Sentiment Analysis of Tweets on 2016 US Presidential Election Candidates

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Abstract

Sentiment analysis is a process that focuses on the understanding of the opinions or emotions from text messages. It has been applied to many areas, from product reviews for online marketing to people's opinions for political events. In this paper, we present a sentiment analysis of text messages extracted from the social media Twitter about the candidates of the 2016 US Presidential Election. The objective of this paper is to find how the traditional method for sentiment analysis compares to the polls and if the sentiment measures can be used as an indicator to predict who will win the election. The statistics software system R with its sentiment tool was used in our analysis. We found that Donald Trump has been leading in the sentiment measures up to the present time, immediately after the two parties' national conventions. It appears contradicting to the recent pools that show Hilary Clinton is ahead. However, the trend in the sentiment showed Clinton is on the rise.

keywords: Sentiment analysis, Sentiment measures, tweet, 2016 US presidential election

1 Introduction

Who will win the 2016 US Presidential Election? This is a question many ordinary people are wondering about and many professionals are trying with various methods, from traditional opinion pools to sophisticated statistics algorithms, to make a prediction. At present time of submitting this paper, the two parties have just selected their nominees, and the election day in November is still several months away. The motivation of this paper is to see if we can predict the winner of the election based on the sentiment on the top candidates from text message extracted from the social media Twitter.

Sentiment Analysis is a process of identifying and categorizing opinions computationally from a piece of text data and determining whether the opinion presented in the text is positive, negative or neutral [11, 15]. it is a sub-field of text mining, combining machine learning algorithms with natural language processing (NLP) techniques. On the NLP side, lexicons and n-grams that are meaningful words/phrases in the text are parsed and extracted based on certain semantic definitions, and sentiment values are computed at sentence or document levels.

In this paper, we present a sentiment analysis of tweets related to presidential candidates for the period of January to July 30, 2016. The text messages in the tweets are extracted using R Twitter API and sentiment values (on a scale of -7 to 7) are calculated with R sentiment tool. We then compute several sentiment measures based on the counts of these sentiment values of each candidates. Comparison is then made of these measures and recent pools. Our study found that Donald Trump, the presumptive Republican nominee, leads in all the sentiment measures. If based only on these sentiment measures, we would predict Trump the winner of the election. However, it is still four months to go before the election in November, and even before the national conventions of the two parties, too early to make a good prediction.

2 Related Work

Despite the fact that broad exploration has been completed in the field of sentiment analysis for over several decades, the paradigm change to social networks and online journals can be followed back to the start of the present decade. The gigantic information accessible on social networking site and these being well known venues for individuals to express their perspectives has inspired scientists to experiment on sentiment analysis models for recovering sentiment from such assets.

A survey that addressed the problem of sentiment analysis (also called opinion mining), the challenges, methodologies, and its applications are discussed in [15]. Another survey [11] described some technical issues involved in opinion mining and representative techniques in the literature, as well as topics of online reviews. Most of these techniques deal with lexicons (words, phrases) and their semantics. The paper [4] gave a brief review of sentiment analysis techniques.

Perhaps the most common areas where sentiment analysis and opinion mining have been applied to are customer reviews [5, 8], financial markets [2],

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and political elections [18], including using Twitter data. Researchers have claimed that online messages on Twitter mirror the offline political sentiment [17]; surveys on political opinions are highly correlate to Twitter messages [14]; Twitter is a valid source in predicting future events such as elections [9]. On the other hand, researchers also found that there is no correlation between analysis on Twitter data and election outcomes [6], and cautioned that classifying tweets in sentiment categories may not be accurate depending on the features (lexicon, bag-of-words, etc.) used in the data sets [1]. Some researchers even claimed that data from social media did only slight better than chance in prediction election results [12].

In this paper we try to find out if sentiments in the tweets actually reflect the US political reality. Our study shows not only Trump led in sentiment measures in early months of the primaries, but also continued to lead after all primaries are done. This finding is in apparent contradiction to the recent polls that show Clinton has an edge. There may be many reasons as to why the sentiment on Twitter is not positively correlated with the polls, but this definitely indicates that one of the two (pools and Twitter messages) may not be an accurate source for predicting who will win the election.

3 Methodology

The steps of the analysis are given in Figure 1.

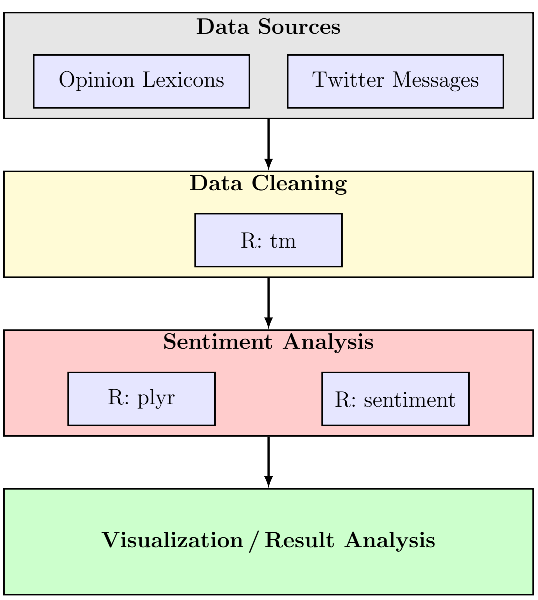

Figure 1: Work flow

We shall describe the steps in this section, focus on the data analysis step.

3.1 Data Sources

We used two data sets for our study: (a) tweets from Twitter from which the basic lexical and syntactic units are extracted, and (b) opinion lexicons that is the database of words and phrases, each of which is associated with a predefined sentiment label (positive or negative). Our task is to match the language units obtained from the tweets against the opinion lexicons to find the strength of the sentiment expressed in each of the tweets so that we can compare the sentiments towards the candidates.

The election stretches from January to November 2016, consists of basically three phases: primary elections (January to early June), national conventions (mid June to late July) of the two parties, and general election (late July to early November). Since the submission of this paper is in late July, we can only do analysis of Twitter data for the first two phases. The primary elections can be further divided into several periods based on the number of candidates remaining in the race. As the race became more intense as the time goes on, we consider longer time periods for early days and shorter periods for more recent days. The number of tweets for each candidate also varies for the different lengths of the periods, as given in Table 1.

Table 1: Number of tweets/per candidate

Label	Period	Candidates	# tweets
P_1	Jan–Apr	Cruz, Trump Clinton, Sanders	20,000
P_2	May 1–31	Trump, Clinton Sanders	10,000
P_3	June 1–15	Trump, Clinton	10,000
P_4	June 22–24	Trump, Clinton	5,000
P_5	June 25–27	Trump, Clinton	5,000
P_6	June 28–June 30	Trump, Clinton	5,000
P_7	July 1–July 3	Trump, Clinton	5,000
P_8	July 4–July 6	Trump, Clinton	5,000
P_9	July 7–July 9	Trump, Clinton	5,000
P_{10}	July 16–July 18	Trump, Clinton	1,500
P_{11}	July 19–July 21	Trump, Clinton	5,000
P_{12}	July 22–July 24	Trump, Clinton	5,000
P_{13}	July 25–July 27	Trump, Clinton	5,000
P_{14}	July 28–July 30	Trump, Clinton	5,000

The database of opinion lexicons contains two dictionaries, one consists of 2,006 positive words, and the other contains 4,783 negative words. These dictionaries were obtained from [10].

3.2 Data Cleaning

The raw data rendered from Twitter API contain many disturbances like unnecessary texts, punctuations, special characters, exta white spaces and mix of lowercase and uppercase letters. The data need to be cleaned before can be used in the next step of the analysis. The cleaning task is performed by the functions in the tm package in R. The piece of R code for this task is shown below.

```
x <- searchTwitter(...parameters...)
y <- sapply(x, function(x) x\$getText())
y_corpus <- Corpus(VectorSource(y))

y_clean <- tm_map(y_corpus,removePunctuation)
y_clean <- tm_map(y_clean,content_transformer(tolower))
y_clean <- tm_map(y_clean,removeWords,stopwords("english"))
y_clean <- tm_map(y_clean,removeNumbers)
y_clean <- tm_map(y_clean,stripWhitespace)
```

3.3 Sentiment Analysis

The clean data of a tweet is a list of words that is fed to functions in the plyr and sentiment packages of R to calculate the sentiment score. The plyr package provides a lapply() function to apply a function to a list. The list and the function, as well as the opinion lexicon, are parameters to lapply(), like this:

```
scores = lapply(sentences, function(sentence,
                             pos.words, neg.words))
```

The sentiment package utilizes a database of positive and negative words to analyze the sentiment of a given text. This package contains two handy functions serving our purposes:

(1) emotion classification. This function helps us to analyze text and classify it in different types of emotion, such as anger, disgust, fear, joy, sadness, and surprise. The classification can be performed using two algorithms: one is a naïve Bayes classification trained on an emotions lexicon, and the other is just a simple voter procedure.

(2) polarity classification. This function allows us to classify text as positive or negative. Similar to emotion classification, it uses naïve Bayes classification trained on a subjective lexicon, and the other use simple voter algorithm.

We used the polarity classification in our study simply because the opinion lexicon available to us is subjective. Some R code for calculating sentiment scores is given below.

```
score.sentiment = function(sentences, pos.words,
                             neg.words, .progress='none')
{
  require(plyr)
  scores = lapply(sentences, function(sentence,
                             pos.words, neg.words))
  sentence = gsub('[[:punct:]]', '', sentence)
  sentence = tolower(sentence)
  word.list = str_split(sentence, '\\s+')
  words = unlist(word.list)

  pos.matches = match(words, pos.words)
  neg.matches = match(words, neg.words)

  pos.matches = !is.na(pos.matches)
  neg.matches = !is.na(neg.matches)

  score = sum(pos.matches) - sum(neg.matches)

  scores.df = data.frame(score=scores, text=sentences)
  return(scores.df)
}
```

3.4 Visualization and Result Analysis

The sentiment scores can be displayed as histograms within system R. Word cloud can also be used to visualize the frequencies of the words. Since we are only interested in the sentiment measures, we display the histograms in Section 4 and do not show the word cloud.

4 Experimental results

Various numbers of tweets extracted from Twitter are analyzed using the sentiment tool in R to obtain a sentiment score for each tweet for the candidates. We first compare the number of positive and negative sentiment scores of the candidates, and then discuss the trend of changes of some calculated measures of the sentiment.

4.1 Sentiment Scores

Sentiment scores are generated by the R tool with sentiment package. The scores generated are used to analyze data visually by generating histograms. The scores are scaled on a scale of $(-7, -6, \cdots, -1, 0, 1, \cdots, 6, 7)$, with -7 being most negative, 7 being the most positive, and 0 being neutral. The positive and negative counts of the tweets for the candidates, divided in several time periods, are discussed below.

4.1.1 Earlier Primaries (Up to April)

This period starts from Iowas caucus and New Hampshire primary in January to two Super Tuesdays in March and April. By the end of April, the two major parties had clear front runners: Donald Trump and Ted Cruz for Republicans, Hilary Clinton and Bernie Sanders for Democrats.

A total of 80,000 (20,000 tweets for each candidate) tweets are processed using the R tool with sentiment package. The tool generates a sentiment score for each tweet. The counts of the sentiment scores of the four candidates are given in Table 2, and the percentage histogram plot is shown in Figure 2. In the percentage plot, the values are calculated for each candidates. During the period Jan-April, for example, Trump has 6189 tweets with sentiment score 2, that is 30.945% of the total 20,000 tweets about him.

The tweets clearly show that although most tweets are neutral, Trump had a highest percentage of positive

Table 2: Counts of sentiment scores

Time Period (ref. to Table 1)	Candidates	Sentiment Score (5,000–20,000 tweets for each candidates)														
		7	6	5	4	3	2	1	0	-1	-2	-3	-4	-5	-6	-7
P_1	Trump	0	5	39	283	1745	6189	5651	3804	2120	150	9	5	0	0	0
	Cruz	0	0	7	42	222	1245	4814	10787	2429	336	104	12	2	0	0
	Clinton	0	0	1	108	179	991	4426	10437	2731	900	172	48	5	1	1
	Sanders	0	0	3	17	154	1967	5015	9421	2785	513	115	8	2	0	0
P_2	Trump	1	13	54	90	294	1808	4375	2332	675	226	84	48	0		
	Clinton	0	0	2	56	65	505	2282	4341	1694	836	209	9	1		
	Sanders	0	0	1	4	73	1850	1897	4655	1092	391	25	12	0		
P_3	Trump	1	5	66	145	485	2001	2391	2580	1550	461	299	13	3		
	Clinton	0	0	1	24	33	522	1389	5682	1906	307	94	40	2		
P_4	Trump			12	50	169	2003	1380	981	331	63	11	0			
	Clinton			0	23	24	443	1221	2008	923	291	61	6			
P_5	Trump			1	17	150	2072	1009	1435	276	30	9	1			
	Clinton			0	20	30	197	1100	2275	1051	235	87	5			
P_6	Trump		1	0	123	242	2481	761	792	419	173	8	0			
	Clinton		0	0	240	19	144	584	2628	1261	109	12	3			
P_7	Trump				145	231	1333	1484	1134	610	48	7	4	0	4	
	Clinton				20	44	137	840	2830	756	255	117	1	0	0	
P_8	Trump		1	4	27	216	1822	1157	1320	377	63	9	2	2		
	Clinton		0	0	4	33	167	862	2418	792	246	474	1	3		
P_9	Trump			112	17	237	3014	782	486	224	106	22	0	0		
	Clinton			1	44	46	171	1012	2402	1008	237	60	18	1		
P_{10}	Trump			9	3	77	771	387	157	42	15	22	17			
	Clinton			0	3	12	52	351	811	205	58	6	2			
P_{11}	Trump		3	142	140	364	1223	1552	1150	309	91	22	4	0		
	Clinton		0	0	44	26	235	1256	2223	843	255	105	12	1		
P_{12}	Trump			0	190	289	1018	1811	1267	256	47	20	102	0		
	Clinton			2	5	28	270	448	3780	358	87	20	1	1		
P_{13}	Trump		1	1	32	698	1100	1696	1151	255	50	12	4	0		
	Clinton		1	2	31	53	212	1091	3025	453	89	35	7	1		
P_{14}	Trump		1	4	47	287	916	1588	1497	497	151	9	2	1		
	Clinton		0	1	7	51	272	1316	2431	749	128	37	8	0		

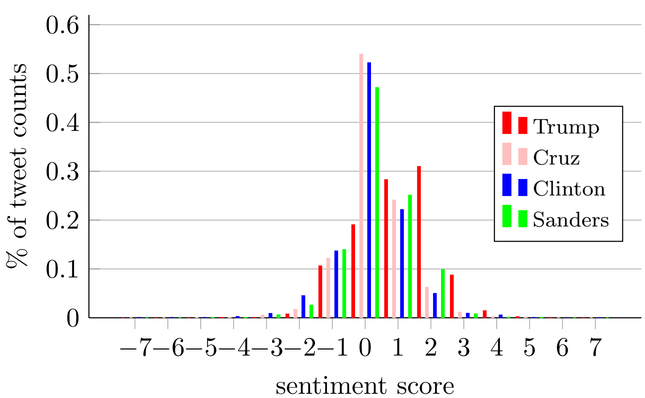

Figure 2: % of sentiment score counts (Jan–Apr 30)

sentiment for that period, and Clinton had the highest percentage of negative sentiment. Among the two democrats, Sanders had higher percentage of positive scores and lower percentage of negative scores comparing to Clinton.

4.1.2 Late Primaries (May 1 – 31)

For this and later periods, we collected 10,000 tweets for each remaining candidates for analysis. The party primaries at the end of May showed clear front runners of the two parties. On the Republican side, Trump was the only candidate left after Cruz dropped out.

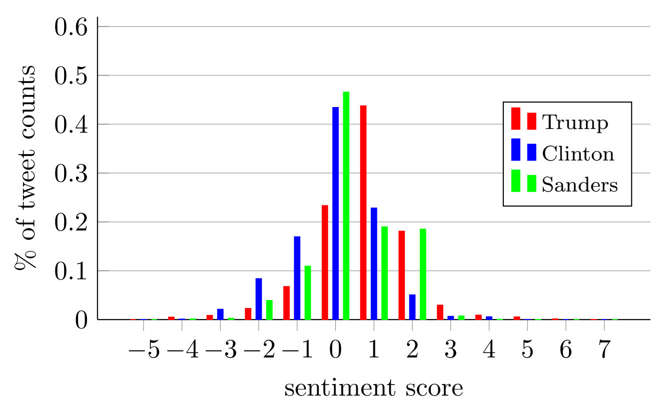

Figure 3: % of sentiment score counts (May 2016)

The sentiment scores of the remaining three candidates are also given in Table 2, and the percentage histogram plot is shown in Figure 3. Trump continued to lead in the percentage of positive sentiment, with a significant increase of tweets with positive score 1 from the previous period when many tweets had positive scores 2 and 3.

4.1.3 Presumptive Nominees (Up to June 15)

After the primaries in California, New Jersey, and few other states in early June, Trump and Clinton clinched as the presumptive nominees of the two parties. We would like to see if the sentiment changed. The percentage histogram plot is shown in Figure 4 with 5,000 tweets for each candidate.

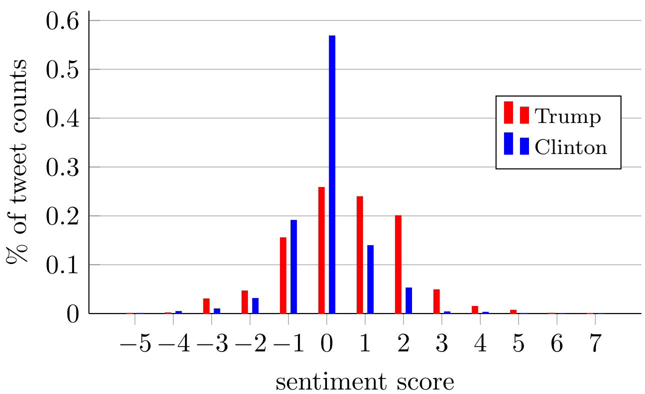

Figure 4: % of sentiment score counts (June 1–15)

It is seen that the sentiment for Trump shifted somewhat becoming less positive. The numbers of sentiment scores 2 and 3 were reduced whereas numbers of negative scores $-1, -2$ and -3 increased. This shift might be due to his comments on the Judge of Mexican heritage and his renewed call for Muslin ban after the shooting at the Orlando night club. Clinton's scores remain pretty much the same.

4.1.4 Before National Conventions (June 22 – July 9)

After Clinton and Trump clinched their presumptive nominee status, they entered a new phase of the race preparing for official nomination at the national conventions of the two parties. During this period, they were also in the mood of general election. The Twitter messages are mostly focused on the two candidates and their policies on various issues. With 5,000 tweets per candidate for each 3-day window, the percentage histogram plot is shown in Figure 5.

The figure shows that Trump shifted back to more positive scores, while the percentage of neutral score for Clinton reduced and spread into weak positive (1) and weak negative (-1) columns but much less positive in comparison to Trump.

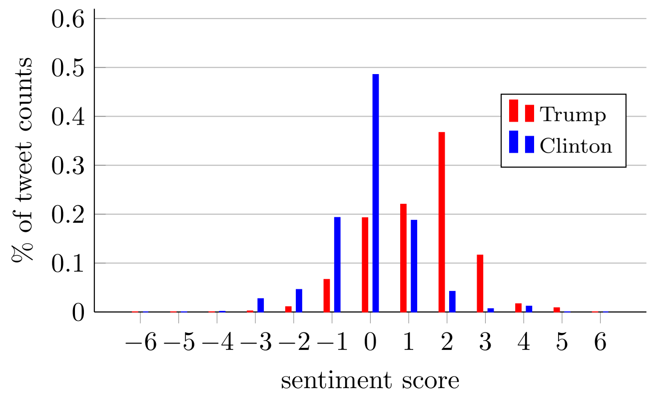

Figure 5: % of sentiment score counts (June 22–July 9)

4.1.5 During and After National Conventions (July 16 – July 30)

Clinton and Trump were formally became their party's nominees at the national conventions. With 5,000 tweets per candidate for each 3-day window, except the period P_{10} (July 16-18) when only 1,500 tweets were collected. The percentage histogram plot is shown in Figure 6.

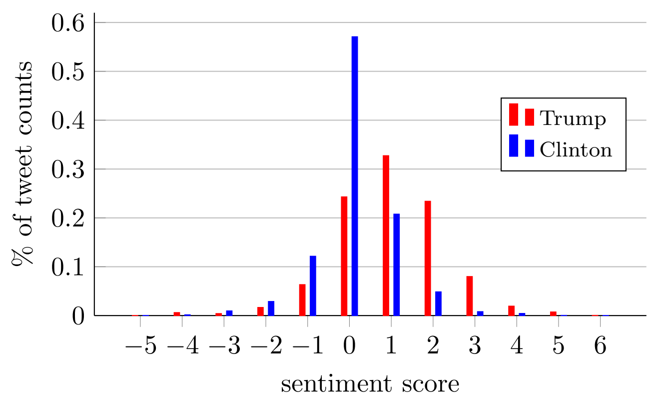

Figure 6: % of sentiment score counts (July 16–July 30)

Trump still leads in positive sentiment although positives for Clinton increased, while the percentage of neutral score for Clinton continue to dominate the opinions towards her.

4.2 Sentiment Metrics

In addition to the counts of sentiment scores, several other sentiment measures were calculated that are more accurate to reflect the people's opinions on the candidates. These measure include average sentiment S_{avg}, net sentiment S_{net}, sentiment ratio S_{rat}, and passion intensity S_{pas}, as defined below.

$$S_{avg} = \frac{\sum_{i=1}^{n}(score_i \times count_i)}{N}$$

$$S_{net} = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg}}$$

$$S_{ratio} = \frac{N_{pos}}{N_{neg}}$$

$$S_{pas} = \frac{N_{love} + N_{hate}}{N_{laden} + N_{pos} + N_{neg}}$$

where n is the number of score scales, N is the total count of tweets, $N_{pos}, N_{neg}, N_{love}, N_{hate}$ are the number of positive, negative, very positive, and very negative tweets, respectively. N_{laden} is the number of tweets that contain words/phrases that are subjective instead of emotional (such as *good* vs *amazing*). However, since we do not have the number of emotion-laden words/phrases extracted from the tweets, we simply set N_{laden} to 0 in the calculation.

4.2.1 Average Sentiment

The average sentiment measure S_{avg} is a weighted average of the sentiment scores with the score values as the weights. The measures for the two candidates are shown in Figures 7, where the time period on the x-axis refer to the time label in Table 1.

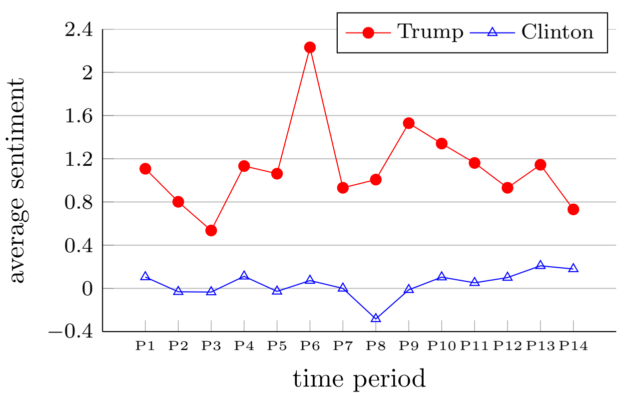

Figure 7: Average sentiment S_{avg}

The average sentiment score for Trump was in the range of (0.53, 2.23) that was positive, while for Clinton it was in the range of $(-0.03, 0.38)$, considered mostly neutral. This indicates that the tweet messages were more in favor of Trump than Clinton. However, the difference of the average sentiments has narrowed after the national conventions.

4.2.2 Net Sentiment

The net sentiment measure S_{net} is the ratio of the difference between the positive and negative counts and the total non-neutral counts. A net sentiment value of 1 indicates all opinions are positive, a value of -1 means all opinions are negative, and net sentiment 0 represents the same number of positives and negatives. Figure 8 shows the net sentiment for the two candidates,

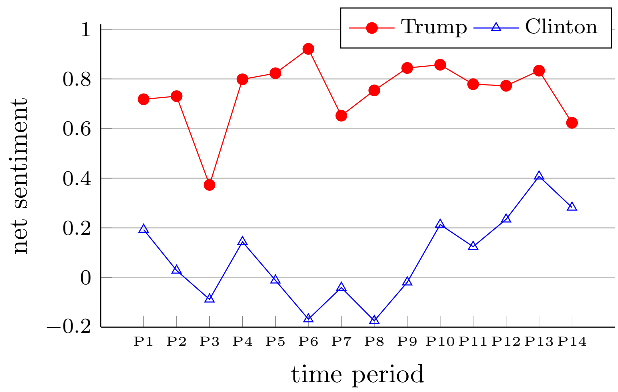

Figure 8: Net sentiment S_{net}

Similar to S_{avg}, the figure shows that Trump S_{net} had higher S_{net} in all the periods, but the net sentiment for Clinton has a up-tick trend after the national conventions.

4.2.3 Sentiment Ratio

The sentiment ratio is simply the ration of positives and negatives. Higher ratio indicates more positive opinions comparing to negative opinions. The sentiment ratio of Trump and Clinton is given in Figure 9 that shows a similar comparison of the two candidates – Trump had higher sentiment ratio in all the periods but fluctuated quite a lot, whereas Clinton's stayed constantly around 1 before the national convention indicating almost the same number of positives and negatives for her, but increased to the range of (1.6, 2.4) after the convention.

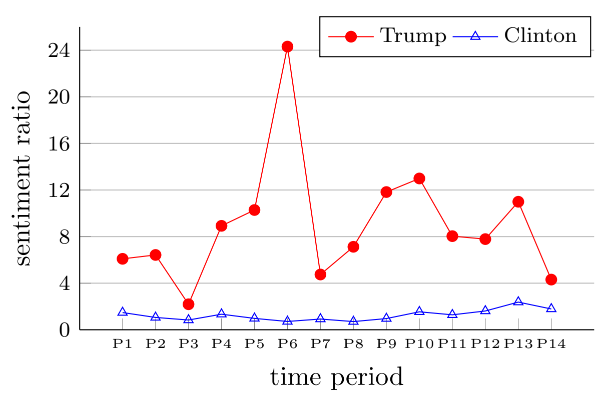

Figure 9: Sentiment ratio S_{ratio}

4.2.4 Passion Intensity

The passion intensity measures the degree of how passionate (love or hate) a person is towards the subject. The passion intensity values of Trump and Clinton are shown in Figure 10. The passion intensity for Clinton was pretty much flat at a low level (between 0.002 and 0.22) meaning most tweets for her was neutral, except the period of P_6 (late June) when her private email sever issue was intensely covered in the media. Trump's passion intensity measure shot up sharply in P_6 (late June) when he made controversial comments on the judge of Mexican heritage, and during the national convention periods P_{11} and P_{12} when he was selected to be the Republic nominee.

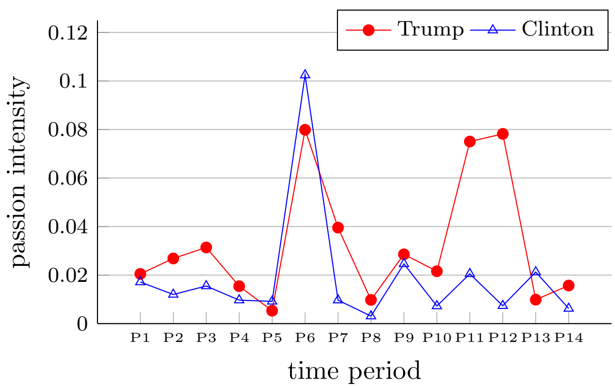

Figure 10: passion intensity S_{pas}

4.3 Correlation of Sentiments and Pools

Are the sentiment measures from Twitter data a reliable indicator for predicting the winner of the election? Researchers have augured both ways. For example, Austin Carr [3] cited an analysis on Twitter data for Nevada congressional election in 2010 that was more accurate than the polls. However, Goldstein and Rainey [7] pointed out just the opposite for the same election. It is desirable for us to find out how the sentiments from the Twitter data correlate with the polls. O'Conner et al analyzed poll data in 2008-2009 and sentiment from tweets and found a high correlations (as high as 80%) between them [14]. Our study, however, suggests otherwise that the sentiment on Twitter is just opposite of the polls.

We tried to study the correlation of our Twitter sentiment results and the recent polls. Since the tweet data were not collected on a daily (or even weekly) basis for before Mid June, we can only do the correlation analysis of data after June 22 when we use a 3-day slicing window for both tweet and pool. To do this, we introduce two variables:

$$x = \bar{s}_{Clinton} - \bar{s}_{Trump}$$
$$y = \bar{p}_{Clinton} - \bar{p}_{Trump}$$

representing the difference of Clinton and Trump in average of net sentiment ($\bar{s}$) and difference in average polls ($\bar{p}$). The poll data is from the RealClear Politics website [16]. Figure 11 is a plot of the two variables x and y, showing that net sentiment for Clinton is always lower than Trump's ($x < 0$) and average poll for Clinton is mostly higher than Trump's ($y > 0$). The two variables x and y do not correlate at all with correlation coefficient 0.00825.

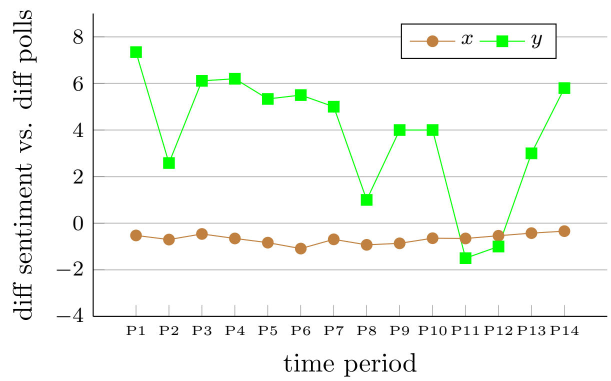

Figure 11: Difference of Clinton-Trump in net sentiment (x) vs difference of Clinton-Trump in polls (y)

The Twitter sentiment for Trump has been consistently more positive than Clinton, while Clinton has been leading in the polls, except the periods P_{11} and P_{12} when the Republican national convention was in session. Polls normally shot up during and immediately after the party's national convention of the party's nominee. This is also evident here that the poll for Clinton increased significantly during the Democratic national convention P_{13} and P_{14}.

5 Conclusion

In this paper we present a sentiment analysis by using opinion lexicon and a R tool on twitter data of public opinions on the USA 2016 presidential election candidates. All the measures show that public sentiments are more positive towards Donald Trump than Hilary Clinton, but the positive opinions for Trump have gradually declined in recent weeks after they became the nominees of the two parties.

Most predictions for elections have been rely on polls. Research showed that polls are quite accurate when the time is close to the election date, but not very reliable if the polls are still months away from the election date. The sentiment measures in our study, in fact, do not seem to agree with the recent polls that showed Clinton is leading for 4-5%. It is hard to say which of the two (Twitter sentiment or the polls) will be a more accurate indicator to predict the winner of the election. If we just use the public opinions expressed in their tweets (up to end of July) for the prediction, all the analysis results show that Trump will win. However, the most recent sentiment measures for Trump has declined whereas Clinton's has increased, showing the trand is in "agreement" with the polls.

There are some factors that Twitter sentiment may not be reliable. One is that there might be the sample bias in the collection of public opinions on Twitter. As stated in [13], "Twitter users significantly over-represent the densely population regions of the U.S., are predominantly male, and represent a highly nonrandom sample of the overall race/ethnicity distribution." People who are more likely express their opinions on the candidates on Twitter may not represent the whole voting population.

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