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Sentimental Analysis of Election Slogans

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ABSTRACT
Social media has gained tremendous importance as a mass communication and public engagement tool for political functions, in a comparatively short amount of your time. Fast dissemination of knowledge through social media platforms like Twitter, provides politicians and authorities with the flexibility to broadcast their message to a huge audience directly whereas bypassing the standard media channels. In this paper, we tend to analyze the characteristics of the political discourse that came about on Twitter throughout the elections. The goal of this study is to perform explorative sentiment-based analysis of Twitter information that was gathered each before and once the polling day. Our objective is to spot the character and sentiment of discussions in conjunction with understanding the behavior of users with relevance to their Twitter profile and associated attributes of their tweets. The result of the study shows a significant difference among the candidates in terms of joy, fear, surprise, disgust, trust, while the difference in the rest of the sentiments was not significant.
Keywords:Sentimental analysis,Opinion Mining,
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I. INTRODUCTION

In the past decade, a vast amount of data on public opinions has been collected and analyzed. Although more data on public opinions are accessible, determining relevant information from data collected on opinions has proven to be difficult. Sentiment analysis provides an overview of favorable and unfavorable opinions on various topics and subject matter. Sentiment analysis is many a times referred to as opinion mining. Sentiment analysis assists researchers in analyzing opinions. Sentiment analysis provides the edge for analyzing opinions on important events such as political movements. Sentiment analysis can also provide organizations information on their completion, marketing, public relations, and risk management. However, the interpretation of opinions can be debatable because determining the emotional tone or conjecture of text has proven to be difficult. Sentiments are analyzed into categories such as positive, negative, or neutral. Sentiment analysis lays the path to the computational study of people’s opinions, appraisals, attitudes, and emotions.We prepared datasets of a total of 259 tweets from the date of 28 February 2014 to 28 May 2014 just before the time of Indian elections to know the public trend and general opinion about the elections.Twitter had an awfully vital role within the dissemination of data concerning numerous policy points for each major candidate. Each candidate had voluminous followers on Twitter and had their tweets closely monitored by the general public and by the thought media. Indeed, even today, the talk concerning the circulation of pretend news on social media and its result on the elections still rages on. Although it's exhausting to quantify the role Twitter plays within the elections 2014, all are in agreement that it had been however vital. This implies that political players cannot ignore the role of social media as a communication tool. Overall, social media presents an exciting avenue of chance for politicians, campaigners and political activists to not solely broadcast their message however additionally to have interaction in dialogue with proponents of competitive political concepts and ideologies. This is often an explorative study wherever we have a tendency to analyze Twitter knowledge to identify user behavior on Twitter together with the character of their sentiments towards the candidate standing within the elections.

II. RELATED WORK

Previous studies [14, 15, 16] show that analyzing these sentiments and patterns can generate useful results that can be handy in determining the opinions of the public on elections and policies of the government. In [14], authors extract sentiments (positive, negative) as well as emotions (anger, sadness, etc.) regarding the major leading party candidates, and based on that they calculate a distance measure. The distance measure shows the proximity of the political parties, the smaller the distance higher the chances of close political connections between those parties. [15] and [16] also shows how twitter data can help predict election polls and derive useful information about public opinions.Existing problems on analyzing different political tweets have been discussed in [11]. Sarcasm tends to reduce the accuracy of the classifier. [1] shows how Sarcastic tweets in which a positive sentiment followed by a negative situation is handled. For a deep analysis of the sentences, the dependency parsing tool should be used which can extract relations among the words that are forming the sentence. [12, 19] show the usage of Stanford Dependency Parser in extracting these relations.We also used categorization specified in [12] but modified them a little to suit our approach. Our categorization consists of six entities namely: Modifiers, Intensifi-ers, Dividers, Negations, Verbs, and Objects. We believe that these entities are important as they can significantly affect the sentiment of the overall sentences.

III. PROPOSED APPROACH

In this paper, we proposed an approach for sentiment analysis of slogans. We believed in a common system that will be able to solve different problems like Sarcasm, Conjunction, and Implicit negation combined.For this, we proposed an unsupervised hybrid approach of Lexicon Based and Rule-Based Sentiment Analysis which will analyze words related to other words, thus giving the overall sentiment of the sentence. For lexicon, SentiWordNet is used which can give us the sentiment scores of a word. A negative score signifies a negative connotation and a positive score signifies a positive connotation of the word. Slogans were manually downloaded from a time period of 28 February 2014 to 28 March 2014. Our system follows in mainly 4 steps which are explained below:

A. DEPENDENCY EXTRACTION

We used SDP to extract rules from the slogans. The sole reason is to remove extra words that are not related to overall sentiment or contribute very less to the overall sentiment. From these rules, those that are containing verbs, adjectives, adverbs, nouns, conjunctions, and negations are extracted and the rest are discarded.When analyzing twitter sentences we found out that due to wrong grammatical formations, the efficiency of SDP decreases which will affect our system. When SDP is unable to detect the relation between two words, it uses rule „dep" which shows the unknown dependency between those words. To improve this we used the Ark twitter POS tagger. ATP enables us to determine the part of speech of the two words thus giving us the dependency.

B. SET DISTRIBUTION

We approach the problem in a set wise manner. It is easier to deal with the problem when it is divided into sets. A natural language sentence is divided into 6 sets according to their part of speech and the polarity of the whole sentence is described by describing the polarity of each set in relation to the other sets. Word phrases in the sets contain a reference to the words of the previous sets to which they are specifically connected. This helps us in extracting features that will be vital in classifying the sentences according to the rules in the next section. The functionality of each set is explained below with the help of an example sentence.

1." BJP will make good government and will be successful in removing corruption from India." · Set W0 (Keyword Set) – Includes Subject or Objects containing Keywords Like „BJP". These contain Noun or Noun + Noun. From the above sentence (1) this set will include „*BJP*".

· Set W1 (Verb Set) – Includes verbs that describe the action performed by the contents of Set W0 with a reference to the specific noun to which it is connected. From the above example (1), this set includes *'make', 'removing*" because of the extracted rules *subj(make-3, BJP-1) and subj(removing-11, BJP-1)* from figure 2 and we will extract features „*BJP_make'*, „*BJP_removing'*.

· Set W2 (Object/subject set) – Includes objects on which the Set W0 is performing actions. This set also includes a Noun and Noun + Noun. From (1) this set includes „*government*", „*India*" because of the relations *dobj(make-3,government-5),dobj(removing-11,corruption-11), prep_from(removing-11, India-14)*. We will extract features,„*make_government','remove_corruption','remove_India'*.

· Set W3 (Modifier Set) – Includes adjectival and adverbial modifiers that are providing or modifying sentiments from the above sets (W0, W1, W2). From (1) this set includes „*good',"successful"* due to the relation *amod(government-5, good-4,),amod(BJP-1,successful-9)*. We will extract features from this as „*government_good'," BJP_successful"*.

· Set W4 (Intensifier Set) – Includes adverbial intensifiers that are strengthening or weakening the sentiment scores from the Sets above. From (1) this set includes „*be'* from the relation *advmod(successful-9, be-8)*. We will extract the feature „*successful_be.*‟

· Set W5 (Buffer or Divider Set) – Includes conjunctions like „but‟ and „and‟ with references to two words which it is dividing. From (1) this set will include „*and*‟ from the relation *conj_and(make-3, remove-10)*. We will extract the feature „*remove_make_and*‟.

· Set W6 (Negation Set) – includes the negation words like „not‟, „never‟ which flips the sentiment score from the sets above. From the above example (1) there is no negation word in this example so it won't include any of the words.

C. CONTEXT RULES FORMATTING

Table-1: Context rules (Verb - VB, Noun – N, Adjective - J, adverb – RB, * - doesn‟t matter, positive +, negative)

Rule	Set W1 Verb Set	SetW2 Object Set	Set W3 Adjective Set	Set W4 Adverb Set	Polarity
1	VB -	N +/neutral	*	*	-ve
2	VB -	N -	J -	*	+ve
3	VB +/neutral	N-	*	*	-ve
4	VB +/neutral	N +/neutral	J +/neutral	*	+ve
5	VB +/neutral	N +/neutral	J -	*	-ve
6	VB +/neutral	N +/neutral	J +	RB +	+ve
7	VB +/neutral	N +/neutral	J -	RB +	-ve
8	VB +/neutral	N +/neutral	J +	RB -	+ve
9	VB +/neutral	N +/neutral	J -	RB -	-ve

We developed rules to determine the sentiment of tweets into positive and negative. These rules are presented in Table 1 and each rule is explained with example further. The polarity of the words is determined by the SentiWordNet. We used the following abbreviations for the rules.

Example: Consider the tweet „AAP bhakts are always right, BJP wastes time for Dharnas. If u don't trust then see it‟ for the above rule. Here the keyword is „BJP‟ and set W1 includes „trust‟ which is a positive verb in SentiWordNet and W2 includes „time‟ and „waste‟ both of these are minor positive and neutral nouns respectively. Notice that negator „don't‟ (placed in W6) is attached to trust i.e. we extract the feature „trust_don't‟ which will reverse the polarity of Set W1 containing „trust‟, thus classifying in Rule 1.

D. DETERMINING SENTIMENT SCORE

Once the rule formation occurs, sentiment scores are calculated using SentiWordNet. We used a method similar to specified in calculating and distributing scores. Let $\boldsymbol{Spre}$ be the polarity from the previous sets with which it is connected to, $\boldsymbol{Sset}$ be the polarity of the particular set, and $\boldsymbol{Snew}$ be the updated polarity. Figure 1 shows the algorithm used for the sentiment score calculation.

Algorithm for sentiment score calculation:

Function sentiscore(set(sets)) Begin:

If set is W1(verb Set)) then $Snew$ = 0.0 + $Sset$;

If the set is W2(object set) or W3(modifier set) then

If Spre!=0 then $Snew$ = $Spre{*}Sset|Sset|$+$Sset$;

Else $Snew$ = $Sset$;

If the set is W4(intensifier set) then

If Spre!=0 then $Snew$ = $Spre{*}$ 1+$Sset$;

If the set is W6(negator set) then $Snew$=$-Sprev$;

Return Snew;

IV. RESULTS

We prepared datasets of a total of 259 tweets from the date of 28 February 2014 to 28 May 2014 just before the time of Indian elections to know the public trend and general opinion about the elections. Among the total tweets, 116 are positive, 92 are negative and the remaining 51 are objective tweets. We used accuracy as an evaluation measure and it is computed by dividing the correctly classified tweets with the total number of tweets. Our approach correctly predicted 76 positive tweets and 55 negative tweets. Further, we investigated manually that tweets containing colloquial language (containing Hindi words) are 56 out of which 20 were positive and 17 were negative. We removed these tweets from total tweets. The results are presented in Table 2.

Table-2: Results

Accuracy - positive tweets	(76/96)x100=79.17 %
Accuracy-negative tweets	(55/75)x100=73.33%
Overall Accuracy	(131/171)x100 = 76.61%

Table-3: Results related to modelling elections in NCT Delhi

Number of tweets evaluated containing keyword AAP	106
Tweets containing positive sentiment towards AAP	37
Percentage of users positive about AAP	(37/106)x100= 34.91%
Tweets containing negative sentiment towards AAP	51
Percentage of users Negative about AAP	(51/106)x100= 48.11%

Next, we tried to model elections in the National Capital Territory (NCT) Delhi region. For this, we manually downloaded 106 tweets giving sentiments for the Aam Admi Party (AAP) and its party leader Arvind Kejriwal from the same period by the users of the Delhi Region. We investigated tweets with #AamAdmiParty, #AAP and #ArvindKejriwal. The results are presented in Table 3.

A. DISCUSSIONS AND COMPARISON WITH OTHER APPROACHES

The above results show that 34.91% of users were positive towards the AAP party in the NCT Delhi region. From the Indian General Election results 2014 we know that all the 7 seats of the Delhi region were won by Bhartiya Janta Party (BJP). Although AAP was not able to win any seat in NCT Delhi, there voting share in the elections was 32.90%. This gives us an error percentage of 6.11%. So we were able to predict the voting share of AAP with an acceptable error percentage.

We compared our proposed approach with state-of-art approaches. Table 4 presents some cases where other approaches fail whereas the proposed approach performs better than other methods. The example tweets are chosen from the dataset according to the classification type by the algorithm.

V. CONCLUSION

People are increasingly using Social media to express their opinion. And, Twitter is a great source to investigate public opinion, especially during election time. Observing the results has led us to believe that there is a great scope in analyzing Indian political twitter data and considering its sentiment alone can result in giving a general idea about the election results. In this paper, we proposed various rules based on the semantic structure of the sentence. Experimental results show the effectiveness of the proposed approach over existing methods.

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