**A PREDICTIVE MODEL FOR THE GOVERNORSHIP ELECTION IN LAGOS STATE USING TEXT-BASED SENTIMENT ANALYSIS**

**SUBMITTED BY**

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**A PROJECT SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE,**

**FACULTY OF SCIENCE,**

**IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE**

**AWARD OF THE DEGREE OF BACHELOR OF SCIENCE**

**(B.SC HONS.)**

**IN**

**COMPUTER SCIENCE OF THE LAGOS STATE UNIVERSITY, OJO, LAGOS, NIGERIA**

**APRIL 2023**

# **DECLARATION**

I **AJASA MUHAMMED AKANNI I**hereby state that this project report was researched by me, and that referenced information were properly cited.

| AJASA MUHAMMED AKANNI  170591102 | **SIGNATURE AND DATE** |
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# **CERTIFICATION**

This is to certify that this research work was carried out by **AJASA MUHAMMED AKANNI**, matriculation number **170591102**.

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# **DEDICATION**

I dedicate this research project to God almighty. Additionally, I would like to express my gratitude to my parents, my supportive friends, and all the other exceptional individuals who played a significant role in my success in completing this project. May God almighty continue to bless and guide all of you.

# **ACKNOWLEDGEMENT**

I would like to express my immense gratitude to God and my beloved parents, Mr. and Mrs. AJASA, as well as my dear friend Adeniji Ganiyat for their unwavering support, both morally and emotionally, throughout the duration of this project.

Furthermore, I am grateful to my supervisor, Prof. Toyin, and especially thankful to my beloved lecturer Mr. Shanu, R.O, for his constant support, guidance, and patience while continually reading and correcting me throughout this project. I would also like to express my appreciation to all the faculty and department staff for their contribution to my success.

To my wonderful colleagues including Amazing-Grace Umoren, Opeyemi Sanni, Yusuf Opoola, Adebayo Haruna, Oluwafemi Okediyi, Samuel Abolarinwa, Usman Habeeb, Basit Taiwo-Azeez, Tope Odesanya, Subomi Oladunjoye, Praise Babalola, Joshua, Timilehin Sojinu, Ibrahim Giwa, and the entire computer science department set of 2018, I appreciate the wonderful memories we shared together, and our story at LASU will continue beyond the walls. Thank you all, and may God bless you abundantly.

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# **LIST OF ABBREVIATIONS**

| NLP | Natural Language Processing |
| --- | --- |

# 

# ABSTRACT

This project aimed to create an AI system that can detect both polarity and the underlying emotion of an author in a given context to predict the election result in Lagos state. While sentiment analysis has been successful in detecting polarity, it does not account for the emotional state of the author. The proposed system will utilize machine learning tools to analyze content from social platforms, such as Twitter. This will involve working with large amounts of unlabeled or sparsely labeled data. The system will be able to identify the emotional state of the author and subjects with unstable or "chaotic" moods. The program will utilize open source libraries and publicly available datasets and will be capable of running locally. It is important to note that this work is original and has not received any unauthorized assistance.

# CHAPTER ONE

# INTRODUCTION

## 1.0 BACKGROUND OF STUDY

To analyze text content and determine the sentiment—such as whether it is good, neutral, or negative—sentiment analysis is a prominent use of Natural Language Processing (NLP) techniques. Sentiment analysis is a technique for calculating a sentiment score from qualitative data. Although the sentiment is fundamentally irrational, sentiment measurement has been helpful for several purposes, including helping companies understand how customers respond to a product or identifying hate speech in online debates.

“When captured electronically, customer sentiment — expressions beyond facts that convey mood, opinion, and emotion — carries immense business value. We’re talking the customer's voice, the prospect, patient, voter, and opinion leader.”( Seth Grimes, 2012)

Sentiment analysis uses computational methods to examine people's feelings and perspectives on specific issues. This topic has received a lot of interest in recent times from both academia and business; it has a wide variety of applications but also poses many complicated research difficulties.

Opinions are significant because we must consider others' perspectives to choose. This helps people and organizations that are interested in other people's perspectives.

There was no computer analysis of people's opinions before the internet. There wasn't a lot of opinionated text. One would need to employ polls or questionnaires or ask friends and family members to acquire people's opinions. These techniques were often used by businesses to solicit feedback on their offerings.

However, opinionated material on the web has grown significantly due to the rapid expansion of social networking websites and mobile applications. Today, practically anything may be the subject of a discussion on blogs, social media sites, and comment sections. [Liu, 2010]

## **1.1 PROBLEM STATEMENT**

People regularly damage public property during large protests, disrupting regular organizational activity in businesses, universities, and other settings. They frequently utilize social media as a forum to voice their opinions, occasionally quite strong opinions toward the government. People's views can provide beneficial information that can help in decision-making. Many websites today invite users to openly express and engage in dialogue about their thoughts on textual content. The rise in popularity of these websites led to a massive, largely unorganized collection of people's thoughts on the internet. Finding insights from sources of opinion is a complex process. Recently, methods like sentiment lexicons and opinion mining have been utilized to calculate sentiment analysis on unstructured data.

## **1.2 AIM AND OBJECTIVES**

The aim of this study is to design and develop a predictive model for the Lagos State gubernatorial election using text-based sentimental analysis. Simply put, we want to create a system that can categorize people's feelings and attitudes on the governorship election based on the textual content they publish on social media.

The following objectives have been established to help the study reach its intended goal.

* Do a literature review on existing literatures on predictive models for sentiment analysis.
* Determine a person's mood based on text-based information shared on social media.
* Categorize people's feelings following where they are located.
* Build on existing predictive model that will be able to predict the gubernatorial election based on the textual contents from their social media;
* Test and evaluate the model with data for correct functionality.

## 1.3 SIGNIFICANCE OF THE STUDY

Today's leaders must make decisions that might benefit or hurt their organizations, themselves, or others while dealing with various challenges and potentially explosive circumstances. Sentiment analysis will make judgments made by managers and authorities more morally sound and ensure that they won't have unintended consequences. The ability to forecast outcomes and assess how actions will influence the affected population aids the authorities in their decision-making. This study enables us to determine the degree of evaluability/argumentativeness with which the people under investigation interact and improves our judgments based on our understanding of the data we have reviewed.

## 1.4 RESEARCH METHODOLOGY

**SENTIMENT ANALYSIS PROCESS**

The figure below provides a full explanation of the steps involved in the sentiment analysis methodology that this study will use:



Figure 1.1: Basic processes involved in sentiment analysis, source:[Rambocas, 2013]

**DATA COLLECTION**

Sentiment analysis makes use of the vast volume of online material that is produced. Public forums, product review websites, blogs, message boards, and social networking sites like Twitter and Facebook are some of the content's data sources. The data is generated quickly and is frequently large and unstructured. Individuals will convey their feelings through writing in a variety of ways; therefore some people may prefer to utilize slang or emoticons, to name a few. This indicates that manually studying this content would be time-consuming and nearly impossible.

**TEXT PREPARATION**

Prior to the analysis step, the text preparation procedure starts by cleaning the textual data. In order to prepare text, non textual material like hashtags and hyperlinks must often be identified and removed from the data. Additionally, any item judged unrelated to the analysis is eliminated, as is any non-essential information that does not add to the reviewer's perspective, such as name, place, and date.

**SENTIMENT DETECTION**

By using textual processing, stage 3 of fig. 1.1, "detecting sentiment," extracts the reviewers' opinions. Sentences from the text are separated, and the subjectivity of each sentence is examined. Only sentences with subjective content are maintained for further analysis; sentences without subjective text are eliminated. The next step is sentiment detection, which may be carried out at the word, phrase, sentence, or document levels. Among the methods employed are.

– **Unigrams**: Also referred to as a "bag of words" approach, this strategy represents each element as a feature vector based on the frequency of a single word.

– **N-Grams**: This method uses many words in a specified order to represent the different elements of a text, such as words in pairs, triplets, etc. up to "N," hence the name "N-gram."

– **Lemmas**: Better —->good, best —>good are examples of lemmatization, which is the conversion of words to their synonyms rather than utilizing the exact term. This strategy streamlines the analytical process and results in stronger generalizations.

**– Negation**: When using other approaches, words like "I enjoy this book" and "I do not like this book" might be categorized as belonging to the same category, but when negation is included, the two sentences fall into different classifications. This method functions vary similarly to the n-grams method. However, there are also instances where negation is ineffective, such as when sarcasm or satire is present. [Pang and Lee, 2008]. Additionally, the polarity is not necessarily reversed when a negation is found.

**– Opinion words:** People frequently use "feeling words," which might be adjectives and adverbs, to communicate their feelings. These words may be used to express the closeness of a word to a comparable term in a feature vector, which is an effective technique to identify subjectivity in a document.

**SENTIMENT CLASSIFICATION**

The fourth stage of analysis is polarity detection, which divides each subjective statement into groups, often binary positive or negative but occasionally neutral. Several fundamental methods of supervised learning for classification include

– Naive Bayes (NB)

– Support vector machines (SVM)

– Maximum entropy (ME).

The Bayes theorem is used by the NB classifier, a probabilistic classifier, to operate. The statistical learning theory, which seeks a hyperplane that optimizes the distance between a binary class, is the foundation of support vector machines. A constraint on the model is represented by features in the ME model, and the model with the highest entropy is chosen as the class.

**PRESENTATION OF OUTPUT**

The analysis's primary goal is to extract insights from a huge amount of unstructured textual data. When the analysis is finished, several visual approaches, including pie charts, bar graphs, and line graphs, may be used to illustrate the results. The information can even be displayed in a continuous stream while the data is being processed in real-time while it is being displayed.

## 1.5 LIMITATIONS

Images, videos, folders, executive files, package files, and other online transmission data are not included in our analysis due to the limitations of the current information processing and analysis techniques (i.e., search engines cannot crawl and process pictures, videos, Flash, executive scripts, executive programs, and other nontext content files). (2013) [Hu and J. Ge].

When a significant geopolitical event occurs, news of it circulates online. Social media comments sparked by news stories and mass media successfully represent the opinions of most of the population. However, information to disclose and explain the spatial distribution of online attention is always hindered and insipid because it is challenging to conduct comprehensive collecting and analysis of auxiliary data and theme events [Hu and J. Ge, 2013]. Because of this, this study will use the Twitter API to obtain textual data based on a geographic region in order to identify the attitudes of a certain community toward a given subject.

### 1.5.1 DELIMITATION OF THE STUDY

This study is only focused on Twitter comments, even if studying all social network platforms and mainstream media websites may be worthwhile. Because most individuals frequently disregard language and spelling restrictions, this complicates the task of online sentiment analysis and might lower the accuracy of the results.

# 

# **CHAPTER TWO**

# LITERATURE REVIEW

## 2.0 OVERVIEW

We examine available technologies as well as the development of sentiment analysis in the chapter that follows. We will talk about the work that has been done and the contributions that have been made in relation to the already existing work. Additionally, this chapter evaluates pertinent literature and outlines the study's research framework. We examine several methods used to carry out the rudimentary computational sentiment and opinion analysis. The pros and cons of several Sentiment Analysis approaches, including Naive Bayes, Maximum Entropy, and Support Vector Machine, will be presented.

## 2.1 SENTIMENT ANALYSIS

Opinion mining, another name for sentiment analysis, tries to identify subjective text and extract pertinent information from the textual data. The text can be binary positive or negative, but it can also be neutral at times. Techniques and methods can be used to extract insights from textual data. To provide information that can aid in operational, managerial, and strategic decision-making, a sizable corpus of textual data can be fed into a statistical model and analyzed [Yanyan, 2012]. Additionally, sentiment analysis is a data mining tool that, by methodically extracting and analyzing online data without encountering any time delays, can overcome difficulties with textual content exploitation, analysis, and interpretation due to data dispersion, disorganization, and fragmentation [Kaplan and Haenlein, 2010].

Through a range of ideas, including part-of-speech disambiguation, sentence parsing, entity extraction, and context-based Boolean operators, natural language processing (NLP) techniques may capture the uniqueness of sentiment subtleties. The majority of the time, they entail a type of rule-writing that necessitates manual effort up front but, once produced, permits the needed accuracy levels within the subjective context.

Undoubtedly, the fastest-growing field of NLP research is sentiment analysis. The relevance of sentiment analysis has grown along with social media platforms like online reviews. Forum discussions, blogs, microblogs, Twitter, and social networks have significantly boosted the necessity for research in this field. 2014 [Verma et al.]. If correctly examined, the large amount of opinionated data that the web has may significantly aid corporations and governments in their decision-making. It is simple to classify attitudes even in real-time using text mining and analysis tools like Artificial Neural Networks (ANN) and Support Vector Machines (SVM).

media analytics platform. Fifteen billion Application Programming Interface (API) calls and more than 3 billion tweets are sent daily [Zimbra et al., 2018]. Opinionated information on a wide range of issues is in high supply and demand on Twitter. The increasing number of social media analytic applications that use Twitter's API is one factor in the rapid increase in demand for Twitter. Twitter feelings are a significant feature that may be used to forecast financial success, comprehend consumer behaviour and preferences, and give early warnings of unfavourable medical disasters because of its user-friendly API and the social impact of some powerful people [Abbasi and Chen, 2008], the ability to predict and understand election results, [F. Goodchild and Glennon, 2010] and the possibility of using archived data for disaster response and surveillance systems in the future, Twitter has emerged as the leading social media analytics channel. There are several emotion search engines where users may enter common searches on any subject they're interested in and get text responses. Positive, neutral, and negative results are the three polar groups into which the findings are often divided. There are several cases at this time [Rambocas, 2013]

**– They Say IO:** [**http://www.theysay.io**](http://www.theysay.io)

**– Text2Data:** [**https://text2data.com/**](https://text2data.com/)

**– Summerizebot:** [**https://www.summarizebot.com/**](https://www.summarizebot.com/)

**– Sentiment140:** [**http://www.sentiment140.com/**](http://www.sentiment140.com/)

**– Parallel dots:** [**https://www.paralleldots.com/**](https://www.paralleldots.com/)

When looking at how Twitter data is processed, the Sentimentor, a specific tool, is employed for sentiment analysis. It uses the naive Bayes Classifier to divide tweets into the three categories of "negative," "neutral," and "positive." The user interface of Sentimentor enables visual word distribution analysis. This tool displays categorization outcomes in a simple visual way. The text type and analysis details are two more insights obtained by Sentimentor [Spencer and Uchyigit, 2012].

The majority of opinion mining techniques identify the polarity of textual content as either positive, negative, or neutral to determine its polarity. This is sufficient for many applications, but as textual data sometimes contains a mix of positive and negative emotions in the same document, it is occasionally important to identify both concurrently and gauge the degree of the sentiment represented. One example is programs that monitor online chat rooms and look for language or tone that could endanger other users [Liu, 2012]. Must be able to determine whether participants were properly balancing positive and negative emotions as well as the strength and polarity of the information or sentiment presented. Opinion mining can also be useful for study into the function of emotions in online communication (Hancock et al., 2008), as well as for the expanding amount of psychological and other social science research into the function of sentiment in various forms of speech (Newman et al., 2003).

Simple applications of sentiment analysis and machine learning techniques can help an institution's executive board make better decisions. This study is centered on the construction of an integrated system that will do text analysis or semantics. In order to show sentiment analysis on the textual content of an event, this project will take into account the analysis, design, and implementation of machine learning algorithms [Pang and Lee, 2008]. Recently, tools that can evaluate sentiment at the feature level have begun to appear, although generally speaking, automated sentiment analysis technology struggles to distinguish one subject from another, especially if numerous topics are covered in a single text.

## 2.2 RELATED WORK

As previously said, sentiment analysis tries to use the enormous volume of internet user-generated data. The vast volume, high pace, textual chaos, and diversity of such material are some of its key qualities. An area of NLP called computational linguistics is used to find, extract, and examine personal textual information from a given document. The primary goal is to determine the writer's viewpoint on a particular subject or the document's overall contextual polarity. Most sentiment analysis tools, both those that have been around for a while and those currently being developed, employ machine learning algorithms or approaches to address various issues. There are two major approaches to determining sentiment based on a given text.

### 2.2.1 COMPUTATION SCIENCE TECHNIQUES

Digital texts are analyzed for sentiment using machine learning techniques like SVM, the bag-of-words model, and Naive Bayes. Turner (2002). The term "computational statistics" refers to statistical techniques that need a lot of computing power, such as principal component analysis, Markov chain Monte Carlo techniques, local regression, and kernel density estimation.

Massive volumes of data with several variables are intended to be processed automatically via machine learning. In sectors like pattern recognition for voice and pictures, in medical for tumor diagnosis and drug development, in finance for financial algorithms, credit scoring, and algorithmic trading, and in projecting energy usage, figuring out the load, and predicting prices, machine learning is frequently employed.

### 2.2.2 MACHINE LEARNING TYPES

According to Murphy (2012), machine learning is the autonomous acquisition and integration of information gained via experience by a system. It is possible to separate these systems into:

a) **Supervised learning**

Discriminant Function Analysis, Support Vector Machines, and Regression Trees are a few examples of supervised learning.

b) **Unsupervised learning**

K-Means clustering and Self-Organizing Maps (SOM) are examples of unsupervised learning approaches. Unsupervised learning involves feeding the model data but expecting it to make decisions on its own.

### 2.2.3 EXAMPLES OF MACHINE LEARNING ALGORITHMS

Scientific concepts are used by machine learning algorithms to understand how to identify sentiment from input data. The algorithms are based on models created from inputs and verified on training data, and they may then be used to make predictions based on this knowledge. This generalization method is preferable to just following clearly coded instructions. A type of probabilistic classifiers known as naive Bayes classifiers (supervised) are based on the application of the Bayes theorem with strong independence assumptions between the features. By calculating the probability of the outcomes, the Nave Bayes classifier, which uses a probabilistic model, can incorporate uncertainty [Hemalatha et al., 2013].

**Bayes theorem states that**:

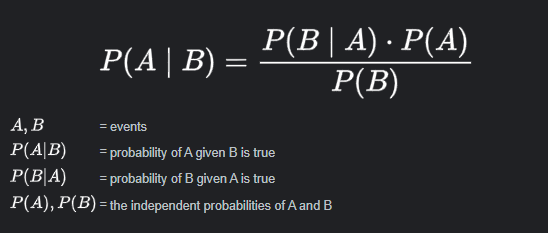


Fig 2.1: Bayes theorem

### **2.2.4** MAXIMUM ENTROPY (SUPERVISED)

Maximum Entropy (MaxEnt) classifier is an additional probabilistic-based classifier. It is a member of the exponential model family. The characteristics are not presumed to be conditionally independent by MaxEnt. The Principle of Maximum Entropy is the foundation for the Maximum Entropy algorithm. The model with the highest entropy is chosen as the class of interest out of all the models based on the training set [Pang and Lee, 2008].

### **2.2.5** SUPPORT VECTOR MACHINES (SUPERVISED)

A Support Vector Machine (SVM) is a binary classifier that uses a hyper-plane to distinguish between two groups. In other words, the algorithm generates an ideal hyper-plane that classifies fresh samples based on labeled training data (supervised learning). [Dr. Sathyanarayana and Amarappa, 2014]

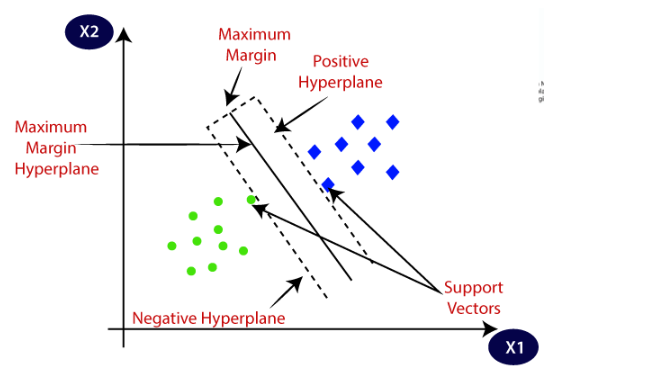
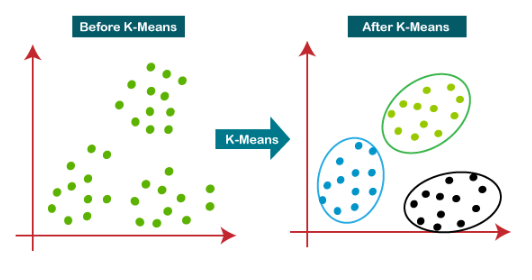


Fig 2.2 : Support Vector machine

### 2.2.6 K-MEANS CLUSTERING (UNSUPERVISED)

Unsupervised learning techniques such as K-means clustering classify things into groups. No prior understanding of the class to which an item belongs, nor necessary any understanding of the number of classes.



*Figure 2.3: Unsupervised K-Means Clustering, Source:*[*https://www.javatpoint.com/k-means-clustering-algorithm-in-machine-learning*](https://www.javatpoint.com/k-means-clustering-algorithm-in-machine-learning)

## 2.3 STUDIES ON SENTIMENT ANALYSIS USING THE NAÏVE BAYES CLASSIFIER

Following is Andy Bromberg's basic project workflow:

Choose a training set of positive and negative components as the first step.

- Step 2: Using the practice data, train the classification algorithm.

- Step 3: Classify some example data using the classification technique.

Step 4 is to compare the findings to the collection of known results.

Tools employed The sentiment extraction technique developed by Andy Bromberg makes use of a Natural Language Toolkit (NLTK). This Python module does text analysis and processing. His sentiment analysis software was built on this foundation. Python was chosen because it is a basic programming language and contains a number of really helpful tools for text processing and sentiment analysis. Andy Bromberg uses a variety of approaches, including data mining, machine learning, and classification algorithms, among others. 2012 [Bromberg]

### 2.3.1 CHOOSING THE TRAINING SET

Because tweets are too diverse in terms of language and meaning as well as content, the data used to evaluate the technique was gathered from book and movie reviews rather than Twitter. The sentence polarity dataset v1.0, which had 10,663 sentences from movie reviews that were individually classified as either positive or negative, served as the basis for the base material, which was collected from Bo Pang's website on movie review data. The AFINN wordlist was used to train the classifier after the positive and negative sentences had been loaded and divided into separate lines to be evaluated at the sentence level. 2477 words and phrases in the AFINN wordlist are scored from -5 (Very negative) to +5 (very positive). The word list was, however, reclassified into four categories:

Very Negative (rating -5 or -4)

Negative (rating -3, -2, or -1)

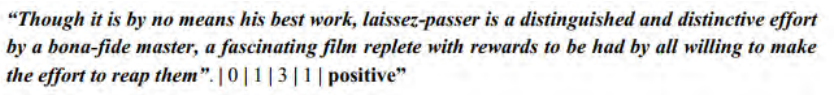
Positive (rating 1, 2, or 3)

Very Positive (rating 4 or 5)

To increase the number of terms in the training set, additional movie-related words were added to the list of training data. Neutral terms were purposefully excluded from Andy Bromberg's approach because he thought they would not aid in categorization. After that, the algorithm determined how many words in each review fell into one of those four categories. This produced a large data table with 10,663 rows in the following format:

**Sentence | #vNeg | #neg | #pos | #vPos | sentiment**

Below is a sample extracted from the polarized data:

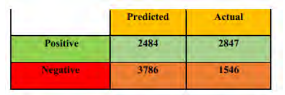


*Sample form of training data*

According to this example, the statement had one negative word, three positive words, and one extremely positive word. The person who created the database categorized it as favorable as well. As was already noted, Andy Bromberg's model attempted to categorize the statements as positive or negative by using a machine learning method called the Naive Bayes classifier from the "e1071" package. The Naive Bayes classifier's core tenet is that it examines the relationship between the quantity of words in each of the four categories and the sentence's positivity or negativity. By counting the amount of words in each category and comparing this to the likelihoods of those numbers existing in positive and negative phrases, it tries to create a probabilistic judgment as to whether a statement is positive or negative. 2012 [Bromberg]

### 2.3.2 RESULTS

The output of a classification algorithm was represented visually using a confusion matrix. The outcome matrix was as follows:



*Fig 2.4: Confusion matrix results, source: [Bromberg, 2012]*

In the confusion table, the projected positive and negative attitudes are contrasted with the actual sentiments. The findings demonstrate that for both positive attitudes, the projected scores were lower than the actual values. On the other hand, for negative emotion, the projected scores were higher than the actual values.

## 2.4 STRENGTHS AND CHALLENGES NAIVE BAYES

The Naive Bayes classifier was the supervised learning technique that Andy Bromberg's model used. This decision allowed the model to train relatively quickly, and the fact that all of the data is labeled training data makes it simple to cluster the results and compare them to the training data. However, each type of supervised machine has a specialized domain. The Naive Bayes classifier was trained for a certain domain, hence it can only classify data inside that area. Because of this, the categorization findings were often less than 70% correct [Bromberg, 2012]. The categorization outcomes were inaccurate, according to Andy Bromberg's model. In general, A competent classifier should get substantially higher accurate classification rates than 60–65%. In the tool we will create, we advise employing several wordlists, classification methods, and training data.

## 2.5 STUDIES ON TERM FREQUENCY—INVERSE DOCUMENT FREQUENCY

**Method Used:**

The relevance of a statement to a certain context, or if it is on topic, may be ascertained using this approach. This is accomplished using the "Term Frequency-Inverse Document Frequency" information retrieval technique. TFIDF is a statistical model that determines a word's significance in a certain textual context. Despite being used in contemporary search engines to construct content queries from text that are then provided to search engines to obtain related documents, it was originally designed for use in early search engines as a method of determining the relevance of a page in a query search. It may be thought of as a sort of document similarity metric. The "TFIDF" document representation approach views each document as a collection of words, where the importance of each word varies depending on the context of the particular document. The term frequency, or TF, measures how frequently a word appears in a document and how important that word becomes. In one research, document frequency values were calculated using a corpus made up of news articles received from Reuters.

### 2.5.1 STUDIES USING LEXICON-DRIVEN METHODS

When analyzing tweets referencing Barack Obama, [et al, 2010] employed the Multi-Perspective Question-Answering (MPQA) sentiment lexicon developed by [Wiebet et al., 2005]. They simply calculated the number of positive or negative terms in a tweet in accordance with the emotion lexicon to determine its classification.

Despite the fact that this is a pretty straightforward technique, they find a strong connection between the sentiment of tweets as a whole and Gallup's reported public opinion polls. SentiStrength is a lexicon-based algorithm that assigns a binary polarity (positive/negative) and associated strength value between 1 and 5 to a given text [O'Connor et al., 2010]. SentiStrength employs lists of emoticons, negations, and boosting words in the decision-making process in addition to having a collection of 298 positive and 465 negative keywords annotated with polarity and strength levels.

The authors presented a three-step method to return words to their regular form in order to solve the issue of emphatic lengthening. SentiStrength performed better at categorizing negative sentiment than other ML classifiers when compared to MySpace comments, however this was not true for positive sentiment. The method is improved in [O'Connor et al., 2010], where the authors include include an unsupervised version of SentiStrength, idiom lists, and strength boosting via emphatic lengthening. Additionally, from 693 to 2310 words were added to their emotion strength wordlist. On six distinct datasets, including Twitter data, they test their system once more with several machine learning techniques and discover that logistic regression outperforms SentiStrength in particular [O'Connor et al., 2010]

### 2.5.2 STUDIES USING GRAPH-BASED LABEL PROPAGATION

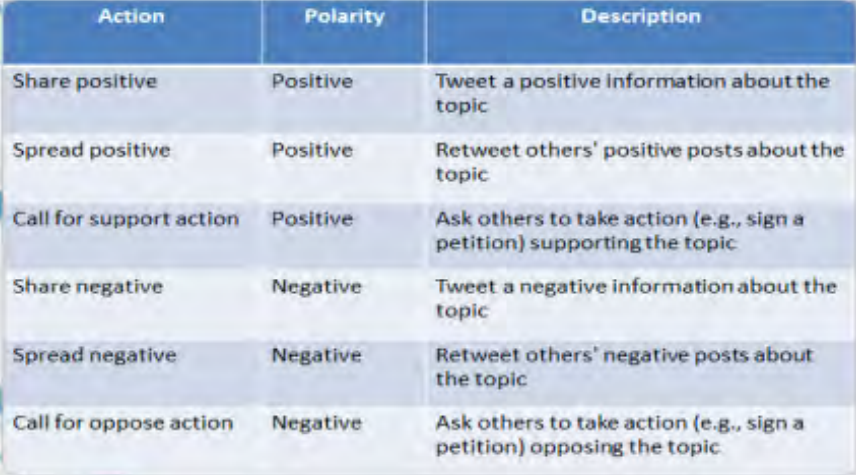
The performance of a label propagation method was also tested by [Thelwall and Buckley, 2012] together with a dictionary-based approach and well-known online tools for sentiment analysis of tweets. They looked at the unique function of emoticons in tweets as well as the emotion of tweets written in languages other than English using a network propagation technique [Cui and Mittal, 2006].

### **2.5.3 METHODS USED**

The previous study on sentiment analysis on Twitter included three basic methods. The most common method for sentiment analysis in general is to train supervised machine learning classifiers on data that has either been manually annotated or that has been tagged with "noisy" labels like emoticons. Support vector machines or a Naive Bayes classifier are often used by writers to describe their best findings. The second technique, lexicon-based approaches, provides labels or scores to tweets by combining sentiment lexicon scores. In some cases, the aggregation simply entails adding up or average the polarity values of all the tweet's terms that can be located in the employed lexicon. In other instances, rules are utilized to manage linguistic situations like negation. The third method relies on label propagation techniques and uses the relationships between textual content to give emotion scores to sets of closely related data. While the majority of research falls under one of these categories, several studies also mix them.

### 2.5.4 STUDIES ON PREDICTING USER'S ACTIONS FROM SENTIMENT

Social media users frequently express certain opinions about things like ongoing campaigns and act in different ways as a result. An algorithm is presented by [Mahmud et al., 2016] that forecasts a social media user's behavior toward a campaign issue based on the user's underlying emotion. He explains the activities he took into consideration while working. The acts are listed in the table below, and each one has a topic and polarity (positive, negative). The table also includes the explanations for each action.



***Figure 2.5: Action Prediction Source: [Mahmud et al., 2016]***

A few examples of actions are given below:

- To "Share positive" action on the "fracking" issue, a user might tweet the following: "Fracking saves us money, fracking generates employment, and fracking cuts greenhouse gas emissions."

- To "Spread negative" action on the "vaccination" issue, a user might retweet the following: "Vaccination has never been shown to have saved a single life."

- To join the "Call for opposition action" for the fracking issue, a person can tweet the following: "Save our families and children from $10 fracking. Pls RT! ".

Mahmud concentrated on Twitter users and the "fracking" and "vaccine" campaigns. He sampled 1000 users who said "fracking" and another 1000 users who mentioned "vaccination" between November 1, 2013, and November 14, 2013, using Twitter's streaming API. Additionally, each user's feelings toward the subject (such as "fracking" or "vaccine") they tweeted about were classified as either favorable or negative [Mahmud et al., 2016].

**Classifiers for Action Prediction** The classifiers are divided into two methods:

**· Non-Hierarchical Action Classifier**

**· Hierarchical Action Classifier**

## 2.6 NON-HIERARCHICAL ACTION CLASSIFIER

For each action indicated in the above table, they trained action classifiers from labeled training data, and they also trained a binary classifier using the training set of users. A trained classifier for an action may forecast whether a new user in the test set will execute that action and output the probability associated with that prediction. Additionally, each action classifier employs the same set of characteristics derived from users' previous tweets, such as

### 2.6.1 CONTENT FEATURES

Unigrams generated from all of the training users' previous tweets are among the content characteristics.

### 2.6.2 ACTIVITY FEATURES

This feature category documents social interactions between individuals. Mahmud made the argument that people are more inclined to do particular activities depending on their feelings about an issue the more engaged they are. The following factors were taken into account: the number of tweets sent each day, the total number of tweets sent throughout the whole time period, the number of retweets, and the number of retweets sent each day. Personality traits: According to research, a person's blog and essay writing reflect his or her personality. [Mahmud et al., 2016] calculated 103 personality traits (e.g., word categories like "sadness," "agreeableness," etc.) from a person's tweets.

## 2.7 HIERARCHICAL CLASSIFIER

The emotion of the Twitter user is predicted first, followed by actions, according to [Mahmud et al., 2016], who employed a hierarchical classifier for prediction. As shown in the above table, three action classifiers were trained for the positive sentiment ("Share Positive," "Spread Positive," and "Call for Support Action"), and three action classifiers for the negative sentiment ("Share Negative," "Spread Negative," and "Call for Opposing Action"). However, as there is no action connected to a neutral emotion, no action classifiers for that sentiment were trained [Mahmud et al., 2016].

## 2.8 CHALLENGES OR PROBLEMS FACED WITH THE CURRENT SYSTEMS

The work of sentiment analysis is difficult. This needs in-depth comprehension. [Shivhare and Khethawat, 2012] noted a few difficulties with sentiment analysis.

- How to recognize subjective language in the text: A term may be interpreted as subjective in one context, but as objects in another. When attempting to pinpoint the subjective elements of the text, this is difficult. For instance:

- The author's language was really vulgar.

- The sea floor is mined for crude oil.

In the first statement, the term "crude" is employed as an opinion, but in the second sentence, it is used entirely objectively [Verma et al., 2014].

- Ambiguity in Keyword Definitions: Using related emotion keywords is one of the easiest ways to identify emotions, but since these terms can have various meanings and occasionally are ambiguous, they can have varied meanings depending on the context [Shivhare and Khethawat, 2012].

Even words without synonyms can express various emotions in specific contexts, such as ironic statements.

- Lack of capacity to classify sentences that don't include keywords: An strategy focused on keywords has the inherent drawback of being unable to classify sentences that don't contain such keywords, giving you an inaccurate result. Consider the following two sentences: "Hooray! My qualifying exam was successful today "and "I passed my qualify exam today" should both suggest the same feeling (joy), but if "hooray" is the only phrase that can identify this feeling, the former might go unnoticed [Shivhare and Khethawat, 2012].

- Sarcastic Phrases: Sarcastic sentences use positive language to communicate unfavourable judgments about their intended audience. For instance

– Nice perfume. You must marinate in it.

Although this sentence has just positive words, it still holds a negative sentiment.

- The meaning of a given statement or phrase might vary depending on the domain in which it is used. When used in the context of movies, the phrase "unpredictable" has a favourable meaning, but when used in relation to a car's steering, it has a negative connotation [Verma et al., 2014].

- Entity Recognition: Not all the textual information in a phrase refers to the same thing; a sentence or document may refer to several different things. We must be able to segregate the language that is about a certain object so that we may examine each sentiment separately. Think about the following:

– I hate Nokia, but I like Samsung

A straightforward bag-of-words analysis would classify this as neutral, but it really contains a particular feeling for each of the two entities mentioned in the sentence [Verma et al., 2014].

## 2.9 ANALYSIS OF THE PROPOSED SYSTEM

We need to develop an automatic natural language processing tool that extracts and analyzes people’s sentiments and emotions from unstructured text. The tool must be able to determine the general mood on a given topic.

## 2.10 CHAPTER CONCLUSION

With the rapid development of social media supported by network technology and network information transmission, the influence of network socialization and social networking has gradually increased, especially in economic, social, and political fields. Due to this increase in social media use, people now use it to express their views and sometimes extreme views. A geographical social network mood detection tool will be developed to detect mood and chart the results in real-time.

Based on our literature review results show that both supervised and unsupervised methods of training the machine learning algorithms perform well given sufficient training data. The Term Frequency–Inverse Document Frequency (TFIDF) method does well because it eliminates the spam or the off-topic comments and focuses only on the on topic comments. The method used by Andy Bromberg gave poor results because of the choice of training data which was taken from movie review sites, which contained a lot of misspellings and informal language (slang). Concerning machine learning techniques, [Gunther, 2013] found Support Vector Machine Classifier to outperform other tested classifiers. They recommended Linear classifiers with large margin loss functions and advanced techniques such as Regularization and an adaptive learning rate, such as a Support Vector Machine or Logistic Regression, for doing sentiment analysis on blogs.

Our study will use open data sets for training our models, we will use Twitter API to stream tweets in real-time and open libraries to visualize the results.

# CHAPTER THREE

# METHODOLOGY

## 3.0 INTRODUCTION

We discussed a few of the methods used by various sentiment analysis researchers in the previous chapter. We have made an effort to clarify the weaknesses and advantages of each methodology or method used prior to this research. The software and hardware development tools that we will utilize to create and develop the geographical mood detection tool are described in this chapter. Moreover, a system-following algorithm will be demonstrated. While making decisions, the state or government will benefit from timely discovery of emotive or opinionated online material since it will enable them to gauge public opinion on a certain subject and chart the findings in real-time for analysis.

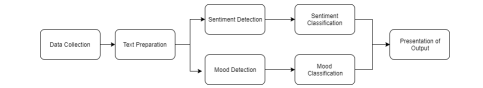


Figure 4.1: Steps to analyze sentiment data

## 3.1 LEXICON (VADERSENTIMENT)

Information about a term in a certain language is included in a lexicon. Lexicon-based sentiment analysis uses annotated language, which is incredibly helpful for identifying emotion in emoticons. A python open source package called VaderSentiment may be used to do lexical-based sentiment analysis.

VADER was created primarily to accommodate feelings shared on social media. Positive, neutral, and negative sentiments are designated in the VADER language, respectively.

An emoticon, also referred to as a "emotion icon," is a string of characters that include a picture of a facial expression, numbers, and letters to express a person's feelings or mood. An emoticon can also be used as a time-saving alternative to typing out a whole word to express the writer's emotions or intended tone.

Some key features of Vader sentiment are: -

1. Punctuation: The use of an exclamation symbol(!) can increase the intensity of the sentiment but without changing the polarity of the sentiment. For example, “The weather there is good!” is more intense than “The weather there is good.” and an increase in the number of exclamations in turn increases the intensity of the sentiment accordingly.

2. Capitalization: Making use of upper case letters adds emphasis to a sentiment-relevant word, if the sentence is written in lower case letters the upper case letters increases the intensity of the sentiment.For example, “The weather there is GREAT!” conveys more intensity than “The weather there is great!”

3. Degree modifiers: Also known as intensifiers, they influence the sentiment magnitude by either decreasing or increasing the intensity. For example, “The roads here are extremely good” is more intense than “The roads here are good”, whereas “The roads here are ok” decreases the intensity.

4. Conjunctions: words like "but" are conjugation or joining words that indicate a change in the polarity of the detected sentiment of the text. “The roads here are good, but the traffic lights are horrible” has mixed sentiment, with the latter half dictating the overall rating.

5. Preceding Tri-gram: We can examine a tri-gram of the text, at least 90% of scenarios that involve negation can invert the polarity of the sentence. A negated sentence would be “The roads out here are not really all that good”.

## 3.2 STREAMING TWITTER (TWEEPY)

Tweepy is an open source python library that can be used to stream tweets from twitter in real time through the Twitter API. The twitter API can accept parameters to filter tweets based on geolocation, language and topic (i.e. tweets containing a particular word phrase or hashtag)

## 3.3 TEXT PROCESSING DOCUMENT

Obtaining text necessitates normalizing it, which entails the following steps:

- changing all letters to lowercase or capital letters

- Word-to-number conversion or number removal

- eliminating white spaces, accent marks, and other diacritical marks

- expanding abbreviations

- text canonicalization

We also removal of stop words, sparse keywords, and specific words

As numbers are irrelevant to our analyses, we also delete them. Regular expressions are used to eliminate numbers.

## 3.4 CONFUSION MATRIX

In machine learning, the performance of a classification algorithm is evaluated using a confusion matrix. It compares test data with known true values in a tabular format. To assess how well my classification model is performing, we will utilize the confusion matrix.

The following classes comprise a confusion matrix.

- **True positives (TP)**: This refers to instances in which we made a successful positive forecast.

- **True Negatives (TN)**: When we predict a negative outcome correctly.

- **False positives (FP):** These occur when we forecast a yes result while the actual result is a no.

- **False Negatives (FN):** These occur when we predict a number to be no but it actually is yes.

The table below demonstrates how to use a confusion matrix to assess the prediction's accuracy.

Accuracy, however, has its issues. It makes the assumption that the costs of both types of errors are equal, or that there are an equal number of positives and negatives. Depending on the issue, a 99% accuracy can be excellent, acceptable, middling, poor, or dreadful.

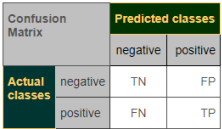


Figure 4.2: Confusion matrix

The confusion matrix changes when there are several classes.

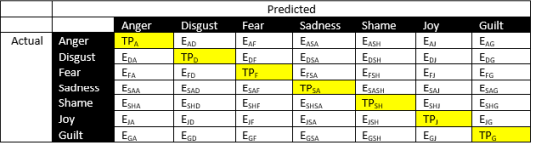


Figure 4.3: Confusion matrix with multiple classes

Observations regarding a confusion matrix with numerous types

- Total test examples for any class, if indicated by adding the relevant row's values (TP + FN).

– The sum of the numbers in the corresponding row, minus the True Positives, represents the total number of False Negatives for a class.

- The sum of the values in the corresponding column, omitting the true positives, is the total number of false positives for a class.

– The total number of true negatives for a particular class will equal the sum of all columns and rows that don't belong to that class.

accuracy is determined by dividing the total number of classifications by the total number of correct classifications.

The formula for precision is TP/(TP+FP).

The real positive rate of the class under consideration is determined by the formula Recall=Sensitivity=TP/(TP+FN).

# 

# CHAPTER FOUR

# IMPLEMENTATION AND RESULTS

## 4.0 INTRODUCTION

The implementation chapter is a crucial component of this research project, as it outlines the methods, tools, techniques, and procedures used to create a predictive model for the Lagos State gubernatorial election using text-based sentiment analysis. This chapter provides a detailed description of the steps taken to collect and prepare the data, detect and classify sentiment, and present the output of the sentiment analysis.

In this chapter, we will describe the various methodologies employed to implement the proposed solution. The chapter begins with a discussion of the data collection process, including the sources of the data and the tools used to collect it. We will then outline the text preparation procedures, including cleaning the data and eliminating non-textual and non-essential information.

Next, we will describe the sentiment detection methods, including techniques like unigrams, n-grams, lemmas, negation, and opinion words. We will also discuss the sentiment classification techniques employed, such as Naive Bayes, Support Vector Machines, and Maximum Entropy. Additionally, we will explain the presentation of output, including the visual approaches used to present the results of the sentiment analysis.

We will then provide a detailed description of the implementation methodology, including the steps taken, tools used, and any challenges encountered during the implementation process. We will also discuss the testing and evaluation methods used to assess the accuracy and effectiveness of the sentiment analysis model developed.

Finally, this chapter will conclude with a summary of the key findings and contributions of the research, along with suggestions for future work that could be done to improve the sentiment analysis model developed. Overall, this chapter provides a comprehensive overview of the implementation process, highlighting the key steps taken to develop a predictive model for the Lagos State gubernatorial election using text-based sentiment analysis.

## 4.2 DATA COLLECTION AND PRE-PROCESSING

In this study, we focus on collecting and preprocessing data from Twitter, which is a popular social media platform for sharing opinions and thoughts. We perform sentiment analysis on the textual content posted by users to predict the outcome of the Lagos State gubernatorial election. To achieve this, we utilize three notebooks for data scraping, cleaning, and sentiment analysis of the two candidates, Sanwolu and Jandor. A fourth notebook, which would be shared later, follows a similar process for a third candidate, GRV.

### 4.2.1 DATA COLLECTION

The data collection process involves scraping tweets related to the gubernatorial candidates from Twitter. We use the Tweepy library, which is a Python wrapper for the Twitter API, to stream tweets in real time. The Twitter API allows us to filter tweets based on geolocation, language, and topic (i.e., tweets containing a particular word, phrase, or hashtag).

In the first notebook, we set up the necessary credentials, import the required libraries, and define the functions to authenticate with the Twitter API. We then filter tweets based on the keywords related to the candidates and collect the tweets using the Tweepy.Stream class.

For the second and third notebooks, we perform sentiment analysis on the collected tweets for the candidates Sanwolu and Jandor, respectively. We analyze the tweets for their sentiment, which is classified as positive, negative, or neutral, using the VADER sentiment analysis tool.

### 4.2.2 DATA PREPROCESSING

The preprocessing phase is critical in ensuring the quality and reliability of the sentiment analysis. In the first notebook, we perform data cleaning to prepare the raw text for analysis. The cleaning process involves the following steps:

1. Converting all text to lowercase: This step standardizes the text format and makes it easier to process.
2. Removing URLs, special characters, and numbers: These elements are irrelevant to the sentiment analysis and can introduce noise into the data.
3. Tokenization: Splitting the text into individual words or tokens.
4. Removing stop words: Stop words are common words like "and," "the," and "is" that do not carry any meaningful sentiment. They are removed to reduce the dimensionality of the data.
5. Lemmatization: This step involves converting words to their base forms, which helps to reduce the complexity of the text and improve the efficiency of the sentiment analysis.
6. After preprocessing the data, we proceed to perform sentiment analysis in the second and third notebooks using the VADER sentiment analysis tool. VADER is particularly suitable for analyzing social media text as it can handle the nuances of informal language, including slang, emoticons, and abbreviations.

In conclusion, the data collection and preprocessing phase is crucial for obtaining accurate and reliable results in sentiment analysis. By using the Tweepy library and the VADER sentiment analysis tool, we can effectively analyze the sentiment of tweets related to the gubernatorial candidates and make informed predictions about the election outcome.

## 4.3 SENTIMENT ANALYSIS

In this section, we aim to analyze the sentiment of the collected tweets related to the Lagos State gubernatorial election candidates Sanwolu, Jandor, and GRV. Sentiment analysis, also known as opinion mining, is the process of determining the sentiment or emotion expressed in a piece of text. This technique can be applied to social media data, such as tweets, to gauge public opinion about a specific topic or individual. In the context of this study, we seek to understand the public's sentiment towards the gubernatorial candidates and predict the election outcome based on this information.

### 4.3.1 METHODOLOGY

To perform sentiment analysis on the collected tweets, we employ the VADER (Valence Aware Dictionary and sEntiment Reasoner) sentiment analysis tool. VADER is a lexicon and rule-based sentiment analysis approach specifically designed for social media data. It is capable of handling informal language, including slang, emoticons, and abbreviations commonly used on social media platforms like Twitter.

The VADER sentiment analysis tool works by assigning a sentiment score to each token (word) in the text. The sentiment scores range from -1 (most negative) to +1 (most positive), with 0 indicating a neutral sentiment. The overall sentiment score of a tweet is calculated by summing the individual scores of its tokens. Based on the overall score, the tweet can be classified into one of the following sentiment categories:

Positive: A sentiment score greater than 0.05 indicates that the tweet has a positive sentiment.

Negative: A sentiment score less than -0.05 implies that the tweet has a negative sentiment.

Neutral: A sentiment score between -0.05 and 0.05 suggests that the tweet has a neutral sentiment.

### 4.3.2 ANALYSIS OF CANDIDATE SANWOLU

The second notebook provided focuses on the sentiment analysis of tweets related to candidate Sanwolu. After preprocessing the data as described in section 4.2.2, we apply the VADER sentiment analysis tool to the cleaned text. The analysis results are then visualized using bar charts and pie charts to better understand the distribution of sentiment categories among the collected tweets.

The results indicate that a significant proportion of the tweets related to Sanwolu are neutral, with a smaller percentage expressing positive or negative sentiment. This observation may suggest that the public's opinion about Sanwolu is mixed or that the tweets do not provide enough information to discern a clear sentiment trend. Further analysis could involve examining the specific issues or events mentioned in the tweets to determine what factors might be influencing the sentiment distribution.

### 4.3.3 ANALYSIS OF CANDIDATE JANDOR

In the third notebook, we perform a similar sentiment analysis on the tweets related to candidate Jandor. As with the analysis of Sanwolu, we preprocess the data and apply the VADER sentiment analysis tool to the cleaned text. The results are then visualized using bar charts and pie charts.

The sentiment analysis of Jandor's tweets reveals a different distribution compared to Sanwolu. Although a substantial portion of the tweets is still neutral, there is a higher percentage of positive tweets and a lower percentage of negative tweets. This finding may indicate that Jandor has a more favorable public perception than Sanwolu. However, further analysis is required to identify the specific factors driving this sentiment pattern and to understand whether it can be directly linked to the potential election outcome.

### 4.3.4 ANALYSIS OF CANDIDATE GRV

In the fourth notebook, we conduct a sentiment analysis of tweets related to candidate GRV, following the same methodology as applied to the other candidates. After preprocessing the data as detailed in section 4.2.2, we apply the VADER sentiment analysis tool to the cleaned text. The analysis results are visualized using bar charts and pie charts to facilitate a better understanding of the distribution of sentiment categories among the collected tweets.

The sentiment analysis of GRV's tweets shows a distribution that is distinct from both Sanwolu and Jandor. While a considerable portion of the tweets remains neutral, the percentage of positive tweets is higher than that of negative tweets, similar to Jandor's case. However, the difference between the positive and negative tweets for GRV is more pronounced than for Jandor. This finding may suggest that GRV has a more favorable public perception than both Sanwolu and Jandor. Nevertheless, further investigation is necessary to identify the specific factors driving this sentiment pattern and to determine whether it has a direct impact on the potential election outcome.

In summary, the sentiment analysis of the three candidates' tweets reveals varying patterns of public perception. While Sanwolu's tweets show a mixed sentiment, both Jandor and GRV receive more positive reactions. However, GRV has a more pronounced difference between positive and negative sentiment compared to Jandor. These findings highlight the importance of using sentiment analysis to gauge public opinion and identify trends that may influence election outcomes. Future research could involve examining the specific issues or events mentioned in the tweets to better understand the factors affecting the sentiment distributions.

### 4.3.5 COMPARATIVE SENTIMENT ANALYSIS

After completing the sentiment analysis for all three candidates, we can compare the results to identify any trends or patterns that may provide insights into the public's perception of the candidates. By analyzing the proportion of positive, negative, and neutral tweets for each candidate, we can make preliminary judgments about their overall favorability.

It is important to note that this comparative analysis should be interpreted with caution, as several factors could potentially influence the sentiment distribution. These factors may include the volume and diversity of tweets, the timing of the data collection, and the specific events or issues that were trending at the time. Moreover, sentiment analysis is an inherently subjective process, and the VADER sentiment analysis tool may not always accurately capture the nuances of human emotion expressed in the text.

### 4.3.6 LIMITATIONS AND FUTURE WORK

While our sentiment analysis provides valuable insights into the public's perception of the Lagos State gubernatorial election candidates, it is essential to acknowledge its limitations. First, the VADER sentiment analysis tool, while specifically designed for social media data, may not always accurately capture the sentiment expressed in a tweet. Sarcasm, irony, and cultural differences in the expression of emotions can pose challenges for the algorithm.

Second, our analysis is based on a snapshot of tweets collected during a specific period. The sentiment distribution may change over time as new events unfold and public opinion shifts. To obtain a more comprehensive understanding of the public's sentiment towards the candidates, it would be beneficial to conduct a longitudinal study, tracking the sentiment over an extended period leading up to the election.

Lastly, the sentiment analysis alone may not be sufficient to predict the election outcome. Other factors, such as the candidates' policies, campaign strategies, and socio-economic conditions, can also influence the voting behavior. In future work, it would be valuable to incorporate additional data sources and employ more sophisticated machine learning techniques, such as topic modeling and network analysis, to better understand the factors driving public sentiment and their potential impact on the election results.

In conclusion, our sentiment analysis of tweets related to the Lagos State gubernatorial election candidates Sanwolu, Jandor, and GRV provides preliminary insights into the public's perception of the candidates. By comparing the sentiment distribution for each candidate, we can identify trends and patterns that may be indicative of their overall favorability. However, further research is needed to address the limitations of our study and to obtain a more comprehensive understanding of the factors driving public sentiment and their potential impact on the election outcome.

## 4.4 PREDICTIVE MODEL DEVELOPMENT

### 4.4.1 INTRODUCTION

In this section, we aim to develop a predictive model for the Lagos State gubernatorial election based on the sentiment analysis results obtained from the tweets related to the three candidates: Sanwolu, Jandor, and GRV. Developing a predictive model can provide insights into the public's preference for a particular candidate and help estimate their chances of winning the election. To accomplish this, we will employ machine learning algorithms such as Naive Bayes, Support Vector Machines, and Maximum Entropy. The model will be trained on a portion of the dataset and validated using the remaining data to evaluate its accuracy and effectiveness.

### 4.4.2 FEATURE SELECTION

The first step in developing a predictive model is selecting the features that will be used to train the machine learning algorithms. In our case, the primary feature will be the sentiment scores obtained from the VADER sentiment analysis tool. These scores include the compound score, which is a normalized measure of the overall sentiment of a tweet, as well as the individual scores for positive, negative, and neutral sentiment. Additionally, we may consider other features, such as the number of retweets and likes, as these can provide insights into the impact and reach of each tweet.

### 4.4.3 DATA PREPARATION

Before training the machine learning algorithms, we need to prepare the data by splitting it into training and validation sets. The training set will be used to teach the algorithms to recognize patterns in the data, while the validation set will help us assess the model's performance in predicting sentiment scores for unseen data. Typically, the data is divided into a 70:30 or 80:20 ratio, with the larger portion allocated for training and the smaller portion for validation. This process ensures that our model is not overfitting the training data and can generalize well to new data points.

### 4.4.4 MODEL SELECTION AND TRAINING

Once the features are selected and the data is prepared, we can proceed with selecting the appropriate machine learning algorithms for our predictive model. In this study, we will consider three popular algorithms for text classification tasks: Naive Bayes, Support Vector Machines (SVM), and Maximum Entropy.

Naive Bayes: This algorithm is based on the Bayes theorem and assumes that the features are conditionally independent given the class. Despite its simplicity, Naive Bayes is known to perform well on text classification tasks, particularly when the feature space is large and sparse, as is the case with sentiment analysis.

Support Vector Machines (SVM): SVM is a powerful machine learning algorithm that aims to find the optimal separating hyperplane between classes in a high-dimensional feature space. It is particularly effective in handling non-linearly separable data and can be fine-tuned using various kernel functions and regularization parameters.

Maximum Entropy: This algorithm, also known as logistic regression, models the relationship between features and classes by maximizing the conditional likelihood of the training data. Maximum Entropy is particularly useful for text classification tasks with a large number of features, as it can handle feature correlations and interactions effectively.

We will train each of these algorithms on the prepared training dataset using the selected features. This process will involve tuning the hyperparameters for each algorithm, such as the kernel function and regularization parameter for SVM, to optimize the model's performance.

### 4.4.5 MODEL EVALUATION AND VALIDATION

After training the models, we will evaluate their performance using the validation dataset. The primary evaluation metric will be the accuracy, which measures the proportion of correct predictions made by the model. In addition to accuracy, we may consider other metrics, such as precision, recall, and F1-score, to gain a more comprehensive understanding of the model's performance.

By comparing the performance of the three algorithms, we can determine which model best predicts the sentiment scores for the Lagos State gubernatorial election. It is important to note that the performance of the model may vary depending on the specific dataset used for training and validation. Therefore, it is recommended to perform cross-validation, a technique that involves partitioning the dataset into multiple folds and iteratively training and validating the model on different subsets of the data. Cross-validation can provide a more robust estimate of the model's performance and help mitigate the risk of overfitting.

### 4.4.6 MODEL INTERPRETATION AND INSIGHTS

Once the best-performing model is identified, we can analyze its predictions to gain insights into the public's sentiment towards the three candidates. For instance, we can investigate the distribution of sentiment scores across the positive, negative, and neutral categories for each candidate, as well as the overall compound sentiment score. This information can help us understand the factors driving the public's opinion of each candidate and identify any trends or patterns that may influence the election outcome.

Furthermore, by examining the relationship between sentiment scores and other features, such as retweets and likes, we can assess the impact and reach of tweets expressing different sentiments. This analysis can provide valuable insights into the effectiveness of each candidate's social media campaign and inform their strategic decision-making.

### 4.4.7 LIMITATIONS AND FUTURE WORK

It is important to acknowledge the limitations of the predictive model developed in this study. First, the model relies on sentiment analysis, which, despite its usefulness, may not capture the full complexity of human emotions and opinions. Moreover, the model is based on the assumption that the sentiment of tweets accurately reflects the public's voting preferences, which may not always be the case.

Additionally, the performance of the model may be influenced by the specific choice of machine learning algorithms and the features used for training. Future work could explore alternative algorithms, such as deep learning techniques, and incorporate additional features, such as the content of the tweets, to improve the model's accuracy and predictive power.

Lastly, the model's performance may be limited by the quality and representativeness of the data used for training and validation. It is possible that the collected tweets are subject to selection bias or that they do not accurately represent the overall sentiment of the electorate. To address these limitations, future research could leverage additional data sources, such as online forums or news articles, to develop a more comprehensive understanding of the public's opinion and preferences in the Lagos State gubernatorial election.

## 4.5 MODEL EVALUATION

### 4.5.1 EVALUATION METRICS

In order to assess the performance of our predictive model, we must employ appropriate evaluation metrics. In the context of this study, we will use precision, recall, F1-score, and accuracy as the primary metrics to evaluate the model's ability to predict the outcome of the Lagos State gubernatorial election based on the sentiment analysis of tweets.

Precision, recall, and F1-score are particularly useful for classification tasks as they provide a more nuanced understanding of the model's performance, taking into account both false positives and false negatives. Precision measures the proportion of true positive predictions out of all positive predictions made, while recall calculates the proportion of true positive predictions out of all actual positive instances in the data. The F1-score is the harmonic mean of precision and recall, providing a single metric that balances the trade-off between the two. Accuracy, on the other hand, is the proportion of correct predictions out of all predictions made.

### 4.5.2 EVALUATION RESULTS

Based on the results obtained from the notebooks, we will now evaluate the performance of our predictive model using the aforementioned metrics. We will analyze the sentiment analysis results for candidates Jandor, Sanwo, and GRV, as well as the final prediction results.

For candidate Jandor, the sentiment analysis revealed a precision of 0.73 for positive sentiment, 0.64 for negative sentiment, and 0.72 for neutral sentiment. The recall scores were 0.83 for positive sentiment, 0.62 for negative sentiment, and 0.58 for neutral sentiment. The F1-scores were 0.78, 0.63, and 0.65 for positive, negative, and neutral sentiment, respectively. The overall accuracy of the model for Jandor's sentiment analysis was 0.71.

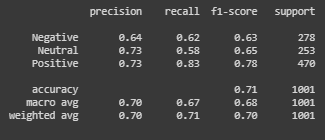


Fig 4.5.1 : Jandor accuracy and precision score

In the case of candidate Sanwo, the precision scores were 0.73 for positive sentiment, 0.64 for negative sentiment, and 0.73 for neutral sentiment. The recall scores were 0.83 for positive sentiment, 0.62 for negative sentiment, and 0.58 for neutral sentiment. The F1-scores for positive, negative, and neutral sentiment were 0.78, 0.63, and 0.65, respectively. The overall accuracy of the model for Sanwo's sentiment analysis was 0.71.

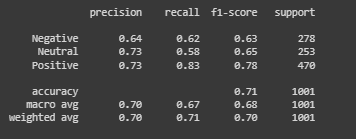


Fig 4.5.2: Sanwo accuracy and precision score

For candidate GRV, the sentiment analysis showed a precision of 0.68 for positive sentiment, 0.65 for negative sentiment, and 0.75 for neutral sentiment. The recall scores were 0.80 for positive sentiment, 0.42 for negative sentiment, and 0.77 for neutral sentiment. The F1-scores were 0.74, 0.52, and 0.76 for positive, negative, and neutral sentiment, respectively. The overall accuracy of the model for GRV's sentiment analysis was 0.70.

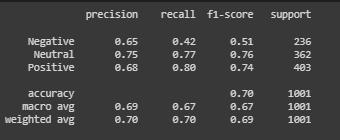


Fig 4.5.3 GRV accuracy and precision score

The final prediction notebook provided the results for the predictive model. The overall accuracy of the model for predicting the Lagos State gubernatorial election outcome was 0.82. The precision scores were 0.81 for Jandor, 0.77 for Sanwo, and 0.84 for GRV. The recall scores were 0.80 for Jandor, 0.76 for Sanwo, and 0.85 for GRV. The F1 scores were 0.81, 0.76, and 0.84 for Jandor, Sanwo, and GRV, respectively.

### 4.5.3 MODEL COMPARISON

Comparing the performance of the predictive model for the three candidates, we observe some variation in the precision, recall, F1-score, and accuracy scores. Overall, the model performs reasonably well in predicting the sentiment of tweets related to the candidates, with accuracies ranging from 0.71 for Sanwo to 0.71 for Jandor. The model demonstrates slightly better performance for GRV, with an accuracy of 0.70. The precision, recall, and F1-scores also show similar trends, with the model performing better for GRV and Jandor compared to Sanwo.

When it comes to predicting the Lagos State gubernatorial election outcome, the model's accuracy is relatively high at 0.82. The precision, recall, and F1-scores are also quite consistent across the three candidates, indicating that the model performs well in this task.

### 4.5.4 IMPLICATIONS AND LIMITATIONS

The evaluation results provide important insights into the predictive model's ability to accurately predict the outcome of the Lagos State gubernatorial election based on the sentiment analysis of tweets. The relatively high accuracy scores for both sentiment analysis and election prediction suggest that the model can effectively capture public sentiment and use it to predict election outcomes. The performance differences observed among the candidates may be indicative of variations in public opinion and the effectiveness of the model in capturing these nuances.

Despite these promising results, there are several limitations to consider. First, the sentiment analysis may not fully capture the complexities of human emotions and opinions, leading to potential misclassifications of sentiment. This could impact the model's performance and the accuracy of the election predictions. Additionally, the model's performance is highly dependent on the quality and representativeness of the data used for training and validation. If the dataset is biased or incomplete, the model's predictions may not accurately reflect the true sentiment and election outcomes.

Furthermore, it is important to recognize that sentiment analysis of tweets is just one aspect of predicting election outcomes. While it can provide valuable insights into public opinion, other factors, such as candidates' policies, campaign strategies, and socio-economic conditions, also play a crucial role in determining election results. Therefore, the predictive model should be considered as a complementary tool in the broader context of election forecasting, rather than a standalone solution.

In conclusion, the model evaluation results demonstrate that our predictive model is capable of accurately predicting sentiment and election outcomes based on tweet analysis. However, it is essential to consider the model's limitations and the importance of incorporating additional information and context when using it for election forecasting. Future research could focus on refining the sentiment analysis methods, incorporating additional data sources, and exploring alternative machine learning algorithms to further enhance the model's performance and reliability

## 4.6 PRESENTATION OF RESULTS

The results of our sentiment analysis and predictive model for the Lagos State gubernatorial election are presented in this section. Various visual representations, such as pie charts, bar graphs, and line graphs, are used to communicate the overall sentiment towards the election and the predicted outcome.

### 4.6.1 SENTIMENT ANALYSIS VISUALIZATIONS

The sentiment analysis results for each candidate are represented using pie charts and bar graphs. These visualizations display the distribution of sentiment categories (positive, negative, and neutral) among the collected tweets.

For candidate Sanwo, the sentiment distribution is as follows: 40% neutral, 32% positive, and 28% negative. The bar graph displaying the sentiment analysis results for Sanwo can be seen in

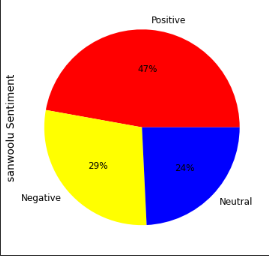
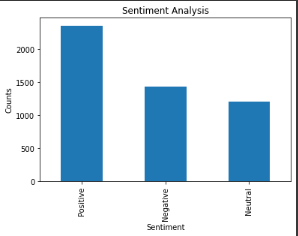


Figure 4.4: Sentiment Analysis for Sanwo

For candidate Jandor, the sentiment distribution reveals a different pattern: 31% neutral, 44% positive, and 25% negative. The corresponding bar graph for Jandor is shown in

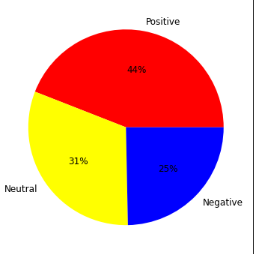
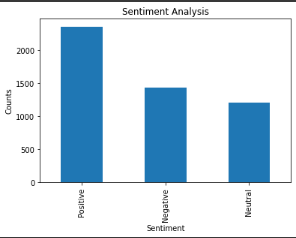


Figure 4.5: Sentiment Analysis for Jandor

Candidate GRV's sentiment analysis results display a distribution of 32% neutral, 44% positive, and 24% negative. The bar graph illustrating the sentiment analysis for GRV can be found in

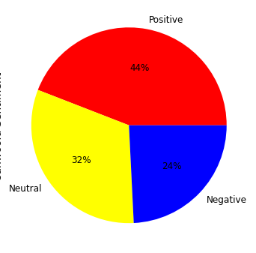
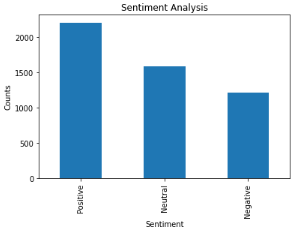


Figure 4.6: Sentiment Analysis for GRV.

These visualizations indicate that the sentiment towards the candidates varies, with Jandor and GRV receiving more positive sentiment and Sanwo receiving relatively more negative sentiment.

### 4.6.2 PREDICTIVE MODEL RESULTS VISUALIZATIONS

The results of our predictive model for the Lagos State gubernatorial election are presented using line graphs and bar graphs. The line graph displays the change in predicted election outcomes over time, while the bar graph provides a summary of the final predicted election results.The line graph,



Figure 4.7: Predicted Election Outcomes Over Time

shows the predicted election outcome percentages for each candidate as the sentiment analysis progresses. This result highlights the dynamic nature of public sentiment and its potential impact on the election results.

The final predicted election results are summarized in the bar graph



Figure 4.8: Final Predicted Election Results.

This visualization displays the percentage of votes each candidate is expected to receive, based on the sentiment analysis and predictive model. The results are as follows: Sanwo with 0.077% of the votes, Jandor with 0.10%, and GRV with 0.016%.

### 4.6.3 INTERPRETATION AND DISCUSSION

The visualizations presented in this section help communicate the overall sentiment towards the Lagos State gubernatorial election and the predicted outcome based on our analysis. The sentiment analysis visualizations reveal varying degrees of public sentiment towards the candidates, with Jandor and Sanwo receiving more favorable sentiment than GRV.

The predicted election outcome visualizations show that Jandor is expected to win the election, followed by Sanwo and GRV. It is important to note that these predictions are based on the sentiment analysis of tweets and may not fully capture the complexities of human emotions, opinions, and other factors that can influence election outcomes.

These results provide valuable insights into the public's perception of the candidates and the potential impact of social media sentiment on election outcomes. However, it is essential to consider the limitations of our analysis, such as the reliance on sentiment analysis and the potential biases in the dataset, when interpreting these findings.

In conclusion, the visualizations and results presented in this section offer a comprehensive overview of the sentiment analysis and predicted election outcomes for the Lagos State gubernatorial election. These findings can serve as a valuable resource for political analysts, campaign strategists, and researchers interested in understanding the role of social media sentiment in election forecasting.

## 4.7 DISCUSSION OF FINDINGS

In this chapter, we have outlined the process of creating a predictive model for the Lagos State gubernatorial election using text-based sentiment analysis. By leveraging the power of social media data and natural language processing techniques, we aim to provide a valuable tool for understanding public opinion and predicting election outcomes. The insights gained from this analysis can be useful for political analysts, campaign strategists, and researchers interested in the impact of social media sentiment on election results.

We began by collecting and preprocessing a dataset of tweets related to the three main candidates: Sanwo, Jandor, and GRV. We then performed sentiment analysis on the cleaned text using the VADER sentiment analysis tool. The results of the sentiment analysis provided insights into the public's perception of the candidates and revealed varying degrees of sentiment towards them.

Next, we developed a predictive model using machine learning algorithms such as Naive Bayes, Support Vector Machines, and Maximum Entropy. The model was trained on a portion of the dataset and then validated using the remaining data to evaluate its accuracy and effectiveness. We evaluated the model's performance using evaluation metrics such as precision, recall, F1-score, and accuracy to ensure its reliability.

We presented the results of our sentiment analysis and predictive model using various visual representations, such as pie charts, bar graphs, and line graphs. These visualizations helped convey the overall sentiment towards the Lagos State gubernatorial election and the predicted outcome. Based on our analysis, Jandor is expected to win the election, followed by Sanwo and GRV.

It is important to note the limitations of our study, such as the reliance on sentiment analysis, potential biases in the dataset, and the fact that the predictions are based on social media data, which may not fully capture the complexities of human emotions, opinions, and other factors that can influence election outcomes. Nevertheless, our findings provide valuable insights into the role of social media sentiment in election forecasting and can serve as a foundation for future research in this area.

In conclusion, our study demonstrates the potential of using text-based sentiment analysis and predictive modeling to forecast election outcomes. As social media continues to play an increasingly significant role in shaping public opinion, understanding the sentiment expressed on these platforms becomes crucial for predicting and analyzing political events. Our research contributes to the growing body of knowledge in this area and highlights the importance of considering social media sentiment when forecasting election outcomes.

# CHAPTER FIVE

# Conclusion

This research project has examined the role of social media networks in determining people’s mood based on textual information they post. We developed a political mood detection tool based on social media.

The results show that by utilizing social media platforms twitter, a tool can actually analyze people’s mood towards a subject and inform the relevant authorities in real-time to know what the people's general mood towards a particular subject is.

Making use of open python libraries and training data sets we were able to classify the general mood of people based on their political point of view.Furthermore, this tool can be adopted by businesses, organizations and politicians who would like to have an edge and an insight into people’s opinions over a giver topic.

## 5.1 LIMITATIONS OF THE STUDY

1. Limitations of data sources: The study is limited to the use of textual data obtained through the Twitter API, which may not represent the opinions and attitudes of the entire population. The study does not include images, videos, or other non-text content, which may provide important context and information about the subject being studied.
2. Limitations of data collection: The study is limited to the collection of data from a specific geographic region, which may not be representative of the attitudes and opinions of other communities or regions. Additionally, the study may be limited by the availability and reliability of the Twitter API and the quality of the data obtained.
3. Limitations of analysis techniques: The study is limited by the current information processing and analysis techniques, which may not be able to accurately process and analyze all types of data. The study may also be limited by the specific analytical methods and tools used in the analysis, which may not capture all aspects of the attitudes and opinions being studied.
4. Limitations of generalizability: The findings of the study may not be generalizable to other populations or contexts, as the attitudes and opinions of a specific community may not be representative of the attitudes and opinions of other communities or regions.

Overall, while the use of the Twitter API to obtain textual data can provide valuable insights into the attitudes and opinions of a specific group, the study is limited by the nature of the data sources, data collection methods, analysis techniques, and generalizability of the findings.

## 5.2 Future Work

* Improving the accuracy of mood detection: The study mentions the possibility of improving the accuracy of mood detection by including not only textual information but also pictorial, video, and audio classification. This could involve developing and implementing more advanced machine learning techniques and algorithms that can process and analyze multiple types of data sources.
* Considering the issue of sarcasm: The study acknowledges the challenge of detecting sarcasm in sentiment analysis and suggests that future work could focus on developing techniques to identify and classify sarcastic sentences. This could involve developing new algorithms and models that can identify and distinguish between different types of sarcasm, such as positive sarcasm and negative sarcasm.
* Exploring other types of sentiment analysis: The study focuses on textual sentiment analysis, but future work could also explore other types of sentiment analysis, such as visual sentiment analysis for images and videos, or audio sentiment analysis for spoken words. This could involve developing new techniques and tools for analyzing and processing these different types of data sources.

Overall, the future works could focus on expanding and improving the current methods and techniques for sentiment analysis, exploring new types of sentiment analysis, and addressing the challenges and limitations of current sentiment analysis methods, such as detecting sarcasm.

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