LOCATION-BASED SENTIMENT ANALYSIS OF 2019 NIGERIA PRESIDENTIAL ELECTION USING A VOTING ENSEMBLE APPROACH

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ABSTRACT

Nigeria president Buhari defeated his closest rival Atiku Abubakar by over 3 million votes. He was issued a Certificate of Return and was sworn in on 29 May 2019. However, there were claims of widespread hoax by the opposition. The sentiment analysis captures the opinions of the masses over social media for global events. In this paper, we use 2019 Nigeria presidential election tweets to perform sentiment analysis through the application of a voting ensemble approach (VEA) in which the predictions from multiple techniques are combined to find the best polarity of a tweet (sentence). This is to determine public views on the 2019 Nigeria Presidential elections and compare them with actual election results. Our sentiment analysis experiment is focused on location-based viewpoints where we used Twitter location data. For this experiment, we live-streamed Nigeria 2019 election tweets via Twitter API to create tweets dataset of 583816 size, pre-processed the data, and applied VEA by utilizing three different Sentiment Classifiers to obtain the choicest polarity of a given tweet. Furthermore, we segmented our tweets dataset into Nigerian states and geopolitical zones, then plotted state-wise and geopolitical-wise user sentiments towards Buhari and Atiku and their political parties. The overall objective of the use of states/geopolitical zones is to evaluate the similarity between the sentiment of location-based tweets compared to actual election results. The results reveal that whereas there are election outcomes that coincide with the sentiment expressed on Twitter social media in most cases as shown by the polarity scores of different locations, there are also some election results where our location analysis similarity test failed.

KEYWORDS

Nigeria, Election, Sentiment Analysis, Politics, Tweets, Exploration Data Analysis, location data

1. INTRODUCTION

Social media platforms such as Twitter have not only changed the way we interact with one another but also have become very popular communication tool for the Internet and Mobile users. Twitter is one of the world's top social platforms with its monthly active users counting approximately 290.5 million worldwide in June 2019 and generating about 500M tweets per day [1, 2]. This high level of public connectedness has empowered Twitter users to use the medium as a varied way to express their thoughts and feelings, and as such, a huge quantity of data is generated. Twitter is a micro-blogging platform that allows users to post real-time messages about their opinions on a variety of topics, discuss current issues, complain, and express sentiments (positive/negative) about things that influence their daily lives [6].

In recent times, Twitter has become an important communication tool for electoral campaigning. We have seen a massive increase in politicians and political parties currently maintaining an active presence on the micro-blogging platform. This surge in Twitter usage for political campaigning and its elections has increased the interest of researchers in predicting election outcomes and/or electorates' attitudes towards political key players [3, 4, 6]. Researchers use citizen sentiment to estimate candidate performance in general elections [5].

However, some features of Twitter meta-data are yet to be fully explored in data analyses. For example, [7] observed that features such as followers and re-tweets have been researched extensively in Twitter data analysis, but utility features, such as location, have mostly been overlooked. Although Twitter allows its users to optionally provide location information in their profiles, a significant number of users still choose to give their city/state and country information voluntarily. In addition, users can allow Twitter to access their device's location. In this case, Twitter utilizes the device's GPS for accurate latitude and longitude coordinates of user location. Unfortunately, a very small number of users, usually less than 1%, enable this feature [7, 8]. Moreso, a large number of election-related researchers have utilized Twitter discussions to predict/evaluate elections such as if political parties or their candidates could influence the winning or losing an election [6] while very few have used location parameters to chunk tweets [7]. We believe that through utilizing location data, we can accurately gauge support levels for candidates and their political parties in each region of the country, giving us a more detailed picture of public opinion.

Nigeria is fragmented into states and the states are grouped in geopolitical zones. According to [10] on Nigeria states and geopolitical zones, Nigeria before the advent of colonial rule was non-existent. For administrative convenience, the British divided the country first into two regions (Northern and Southern protectorates) and later amalgamated the two regions to form what is known today as Nigeria. However, the existence of several unique nations within theseregions necessitated further divisions [9]. Today, thereare thirty-six states in Nigeria excluding Abuja the capital. Consequently, the thirty-six states in Nigeria, for easy political interaction and relation, have been politically zoned into six geopolitical zones, namely, the North East Zone (NE), the North- Central Zone (NC), the North West Zone (NW), the South-East Zone (SE), the South-West Zone (SW), and South-South Zone (SS). It is interesting to note that these zones have not been entirely carved out based on geopolitical locations, but rather states with similar cultures, ethnic groups, and common history were classified in the same zone. This explains why Nigeria, though geopolitical have different backgrounds, unique features and unequal human development levels.

In this article, we perform sentiment analyses of Twitter data with respect to the location of tweets. Here, we use tweets live-streamed during the 2019 Nigeria General Elections (NGE). NGE comprises presidential alongside senate and House of Representatives in one part and gubernatorial alongside the house of assembly in all 36 states in another part. We used Twitter streaming API to download the tweets datasets for only the presidential election using hashtags NigeriaDecides2019, atiku, buhari, pdp, apc, 2019elections, theVerdict. We use location information, which is present as tweet meta-data, for sentiment analyses. Atiku and Buhari are candidates of two major parties in Nigeria, namely the People's Democratic Party (PDP) and All Progressives Congress (APC) respectively. For location information, we utilize the Nigeria 36 states/6 geopolitical zones mentioned above and tweets' user-provided location to cluster tweets using our parser and then map the aggregated sentiment of these tweets. We then created data visualizations to show the graphical views of the sentiments expressed towards the presidential candidates and their parties by plotting their polarity scores. Sentiment analysis is used to observe the attitudes, opinions, views, and emotions from text using Natural Language Processing (NLP). Thus, although sentiment analysis is primarily associated with classifying opinions in text into categories suchas “positive”, “negative”, or “neutral”, it also involves subjectivity analysis.

For this research, we perform both subjectivity and polarity analyses of Twitter data. Polarity Sentiment Analysis (PSA) enables us to gain political insight by quantifying the sentiment of the text. The text can thus be classified as negative, positive, or neutral. These polarity scores range from -1 to 1, where -1 represents extremely negative sentiment and 1 represents extremely positive sentiment. A polarity scoreof 0 suggests a neutral sentiment. PSA has been extensively used to determine the underlying feelings of a post/comment creator for the topic under discussion [7]. Datasets downloaded from communication tools such as Twitter and Facebook are used by researchers to determine the public mood or opinion towards a topic or a popular personality or a strong correlation between Twitter sentiment and public opinion polls. Examples of such research range from election predictions to stock price forecasts [7]. Moreso, PSA considering location can help during elections to determine regional approval ratings of political actors based on discovering a strong correlation between Twitter sentiment and the opinion polls representing the ideology of the selected regions. Furthermore, the user location obtained from the metadata associated with each tweet is rich in detail. Our study, therefore, uses this location attribute to evaluate the sentiment of the key political actors across the 36 states and 6 geopolitical zones of Nigeria. We then compare these sentiment scores of the political actors with the election results and people’s ideologies. This will allow us to evaluate how indicative Twitter location data are of public opinion in these states/geopolitical zones. To achieve this, we applied the voting ensemble approach (VEA) utilizing 3 different sentiment classifiers to get the choicest polarity given in a tweet (see section 4 for details). Subjectivity Sentiment Ananlysis (SSA) is where parts of speech such as adjectives, adverbs, and some group of verbs and nouns are taken as indicators of a subjective opinion [6, 7]. Hence, through subjectivity analysis, we determine how opinionated a tweet is. For a set of tweet messages in our dataset, we identify sentences that are subjective from those that are objective.

Thus, to analyze tweets based on the Nigeria states and geopolitical zones information, we present the research questions on PSA and SSA for the Nigeria 2019 presidential election:

1. How does the sentiment of tweets based on state/geopolitical zone locations correlate with the electionresults expressed towards the candidates and their political parties?
2. How are subjectivity scores for each candidate varied in the overall performance across Nigeria’sgeopolitical zones and who was mentioned in more subjective tweets?

In the next section, we present related works in the area of Twitter data analysis, while in Sections 3 and 4, we discuss methodology (data collection and experimental tools adopted) and result analyses respectively. In Sections 5 and 6, we discuss these results and conclude our article.

2. Related Works

Politicians have chosen Twitter as one their platform for disseminating information to their constituents because of its popularity as a communication tool in modern politics. This has instigated parties and their candidates to an online presence which is usually dedicated to social media coordinators. In this section, we present some previous works related to sentiment analysis of Twitter discussions on elections. According to [12], social media emerge as an important tool for people to express their opinions about candidates in electoral scenarios. In this context, there is an increasing number of election prediction approaches using social media and opinion mining; modeling this problem in different ways. This work by [6] investigates empirically the impact of political party control over its candidates or vice versa on winning an election using a natural language processing technique called sentiment analysis (SA). The authors used a set of 7430 tweets bearing or related to #AnambraDecides2017 streamed during the November 18, 2017, Anambra State gubernatorial election. [13]'s employed a case study of US Presidential Elections 2012 and Karnataka State Assembly Elections (India) 2013 to study the sentiment prediction task over Twitter using machine-learning techniques, with the consideration of Twitter-specific social network structures such as retweets. Their research concentrates on finding both direct and extended terms related to the event and thereby understanding its effect. [14] used tweets collected during the Spanish 2019 presidential campaign between April 12 and April 26 to perform a statistical and computing analysis (based on R software) to reveal the political discourse of the parties engaged and highlight the main messages conveyed and their resulting impact on the share of candidates' voices. The Twitter sentiment research of [15] provides a precise view of the 2020 US presidential election by jointly applying topic discovery, opinion mining, and emotion analysis techniques on social media data. The work exploited a clustering-based technique for extracting the main discussion topics and monitoring their weekly impact on social media conversation. The authors further used a neural-based opinion mining technique for determining the political orientation of social media users by analyzing the posts they published which enable them to determine in the weeks preceding Election Day which candidate or party public opinion is most in favour of. More so, the authors investigated the temporal dynamics of the online discussions, by studying how users' publishing behaviour is related to their political alignment. [17] mined tweets to capture the political sentiments from it and model it as a supervised learning problem. The extraction of tweets on the General Elections of India in 2019 is carried out along with the study of sentiments among Twitter users towards the major national political parties participating in the electoral process. The classification model based on sentiments is prepared to predict the inclination of tweets to infer the results of the elections. [18] analyzed Twitter sentiment of U.S. Election 2020 Twitter Data to determine public views before, during, and after elections and compared them with actual election results. They also compared opinions from the 2016 election in which Donald J. Trump was victorious with the 2020 election. Their results reveal that the election outcomes coincide with the sentiment expressed on social media in most cases. The following paragraph looks at Twitter sentiments based on location.

The authors [16] introduced Hybrid Topic Based Sentiment Analysis (HTBSA) to capturing word relations and co-occurrences in short-length tweets for election prediction using tweets. They used over 300,000 tweets, collected from 1st-20th February 2017, to predict Uttar Pradesh (U.P) legislative elections. Geotagging is employed for keywords which are not exclusive to the elections. This work by [7] performs sentiment analyses of Twitter location data. The authors used two case studies for their research, viz; the US presidential elections of 2016 and the UK general elections of 2017. For US elections, they plot state-wise user sentiment towards Hillary Clinton and Donald Trump. For UK elections, they used two disparate datasets, using keywords and location coordinates, looking for similar tendencies in sentiment towards political candidates and parties. The overall objective of the two case studies is to evaluate the similarity between the sentiment of location-based tweets reflected in election results. Geolocation information from social media data is essential for conducting geolocation-based analyzes such as traffic analysis and tourism analysis [19]. This paper by [19] reviewed geolocation prediction approaches based on text analysis in social media data. Their review result shows that geolocation prediction approaches can be categorized into two categories called Content-based Geolocation Prediction and User-profiling-based Geolocation Prediction. This review further concludes that Content-based Geolocation Prediction is suitable for addressing geotagged data limitations in Location-specific Analysis because the location prediction results are specific to the place level.

The majority voting ensemble technique has been applied in several kinds of researches such as [38] and [36]. The former performs emotion classification with an ensemble majority voting classifier that combines three certain types of base classifiers which are of low computational complexity while the latter used it to choose the most agreed grammatical classifications of a word given different machine learning techniques.

The above-cited papers demonstrated that political insight is a phenomenon present on social networks such as Twitter. The use of Twitter location features can help find correlations between location-specific analysis and public opinion. Hence, this paper presents a location-based sentiment analysis considering common co-occurring tweet words and polarized tweets connections among such groups as the Nigeria 36 states and geopolitical zones and how such connections influenced a political party and its candidates.

3. METHODOLOGY

Figure 1 shows the methodological steps we followed in this research. The first step is the Twitter data streaming and the description of the process of tweet collection that formed the data of this paper (section 3.1). The next step is the cleaning up of the data collected discussed in detail in section 3.2. The third step is case selection to get the number of users tweeting from different locations such as the 36 Nigeria states and geopolitical zones which are the groups of data recorded in the collection column of Table 1. We perform the tweets' text sentiment analyses for the locations in our case selection considering the individual parties and the candidates in section 4. C in this Figure denotes where location sentiment analysis coincides with the actual election results whereas A and B represent otherwise. We performed the tweets' texts exploratory data analysis using word cloud to gives us quantitative insights on how topics are mentioned in our Twitter dataset.

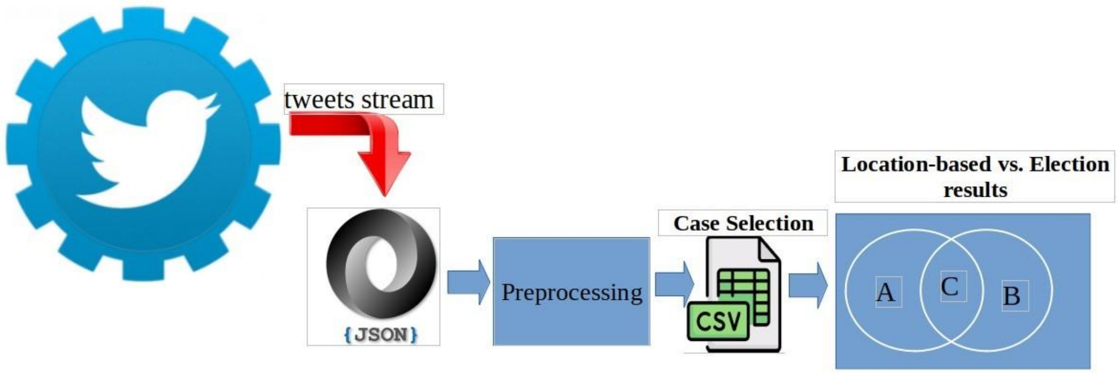

Figure 1: Methodology steps

3.1. Twitter Data Collection

This section presents information about the Nigeria General election and the Twitter social network and its features. The Twitter streaming used to collect the election Twitter data is discussed in the following subsections.

3.1.1. The 2019 Nigeria General Election

For this paper, we concentrate on the General elections held in Nigeria on 23 February 2019 to elect the President, Vice President, House of Representatives and the Senate [20, 21]. The

President of Nigeria is elected using a modified two-round system. To be elected in the first round, a candidate must receive a majority of the votes and over 25% of the votes in at least 24 of the 36 states. If no candidate passes this threshold, a second round is held [22]. Our research considered the two most popular presidentialcandidates and their parties, viz; Atiku Abubakar of the People's Democratic Party (PDP) and Muhammadu Buhari of All Progressives Congress party (APC). The PDP held its presidential primaries on 5 October 2018, at the Adokiye Amiesimaka Stadium, Port Harcourt, Rivers State. Thirteen aspirants contested for the ticket of the PDP, with Atiku Abubakar emerging as the winner [24]. In APC party,somemembers aspired for the office of the president, notably, Dr. SKC Ogbonnia, Chief Charles Udeogaranya, and Alhaji Mumakai-Unagha, the incumbent President Muhammadu Buhari was selected as the sole flag bearer of the party primaries held on 29 September 2018 amidst charges of imposition [25].

The incumbent president, Muhammadu Buhari and the APC flag bearer pulled 15,191,847 (55.60%) [28, 29] votes to defeat his closest rival Atiku Abubakar by over 3 million votes. He was issued a Certificate of Return [27] and was sworn in on 29 May 2019, the former date of Democracy Day [26]. According to the election conduct from [29], immediately following the elections were claims of widespread fraud by the opposition. The claims included accusations of ballot box snatching, vote buying, and impersonation. There were also claims that caches of explosives were found by police [30, 31]. The defeated candidate, Atiku Abubakar, filed a case in the Nigerian supreme court citing widespread irregularities in the polls. The African Union affirmed that the elections were "largely peaceful and conducive." Similarly, the electoral commission described the elections as mostly peaceful [32]. On the contrary, US-based organisation Freedom House severely criticised the conduct, saying that they were marred by irregularities and intimidation [33].

Consequently, the sentiment analysis captures the opinions of the masses over social media for global events. In the following subsections, we discuss Twitter and collection of tweets, then applied sentiment analysis on the tweets to determine public views on the elections and compared them with actual election results.

3.1.2. Datasets and Twitter Data Streaming

A total of 583816 tweets were collected and dumped as JSON, employing streaming Tweepy API across Nigeria between February 16, 2019, and February 26, 2019. We used the Twitter Streaming API to download tweets related to Nigeria General Election using the following keywords: NigeriaDecides2019, 2019elections, atiku, buhari, pdp and apc. The aim is to collect only tweets about the election in real time based on the hypothesis that if there is a tweet about the General Election that same day, then that tweet could be referring to what the user is experiencing at the moment about the election.

3.2. Data Pre-Processing

This section uses the filtration process of python libraries to retrieve the most important and meaningful parts of the tweets by excluding the unnecessary content. Tweets streamed via Twitter API are in raw form (stored in JSON) and usually contain several irrelevant attributes, e.g., links, URLs, retweets, usernames, stopwords, emoticons, etc. The tweets are required to be pre-processed accordingly before analysis by removing all the irrelevant attributes from the dataset to avoid any contradiction of the results. Text pre-processing comprises several steps, including data cleansing that includes excluding unrelated data in terms of stop words, slang, URLs, smilies, irrelevant and redundant data. We mainly used five steps to pre-process the data, including tokenization, stopwords, slang elimination, unique character extraction, and URL removal. In particular, we carried out this by returning a dataframe with duplicated tweets and retweets removed. By default, this keeps the first occurrence only. Furthermore, we extracted only tweets attributes that are relevant to our research such as cols = [’id’, ’geo’, ’name’, ’screen name’, ’location’, ’user created at’ ,’tweet created at’, ’tweet’].

Table 1 Tweets Dataset used in this study

SN	Political Actors Collection	Tweets Total Before Pre-Processing	Total Tweets After Pre-Preprocessing
1	atiku	52844	3166
2	buhari	94411	7165
3	pdp[1]	101520	4850
4	apc[2]	101894	5591
5	atiku-buhari[3]	23958	1309
6	buhari-apc[4]	15009	607
7	atiku-pdp[5]	8000	295
8	apc-pdp[6]	67464	2611
9	unclassified[7]	118716	27450

[1]Tweets that mention People’s Democratic Party. Presidential candidate = Atiku.

[2]Tweets that mention All Progressives Congress party. Presidential candidate = Buhari.

[3]Tweets that mention Atiku and Buhari.

[4]Tweets that mention Buhari and APC.

[5]Tweets that mention Atiku and PDP.

[6]Tweets that mention APC and PDP.

[6]Tweets not fall within SN 1-6 mentions.

Table 1 shows the total of tweets collected and the tweets associated with each political actor before and after preprocessing. Rows 1 to 8 show the names of investigative interest as stated in this study, columns of Booleans were added which indicated whether a name of interest was in the tweet or not. The Total of Tweets After Preprocessing column shows that the names of interest for this paper formed 51.75% of 53044 total tweets. The remaining percentage is unclassified tweets. This experiment focuses on evaluating the research questions stated in section 1, finding location sentiment expression correlations on each political actor and the election outcomes as shown in A, B, C of Figure 1. Since the Nigerian zones (states and geopolitical) were classified based on states with similar cultures, ethnic groups, and common history, are there correlations that exist between the public opinions and the sentiment analysis of the Nigerian zones compared with the outcome of the presidential election? See Figure 7 and section 5 for theresults and discussions on this question.

3.3. Case Selection

As Twitter users do not need to share their location information, many tweets contain null, some arbitrary values for location variables or locations not within the Nigerian zones. This affects the number of tweets used in our data analysis. In total, 19216 tweets with valid user location *(Nigeria states and geopolitical zones. Any other location outside this definition is not valid)* values were clustered according to the 36 states of Nigeria for this study. The states' tweets are further collapsed to the 6 geopolitical zones in Nigeria. We achieved this process using the location dictionary developed for this paper. The dictionary acts as a parser containing the 36 states and 6 geopolitical zones of Nigeria. The results of the preprocessed tweets are stored in the CSV file. CSV file enables data storage into columns of variables and rows of observations.

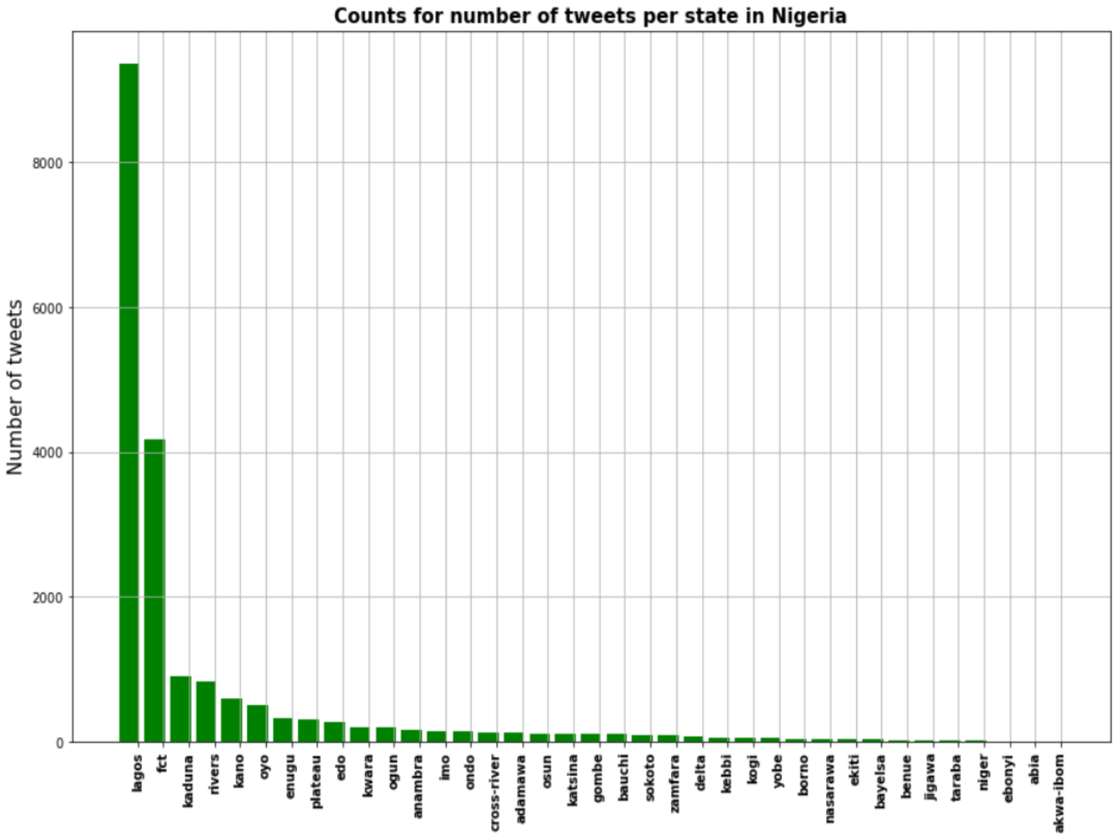

Figure 2: Count sizes of tweets per Nigeria state

From Figure 2, observe that all 36 states plus the federal capital territory were represented in our dataset. However, we decided to utilize the 10 largest states by tweet counts for our analyses. For the state location-based analysis, we restrict our experiment to these states, as they were considerably represented in our data and accounted for over 90% of all tweets in our case selection dataset. Figure 3 provides details on the number of tweets captured from collapsing all the states into their respective geopolitical zones. Table 2 shows the make-up of each geopolitical zone starting with the state with the highest number of tweets down to the least.

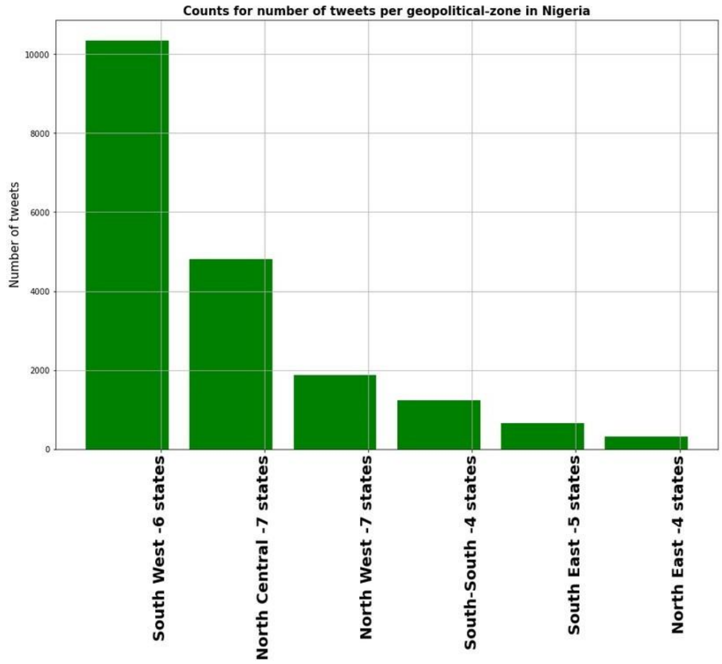

Figure 3: Count sizes of tweets per Nigeria geopolitical zone

Table 2 Geopolitical Zones Location-Based Dataset

SN	Geopolitical zones	States	Total Tweets Counts
1	South West	('lagos', 'oyo', 'ogun', 'ondo', 'osun', 'ekiti')	10352
2	North Central	('fct', 'plateau', 'kwara', 'kogi', 'nasarawa', 'benue', 'niger')	4804
3	North West	('kaduna', 'kano', 'katsina', 'sokoto', 'zamfara', 'kebbi', 'jigawa')	1229
4	South-South	('rivers', 'edo', 'delta', 'bayelsa')	5591
5	South East	('enugu', 'anambra', 'imo', 'ebonyi', 'abia')	650
6	North East	('adamawa', 'bauchi', 'borno', 'taraba')	303

4. EXPERIMENTAL TOOLS

TextBlob, SentiWordNet and VADER (Valence Aware Dictionary and Sentiment Reasoner) are commonly used sentiment analysis classifiers in Python. They use different methods to do sentiment analysis. Compared to machine learning approaches for sentiment analysis, TextBlob and VADER use a lexicon based method. The lexicon approach has a mapping between words and sentiment, and the sentiment of a sentence is the aggregation of the sentiment of each term. Lexicon sentiment analysis such as TextBlob (TB) function returns polarity and subjectivity properties while polarity determines the positivity/negativity of a text, subjectivity validates how someone's post/comment/review is influenced by personal opinions/feelings (fact or not). Considering polarity, it is a floating-point number that lies in the range [-1,1] meaning negative and positive sentiments, and subjectivity is [0,1]. A value near/of 0 represents neutral sentiment. While TextBlob performs strongly with more formal language usage, VADER seems to work better with things like slang, emojis, etc. It is a lexicon and rule-based sentiment analysis tool that performs exceptionally well in the social media domain [34]. Therefore, VADER puts a lot of effort into identifying the sentiments of content that typically appear on social media, such asemojis, repetitive words, and punctuations (exclamation marks, for example). According to [35], Senti-WordNet is an opinion lexicon derived from the WordNet database where each term is associated with numerical scores indicating positive and negative sentiment information. A quick overview of the polarity and subjectivity analysis using TextBlob sentiment on the NigeriaDecides2019 tweets dataset with this function:

begin
comment: Import TextBlob
sent = df preprocessed tweets copied2['tweet'][71].strip()
TextBlob(sent).sentimentend

output: Sentiment(polarity=0.4, subjectivity=0.7)
df preprocessed tweets copied2[‘tweet’][71].strip() is a copy of the original dataframe that contain all the preprocessed tweets. “sent” variable contains a tweet value located in column “tweet” and row 71 which is:

“This man will very likely win . It’s all been set up like that.”

From the output, TextBlob claims that this tweet is positive and it is just an opinion/feeling of the user that posted it. The polarity score is 0.4 and subjectivity is 0.7 which can be read as 40% positive and 70% subjective opinion. A subjective score of zero indicates objective fact (i.e. a factual statement). Figure 4 shows the TextBlob sentiment scores of all tweets in a histogram. Observe the frequency distribution of sentiment polarity in the NigeriaDecides2019 tweets dataset (mainly ranges between 0.00 and 0.20.). This indicates that the majority of the tweets are neutral according to TextBlob.

Further comparison exploration of the selected sentiment classifiers gave Figure 5. That is, digging a bit deeper by classifying the tweets as negative, positive and neutral based on the sentiment scores using TextBlob (TB), SentiWordNet (SWN) and VADER classifiers. TB says that 55.52% of tweets are

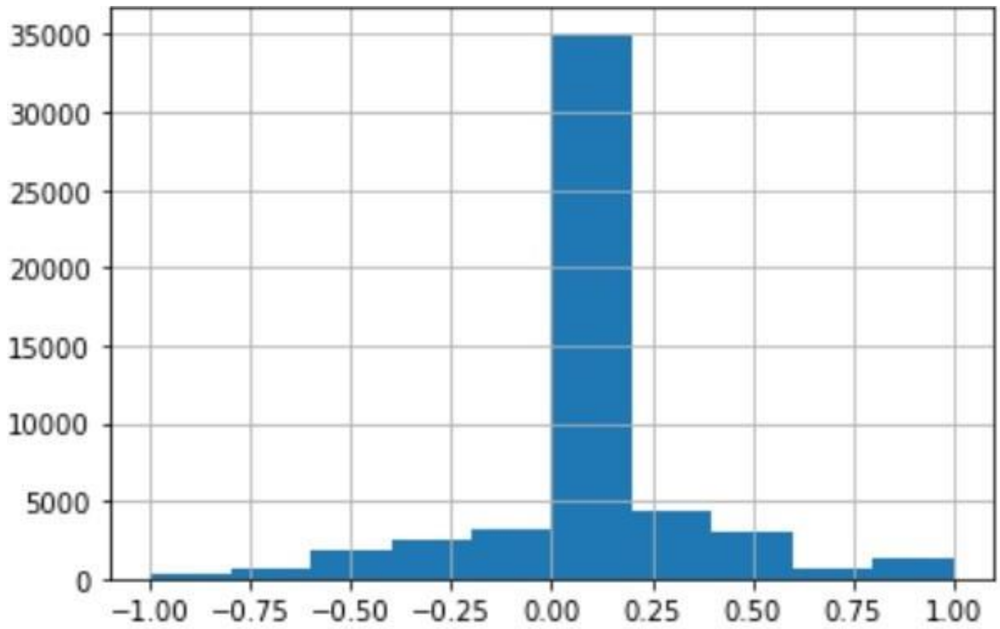

Figure 4: Visualizes the sentiment scores of all tweets in histogram.

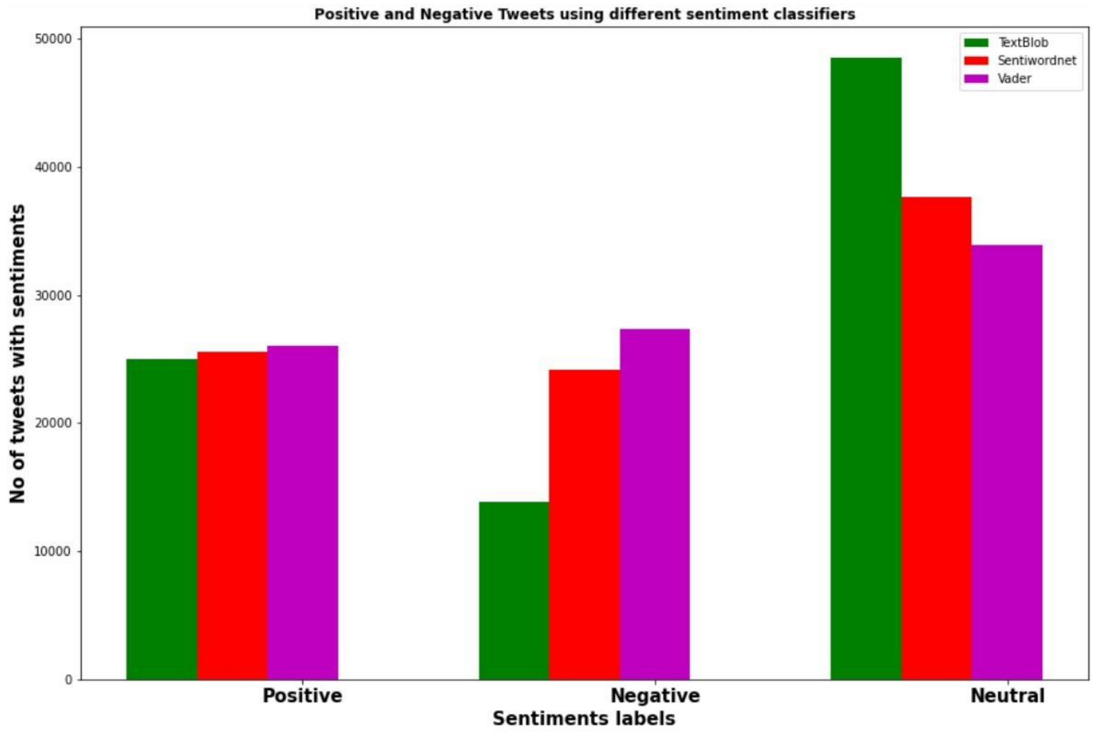

Figure 5: TextBlob, SentiWordNet and VADER sentiment classifications.

neutral with only 28.65% positive and 15.83% negative. SWN says 43.08% of tweets are neutral with only 29.23% positive and 27.70% negative. VADER says 38.84% of tweets are neutral with only 29.83% positive and 31.33% negative.

As shown in Figure 6, we employ a voting ensemble technique by combining the predictions from TB, SWN and VADER classifiers. This technique is used to improve the technique for finding better polarity results of a tweet, ideally achieving better performance than any single sentiment classifier used in the ensemble method. Since there are 3 classifiers used on x tweet, they produced 3 predictions of x selected tweet, and from these predictions, we collate final output y through Simple Majority voting. That is, for each set of predictions, we consider one with the highest agreement among classifiers [36]. It is a decisionrule which selects the highest number of correctly predicted values based on the predicted classes with themost vote [37].

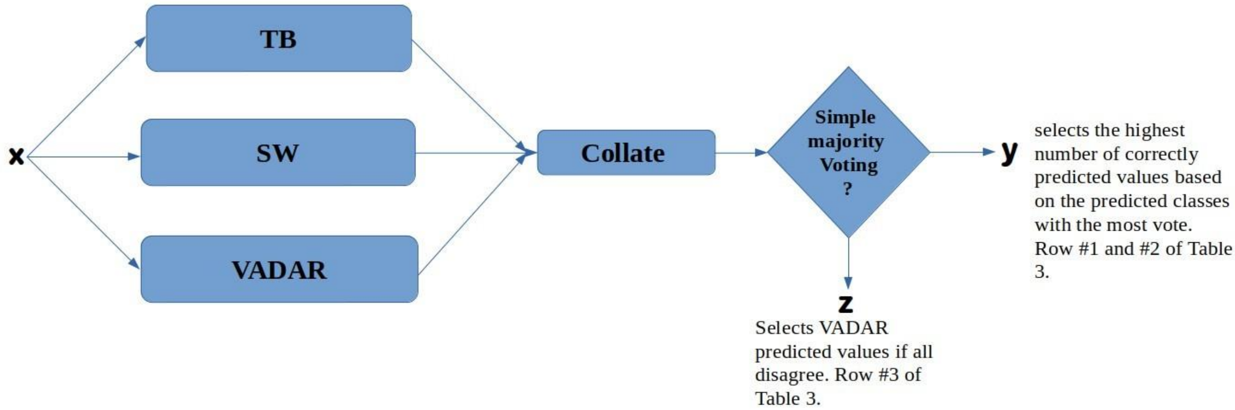

Figure 6: The voting ensembled framework used.

For example, Table 3 first row #1 presents that all classifiers predicted 2 positive, which implied that the three classifiers agreed that the tweet “When will Nigerians notice that Sowore and Kingsley are better options than Buhari and Atiku ?” is positive. In the second row #2, TB (TextBlob) claimed that the tweet is 0 (neutral) while (SWN) SentiWordNet and V (VADER) claimed 1 each. Hence we chose 1 as the mostagreed prediction. Row #3 is the case where TB and V predicted neutral against the positive prediction of SWN. Rows #4 and #5 are the cases where TB and SWN agreed on neutral and negative predictions respectively. Row #6 shows where all the 3 classifiers disagreed so we chose V’s prediction 1. There area few cases of this in our experiment. We chose V because it has been proven to do exceptionally well in social media texts. From close observations on the Voting Ensemble approach (VEA) results as shown in this Table, it reveals that we achieved better performance than using any of the single classifiers. For instance, we would have lost the true sentiment polarity of tweets in rows #2, #3, #4 and #5 due to misclassifications if we had used single classifiers.

Table 3 Classification samples of our voting ensembled technique

SN	TB[1]	SWN[2]	V[3]	CP[4]	Tweets
1	2	2	2	2	When will Nigerians notice that Sowore and Kingsley are better options than Buhari and Atiku ?
2	0	1	1	1	One thing that is quite glaring about Buhari and this APC government is their lack of empathy . They don't care how ...
3	0	2	0	0	These are the issues
4	0	0	2	0	I hope he's planning to stay till next week ?
5	1	1	0	1	I can hear Hadi cursing Buhari in the other room ...
6	0	2	1	1	Voting for Buhari for a second term will take Nigeria ten years backward . He has already lost his memory and he is b ...

[1]TextBlob Sentiment Classifier.

[2]SentiWordNet Sentiment Classifier.

[3]VADER Sentiment Classifier.

[4]Chosen Prediction based on the highest agreement among classifiers.

[5]2-Positive, 1-Negative, 0-neutral.

5. RESULTS AND DISCUSSION

We applied Exploratory data analysis (EDA) to help us decipher if there are correlations that exist between the public opinions and the sentiment analysis of the Nigerian states compared with the outcome of the presidential election. Because of space, we performed this on the top 3 states and Federal Capital Territory (FCT) according to Figure 2 to explore the most frequent words associated with the political actors. These 4 locations are part of the case selection of subsection 3.3. We added columns for tokens in our Pandas dataframe to generate word cloud images for the most frequent words. For example, words that co-occurred most frequently with the Political candidates and their parties are shown in Figure 7. The word clouds A, C, E, G, and I that represent Buhari and APC show some words that correlate negatively with some public opinions on the claims ofwidespread fraud by the opposition stated in subsection 3.1.1. Moreso, we used word clouds to visualize how topics mentioned in our dataset reflect higher/lower sentiment polarity plots in Figure 8. Compare Lagos, FCT, Kaduna, Rivers locations in Figures 7 and 8.

Furthermore, we evaluate how the polarity score compares with the actual election results to answer research question 1 in section 1. From Figure 6, we compute the average polarity scores of the sentiment classifiers that predicated the same values.We have also used location data to perform a polarity analysis of tweets mentioning selected political key actors such as Atiku and Buhari. The location data we usedare Nigeria's 36 states and 6 geopolitical zones. Along with the tweet's predicted values are polarity scores, we calculate the average polarity of each state using the location of tweets. Figures 8 and 9 show the average polarity scores of tweets computed across Nigeria's 36 states and 6 geopolitical zones for the political actorsAtiku, Buhari, Buhari and APC, Atiku and PDP, PDP and APC respectively. From Figure 8 we observe Atiku and PDP as having higher polarity than other political actors in the states of Plateau, Oyo, and Kaduna. However, the state of Enugu is strangely found to be 0.0 score given that PDP (Atiku's party) pulled 355,553 [28] votes to win over other political parties. We observe that Atiku's polarity scores are highest in states such as Lagos, FCT, Rivers and Enugu whereas Buhari's polarity scores can be found to be all-time low except in states like Kaduna and oyo.

Fig. 7 Most frequent words associated with either Atiku and PDP or Buhari and APC on tweets where either Atiku and PDP or Buhari and APC are mentioned. Atiku was the presidential candidate of the People's Democratic (PDP) Party while Buhari was the presidential candidate of All Progressive Congress (APC) and incumbent president. The alphabets represent wordclouds plotted for Buhari and APC (A, C, E, G, I) or Atiku and PDP (B, D, F, H, K) based on different locations according to the case selection in section 3.3. A and B - tweets across all the states. C and D - Lagos state tweets only. E and D-Federal Capital Territory (FCT) tweets only. G and H - Kaduna state tweets only. I and K- Rivers state tweets only.

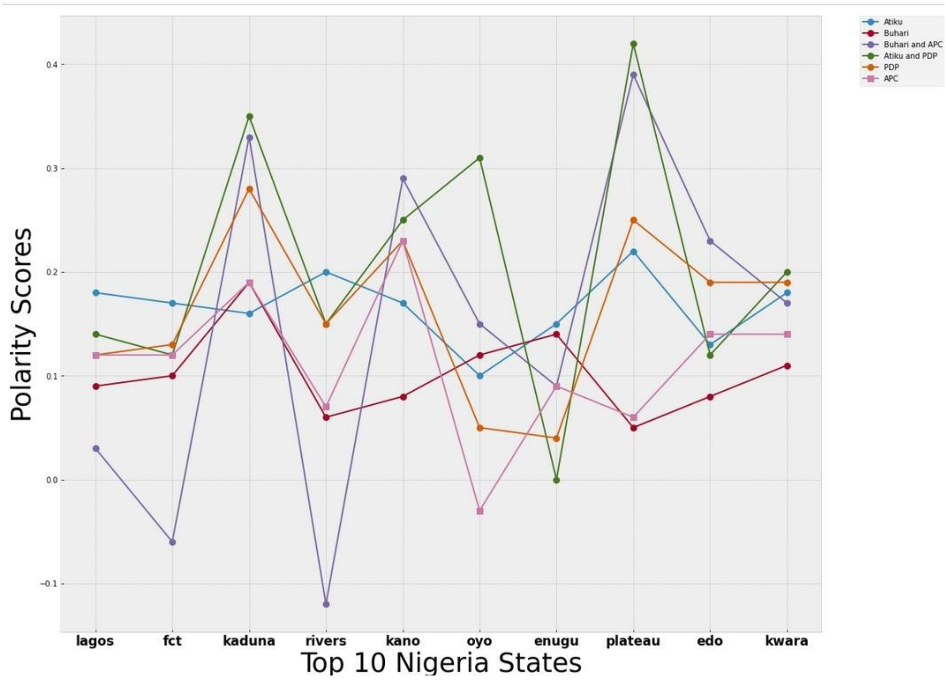

Figure 8: Polarity scores of Atiku, Buhari and their parties in top 10 states of Nigeria. Higherpolarity score indicates strong positive sentiment.

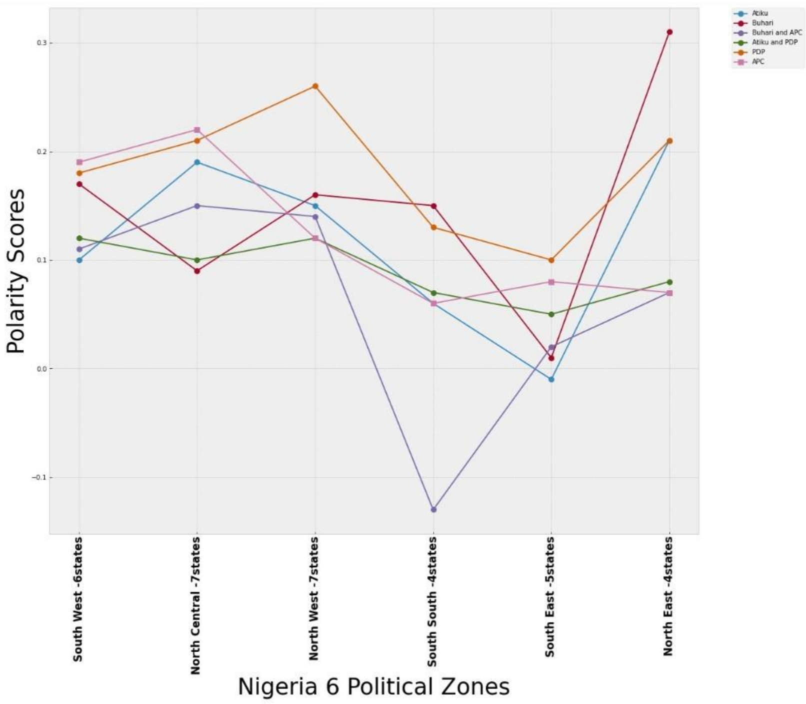

Figure 9: Polarity scores of Atiku, Buhari and their parties in the six geopolitical zones ofNigeria. Higher polarity score indicates strong positive sentiment.

Generally, Atiku is 40% higher compared to Buhari which is 20% higher across the 10 given states. Moreso, tweets where the candidates and their political parties are mentioned indicate that atiku and PDP has higher polarity scores in Kaduna, Oyo, Plateau and Kwara compared with

Buhari and APC which is only higher in two states Kano and Edo. Comparatively, looking at Figure 8, Atiku, PDP, and Atiku and PDP have higher polarity score than Buhari, APC and Buhari and APC. This can be attributed to hardship and insecurity (in states like Kaduna, Plateau, Oyo, Kwara, Enugu etc.) people were experiencing in current administration. See the following sample tweets:

1. “Residents of Kaduna State are enjoined to uphold peace and harmony , shun violence and allow the elections to be held”
2. “APC broom has failed to sweep away corruption in Nigeria ” – Foreign Journalist mocks Buhari”

The winner of the 2019 Presidential Election President Buhari and his party are all-time low in the state level polarity scores. Though Buhari and his APC associates show positive polarity scores most of the time but that does not reveal that he was the most accepted public opinion. For example, the election result reveals that Buhari pulled 580,825 (53.31%) votes in Lagos to win Atiku [28]. However, the polarity scores in Figure 8 reveal that Atiku and his political party are the most accepted public opinion (A and B of Figure 1).

Furthermore, we observe some election outcomes coincide with the sentiment expressed on social media. Atiku (PDP presidential candidate) won in the following states FCT, Rivers, Oyo, Plateau and Enugu which coincide with the sentiments expressed in fct, rivers, oyo, plateau, enugu locations of Figure 8 (reflecting C in Figure 1). In comparison with President Buhari, he won in states such as Lagos, Kaduna, Kano and Kwara [28]. However, we only observe a state like Kano coinciding with kano label in Figure 8. States such as Lagos, Kaduna, Kwara fail to coincide with the sentiments expressed in the social media compared to lagos, kaduna, kwara labels of the same figure. The failure of polarity scores to coincide with the real election outcome may be attributed to certain factors. These include:

1) Poverty: most of the electorates are not social media (Twitter) inclined. Figure 2 shows a high level of poor participation of the electorates when compared with [28] the number of people that voted from those states. This can be a result of an inability to afford android phones and data subscriptions to participate in online debate/tweets. The population that defined the election victory is found in the north (west, central and east) [28]. This zone is known for the lowest per capita income in Nigeria when compared with the south (east, west, south) [48].

2) Access to online platforms: so many areas in Nigeria especially the rural areas which coincidentally have the population, especially in the north lack access to the Internet.

3) Literacy level: the Twitter platform is an elite or enlightened class domain. However, in Nigeria, there is a high illiteracy level in Information Technology usage such as utilizing Twitter operations especially, among the rural dwellers. Thus, the class that participated in this discussion does not reflect the true nature, character, disposition, and understanding of the entire populace (see Figure 2).

4) The character and expressed meaning underscored in Figure 7 (rig, rigged, blocked, blocking, evil, died, scared, fear, govt plot, corruption, failed, heineous, scheme, rejects, thumbprint, DSS, DSS planning, aligned, official results, destroy result, attack, shocked, postponed, postponement, rice, bribe, broom, government, people, etc.) indicate there were reported cases of electoral malpractices which include (i) vote buying: This is usually easy as a result of the level of poverty the political elites in Nigeria subject

the citizens to, therefore making them quick tools for the actualization of their political interests. (ii) Militarization of opposition strongholds and intimidation of electorates, observers and INEC/EMB (Independent National Electoral Commission/Election Management Board) officials which led to poor turnout of voters, (iii) Partiality of INEC/EMB official in timely dispatch of election materials and arbitrary cancellation of poll results over spurious reasons, especially in the areas considered as strongholds of the opposition parties, etc [44–46].

5) Power of Incumbency: Nigeria's political culture is designed such that the party in power utilizes states' resources and apparatus to influence or manipulate the electoral processes [47]. Thus, the governors were mandated to win their states for their parties. This only determines their stake and part in the authoritative allocation of value after election victory. Twenty one APC-controlled states got the victory for their party except in Adamawa (Atiku's state), Imo, Ondo, and Oyo where it lost to PDP.

PDP also won in the fourteen states and FCT it controls except in Gombe, Kwara, and Sokoto where it lost to APC [49]. Therefore, the determination to achieve this intention distorted the natural flow and reflection of the electorates' tweets expression. Also, it contributed to other electoral malpractices that were prevalent during the election stated in 4 above. These undemocratic dispositions affected systematic correlation between sentiment expressed via polarity score and election outcome. Further zooming into the polarity scores given the 6 geopolitical zones where all the 36 states are classified gave rise to Figure 9. The states under each zone can be found in Table 2. We observe that political actors such as buhari, apc, pdp scored higher positive polarity values at different zones. We can infer from this location analysis that President Buhari and his party APC enjoy better polarity scores in 4 out of 6 geopolitical zones in Nigeria. This can be attributed to the Lagos tweet location analysis where it has the largest number of tweets. Lagos is Nigeria's largest city and a major African financial centre. It is the economic hub of Lagos State and Nigeria at large. The APC victory in Lagos can be attributed to the political kingpin, Bola Ahmed Tinubu who was the former APC national leader and Governor of Lagos state.

We performed a subjectivity analysis of tweets for both candidates using the Twitter location data to answer research question 2 in section 1. In subjectivity analysis, we determine how emotion, speculation, opinion, and sentiment are expressed in natural language [7] while message polarity determines the positive or negative connotation of a text, subjectivity analysis tries to discern whether the text is subjective in the form of an opinion, belief, emotion, speculation or objective as a fact [7]. We evaluate tweets from NigeriaDecides2019 of the 2019 Nigeria presidential elections in terms of their subjectivityto discover which of the selected political actors in Table 1 that has a higher subjectivity in the tweets mentioning them. Figure 10 displays the subjectivity scores of the tweets mentioning all the selected political actors in the six geopolitical zones of Nigeria while Figure 11 shows overall subjective scores. We can observe from the Figures that tweets mentioning buhari, apc, pdp have a higher subjectivity score for all 6 geopolitical zones and overall compared with those mentioning atiku, atiku and pdp, buhari and apc.

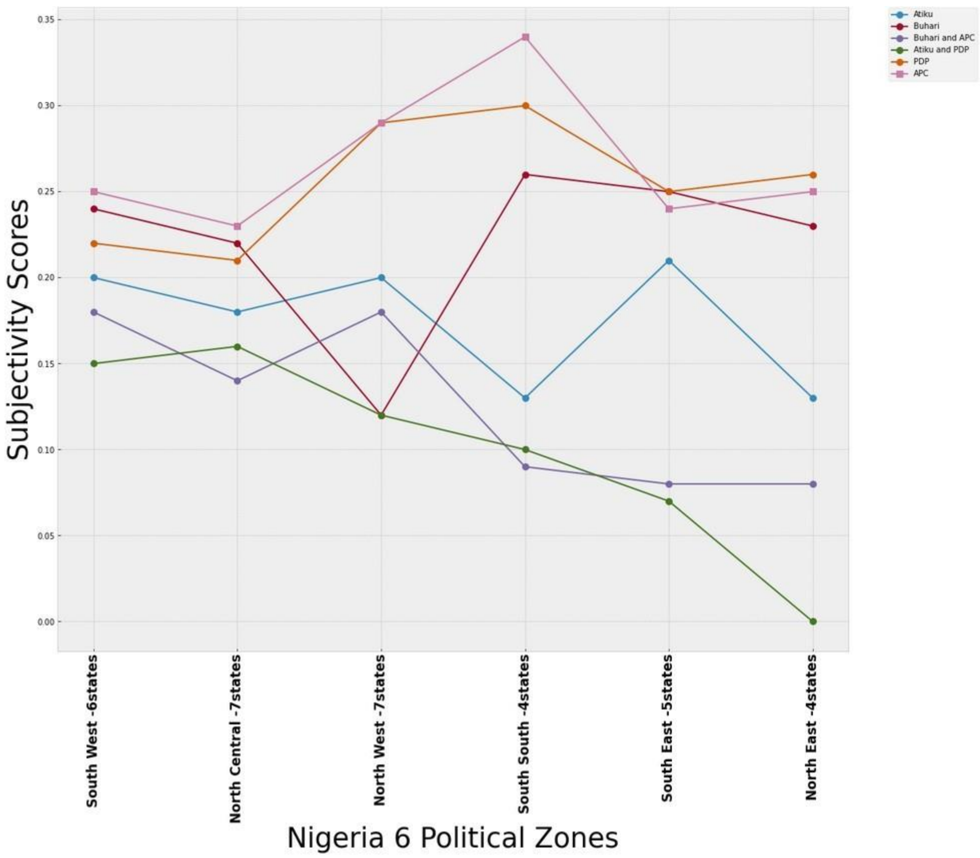

Figure 10: Subjectivity scores of Atiku, Buhari and their parties in the six geopolitical zonesof Nigeria.

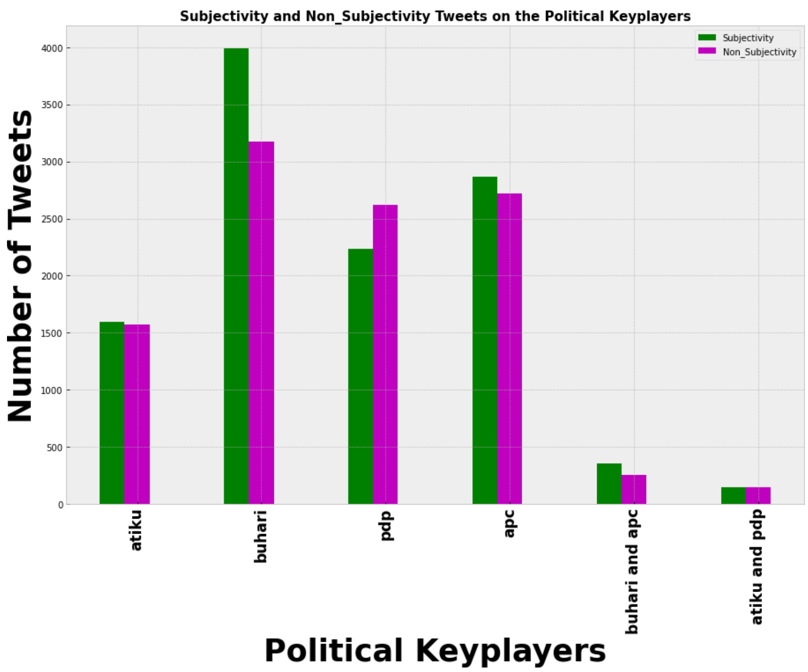

Figure 11: Overall subjectivity scores of Atiku, Buhari and their parties.

6. CONCLUSION

In this paper, we perform sentiment analyses of Twitter location data gathered during the 2019 Nigeria Presidential election using the voting ensemble approach (VEA). To achieve this, We utilized 3 different sentiment classifiers and combined their predictions to get the choicest polarity given a tweet (see section 4 for details). The three (3) sentiment classifiers used are TextBlob, SentiWordNet and VADER (Valence Aware Dictionary and Sentiment Reasoner). Furthermore, we tested our research questions by extracting location data (states in our case) provided by users from tweet metadata and use it to plot aggregated subjectivity and polarity scores of Nigeria states and geopolitical zones. Our tweets are gathered using different hashtags/keywords such as NigeriaDecides2019, atiku, buhari, pdp, apc, 2019elections, theVerdict and geo-location (Nigeria 36 states and 6 geopolitical zones). The states under each zone can be found in Table 2.

Overall, we observe sentiment based on some selected locations that coincide with election results insome states. For example, the polarity scores of Atiku, the closest rival of the 2019 Nigeria presidentialelection winner Buhari defeated by over 3 million votes, is 40% higher compared with Buhari who is 20% higher across the 10 given states. Moreso, We can deduce from the geopolitical location analysisthat President Buhari and his party APC enjoy better polarity scores in 4 out of 6 geopolitical zones inNigeria.

In terms of subjectivity analysis of the election tweets data, we observe tweets mentioning buhari, apc, pdp have a higher subjectivity score across all 6 geopolitical zones than ones discussing atiku, atiku and pdp, buhari and apc. Polarity analyses gave us mixed results. Although Atiku had higher polarity than Buhari in Lagos and FCT, he won in FCT by a wide margin (61.33% [28]) and lost to Buhari in Lagos state.

In the future, we would like to expand this study by performing more detailed analyses considering if thepeople's belief/culture could influence winning or losing an election in Nigeria.

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