Twitter Sentiment Analysis Using Natural Language Toolkit and VADER Sentiment

Shihab Elbagir and Jing Yang

Abstract— **The sentiment analysis of Twitter data has gained much attention as a topic of research. The ability to obtain information about a public opinion by analyzing Twitter data and automatically classifying their sentiment polarity has attracted researchers because of the concise language used in tweets. In this study, we aimed to use the Valence Aware Dictionary for sEntiment Reasoner (VADER) to classify the sentiments expressed in Twitter data. However, because most previous studies were oriented to binary classification, in this study, we propose a multi-classification system for analyzing tweets. We used VADER to classify tweets related to the 2016 US election. The results showed good accuracy in detecting ternary and multiple classes.**

Index Terms— **Natural Language Toolkit (NLTK), Twitter, sentiment analysis, Valence Aware Dictionary and sEntiment Reasoner (VADER)**

I. Introduction

SOCIAL media technologies exist in several different forms, such as blogs, business networks, photo sharing, forums, microblogs, enterprise social networks, video sharing networks, and social networks. As the number of social media technologies has increased, various online social networking services, such as Facebook, YouTube, and Twitter, have become popular because they allow people to express and share their thoughts and opinions about life events.

These networks enable users to have discussions with different people across the world and to post messages in the forms of texts, images, and videos [1], [2]. Moreover, social media are enormous sources of information for companies to monitor the public opinion and receiving polls about the products they manufacture. Microblogging services have become the best known and the most commonly used platforms. Furthermore, they have evolved to become significant sources of different types of information [3]. Twitter is a popular microblogging service that allows users to share, deliver, and interpret real-time, short, and simple messages called tweets [4]. Therefore, Twitter provides a rich source of data that are used in the fields of opinion mining and sentiment analysis. Recently, the sentiment analysis of Twitter data has attracted the attention of researchers in these fields. However, most state-of-the-art studies have used sentiment analysis to extract and classify information about the opinions expressed on Twitter concerning several topics, such as predictions, reviews, elections, and marketing.

Currently, many tools, such as Linguistic Inquiry and Word Count (LIWC) [5], offer the means of extracting advanced features from texts. However, most of these tools require some programming knowledge. In the present work, the Valence Aware Dictionary and sEntiment Reasoner (VADER) [6] is used to determine the polarity of tweets and to classify them according to multiclass sentiment analysis. The remainder of this paper is structured as follows: section 2 provides a brief description of related studies in the literature. In section 3, we present in detail the proposed method, and we describe the tool used in this study. In section 4, we discuss the results. In section 5, we conclude and provide recommendations for future work.

II. Related work

Recently, researchers have shown increasing interest in the field of sentiment analysis, particularly regarding Twitter data. The following are previous studies that have contributed to the field of sentiment analysis in the past few years. Wagh *et al.* [7] developed a general sentiment classification system for use if no label data are available in the target domain. In this system, labeled data in a different domain are used. Moreover, this system was used to calculate the frequency of each term in a tweet. In this study, a dataset containing four million tweets that were publicly available by Stanford University was analyzed. This dataset was used to predict the polarity of sentiments expressed in people's opinions. Traditional classification algorithms can be used to train sentiment classifiers from manually labeled text data, but the manually labeling work is expensive and time-consuming. The study found that if a classifier trained in one domain is applied directly to other domains, the performance is extremely low. The work showed the accuracy of different algorithms for different numbers of tweets, such as the following: Naive Bayes, Multi-nominal NB, Linear SVC, Bernoulli NB classifier, Logistic Regression, and the SGD classifier. The results showed that the proposed system was more efficient than the existing systems.

Manuscript received December 17, 2018; revised January 08, 2019.

This work was supported by National Natural Science Foundation of China (Nos. 61672179, 61370083, 61402126), Heilongjiang Province Natural Science Foundation of China (No. F2015030), Science Fund for Youths in Heilongjiang Province (No. QC2016083) and Postdoctoral Fellowship in Heilongjiang Province (No. LBHZ14071).

Shihab Elbagir is now with the College of Computer Science and Technology, Harbin Engineering University, Heilongjiang, 150001, China (corresponding author phone: 187-046-00712; e-mail: shihabsaad@yahoo.com). He was with Faculty of Computer Science and Information Technology, Shendi University, Shendi, Sudan

Jing Yang is with College of Computer Science and Technology, Harbin Engineering University, Heilongjiang, 150001, China (e-mail: yangjing@hrbeu.edu.cn).

Gilbert [6] developed VADER, which is a simple rule-based model for general sentiment analysis and compared its effectiveness to 11 typical state-of-the-practice benchmarks, including Affective Norms for English Words(ANEW), Linguistic Inquiry and Word Count (LIWC), the General Inquirer, Senti WordNet, and machine learning-oriented techniques that rely on the Naive Bayes, Maximum Entropy, and Support Vector Machine (SVM) algorithms. The study described the development, validation, and evaluation of VADER. The researcher used a combination of qualitative and quantitative methods to produce and validate a sentiment lexicon that is used in the social media domain. VADER is utilizing a parsimonious rule-based model to assess the sentiment of tweets. The study showed that VADER improved the benefits of traditional sentiment lexicons, such as LIWC. VADER was differentiated from LIWC because it was more sensitive to sentiment expressions in social media contexts, and it generalized more favorably to other domains.

Mane *et al.* [8] presented a sentiment analysis using Hadoop, which quickly processes vast amounts of data on a Hadoop cluster in real time. The researchers aimed to determine whether the users expressed a positive or negative opinion. This approach was focused on the speed of performing sentiment analysis of real-time Twitter data using Hadoop. The Hadoop platform was designed to solve problems that involved large, unstructured, and complex data. It used the divide and rule method for processing such data. The overall accuracy of the project was determined by the time required to access from various modules. In the analysis, the code yielded outstanding accuracy. The study used a numbering approach to rate the statements in multi-classes, which assigned a suitable range of different sentiments. Moreover, the approach could be used in other social media platforms, such as movie reviews (e.g., IMDB reviews) and personal blogs. Along the same line, Bouazizi and Ohtsuki [9] introduced SENTA, which helps users select from a wide variety of features those that are the best fit for the application used to run the classification. The researchers used SENTA to perform the multi-class sentiment analysis of texts collected from Twitter. The study was limited to seven different sentiment classes. The results showed that the proposed approach reached an accuracy as high as 60.2% in the multi classification. This approach was shown to be sufficiently accurate in both binary classification and ternary classification.

III. METHODOLOGY

A. Proposed Method

The current study consists of three phases. Phase one concerns the acquisition of Twitter data. Phase two focuses on the initial preprocessing work carried out to clean and remove irrelevant information from the tweets. Phase three deals with the use of the NLTK's VADER analyzer as well as the scoring method applied to the VADER results to assess its ability to classify tweets on a five-point scale.

As aforementioned that, the purpose of the data acquisition phase was to obtain Twitter data. The methods used to extract Twitter data allowed real-time access to publicly available raw tweets. To gather the data, we used Network Overview Discovery and Exploration for Excel (NodeXL) [10]. We collected a total of 2,430 political tweets concerning the 2016 US presidential election, which were published on Twitter's public message board and posted from 22 to 24 November 2016. Also, NodeXL, set the limit to a maximum of 2,000 tweets, from which we obtained a reduced data set. In order to collect the most relevant tweets, we used hashtags containing the candidates' names, Hillary and Trump. These names and "Election" were used as keywords to retrieve tweets, such as #Election Day results, #US Election 2016, #Election 2016, #Hillary Clinton, #Donald Trump.

A tweet is a microblog message posted on Twitter. It is limited to 140 characters. Most tweets contain text and embed URLs, pictures, usernames, and emoticons. They also contain misspellings. Hence, a series of preprocessing steps were carried out to remove irrelevant information from the tweets. The reason is that the cleaner the data, the more suitable they are for mining and feature extraction, which leads to the improved accuracy of the results. The tweets were also preprocessed to eliminate duplicate tweets and re-tweets from the dataset, which led to a final sample of 1,415 tweets. Each tweet was processed to extract its main message. To preprocess these data, we used Python's Natural Language Toolkit (NLTK). First, a regular expression (Regex) in Python was run to detect and discard tweets special characters, such as URLs ("http://url"), retweet (RT), user mention (@), and unwanted punctuation. Because hashtags (#) often explain the subject of the tweet and contain useful information related to the topic of the tweet, they are added as a part of the tweet, but the "#" symbol was removed.

Next, various functions of NLTK were used to convert the tweets to lowercase, remove stop words (i.e., words that do not express any meaning, such as is, a, the, he, them, etc.), tokenize the tweets into individual words or tokens, and stem the tweets using the Porter stemmer. When the preprocessing steps are complete, the dataset was ready for sentiment classification.

In phase three, the sentiments expressed in the tweets were classified. VADER Sentiment Analyzer was applied to the dataset. VADER is a rule-based sentiment analysis tool and a lexicon that is used to express sentiments in social media [6]. First, we created a sentiment intensity analyzer to categorize our dataset. Then the polarity scores method was used to determine the sentiment. The VADER Sentiment Analyzer was used to classify the preprocessed tweets as positive, negative, neutral, or compound. The compound value is a useful metric for measuring the sentiment in a given tweet. In the proposed method, the threshold values used to categorize tweets as either positive, negative, or neutral. Typical threshold values used in this study are Refer to "(1)":

Positive sentiment: compound value > 0.001, assign score = 1

Neutral sentiment: (compound value > -0.001) and (compound value < 0.001), assign score =0

Negative sentiment: compound value < -0.001,
assign score = -1 (1)

In the current study, a tweet with a compound value greater than the threshold was considered a positive tweet, and a tweet with a compound value less than the threshold was considered a negative tweet. In the remaining cases, the tweet was considered neutral. Next, we defined a scoring rule to determine whether the overall sentiment polarity in each tweet was in one of five classes: high positive, positive, neutral, negative, and high negative Refer to “(2)”. In the proposed method, the scoring rule is used to classify tweets into five sentiment classes as follows:

```
Test the overall sentiment of the tweet.
If (score value) = 1:
Calculate the overall tweet polarity as:
If (positive value > 0.5) assign tweet polarity = +2
Else: (positive value < 0.5) assign tweet polarity = +1
If (score value) = -1:
Calculate the overall tweet polarity as:
If (negative value > 0.5) assign tweet polarity = -2
Else: (negative value < 0.5) assign tweet polarity = -1
If (score value = 0) assign tweet polarity = 0          (2)
```

The polarity value gives the overall sentiment polarity of the tweet. The polarity value is set between -2 (highly negative) to +2 (highly positive). Positive tweets are classified as highly positive or positive depending on the positive value; negative tweets are classified as highly negative or negative depending on the negative value; in other cases, tweets are classified as neutral.

B. Tools

1) NodeXL

NodeXL Basic is a free and open-source network analysis and visualization software package that is used with Microsoft Excel [10]. This popular package is similar to other network visualization tools, such as Pajek, UCINET, and Gephi. NodeXL allows the quick and accessible collection of social media data through a set of import tools that gather data from social networks, such as Flickr, YouTube, Facebook, and Twitter. NodeXL focuses on the collection of publicly available data, such as Twitter statuses, and it follows the relationships of users who have made their accounts public. These features allow NodeXL users to instantly retrieve relevant social media data and integrate aspects of these data and their analysis into one tool [11].

2) Natural Language Toolkit(NLTK)

NLTK is a free open-source Python package that provides several tools for building programs and classifying data. NLTK is suitable for linguists, engineers, students, educators, researchers, and developers who work with textual data in natural language processing and text analytics [12]. NLTK provides an easy way to use the interfaces of over 50 corpora and lexical resources. It includes a group of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning [13].

3) Valence Aware Dictionary and sEntiment Reasoner (VADER)

VADER is a lexicon and rule-based sentiment analysis tool that is specifically attuned to the sentiments expressed in social media. It is an entirely free open-source tool. VADER also takes into consideration word order and degree modifiers [6].

IV. Results and discussion

The results of a Twitter sentiment analysis using NLTK and VADER sentiment analysis tools are discussed in this section. Fig. 1 shows the sentiment score of each tweet as positive, negative, neutral, or compound as obtained by the VADER Sentiment Analyzer.

```
[{'compound': -0.1531,
  'neg': 0.164,
  'neu': 0.714,
  'pos': 0.121,
  'tweet': 'presid anti trump tshi 24hr ship small red amazon
2016elect election result im with'},
 {'compound': -0.5859,
  'neg': 0.352,
  'neu': 0.648,
  'pos': 0.0,
  'tweet': 'wtf americain 5 word wtf  trump protest trump
presid trump train election2016 election result 'elect'},
 {'compound': 0.0,
  'neg': 0.0,
  'neu': 1.0,
  'pos': 0.0,
  'tweet': 'ask unifi behind un repent bigot election result'}]
```

Fig. 1. Sentiment score of tweets using the Vader

Table 1 shows the classification of the tweets as positive, neutral, or negative after the thresholds were applied. As shown in Table 1, if we chose an appropriate threshold value, we could categorize tweets directly as positive, negative, or neutral by using VADER.

Table 2 shows the overall sentiment scores value and polarity of every tweet, depending on the scoring rule.

Table 3 displays the total number of tweets and the percentages of each class of the five sentiment classifications in this dataset. Based on the results shown in Table 3, most tweets in our dataset expressed negative or neutral opinions about the presidential election. However, interestingly, 29% of the tweets expressed positive opinions, and 22.89% of the tweets expressed negative opinions. As shown in Table 3, 46.7% of the tweets expressed neutral opinions, and 1.48% expressed highly negative opinions. The neutral percentage was the highest among all other classes because of the small volume of tweets, which led to unbalanced data, and the assumption that the threshold value could provide a large number of neutral opinions. Also may have been based on the use of a general lexicon to categorize the political data.

TABLE I

THE TWEETS CLASSIFICATION

	tweet	score
1	wtf americain 5 word wtf trump protest trump presid...	-1
2	ask unifi behind unrepent bigot election result…	0
3	trump say support practic big otri need stop via…	1

TABLE II

OVERALL SENTIMENT POLARITY FOR EVERY TWEET

Tweets	label	Polarity
first ignor laugh fight win gandhi everi true	+2	Highly Positive
When ev sad sorrow come watch conanobrien elect...	-2	Highly Negative
Unit state hay election 2016 election result ima...	0	Neutral
tom obama pardon Clinton way president trump el...	+1	Positive
play dead soon cat election result	-1	Negative

TABLE III

POLARITY COUNT FOR EACH CLASS

Polarity	label	Count	Percentage
Highly Positive	+2	34	2.402827
positive	+1	375	26.501767
neutral	0	661	46.713781
negative	-1	324	22.897527
Highly negative	-2	21	1.484099

Fig. 2 shows the most common words used in the dataset. We can observe that most of top words deal with election result, Trump, Clinton, and vote.

POSITIVE WORD DISTRIBUTIONS:	**NEGATIVE WORD DISTRIBUTIONS:**	**NEUTRAL WORD DISTRIBUTIONS:**
[('election result', 381), ('election2016', 97), ('trump', 73), ('elect', 45), ('vote', 44), ('like', 33), ('amp', 33), ('popular', 26), ('win', 24), ('support', 21)]	[('election result', 321), ('trump', 76), ('election2016', 63), ('protest', 48), ('elect', 41), ('amp', 32), ('people', 28), ('vote', 26), ('hillari', 21), ('riot', 21)]	[('election result', 633), ('election2016', 178), ('trump', 127), ('elect', 63), ('vote', 52), ('clinton', 28), ('amp', 28), ('not my presid', 26), ('trump protest', 24), ('us', 22)]

Fig. 2. Most Common Words

The classification percentages of the sentiment analysis based on polarity are shown in Fig. 3. Fig. 4 displays the sentiment counts in the tweets in each class.

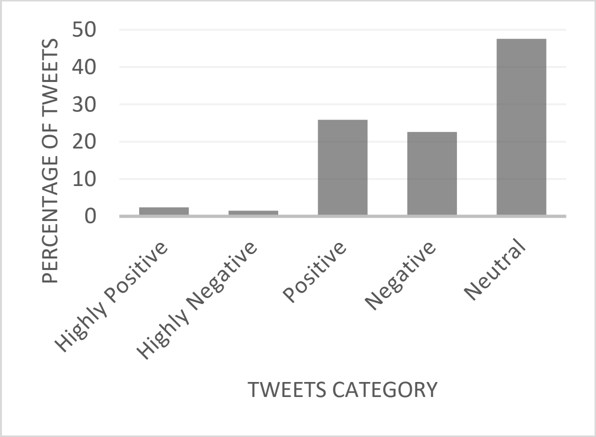


Fig. 3. Sentiment Polarity Percentage for Tweets in each Category

Fig. 5 shows the frequency distributions of positive, negative, and neutral words respectively. Here we examine the pattern of words; the plots show that the majority of words appear less.

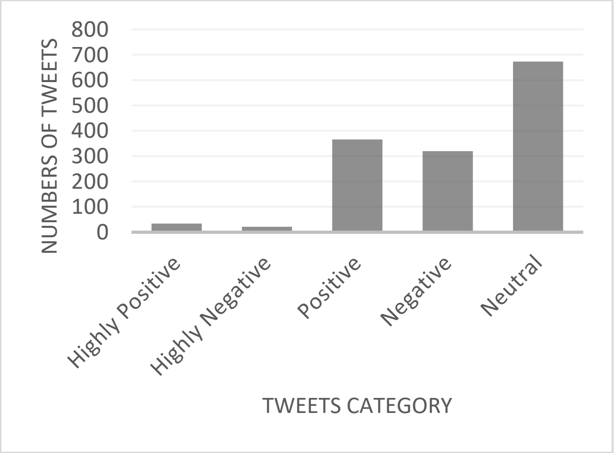
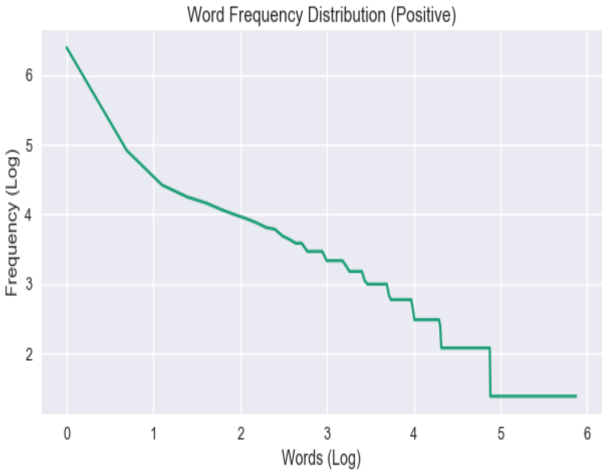
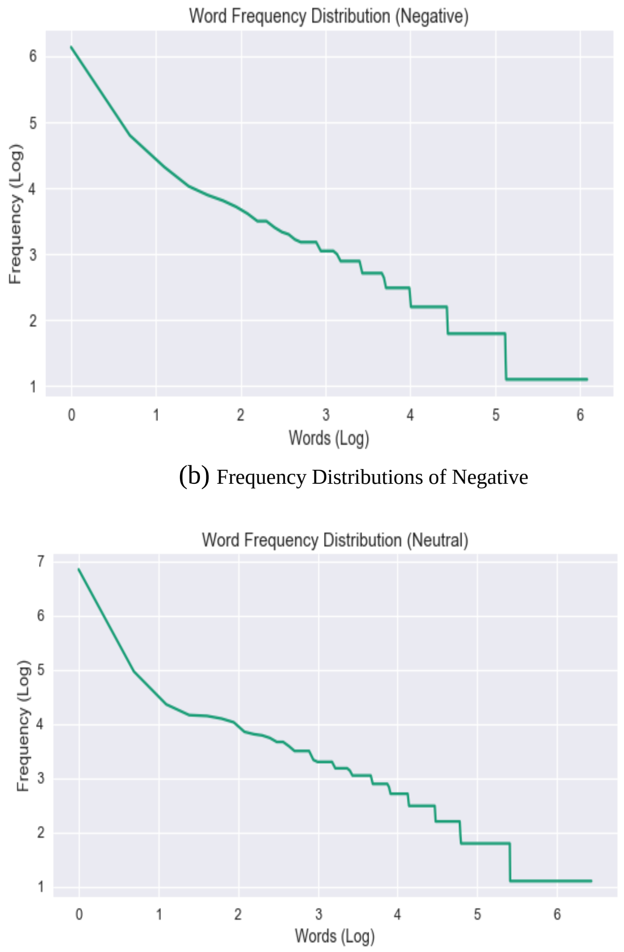


Fig. 4. Sentiment Polarity Count for Tweets in each Category

The findings of the present study suggest that the VADER Sentiment Analyzer could be used to measure sentiments expressed in tweets and classify them accordingly, thereby producing good results.



(a) Frequency Distributions of Positive



(b) Frequency Distributions of Negative

(c) Frequency Distributions of Neutral

Fig. 5. Frequency Distributions of Positive, Negative, and Neutral Words

V. Conclusion

In this study, the NLTK and the VADER analyzer were applied to conduct a sentiment analysis of Twitter data and to categorize tweets according to a multi-classification system. The case study was the 2016 US presidential election. The results indicated that the VADER Sentiment Analyzer was an effective choice for sentiment analysis classification using Twitter data. VADER easily and quickly classified huge amounts of data. However, the present study has the following limitations. First, a small volume of data was used. Second, a general lexicon was used to categorize specific data. Third, the data were not trained. In future work, we will improve our system by using large volumes of data, a specific lexicon, and a corpus for training the data to obtain good results.

References

[1] B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury, “Twitter power: Tweets as electronic word of mouth,” J. Am. Soc. Inf. Sci. Technol., vol. 60, no. 11, pp. 2169–2188, 2009.

[2] V. Kharde and P. Sonawane, “Sentiment analysis of twitter data: a survey of techniques,” arXiv Prepr. arXiv1601.06971, 2016.

[3] P. Selvaperumal and D. A. Suruliandi, “a Short Message Classification Algorithm for Tweet Classification,” Int. Conf. Recent Trends Inf. Technol., pp. 1–3, 2014.

[4] T. Singh and M. Kumari, “Role of Text Pre-processing in Twitter Sentiment Analysis,” Procedia Comput. Sci., vol. 89, pp. 549–554, 2016.

[5] Y. R. Tausczik and J. W. Pennebaker, “The psychological meaning of words: LIWC and computerized text analysis methods,” J. Lang. Soc. Psychol., vol. 29, no. 1, pp. 24–54, 2010.

[6] C. J. H. E. Gilbert, “Vader: A parsimonious rule-based model for sentiment analysis of social media text,” in Eighth International Conference on Weblogs and Social Media (ICWSM-14). Available at (20/04/16) http://comp.social.gatech.edu/papers/icwsm14.vader.hutto.pdf, 2014.

[7] B. Wagh, J. V Shinde, and P. A. Kale, “A Twitter Sentiment Analysis Using NLTK and Machine Learning Techniques,” Int. J. Emerg. Res. Manag. Technol., vol. 6, no. 12, pp. 37–44, 2018.

[8] S. B. Mane, Y. Sawant, S. Kazi, and V. Shinde, “Real Time Sentiment Analysis of Twitter Data Using Hadoop,” Int. J. Comput. Sci. Inf. Technol., vol. 5, no. 3, pp. 3098–3100, 2014.

[9] M. Bouazizi and T. Ohtsuki, “A Pattern-Based Approach for Multi-Class Sentiment Analysis in Twitter,” IEEE Access, vol. 3536, no. c, pp. 1–21, 2017.

[10] M. A. Smith et al., “Analyzing (social media) networks with NodeXL,” in Proceedings of the fourth international conference on Communities and technologies, 2009, pp. 255–264.

[11] D. L. Hansen, B. Shneiderman, and M. A. Smith, Analyzing social media networks with NodeXL: Insights from a connected world. Morgan Kaufmann, 2010.

[12] S. Bird, E. Klein, and E. Loper, Natural language processing with Python: analyzing text with the natural language toolkit. “ O’Reilly Media, Inc.,” 2009.

[13] Natural Language Toolkit http://www.nltk.org/ (Date Last Accessed, November 20, 2018).