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Election Prediction Based on Messages Feature Analysis in Twitter Social Network

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ABSTRACT

With the emergence of virtual social networks, predicting social events such as elections using social network data has attracted the attention of researchers. In this paper, three indicators for election prediction have been proposed. First, the tweets are grouped based on a specific time window. Next, the indicator values for each candidate in each time window are calculated based on the sentiment scores and re-tweet numbers. In fact, the indicators are calculated based on the ratio of features related to positive to negative sentiments. Finally, using the aging estimation method, the indicator values for each party on the election date are predicted. The party with larger predicted indicator values will be considered as the winner. Investigations into Twitter data related to 2016 and 2020 US presidential elections on a four-month time span indicate that the indicator values and elections can be predicted with a high accuracy.

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1. INTRODUCTION

Elections are one of the most important political events in most countries. People have always been interested in predicting elections. Since 1936, surveys have been an integral part of political predictions and, since 1988, numerous business corporations and news organizations have been engaged in predicting elections by using statistical techniques [1]. Academic researchers have also proposed various models for election prediction based on behavior analysis and other factors such as macro-economic conditions including employment, loan rate and inflation rate.

The appearance of Web 2 and the development of electronic communication devices such as mobile phone contributed to the development of virtual social networks. Considering the fact that the data produced in virtual social networks reflect aspects of real societies [2] and are easily accessible to the public through web crawlers, the investigation and analysis of virtual social networks has attracted researchers' attention. Many of these investigations have aimed at predicting real society events including elections based on virtual social network analysis [3]. In-time and accurate prediction of elections is important. Because, it can contribute to the early planning of economic, international policies of the countries, and the prevention of some social crises.

Through analyzing Twitter data as the biggest news resource with over 250 million active users [4], this paper proposes three indicators for election prediction based on such factors as sentiment scores and re-tweet numbers. The first indicator, Sentiment Score ratio (SSr), is defined based on the ratio of sum of positive sentiment scores to negative sentiment scores at specific time intervals. The second indicator, ReTweet ratio (RTr), is defined based on the ratio of positive re-tweets to negative re-tweets at specific intervals. Finally, the third indicator, Sentiment Score and ReTweet ratio ($SSRTr$), is defined as a combination of the two previous indicators, and considers the number of re-tweets as a coefficient multiplied by the sentiment score of each tweet. It specifies the ratio of the sum product of sentiment scores and re-tweet numbers for positive tweets to that for negative tweets.

After specifying the indicator values at initial time intervals before the election, the indicator value at future time intervals and on the election date is predicted based on the aging estimation method [5]. Since, in all three

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proposed indicators, positive emotional values are in the numerator and negative emotional values are in the denominator, any party whose predicted indicator value is higher is declared as the winner of the election.

The novelty of this paper relates to proposing three types of indicators for election prediction based on Twitter data. More especially, it relates to the possibility of specifying the different lengths of the prediction interval, depending on the need from one day to several days.

In the following sections, first, the related literature on the topic will be reviewed (section 2). Next, the proposed methods will be described (section 3). Finally, the results of the experiments on two Twitter datasets relating to 2016 and 2020 US presidential elections will be presented (section 4).

2. LITERATURE REVIEW

Election prediction on the basis of Web and virtual social network data is a relatively new line of enquiry. Election prediction in the United States of America reported in the FiveThirtyEight.com Website attracted people's attention for the first time. The 2009 German election was first predicted based on Twitter data analysis [6]. This prediction was made on the basis of comparing the tweets number for each political party in a way that the party with the larger tweet number was considered the winner. In this paper, it is argued that the number of tweets alone cannot be a good criterion for the prediction [5].

So far, various models have been proposed to improve election predictions based on Twitter features such as hashtags [6], tweet and retweet counts [7], and sentiment analysis [5]. Since social media has become a well-known platform for expressing people's feelings about various social events [8]. The indicators proposed in this paper also categorize and analyze users' tweets based on the sentiment analysis feature. Sentiment analysis in election prediction can increase the accuracy of predictions [9].

In 2015, Burnap et al. [10] predicted British election on the basis of the sentiment analysis. They considered the sum of tweet sentiment scores (-5 to +5) as a criterion for making predictions. However, the sum of tweet sentiment scores can also be liable to error [11]. Therefore, in one of the indicators proposed in this paper, the ratio of the sum of positive tweets to the sum of negative tweets is used instead of the sum of tweet sentiment scores for each political party, which contributed to the accurate prediction of 2016 and 2020 US presidential elections.

Yavari et al. [5] proposed an indicator which predicted the 2020 US presidential election with high accuracy based on the ratio of positive tweets count to negative tweets count:

$$A_i = \frac{(Positive\ Tweets\ Count)_i}{(NegetiveTweets\ Count)_i + 1} \quad (1)$$

In Equation (1), A_i refers to the indicator value at i^{th} interval. Using the exponential averaging method, they predicted the indicator value on the election date. A larger indicator value for a political party denotes its winning the election. They assigned each tweet a sentiment score between -1 to +1, where they counted positive and negative tweets with any magnitude. Therefore, despite a considerable difference in sentiment scores, a tweet with a sentiment score of +0.01 and a tweet with a sentiment score of +1 are assigned equal values in total counts. However, in the proposed method in this paper, the sum of sentiment scores is calculated and, consequently, a tweet with a lower sentiment score will have a smaller effect compared to a tweet with a higher sentiment score.

Oueslati et al. [12], proposed a model based on sentiment analysis on influential messages to predict elections. They identified influential messages based on characteristics such as message content, time and sentiment score. Finally, based on Equation (2), they predicted the winner of the election.

$$R(A) = \frac{infpos(A) + infneg(B)}{Total\ \text{infMessages count(A,B)}} \quad (2)$$

In Equation (2), $infpos(A)$ and $infneg(B)$ refer to the number of influence positive messages and negetive messages for A and B parties, respectively. By examining data from 2016 US election, they showed that influence messages can be a reliable feature.

Singh et al. [13] used Twitter data to predict the 2017 Punjab (a state in India) Parliament election. They used Equation (3) as an indicator for predicting the number of seats won by each party, i.e. to predict the winner of the election.

$$S(A) = \frac{pos(A) - neg(A)}{T(A) + T(B)} \quad (3)$$

In Equation (3), $S(A)$ refers to the sentiment score of A party, $pos(A)$ and $neg(A)$ refer to the sum of positive tweets and negative tweets for A party, respectively, and $T(A)$ and $T(B)$ refer to the sum of tweets for A and B parties, respectively. The party with the largest indicator value will be the winner.

Wang and Gan [14] have proposed the popularity of election candidates using Equation (4). Their proposed method has been used to predict the result of 2017 French presidential election.

$$P(A) = \left[\frac{pos(A)}{pos(A) + neg(A)}\right]\left[\frac{T(A)}{T(A) + T(B)}\right] \quad (4)$$

$P(A)$ in Equation (4) represents the popularity of party A.

Wicaksono [15] proposed a method based on sentiment analysis using Equation (5), to predict the outcome of 2016 US presidential election. Based on this equation, the Success Rate (SR) of each party in an election is calculated, and the party that gets a higher score is predicted as the winner of the election:

$$SR(A) = \frac{pos(A)+neg(B)}{T(A)+T(B)} \tag{5}$$

where SR in Equation (5) represents the success rate of party A.

The three recent related articles introduced above have two shortcomings: firstly, they delay the prediction until election day and secondly, they are not sufficiently accurate in prediction. But as it will be shown in the next sections, these two problems have been solved in the proposed methods.

3. THE PROPOSED METHOD

This section introduces the methods proposed for election prediction. Figure 1 shows the general structure of the proposed method.

The sum of the tweets received are grouped on the basis of how many days prior to the election the prediction is made. For example, if one aims to make a prediction one week before the election, the tweets should be grouped at one-week intervals. In the next step, the intended features for each group such as sentiment scores and re-tweet numbers for each tweet are obtained. Then, based on the proposed methods, an indicator value at each interval is calculated for each party. Now, with a trace of indicator values at successive intervals, the subsequent indicator values can be predicted using the aging estimation method. Finally, the party or candidate

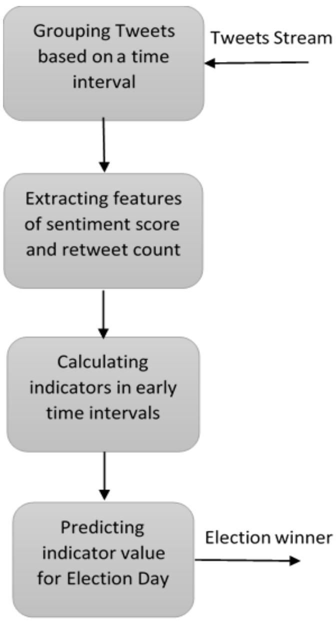

Figure 1. General structure of the peoposed method

with larger predicted values can be introduced as the likely winner. The three newly-proposed indicators are described with details in the following sections.

3. 1. Using the Sentiment Score Feature

This indicator is introduced so that the tweets with different sentiment scores will have different effects on indicator values. Therefore, in the first proposed indicator, Sentiment Score ratio (SSr), the ratio of the sum of positive scores to negative scores for each party or candidate at each interval is calculated by Equation (6).

$$SSr_i(A) = \frac{\sum_{t\in T} PSS_{i,t}(A)}{\sum_{t\in T} NSS_{i,t}(A)} \tag{6}$$

In Equation (6), $SSr_i(A)$ refers to the indicator value for A party at i^{th} interval. $PSS_{i,t}(A)$ stands for the t tweet positive sentiment score for A party at i^{th} interval and T refers to all the existing tweets at that interval. $NSS_{i,t}(A)$ stands for the t tweet negative sentiment score for A party at i^{th} interval.

3. 2. Using Re-Tweet Number

A more important tweet is usually re-tweeted with a higher frequency [16]. It has been tried in the second proposed indicator, RTr (ReTweet ratio), to examine the effect of this feature on election prediction. Hence, the ratio of the sum of re-tweets for each positive tweet to the sum of re-tweets for each negative tweet is calculated for each political party at different intervals (Equation (7)).

$$RTr_i(A) = \frac{\sum_{t\in T} PRT_{i,t}(A)}{\sum_{t\in T} NRT_{i,t}(A)} \tag{7}$$

In Equation (7), $RTr_i(A)$ refers to the indicator value for A party at i^{th} interval. $PRT_{i,t}(A)$ stands for the re-tweets number related to the positive t tweet at i^{th} interval and T stands for all the existing tweets at that interval. $NRT_{i,t}(A)$ refers to the re-tweets number related to the negative t tweet at i^{th} interval. It should be pointed out that the value of this feature for the non-re-tweeted tweets is set to one.

3. 3. A Combined Indicator

The third indicator is, in fact, a combination of the two previous indicators and is obtained from the ratio of the sum product of sentiment scores and the re-tweet number for positive tweets to the negative tweets at each interval (Equation (8)).

$$SSRTr_i(A) = \frac{\sum_{t\in T} PSS_{i,t}(A)*PRT_{i,t}(A)}{\sum_{t\in T} NSS_{i,t}(A)*NRT_{i,t}(A)} \tag{8}$$

In Equation (8), $SSRTr_i(A)$ refers to the indicator value for A party at i^{th} interval.

3. 4. Prediction

To predict indicator values at future intervals, the aging estimation method, which is based on an exponential averaging of previous observations, is used (Equation (9)).

$$A_{i+1} = \alpha O_i + (1 - \alpha) A_i \quad (9)$$

In Equation (9), A_{i+1} is the predicted indicator value at the next interval ($i+1$). O_i and A_i refer to the observed value and the predicted value at the current interval, respectively. α is a parameter within [0,1] which shows the effect of the observations history and the recent predictions. The closer the value of α is to one, the more weight the recent observations will have and the greater their effect will be on the predicted value. The closer it is to zero, the more the old observations, which are involved in calculating the average, will be (Equation (10)).

$$A_{i+1} = \alpha O_i + (1 - \alpha)\alpha O_{i-1} + \cdots + (1 - \alpha)^{i+1} A_0 \quad (10)$$

The use of closer-to-one values for α is an advantage because the quick changes in recent observations are reflected in the indicator value more quickly, and prediction accuracy increases considerably [17]. When the predictions are to be announced, the party with the larger indicator value will be introduced as the likely winner.

4. Experiments and Results

In this section, the proposed methods are tested on two Twitter datasets related to the 2016 and 2020 US presidential elections. They are compared to the methods introduced Yavari et al. [5] Oueslati et al. [12], Singh et al. [13], Wang and Gan [14], Wicaksono [15] in terms of prediction accuracy and result. The proposed indicators and compared methods are all implemented with Python programming language in a computer system with Intel core i5 and 2 GB main memory specifications.

4. 1. Dataset The first dataset includes almost 26 million tweets about 2016 US presidential election collected at the interval between August 30th to November 11th (election date)[1]. A rare incident happened in 2016 election where the Republicans (Donald Trump) won the election, although they had fewer votes than the Democrats (Hilary Clinton). Therefore, this dataset can be useful for investigating the tolerance of the proposed methods.

The second dataset includes about 24 million tweets related to 2020 US presidential at the interval between July 1st to November 12th [18].

In these datasets, using the sentiment analysis method of VADER (Valence Aware Dictionary and sEntiment Reasoner) [19], each tweet has been assigned a score in the range [-1..+1]. A value of +1 indicates strong positive feelings, and -1 indicates strong negative feelings. VADER is actually a rule and dictionary-based sentiment analysis tool. Due to its good performance, VADER method has been widely used for sentiment analysis of social media texts.

4. 2. Results of Experiment This section reports on the prediction of 2016 and 2020 US presidential elections using the three proposed indicators and the methods introduced Yavari et al. [5] Oueslati et al. [12], Singh et al. [13], Wang and Gan [14], Wicaksono [15]. Indicator values at one-day, one-week and two-week intervals are displayed in Tables 1 and 2. As it was mentioned earlier, a larger value for a party indicates winning the election. Hence, larger indicator values are in bold face.

In Table 1, knowing that the Democratic Party won 2020 US presidential election, in addition to Singh, Wang, and Wickasono methods, one of the proposed methods in this paper ($SSRTr$) also made wrong

TABLE 1. Indicator values based on 2020 US presidential election Twitter datasets

Indicators	Number of days until the election					
	One Day		One Week		Two Weeks	
	Dem	Rep	Dem	Rep	Dem	Rep
SSr	**2.7**	1.29	**1.54**	1.14	**1.42**	1.06
RTr	**5.31**	4.65	**4.27**	3.25	**3.5**	2.72
$SSRTr$	**6.5**	2.58	2.32	**2.33**	1.8	**1.88**
Yavari et al. [5]	**3.64**	2.41	**2.67**	2.06	**2.52**	1.93
Oueslati et al. [12]	**0.87**	0.82	**0.86**	0.79	0.4	**0.45**
Singh et al. [13]	0.08	**0.21**	0.09	**0.2**	0.01	**0.2**
Wang and Gan [14]	0.16	**0.49**	0.17	**0.49**	0.17	**0.47**
Wicaksono [15]	0.44	**0.54**	0.44	**0.55**	0.44	**0.56**

TABLE 2. Indicator values based on 2016 US presidential election Twitter datasets

Indicators	Number of days until the election					
	One Day		One Week		Two Weeks	
	Dem	Rep	Dem	Rep	Dem	Rep
SSr	2.09	**2.21**	1.55	**1.77**	1.58	**1.71**
RTr	4.38	**4.56**	3.87	**4.07**	3.36	**3.4**
$SSRTr$	**2.4**	2.36	**1.99**	1.98	1.72	**1.83**
Yavari et al. [5]	**1.76**	1.74	1.43	**1.58**	1.46	**1.55**
Oueslati et al. [12]	0.52	**0.65**	**0.95**	0.85	**0.48**	0.32
Singh et al. [13]	**0.08**	0.05	0.03	**0.05**	**0.04**	0.03
Wang and Gan [14]	0.24	**0.35**	**0.33**	**0.32**	0.22	**0.37**
Wicaksono [15]	0.248	**0.252**	0.229	**0.25**	0.239	**0.252**

[1] https://data.world/alexfilatov/2016-USA-presidential-election-tweets

predictions about the election at one-week and two-week intervals. Oueslati's method has succeeded in predicting the result in the short time periods of one day and one week, but it has predicted incorrectly for the time period of two weeks. Therefore, for examining the 2020 dataset, the SSr and RTr indicators made accurate predictions at different intervals.

Table 2 displays the use of different indicators on 2016 US presidential election Twitter datasets. As it can be seen in Table 2, only the two SSr and RTr indicators managed to accurately predict the election at all intervals (In 2016, the Republicans won the election, although the Democrats had more votes!). The Yavari and Wickasono methods wrongly predicted the election only at the one-day interval with a slight difference in indicator values. Ouesati's method has also managed to make a correct prediction only in one-day interval.

Considering the results in Tables 1 and 2, it seems that the SSr and RTr indicators predicted more consistently than other indicators.

Figure 2, shows the average prediction accuracy of the three proposed indicators and method introduced by Yavari et al. [5]. The accuracy of predicting the value of the indicator for each of the parties was obtained based on Equation (11).

$$Accuracy = 1 - mean\left[\frac{abs(A-O)}{O}\right] \tag{11}$$

In Equation (11), A is the predicted values and O is the observed values.

For the two indicators RTr and $SSRTr$, due to the fact that they are based on the number of retweets, larger jumps and changes occur in the indicator values. Therefore, the accuracy of predicting the value of the indicator is lower than other methods. But the accuracy of predicting the value of the indicator using SSr and the one proposed by Yavari et al. [5] is very good.

According to the results of the experiments, the two proposed indicators, SSr and RTr, have succeeded in correctly predicting the results of the last two American elections.

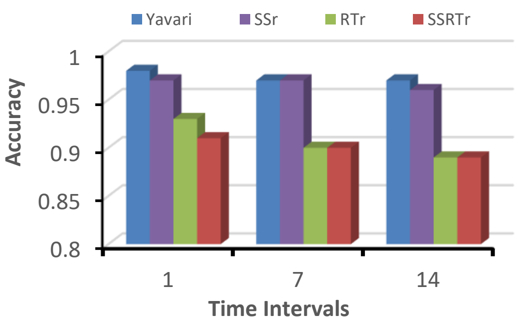

Figure 2. Average prediction accuracy of indicators for the two Republican and Democratic parties

5. CONCLUSION

In this paper, using such features as sentiment scores and re-tweet numbers for each tweet, three indicators were proposed for election prediction. The first indicator (SSr) is calculated based on the ratio of the sum of positive sentiment scores to negative sentiment scores at each interval. The second indicator (RTr) shows the ratio of the sum of positive re-tweets to negative re-tweets. Finally, the third indicator ($SSRTr$) was defined as a combination of the two previous indicators. After grouping the tweets based on an interval, the indicator values for each party at each interval are calculated. Then, using the aging estimation method, the values for these indicators on the election data are predicted. The party with the larger indicator value will be introduced as the winner. The advantages of the proposed method are the simplicity of calculations, easy understanding, and prediction of election results in arbitrary time intervals. Of course, fake messages or messages generated by social network bots can affect the proposed method as well as the methods of others. Comparisons of the proposed methods with other related methods for 2016 and 2020 US presidential elections indicate that the two SSr and RTr methods made accurate predictions for both datasets at all intervals. However, the $SSRTr$ indicator and other indicators being compared did not make accurate and consistent predictions.

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Persian Abstract

چکیده

پیش بینی رویدادهای اجتماعی از جمله نتیجه انتخابات با استفاده از داده های شبکه اجتماعی، یکی از موضوعات مورد علاقه پژوهشگران در دهه اخیر بوده است. از اینرو در این مقاله، سه اندیکاتور برای پیش بینی نتیجه انتخابات پیشنهاد شده است. روش کار بدین گونه است که ابتدا توییتها بر اساس یک پنجره زمانی گروه‌بندی می شوند. سپس مقادیر اندیکاتورها در هر پنجره زمانی و برای هر حزب یا نامزد انتخابات بر مبنای نمره احساسی و تعداد بازتوییت هر پیام در توییتر محاسبه می شود. سپس با استفاده از روش تخمین سالمندی، مقادیر اندیکاتورهای مربوط به هر حزب در روز انتخابات پیش بینی می شوند. مقدار اندیکاتور پیش بینی شده برای هر حزب که بیشتر باشد، بعنوان پیروز انتخابات تعیین می شود. نتایج آزمایشات بر روی داده‌های توییتر مرتبط با انتخابات ریاست جمهوری آمریکا در سالهای 2016 و 2020 در یک بازه زمانی چهار ماه نشان می‌دهد که می‌توان با دقت خوبی مقادیر اندیکاتور و نهایتا نتیجه انتخابات را پیش‌بینی نمود.