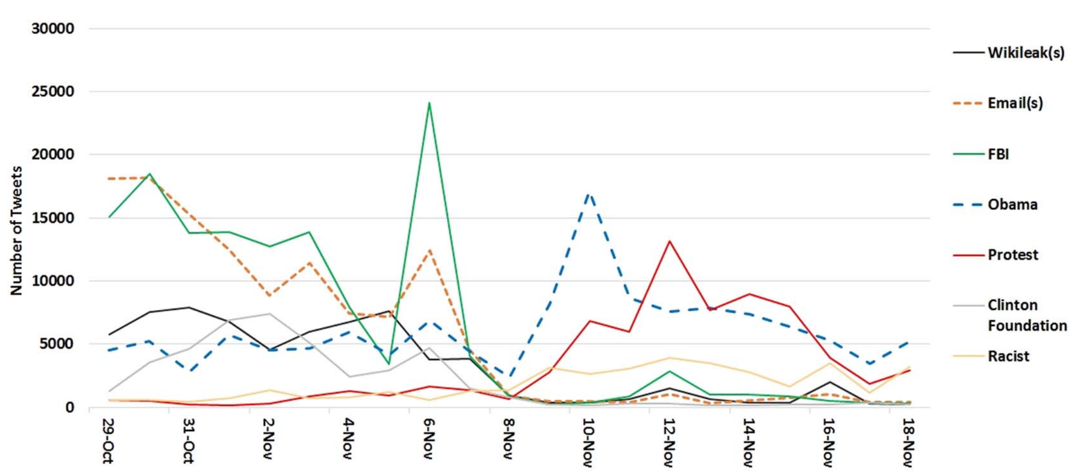

Fig. 5. Frequency diagram of popular discussion terms during elections.

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 such as *Obama* remained relatively frequent during this entire period. This was due to President Obama's 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. 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 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 4 shows the 3 most popular terms for each day from 29th October to 18th of November.

An 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. 6 plots this trend separately it presents a good example of Twitter as an indicator of important events and news.

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 significant 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. Various studies have been conducted linking Twitter sentiment with public opinion. O'Conner et al., used 1 billion tweets between the years 2008–2009 to measure user sentiment comparing it with Reuters/ University of Michigan surveys of consumers and Gallup "Economic Confidence" index. The study claimed a high correlation between these surveys and Twitter sentiment (O'Connor et al., 2010).

We believe that 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 (The Brookings Institution, 2016; The Forbes, 2016; The Washington Post, 2016). 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 (Table 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.

Table 4
Three most frequent daily terms.

	Most Popular 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

5.2. 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 voting day, from 29th Oct – 7th Nov, and assess their impact on the election related discourse on Twitter.

5.2.1. 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 from 29th October to 7th November. 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 5 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 slightly negative average sentiment of -0.0125. Fig. 7 plots the daily sentiment trend of tweets by both candidates along with standard error bars.

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:

$$H_0 \rightarrow \text{Tweets Sentiment}_{\text{Clinton}} \geq \text{Tweets Sentiment}_{\text{Trump}}$$

$$H_1 \rightarrow \text{Tweets Sentiment}_{\text{Clinton}} < \text{Tweets Sentiment}_{\text{Trump}}$$

We used F test for sample variance and discovered F value to be less than F critical. Hence in this case we applied *t*-test for two samples assuming equal variance. Results of the *t*-test are shown below:

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

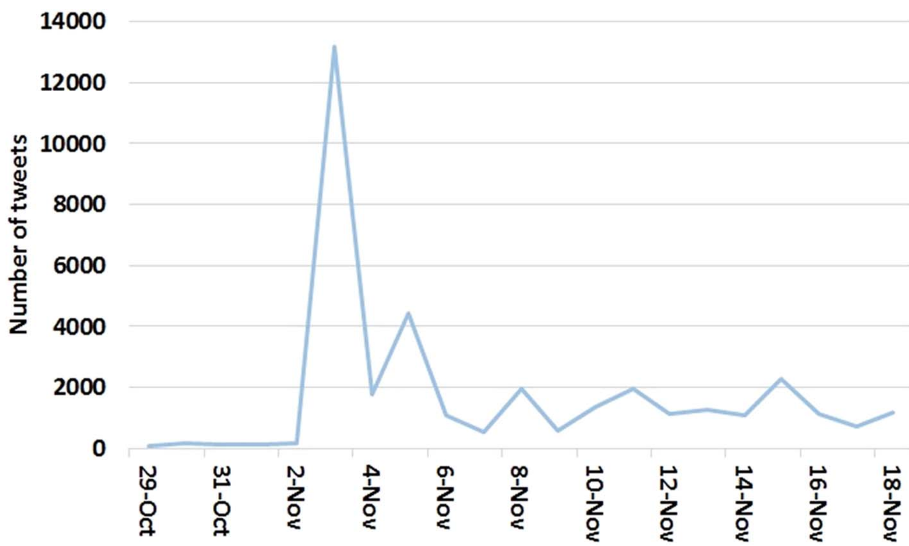

Fig. 6. Daily frequency chart of tweets mentioning "Melania".

Table 5
Average sentiment of tweets created by both candidates from 29th Oct – 7th Nov.

	Avg. Sent.	Total Tweets	Sent. Std. Dev	Sent. Std. Error
Donald Trump	0.3925	110	1.182	0.113
Hillary Clinton	− 0.0125	320	1.039	0.058

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 in-order to better understand the message they conveyed during their campaign. Tables 6a and 6b show the most frequently used words in tweets along with the average sentiment of those messages.

We can observe from Table 6a 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

Table 6a
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 6b
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

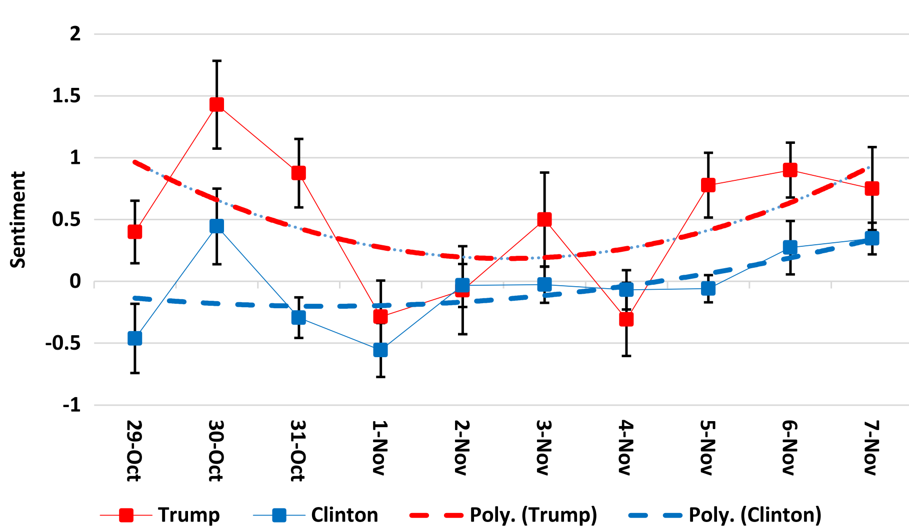

Fig. 7. Daily sentiment average and polynomial sentiment trend of tweets by both candidates along with standard error bars.

and vote and believed that a high voter turnout would be to their advantage.

From Table 6b we can observe that the most frequently used word in Donald Trump's 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 Clinton's 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.

5.2.2. *Impact of candidate sentiment on twitter discussion*

We stated in the previous section that for 10 days prior to the elections (29th Oct–7th Nov), tweets mentioning Donald Trump had a less 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 Section 5.1.3 we calculated the daily sentiment of tweets mentioning ‘Trump’ and ‘Clinton’ only, without any overlap. Table 3 displays the daily number of tweets mentioning each candidate along with average daily sentiment and standard error. In order to gauge the effect of tweets by the two candidates on the election sentiment, we removed retweets of messages by both candidates from our dataset.

Table 7 shows the daily tweets mentioning Donald Trump and their average sentiment along with the number and average sentiment of his retweets within those tweets. Last column of Table 7 displays the daily average sentiment of Donald Trump after his retweets are removed from the dataset.

We used *t*-test on daily average sentiment of Donald Trump before and after removing his retweets from the dataset to gauge their impact. Following were our null and alternate hypothesis:

$$H_0 \rightarrow \text{Trump Sentiment}_{\text{With his retweets}} = \text{Trump Sentiment}_{\text{Without his retweets}}$$

$$H_1 \rightarrow \text{Trump Sentiment}_{\text{With his retweets}} \neq \text{Trump Sentiment}_{\text{Without his retweets}}$$

We used F test for sample variance and discovered F value to be less than F critical. Hence we applied *t*-test for two samples assuming equal variance. Results of the *t*-test are shown below:

Table 7
Retweets of Donald Trump tweets in the “Trump” dataset.

Date	Total Trump tweets	Sent.	Trump retweets	Sent. Trump retweets	Retweets % of total tweets	Sent. without Trump tweets
29-Oct	71,908	− 0.338	1069	1.839	1.49%	− 0.370
30-Oct	68,031	− 0.353	669	0.149	0.98%	− 0.357
31-Oct	72,371	− 0.416	87	0.276	0.12%	− 0.416
1-Nov	71,524	− 0.363	90	0.077	0.13%	− 0.363
2-Nov	76,612	− 0.454	378	− 0.383	0.49%	− 0.454
3-Nov	76,998	− 0.286	132	0.787	0.17%	− 0.287
4-Nov	78,914	− 0.449	299	0.271	0.38%	− 0.451
5-Nov	77,809	− 0.436	69	0.173	0.09%	− 0.436
6-Nov	78,018	− 0.416	211	0.744	0.27%	− 0.419
7-Nov	92,534	− 0.259	385	1.693	0.42%	− 0.267

Table 8
Retweets of Hillary Clinton tweets in the “Clinton” dataset.

Date	Total Clinton tweets	Sent.	Clinton retweets	Sent. Clinton retweets	Retweets % of total tweets	Sent. without Clinton tweets
29-Oct	57,700	− 0.505	166	− 0.753	0.29%	− 0.504
30-Oct	60,919	− 0.415	78	− 0.7821	0.13%	− 0.414
31-Oct	58,046	− 0.459	2435	− 0.9725	4.19%	− 0.436
1-Nov	60,258	− 0.407	594	− 0.6936	0.99%	− 0.404
2-Nov	56,059	− 0.488	191	− 0.5183	0.34%	− 0.487
3-Nov	54,537	− 0.329	586	− 0.4454	1.07%	− 0.327
4-Nov	53,751	− 0.525	585	− 0.2154	1.09%	− 0.528
5-Nov	54,540	− 0.409	226	− 0.354	0.41%	− 0.409
6-Nov	55,338	− 0.426	67	− 0.1194	0.12%	− 0.427
7-Nov	42,318	− 0.359	129	− 0.7984	0.30%	− 0.357

t-stat	0.186
P(T ≤ t) two-tail	0.85
t Critical two-tail	2.10

As the *t*-stat value was lower than t critical value, we cannot reject the null hypothesis in this case and state that impact of Donald Trump tweets was not significant on his overall Twitter sentiment.

Similarly Table 8 shows the number of tweets mentioning Hillary Clinton and their average sentiment along with the number and average sentiment of her retweets within those tweets. Last column of Table 8 displays the daily average sentiment of Hillary Clinton after her retweets are removed from the dataset.

Here we again used *t*-test on daily average sentiment of Hillary Clinton, before and after removing her retweets from the dataset to gauge their impact. Following were our null and alternate hypothesis:

$$H_0 \rightarrow \text{Clinton Sentiment}_{\text{With her retweets}} = \text{Clinton Sentiment}_{\text{Without her retweets}}$$

$$H_1 \rightarrow \text{Clinton Sentiment}_{\text{With her retweets}} \neq \text{Clinton Sentiment}_{\text{Without her retweets}}$$

Again using F test for sample variance, we discovered F value to be less than F critical and applied *t*-test for two samples assuming equal variance. Results of the *t*-test are shown below:

t-stat	0.089
P(T ≤ t) two-tail	0.929
t Critical two-tail	2.10

As the *t*-stat value was lower than t critical value, we cannot reject the null hypothesis and state that impact of Hillary Clinton tweets was not significant on her overall Twitter sentiment.

The share of retweets of tweets by both candidates was less than 1% in our dataset. Hence we can safely state that the retweets of candidate tweets make up a very small part of our overall dataset and had negligible effect on the sentiment calculation for both candidates as shown in Tables 7 and 8. 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. Following are the most frequently retweeted messages of both candidates:

Candidate	Tweet	Sentiment	Retweets
		− 1	2481

Hillary Clinton	"RT @HillaryClinton: It's time for Trump to answer serious questions about his ties to Russia. https://t.co/D8oSmyVAR4 https://t.co/07dRyEmPu2026"		
Donald Trump	"RT @realDonaldTrump: So nice - great Americans outside Trump Tower right now. Thank you! https://t.co/34ATTgICTz"	2	1145

5.3. Analysis of user behavior

We now present the results obtained through analysis of our data that helped test Hypothesis 3 regarding user behavior.

5.3.1. Content creation

We discovered that almost 70% of tweets in our dataset were retweets. Furthermore, 100 most retweeted tweets appeared 7081 times in our dataset. This behavior of high retweets was present among all user groups regardless of the number of followers they had or the frequency with which they tweeted.

Fig. 8 shows retweeting behavior of Twitter users with high following. 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%. Similarly, Fig. 10 displays retweeting behavior of users categorized based on the frequency with which they tweeted during the elections. We can observe that all users groups had a high percent of retweets with users more than 100 associated tweets in our dataset retweeting almost 87% of the time.

This reusing of the information corroborates the study conducted by McKenna et al., which discovered that 87% of political bloggers provide links to news articles and other blogs in their blog posts (McKenna & Pole, 2008). Fig. 9 shows the most popular news outlets mentioned in the tweets. Majority of the users in our dataset, commenting on the elections were not creating any new content but rather reusing the information already present.

5.3.2. Message targeting

Direct interaction between users on Twitter is a popular topic of research in Twitter (Borondo et al., 2012; Shwartz-Asher et al., 2016; Tumasjan et al., 2010). In order to test our message targeting assumption, we looked at all the tweets in our database that started with the expression "@". This approach to gauge one-to-one interactive discussions on Twitter has been utilized by a number of studies (Shwartz-Asher et al., 2016; Tumasjan et al., 2010). We discovered 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 using similar approach (Tumasjan et al., 2010). Fig. 11 shows the percentage of direct messages in our dataset as a whole and according to number of user followers.

Hence Hypothesis 3 (H3) was supported by our dataset: majority of Twitter users were not creating new content but retweeting information among 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.

Similar results have been obtained by other studies looking into user behavior on Twitter during elections. For example studies by Brondo et al. discovered lack of debate along with political conversation centralized around a small fraction of influential accounts by analyzing user behavior on Twitter during Spanish Presidential elections of 2011 and 2012 Catalan elections (Borondo et al., 2012; Borondo, Morales, Benito, & Losada, 2014).

6. Discussion

6.1. 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 (Cheng et al., 2014; Golbeck et al., 2010; McKenna & Pole, 2008; O'Connor et al., 2010; Tumasjan et al., 2010). 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 (The Brookings Institution, 2016; The Forbes, 2016; The Washington Post, 2016).

Similarly, although both candidates had negative sentiment overall, tweets mentioning "Trump" had a comparatively better sentiment than those mentioning "Clinton" (Fig. 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

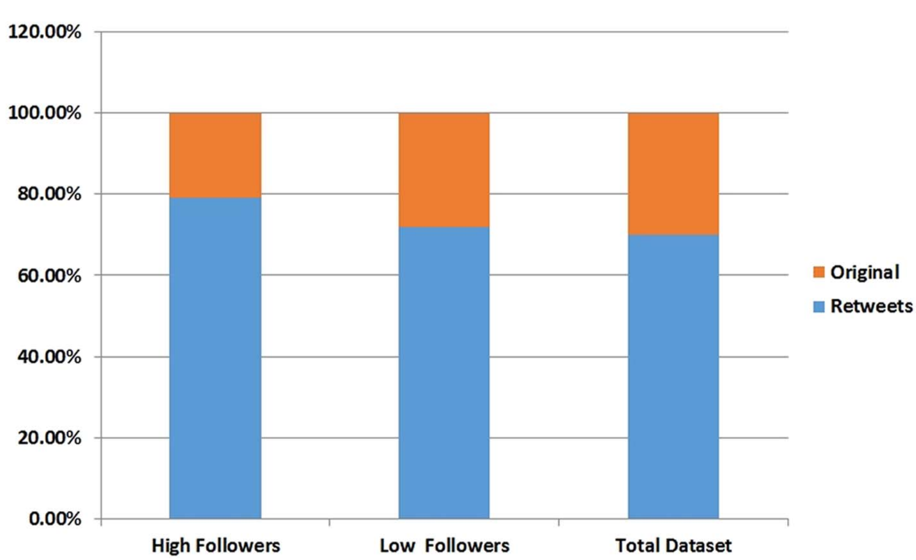

Fig. 8. Tweeting behavior of users based on their number of followers.

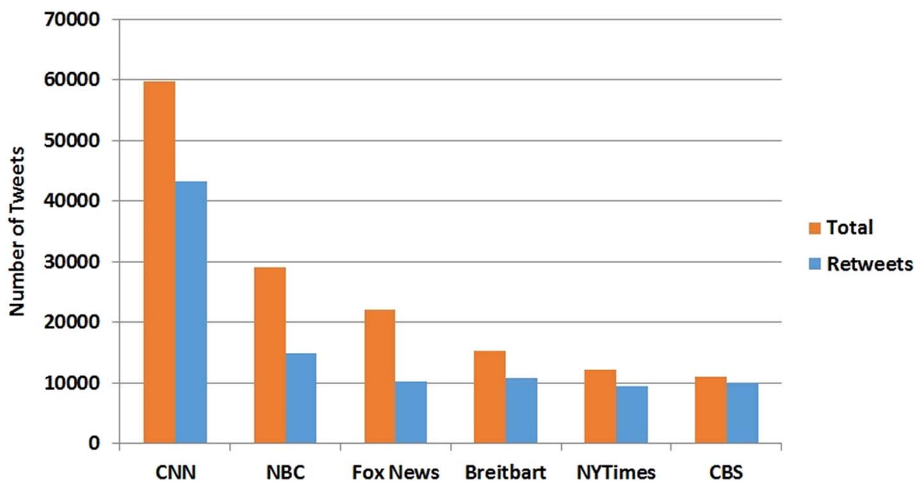

Fig. 9. Popular news outlets mentioned during twitter discussions.

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 (Broersma & Graham, 2012; Thelwall et al., 2011). 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 (O'Connor et al., 2010). We believe that by finding support for Hypothesis 1 (H1), 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.

6.2. Sentiment of twitter messages by both candidates during elections 2016

In sentiment analysis of candidate tweets for 10 days prior to elections (Oct 29th–Nov 7th), we observed that Twitter messages of Donald Trump had a significantly higher positive sentiment than Hillary Clinton's tweets as shown in Fig. 7. We detected a similar pattern in the frequently used terms by both candidates shown in Tables 6a and 6b. 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 observe from Tables 7 and 8, along with the subsequent *t*-test that the 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 6a and 6b, where tweets from both candidates mentioning other candidate's name had a highly negative sentiment.

6.3. 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 shows 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 (H3), 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,

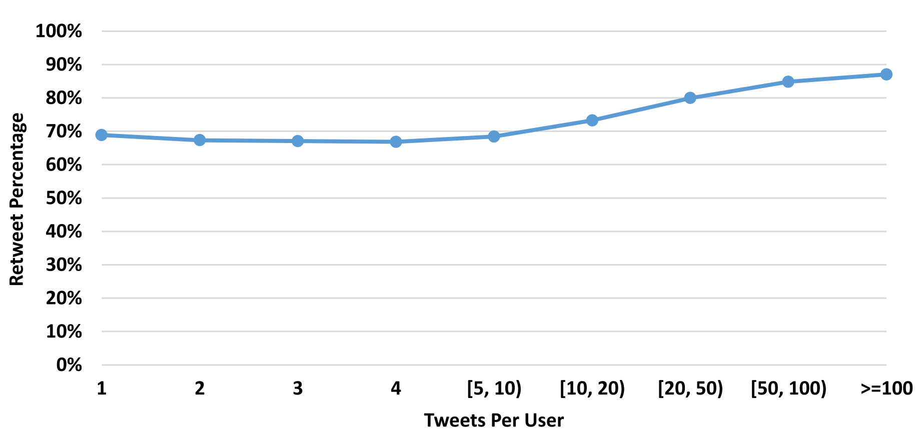

Fig. 10. Retweets as percentage of total tweets by users categorized in terms of frequency of tweets.

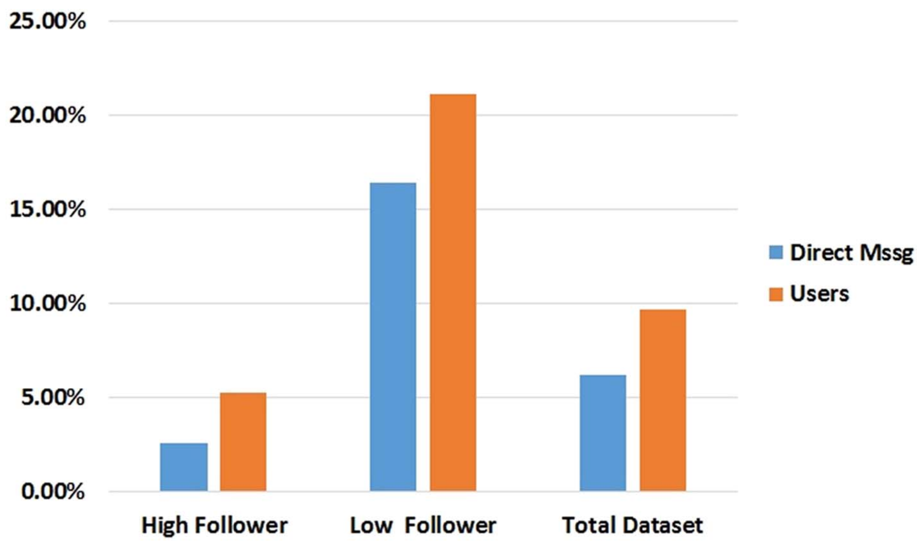

Fig. 11. Comparison of direct messages for users with high and low number of followers.

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 some Twitter studies conducted during elections that claim people use the social media platform to engage in interactive discussions (Tumasjan et al., 2010). On the other hand however, Brondo et al. discovered similar results and found that a small number of users drive discourse on Twitter along with a lack of debate (Borondo et al., 2012; Borondo et al., 2014).

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 where few users interacted with each other and primarily engaged in rebroadcasting few stated opinions.

7. Conclusions

For this data study, we have 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 (Tables 6a and 6b) (The Brookings Institution, 2016; The Forbes, 2016; The Washington Post, 2016). 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.

In this study we also 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.

One of the limitations of this study is the absence of a topic sentiment model. Although we have analyzed frequently discussed topics during the elections, we have not evaluated their impact in terms of sentiment on election related discussion on Twitter. This remains a part of potential future work. Another limitation is the tool used for sentiment tagging. SentiStrength has an accuracy of 60% for positive and 72% for negative short texts (Thelwall et al., 2010). However, SentiStrength is one of the most accurate open source sentiment evaluation tools currently available and has been developed specifically to capture sentiment of short informal texts (Thelwall et al., 2011).

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