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A Machine Learning Based Strategy for Election Result Prediction

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***Abstract*—Predicting election results is a hot area in political science. In the last decade, social media has been widely used in political elections. Most approaches can predict the result of a national election. However, it is still challenging to predict the overall results of many local elections. This paper presents a machine learning based strategy to analyze Twitter data for predicting the overall results of many local elections. To verify the effectiveness of this strategy, we apply it for analyzing the Twitter data based on the 2018 midterm election in United States. The results suggest the predicted results are close to the actual election outcome.**

Keywords—Twitter, election result prediction, recursive neural tensor network, natural language processing

Type of the submission—Short Papers

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I. Introduction

Social media provides a political conversation platform [1]. This platform allows users to easily express their pollical opinions and also gives researchers the opportunity to analyze social media data for predicting election results. Twitter, a microblogging web site, has been recognized as a popular social media platform in political elections [2]. The rules of Twitter are in favor of short messages. For example, each message on Twitter was original required to contain no more than 140 characters. This limit makes it convenient to broadcast short political opinions by Twitter. In 2017, the 140-character limit was replaced by the 280-character limit, but most Twitter messages are still short [3].

Researchers have used different approaches to investigate data from Twitter. These approaches focused on two issues. One is how to select Twitter messages. The other is how to analyze selected Twitter messages. O'Connor et al. selected Twitter message by using names of politicians involved in the elections [2]. Their method used a sentiment score by counting positive and negative messages, which contains positive and negative words, respectively. If a message has both positive and negative words, it is both positive and negative. Wang et al. used keywords based on names of candidates to search related Twitter messages [1]. They applied a Naïve Bayes model for sentiment analysis. Nausheen and Begum also used names of candidates to collect related messages [4]. NLTK [5] and TextBlob [6] were applied in their sentiment analysis. Ramteke et al. focused on messages containing names of candidates and parties [7]. Their sentiment analysis is based on Naïve Bayes and SVM. Budiharto and Meiliana used names of candidates and the country name to search related messages [8]. Their method scored a message by comparing the numbers of positive and negative words in this message. Some researchers directly used existing data sets. Saif et al. used Twitter messages in existing data sets [9]. They conducted sentiment analysis based on semantic features. Trupthi et al. used possibilistic fuzzy c-means to conduct sentiment analysis on an existing data set [10].

Most of the above approaches collect messages related to names of candidates. However, if there are too many candidates in many local elections, we need a new strategy to evaluate the overall situation. In this paper, we present a new strategy for sentiment analysis. The strategy focuses on a high-impact pollical event before the election. Then a machine learning tool is applied to analyze the polarity. The prediction is made based on the polarity analysis.

II. Method

Our strategy chooses a high-impact political event and collects related Twitter messages. The event is usually unique. It brings difficult to directly apply existing trained models for analyzing messages related to this event, because these models were trained based on cases unrelated to this event. Our strategy suggests to select some messages and manually annotate them. These annotated messages can be used to train computational

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models. In practice, we classify each word into five categories, which are very negative, negative, neutral, positive, and very positive. Similarly, we also classify each sentence and message into these five categories.

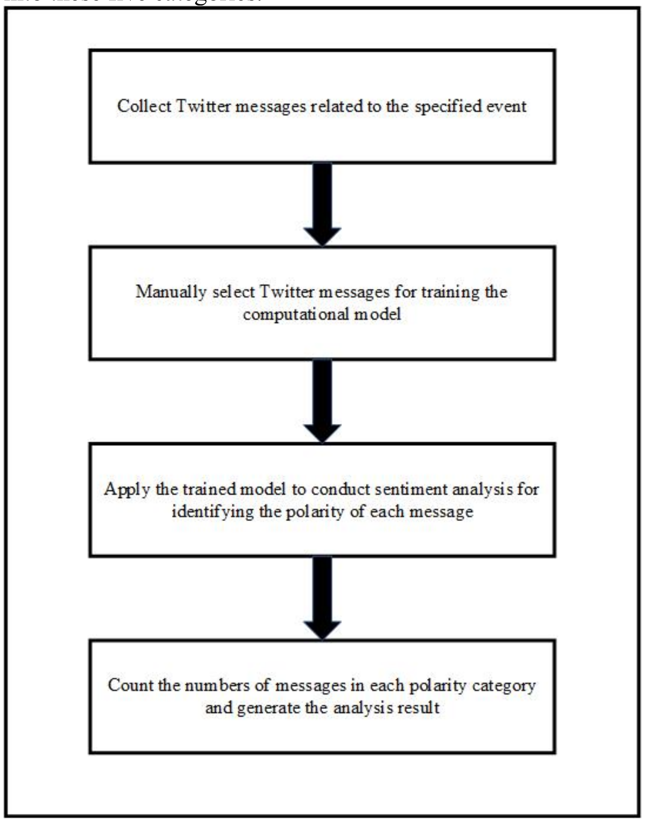

Fig. 1. The whole working flow of the proposed strategy

Computational model selection is also important for Twitter message analysis. Here, we use Stanford CoreNLP toolkit [11]. It applies deep learning in sentiment analysis [12]. This is a recursive neural tensor network (RNTN). This model applies a binary tree to organize all words. The root node represents the whole sentence or message. Each word or sentence is annotated with a sentiment score. We use 0, 0.25, 0.5, 0.75, and 1 to very negative, negative, neutral, positive, and very positive, respectively. After the model is trained by our manually annotated data, this model classifies all Twitter sentences into five categories. The weighted sentiment score can be used to predict the overall election result.

Fig. 1 describes the whole working flow of our strategy. This strategy gives users the flexibility of selecting events. It is worth noting that the selected event should happen closely before the election. Otherwise, the analysis results cannot correctly reflect the election situation. Here, we suggest to select events with less than two months to the election. If an event is politically controversial, people from all sides are likely to express their political opinions.

III. Experiment

To verify our strategy, we applied it to analyze and predict the midterm election in the United States. The midterm election is different from the presidential election. It is composed of many local elections, while there is not a candidate elected for the whole country. The goal of this experiment was to verify the effectiveness of our strategy on this election.

We focused on the Brett Kavanaugh Supreme Court nomination. Brett Kavanaugh was nominated by President Trump to be the Associate Justice of the Supreme Court of the United States. His confirmation in senate was widely discussed in Twitter. Our experiment used the Twitter data related to this event to predict the midterm election, which was about two months after the first confirmation hearing. We used the name of Brett Kavanaugh to collect related live Twitter data. Data collection was conducted three times. Each time lasted 48 hours. We filtered out all retweeted messages. The details of data collection are given in Table I.

We manually selected 796 messages from collected data. The preference was given to long messages without apparent grammar mistakes. Each word was manually classified into very negative, negative, neural, positive, and very positive. The whole message was also manually classified by the same way. Totally 524 messages were randomly picked for the training data set, while 272 messages were used as the validation date set. When the training stopped, 69.6% words and 58.1% messages in the validation data set can be correctly classified.

We applied the trained RNTN model to classify all collected messages. In order to build a baseline, we used the original RNTN model, which was not trained by our manually annotated data. The classification results are given in Fig. 2. The results based on the trained RNTN model are given in Fig. 3. The comparison of two models suggests that the trained model identified more very positive and very negative messages.

TABLE I. Data Collected Through Twitter

Starting Date	Event	Number of messages collected
09/04/2018	First hearing	178,048
09/27/2018	Sexual assault hearing	479,496
10/05/2018	Senators voted	376,095

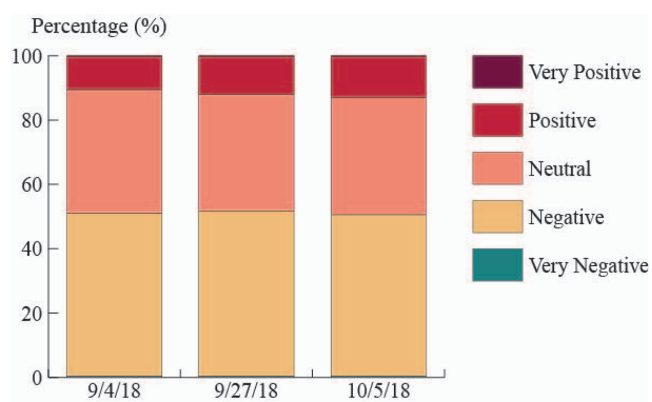

Fig. 2. Message composition generated by the original RNTN model

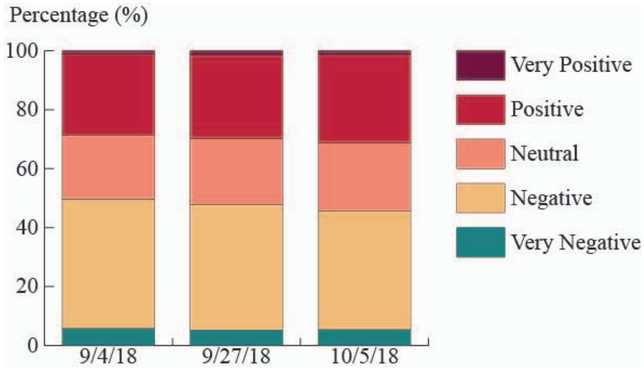

Fig. 3. Message composition generated by the trained RNTN model

TABLE II. Weighted Sentiment Scores

Date / Models	09/04/2018	09/27/2018	10/05/2018
Original RNTN	0.3983	0.4005	0.4054
Trained RNTN	0.4357	0.4450	0.4538

TABLE III. Predicted Overall Advantage of Democrats (OAD)

Date / Models	09/04/2018	09/27/2018	10/05/2018
Original RNTN	0.203	0.199	0.189
Trained RNTN	0.129	0.110	0.092

Based on the classification, each message is assigned a sentiment score. The scores of very negative, negative, neutral, positive, and very positive are 0, 0.25, 0.5, 0.75, and 1, respectively. The weighted sentiment scores of all messages based on original and trained RNTN models are given in Table II. The weighted sentiment score reflects the support to the nominee, Brett Kavanaugh, who was nominated by a Republican president. Here, we assume supporters of the nominee were highly likely to vote for Republican candidates. We also assume people showing no support of the nominee were highly likely to vote for Democratic candidates. So, the predicted approval rates of Republicans and Democrats are the weighted sentiment score (WS) and (1 – WS), respectively. The following formula can be used to compute the overall advantage of Democrats (OAD).

$$OAD = (1 - WS) - WS = 1 - 2WS$$

The calculated OAD is given in Table III. It was reported that the actual OAD is 8.6% [13]. This is very close to the predicted OAD with our trained model based on the data collected on Oct. 5th. It demonstrates our strategy is effective in predicting results of 2018 midterm election in United States.

IV. Conclusion

The paper presents a new strategy for predicting the overall results of many local elections by analyzing Twitter data. The experimental results verified the effectiveness of this strategy. In the future work, we will update and apply this strategy to other national elections.

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