Forecasting the 2016 US Presidential Elections Using Sentiment Analysis

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Abstract. The aim of this paper is to make a zealous effort towards true prediction of the 2016 US Presidential Elections. We propose a novel technique to predict the outcome of US presidential elections using sentiment analysis. For this data was collected from a famous social networking website (SNW) Twitter in form of tweets within a period starting from September 1, 2016 to October 31, 2016. To accomplish this mammoth task of prediction, we build a model in WEKA 3.8 using support vector machine which is a supervised machine learning algorithm. Our results showed that Donald Trump was likely to emerge winner of 2016 US Presidential Elections.

Keywords: Forecasting · Twitter · Sentiment analysis · Support vector machine · WEKA

1 Introduction

Accurate future prediction of an event has always been a tedious task for researchers, but with advancement in technologies and availability of powerful computing devices researchers have started taking keen interest in this research area. One of the key factor in these advancement has been the popularity of social networking websites (SNW) especially Twitter. Twitter is one of the most popular social networking media, with 695,750,000 registered users till date and approximately 135,000 new users are registering every day [1]. This large audience is responsible for tons of tweeting happening everyday i.e. sharing their view in relatively fewer words and hence providing researchers a large pool of tweets, which may contain anger or love towards an entity like an election. Using the concept of sentiment analysis as suggested by Liu [2], we can extract their sentiments from these tweets and use these in predicting the outcome of any event, be it elections. Since US is a developed country [3], with an established fact that 88.5% of the population has access to the internet [4] and approx 67 million Twitter users in the US [5], all these factors give us a perfect platform to carry out our research on 2016 US Presidential Elections.

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For this research paper, we have collected the tweets through Twitter. Then we synthesized these tweets using sentiment analysis that helped us to have a better insight into the outcome of 2016 US Presidential Elections. We would be discussing our approach towards our predicted results in the upcoming sections.

2 Background of US Presidential Elections

US Presidential elections were scheduled to be held on November 8, 2016 to elect the new President of United States of America for the next 4 years, as the second term of the current President Mr. Barack Obama was going to expire on January 2017. Since Obama was holding the presidential chair for the second term, so as per the US presidential ordinances he could not contest these elections. The event became more engaging, as both the candidates contesting the election were first timers. As we know Democratic Party and Republican Party were the two main parties, so the entire paper has been focused on these parties as well as their Presidential candidates.

The selection of both presidential candidates was made through primaries held between February to June 2016. In the Democratic Party Presidential primaries Ms. Hillary Clinton defeated Mr. Bernie Sanders, thus becoming the first female Presidential candidate in the history of United States, to be nominated by a major political party. While the Republican Party Presidential primaries saw 17 candidates were entering the primaries, making it the largest ever presidential primary contesting for any political party in United States history. In the finals Mr. Donald Trump, a businessman manages to defeat Mr. Ted Cruz to be selected as Republican Party Presidential candidate.

None of the candidates had an absolute cakewalk, and both faced their respective ups and downs during the course of their campaign and debates. Donald Trump had easy primaries while Hillary Clinton had a tough fight with Bernie Sanders. During debates, Hillary Clinton always had an edge over Donald Trump. Donald Trump was highly criticized for various comments and attitude toward other nations during campaigns and speeches while Hillary Clinton had tough times for her email controversies. So even up to week before the elections, there was ambiguity about the winner and the lead was constantly swinging among both candidates.

3 Related Work

Twitter and Elections share a strong bond since a longtime now. With advancement in technology and increase in a number of people using Twitter, the researchers working in this domain have a perfect opportunity to work on Twitter based emotions towards election predictions. Though this approach was rather crude and had many flaws yet it provided useful insights that helped us towards making a realistic prediction with some modern prediction tools the task seems realistic.

Tumasjan et al. [6] were the first to make use of Twitter to predict the results of German Federal election held in September 2009. They collected 104,003 tweets over the period of 27 days for the six popular political parties of Germany. Their technique was quite simple and dependent on a basic counting of the number of tweets that a party or its prominent leaders get. Using this simple technique, they were successful in predicting the winner of 2009 German Federal Elections. However this simple technique faced huge criticism, in particular, Jungherr et al. [7] pointed the lack of methodological justification while Gayo-Avello [8, 9] stressed on the need to make true prediction i.e. predictions made prior to the actual election. Another point highlighted by Gayo-Avello [8, 9] was to make use of sentiment analysis in order to know the sentiment of the tweet, which indeed will help to produce more accurate results. The subsequent studies DiGrazia et al. [10], Franch [11], Ceron et al. [12], Caldarelli et al. [13], Burnap et al. [14] have all taken the advice of Gayo-Avello and made use of sentiment analysis in order to produce more accurate results.

Our work is also influenced by the advice of Gayo-Avello [8, 9]. We made a true prediction for 2016 US Presidential elections, instead of simply relying on the amount of tweets for making the prediction we have used sentiment analysis in our methodology along with some scientific tools to make predictions.

4 Proposed Methodology

Data collection is a trivial task and in our case as well the initial hurdle was efficient data collection. So we gathered data from Twitter in form of tweets. For this, we built a system in ASP.Net 2012. Since a person can post multiple tweets on Twitter, so in order to avoid biased results, we have first removed multiple tweets from single source so that only one tweet could be considered from one person. Next we applied sentiment analysis to obtain polarity (positive or negative) of each tweet using WEKA 3.8. All these phases are discussed with suitable explanation in the upcoming sections. The flowchart of the process is given in Fig. 1.

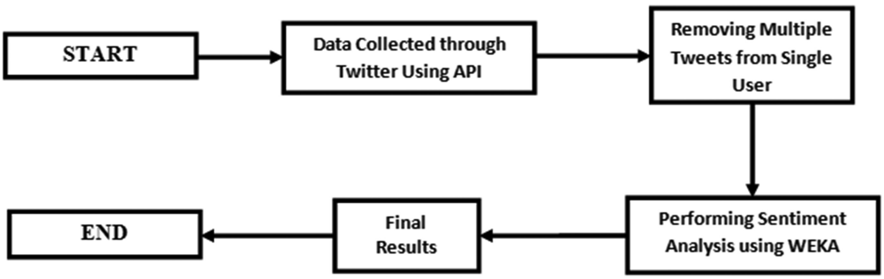


Fig. 1. Flowchart of proposed methodology

5 Data Collection

Data for our research was collected from Twitter. For this purpose, a system was developed in ASP.Net using visual studio [15]. For tweet fetching we used tweetinvi API [16] which is freeware and can be easily integrated with Dot. Net framework. The tweets were fetched using this system based on the hashtags (#) for both the respective candidates. Table 1 shows the hashtags (#) that were used for fetching tweets from Twitter.

Table 1. Hashtags (#) used for fetching tweets

Candidates	Hillary Clinton	Donald Trump
Hashtags(#)	#Hillary, #HillaryClinton, #ClintonKaine, #Votehillary	#DonaldTrump, #TrumpPence16, #Trump, #VoteTrump

A total of 327,127 tweets were collected from September 1, 2016 to October 31, 2016 daily from the USA. This time period was chosen because the election campaigns were in full swing so it was possible to get data from all type of Twitter users at this time. Out of the 327,127 tweets collected from the USA, 194,753 (59.53%) of tweet mentions were in favor of Donald Trump, while 132,374 (40.47%) of tweet mentions were in favor of Hillary Clinton. Table 2 shows the daily tweet collection for both the candidates.

Table 2. Daily tweet collection for both candidates

Date	Donald Trump	Hillary Clinton
01-09-16	3512	1356
02-09-16	2728	1499
03-09-16	2757	1329
04-09-16	2319	1160
05-09-16	2548	1122
06-09-16	2361	2638
07-09-16	2722	1520
08-09-16	3587	2193
09-09-16	2638	1475
10-09-16	1919	1644
11-09-16	2410	4649
12-09-16	2748	1667
13-09-16	2152	1552
14-09-16	2661	1596
15-09-16	3483	1803
16-09-16	3771	2027
17-09-16	3369	1554
18-09-16	3184	1548
19-09-16	2280	1604
20-09-16	2818	1678
21-09-16	3253	4226

(*continued*)

Table 2. (*continued*)

Date	Donald Trump	Hillary Clinton
22-09-16	2960	1524
23-09-16	2902	1392
24-09-16	2617	1454
25-09-16	2729	1640
26-09-16	3717	2491
27-09-16	1822	4344
28-09-16	3870	2073
29-09-16	3643	1775
30-09-16	4017	2028
01-10-16	3178	1814
02-10-16	3309	1672
03-10-16	3084	1978
04-10-16	2398	2008
05-10-16	3018	2326
06-10-16	2742	1468
07-10-16	3289	1841
08-10-16	4039	3078
09-10-16	3790	2299
10-10-16	4205	3666
11-10-16	3903	2574
12-10-16	3998	3379
13-10-16	4279	3247
14-10-16	4198	2705
15-10-16	3858	2442
16-10-16	3868	2120
17-10-16	1502	954
18-10-16	3769	2150
19-10-16	4255	2705
20-10-16	3897	2938
21-10-16	3441	2195
22-10-16	3144	2090
23-10-16	3035	2312
24-10-16	2775	2688
25-10-16	3575	2966
26-10-16	3485	2145
27-10-16	3813	2492
28-10-16	2918	1760
29-10-16	3530	2753
30-10-16	3596	2520
31-10-16	3365	2528
Total	***194,753***	***132,374***

Since in the actual elections, a person can vote only once. We have also applied a similar restriction, that only one tweet would be considered per person. The reason for this restriction was that nowadays many companies and agencies are being hired by the candidates in order to make the analysis bias. To rule out this anomaly, we had simply used the coding skills that if a person who tweeted multiple times, then the first tweet by that person would be considered for evaluation of results. Table 3 shows an example how this restriction works. In this "Roy" has tweeted 3 tweets, while "Sheral" has tweeted 2 tweets. So we set flag '1' for all tweets except the initial/first tweet. So for "Roy" and "Sheral" only one tweet will be counted, hence eliminating the effect of multiple tweets.

Table 3. Example for applying restriction of one tweet per person

Sr. No.	Tweet	Sender	Flag
1	I support Donald Trump	Roy	0
2	Trump you are my hero	Roy	1
3	Hillary we win this elections	Sheral	0
4	Trump: Make US Great again	Roy	1
5	Hillary we support you	Sheral	1

After applying this restriction, we were left with 136,192 (41.64%) tweets, while 190,935 (58.36%) duplicate tweets were removed. This highlights an important point that the number of people posting multiple tweets was quite high. Out of the 136,192 tweets collected from the USA, 81,946 (60.16%) of tweet mentions were in favor of Mr. Donald Trump, while 54,246 (39.84%). Table 4 shows the daily tweet collection for both candidates after applying the restriction of one tweet per person. Our entire experimentation was to be dependent on these 136,192 tweets.

Table 4. Daily tweet collection (With Restriction)

Date	Donald Trump	Hillary Clinton
01-09-16	1372	554
02-09-16	1097	564
03-09-16	1054	523
04-09-16	892	451
05-09-16	966	506
06-09-16	1540	1529
07-09-16	1013	600
08-09-16	1302	823
09-09-16	1063	594
10-09-16	832	668
11-09-16	926	1686
12-09-16	1040	718
13-09-16	927	682

(*continued*)

Table 4. (*continued*)

Date	Donald Trump	Hillary Clinton
14-09-16	1073	712
15-09-16	1306	638
16-09-16	1547	1963
17-09-16	1257	607
18-09-16	1161	590
19-09-16	945	641
20-09-16	1163	690
21-09-16	1277	2058
22-09-16	1237	643
23-09-16	1219	583
24-09-16	1119	542
25-09-16	1171	627
26-09-16	1666	918
27-09-16	1016	1973
28-09-16	1547	895
29-09-16	1466	716
30-09-16	1623	756
01-10-16	1315	725
02-10-16	1334	635
03-10-16	1313	874
04-10-16	1038	772
05-10-16	1418	939
06-10-16	1299	643
07-10-16	1540	762
08-10-16	1786	1064
09-10-16	1679	918
10-10-16	1854	1506
11-10-16	1685	1009
12-10-16	1677	1100
13-10-16	1802	1111
14-10-16	1828	995
15-10-16	1655	963
16-10-16	1604	863
17-10-16	791	515
18-10-16	1500	900
19-10-16	1676	1120
20-10-16	1659	1193
21-10-16	1362	904
22-10-16	1285	793
23-10-16	1294	757

(*continued*)

Table 4. (*continued*)

Date	Donald Trump	Hillary Clinton
24-10-16	1213	892
25-10-16	1444	930
26-10-16	1593	944
27-10-16	1585	966
28-10-16	1360	888
29-10-16	1557	1068
30-10-16	1498	992
31-10-16	1485	1055
Total	***81,946***	***54,246***

6 Results and Findings

As mentioned earlier, volume of tweets is not the deciding factor for the victory of any specific candidate, we computed polarity (positive or negative) for each tweet by applying sentiment analysis. Sentiment analysis is the study of analyzing people's opinions, sentiments, evaluations, appraisals, attitudes and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes [2].

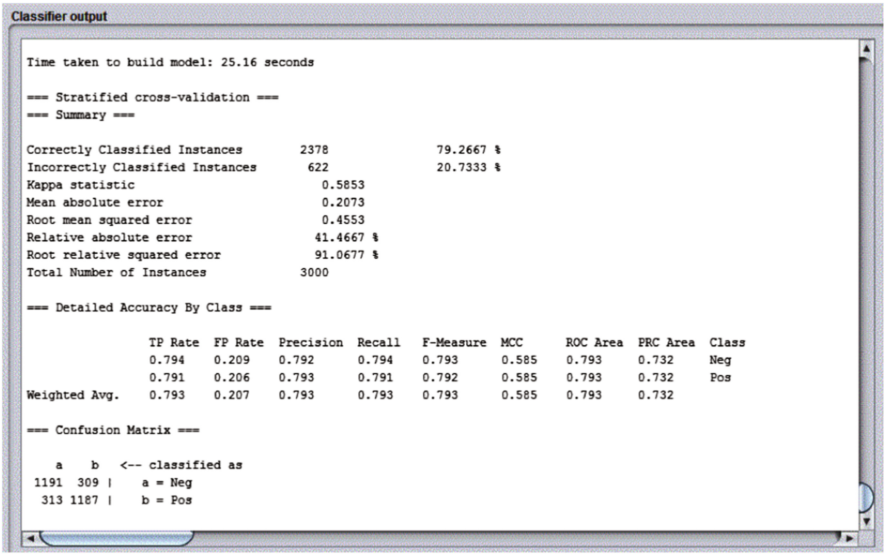
For this, we developed a classification model in WEKA 3.8 [17], which is open source software and consists of a collection of machine learning algorithms for data mining tasks. Further we applied support vector machines (SVM) which is a supervised machine learning approach for performing the sentiment analysis. The SVM is a learning machine for two-group classification problems that transforms the attribute space into multidimensional feature space using a kernel function to separate dataset instances by an optimal hyperplane [18]. The reason for building the model using SVM was that it is often regarded as one of the best classification algorithm [19].

The training data set was same as used by Kotzias et al. [20], which contains reviews and scores from three different datasets i.e. Amazon [21], IMDb [22], Yelp [23]. Each dataset contains a total of 500 positive and 500 negative sentences, so in total the dataset had 1500 positive and 1500 negative sentences. The data set contained two columns first the sentence and second the sentiment of each sentence in form of "0" (negative) and "1" (positive).

For classification, we used filtered classifiers, which enable us to build a classifier with a filter of our choice. As discussed earlier SVM is used as classifier while "String To Word Vector" is used as a filter which convert a string attribute to a vector that represents word occurrence frequencies. In addition to this we used 10 fold cross validation which is also known as rotation estimation to analyze how a predictive model would perform on an unknown dataset. The training set got an efficiency of 79.26%, this means 2378 instances from the training set were correctly classified while 622 instances were incorrectly classified. According to the confusion matrix 1191 negative instances (Class a) were correctly classified while 1167 positive instances

(Class b) were correctly classified. The detailed results along with confusion matrix are shown in Fig. 2, while Fig. 3 shows the graph showing area under the curve (ROC = 0.793).

For testing set, we used the tweets collected from Twitter. Before testing we preprocessed the data in order to remove unwanted Html tags, web links and special symbols (, " ! ' ; : @ #) so that we should not get biased results. The task of data



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Classifier output

Time taken to build model: 25.16 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        2378               79.2667 %
Incorrectly Classified Instances       622               20.7333 %
Kappa statistic                          0.5853
Mean absolute error                      0.2073
Root mean squared error                  0.4553
Relative absolute error                 41.4667 %
Root relative squared error             91.0677 %
Total Number of Instances             3000

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.794    0.209    0.792      0.794    0.793      0.585    0.793     0.732     Neg
                 0.791    0.206    0.793      0.791    0.792      0.585    0.793     0.732     Pos
Weighted Avg.    0.793    0.207    0.793      0.793    0.793      0.585    0.793     0.732

=== Confusion Matrix ===

    a    b   <-- classified as
 1191  309 |    a = Neg
  313 1187 |    b = Pos
```

Fig. 2. Results of classification model

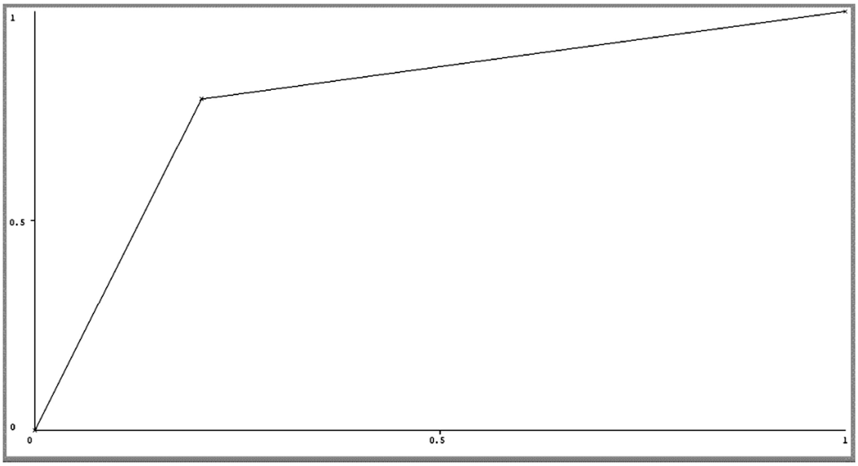

Fig. 3. Area under the Curve (ROC = 0.793)

preprocessing was performed in an automated fashion. Once preprocessing was done, we passed the testing set through the classification model developed earlier and it gave us the classification results i.e. polarity of each tweet. From these results we calculated net positive score (NPS), which is simply the difference between the total number of positive tweets and total number of negative tweets received by a candidate. The results of the same have been shown in Table 5.

Table 5. Result of Sentiment Analysis for both candidates

	Number of Tweets	
	Donald Trump	Hillary Clinton
Positive	42518	27582
Negative	39428	26664
Net positive score (NPS)	3090	918

Out of the total 81,946 tweet for Donald Trump got, 42,518 (51.88%) tweets were positive and 39428 (48.12%) tweets were negative. Similarly out of the total 54,246 tweets Hillary Clinton got, 27,582 (50.84%) tweets were positive and 26,664 (49.16%) tweets were negative. The net positive score (NPS) of Donald Trump was observed to be significantly higher than that of Hillary Clinton. Based upon our experimental results it was evident that Donald Trump would be winning the 2016 US Presidential Elections. Figure 4 shows the results of the same in graphical form.

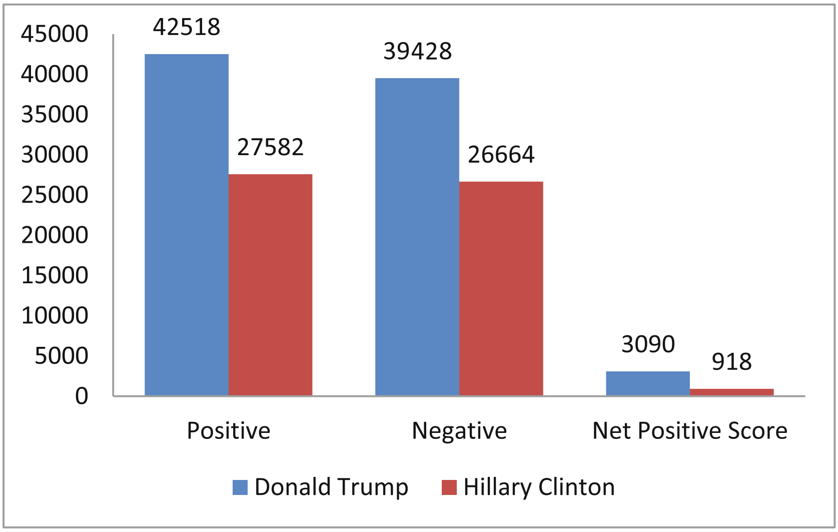

Fig. 4. Final results

7 Conclusions and Future Work

Predicting an event is always an uphill task. There are lots of factors that ought to be considered for making a truthful prediction. The aim of this paper was to predict the winner of 2016 US Presidential Elections. For this we collected data from Twitter. Further we applied a restriction that only one tweet per person will be considered for evaluation. Finally, we build a classification model in WEKA using SVM for performing sentiment analysis. Based upon the results of sentiment analysis we calculated the NPS. The results of our experiments clearly indicate that Donald Trump would be winning the 2016 US Presidential Elections.

Our experiments gave us the probability that the winner will be Donald Trump, however the actual winner in the US presidential election is based on the electoral vote and not the percentage of votes, and we should build a mathematical model that can convert the results of sentiment analysis into electoral votes which indeed will be our future aim.

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