TEXT MINING ON TWITTER DATA TO EVALUATE SENTIMENT

BY

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Abstract

TWITTER DATA ANALYSIS ACCORDING TO SENTIMENT

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Social media platforms have been a major part of our daily lives. But with the freedom of expression there is no way one can check whether the posts/tweets/expressions are classified on which polarity. Since Twitter is one of the biggest social platforms for microblogging, hence the experiment was done on this platform. There are several topics that are popular over the internet like sports, politics, finance, technology are chosen as the source of the experiment. These tweets were collected over a span of time for more than 2 months via a cron job.

Every tweet can be divided into three categories based on sentiment analysis, positive, negative or neutral. In the process of analyzing the sentiment, Natural Language Processing is widely used for data processing like removing stopwords, lemmatization, tokenization and POS tagging. In this work, focus is on the detection and prediction of sentiments based on tweets, associated with different topics. There are several ways to carry out the analysis using libraries, APIs, classifiers and tools. The use of data mining techniques namely data extraction, data cleaning, data storage, comparison with other reliable sources and finally sentiment analysis is followed for this thesis. In this experiments and analysis, a comparative study of sentiment analysis of various tweets collected over a span of time, by using many data mining techniques is presented. The techniques used are mainly lexicon-based, machine learning based using Random Forest Classifier, API based Stanford NLP Sentiment analyzer and a tool called SentiStrength. The fifth way of analysis is an expert, i.e. a human carrying out the analysis. In this approach, the polarity of a particular tweet is found, analyzed and a confusion matrix is prepared. From that matrix tweets are broadly classified into 4 classes, namely False Positive, False Negative, True Positive and True Negative, which are used to calculate parameters like accuracy, precision and recall.

This entire task is transformed to a cloud-based web interface hosted on Amazon Web Services to carry out the operations without human intervention on live data.

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PROBLEM STATEMENT

Twitter is one of the biggest platforms of expressing a person's feeling on a social media. These set of information can be used in several ways as data to analyze or deduce something. There is a lot of things happening around the world in the field of politics. This is affecting the common people in mass. For example, if a new amendment law has been passed it can have its own pros or cons depending on the set of people and how they are affected. I wanted to therefore analyze the sentiment of each tweets and find out whether they are inclined more towards positive or negative polarity. This in future would help in determining whether the political situation is getting better or worse. This kind of analysis would set an alarm in the world and politicians would get a feedback of whether their practices are creating a negative or positive impact to the world.

Plus, the data sources are vast and vivid, that it is difficult to analyze it and access it. Had it been a single source of data, checking the authenticity or polarity would have been easier. However, Twitter seems to be a good source to predict the polarity of several topics like politics, finance, sports and technology.

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Chapter 1

Introduction

1.1 Introduction and background

From the past few years, social media plays a vital role in modern life. Numbers of users of social media goes on increasing day by day. Users post their view, thoughts, life events on social media and that too without any restriction and hesitation. Some of the social media allow users to interact with only with their friends and sharing their post with very easy level of privacy. Due to simple and easy privacy policies, and easy accessibility of some social media, users are migrated from traditional means of communication such as blogs or mailing list to microblogging sites such as Twitter, Facebook etc. Billions of text data in the form of messages on social media make it a very fascinating medium for data analysis for the researchers.

In this thesis, Twitter was chosen as the platform for analysis. This is a social media website where people are able to express with the help of tweets that are basically a string of words. Millions of people are using this platform to express their views on any matter or current affairs. But there is an immense risk of determining how authentic these posts were. So with the help of certain useful parameters like accuracy, false positive tweets, false negative tweets, recall and precision efficiency was measured on the analysis. Each and every term and idea will be discussed in further depth in the upcoming chapters.

On working on this thesis, there were many things to be noted as to how to make use of data analysis to meaningfully carve something. The focus of analysis was then chosen as sentiments of tweets, that is closely connected to opinion mining. There are more heinous crimes that are committed and there has to be some sort of an alarming situation to stop this or at least reduce it. This analysis was done with the profiting the society and the world in future to gradually irradiate the amount of violence in this world. Text analysis and opinion mining have now become a very important part of our daily lives to deduce a lot of results that can be useful.

1.2 Motivation behind the thesis

Staying safe is a topic which continues to be relevant as terrorist attacks are no longer a surprise and mass shootings seem to be increasingly common. Is almost every destination in the world a potential danger?

In fact, according to the latest Safe Cities Index, some places pose considerably more risk than others. The report was released late last year by The Economist Intelligence Unit, the research and analysis division of The Economist Group, a London-based company that specializes in international business.

The index ranked the safety of 60 international cities across four categories, including personal security, which scored each city on factors such as the number of terrorist attacks, crime rates, threat of military conflict and threat of civil unrest.

The Safe Cities Index was first published in 2015, and the not-so-good news in the second version released in 2017 is that levels of personal security appear to have declined in the past two years, said Christopher Claque, a managing editor at The Economist Intelligence Unit and the creator of the index.

In the field of technology too, trending software and digitalization is changing continuously over time. It is very important to keep a check on all the new changes and stay well informed and well equipped with the upcoming technologies.

Under such circumstances, this thesis attempts to provide analysis that may caution the world of the negativity and pain that is occurring around the world. As this analysis will help in the future to detect the polarity of a tweet and would set an alarm to the world and in this way, we can bring a ray of peace and harmony to the world.

1.3 Goal of the thesis

The main objective of this thesis is to implement machine learning based data analysis for finding sentiment or polarity for a particular tweet.

In order to get more appropriate results, the data goes through several steps of data was collected over a large amount of time over many vivid topics. Then a proper cleaning of data was performed to normalize the piece of information received. Steps have also been taken to quantify the attributes with the help of machine learning algorithms and any possible noise or outliers are marked. So that extreme results are not considered. Information regarding possible polarity of tweets helps us in setting alarms of violence or peace in the world.

1.4 Organization of the thesis

The thesis in Chapter 1 start with an introduction and background about the topics, it also covers the motivation and goals of the work. Chapter 2 gives an overview of related work. Chapter 3 dives into an insight into the several components that play a role in this work. Chapter 4 provides the background of the problem statement. Chapter 5 describes the input data that is used, in this case tweets. Chapter 5 discusses the preliminary stages of the experiment performed. Chapter 6 deals with the actual experiment and the analysis of the results obtained with visualization. Chapter 7 performs the usage of cloud in the entire implementation. Chapter 8 discusses a Case Study on discussing various cases of implementing the sentiment analysis. Chapter 9 deals with the conclusion and inference of the thesis. Chapter 10 deals with the Future Work that can be implemented with respect to this experiment.

Chapter 2

Related Work

With the advancement of net and social platforms, the biggest challenge is to obtain data from reliable sources and good data that would obtain results for accurate analysis. In order to conquer the first challenge, Twitter was chosen as the data source. Since the focus was more on sentiment analysis, data was be collected from various people with vivid mentality, living conditions, dwelling areas etc.

Another challenge was data preprocessing and choosing the dimensionality of data, so that the analysis fetched results as efficient as possible. Data preprocessing comprises of several steps and since data here were tweets, the main goal was to remove junk information as much as possible. Also choosing the right dimensions of data and the right column for performing our analysis. In the below section, these are the topics to be discussed about.

2.1 Tweets

Twitter is one of the most popular social networking sites where users could post their thoughts, expressions or beliefs. Every post can be of 140 characters. These posts can be viewed only by their followers. There are numerous topics on which one can write, on a social topic, newsfeed or just a feeling. [1] Twitter gives full freedom to users to choose their followers. A tweet can only be viewed by followers. If one has a public account, then the posts will be visible to all like for celebrities.

2.2 Data Mining

Data mining is the process of collecting data through various resources and finding some useful patterns based on it. Meanwhile the raw data collected is in a raw form and may contain a lot of outliers and have to be normalized. This can be done through the process of data cleaning. Once an analysis is done, the next step is to interpret the analysis through some results. The results obtained are done through some calculations and can also be visualized by charts.

To conclude, the steps that are followed to carry out successful data mining process are

1. Collecting data from various data sources
2. Cleaning the collected data by removing outliers and normalizing the data.
3. Analyzing the data to find some interesting patterns.
4. Interpreting the results and visualizing it.

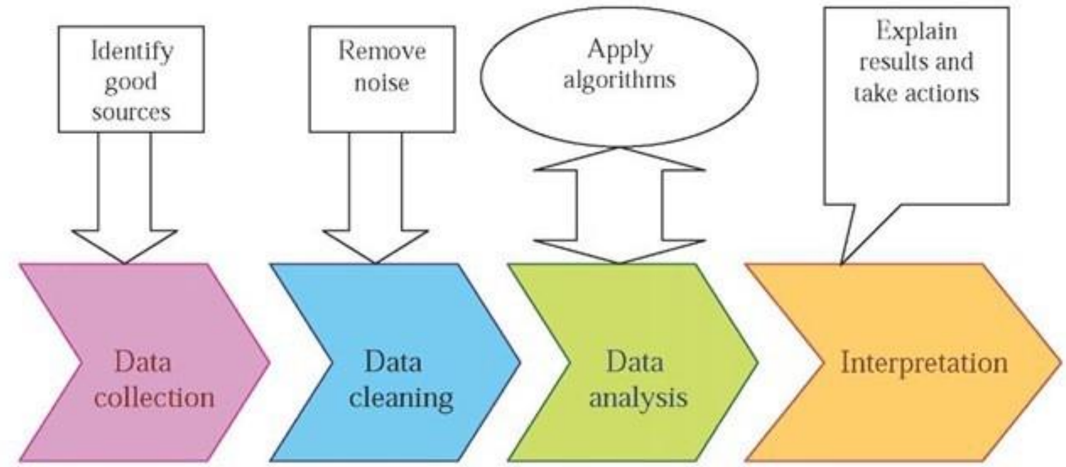


Fig 2.1[37]

2.3 Sentiment Analysis

Sentiments are the emotional condition one portrays while speaking/writing on a topic Analysis of sentiments is to find the attitude of a speaker or writer while they are writing or talking about a post. This can be determined with a measure known as polarity. Polarity can be of three type, positive, negative or neutral. [4]

2.4 Natural Language Processing

Natural language processing is the process of interpreting text or speech with the help of machine learning algorithms. Natural language processing is the machine's approach to interpret texts and divide sentences to words, tag words according to their parts of speech, grammar checking, correction of spelling and further advanced tasks as well like sentiment analysis, context extraction etc.

The common tasks done by NLP are:

- **Tokenization**: A process to break a sentence into individual words or a paragraph to individual sentences.
- **Parts of speech tagging**: A process to categorize every word of a text/speech to 16 categories of parts of speech.
- **Grammar Checking:** Natural language processing can check the grammar for a sentence by introducing regular expressions or using a context-free parser.

- **Sentiment analysis.** Identifying the mood or opinion to how a speaker/writer feels on a particular text/speech.

- **Speech-to-text and text-to-speech conversion.** Transforming voice commands into written text, and vice versa. [5]

2.5 AWS EC2

Amazon Elastic Compute Cloud (Amazon EC2) is a web service that provides secure, resizable compute capacity in the cloud. It is designed to make web-scale cloud computing easier for developers.EC2 is the only service that uses Infrastructure as a Service (IAAS) which gives the user the freedom to choose the server and operating system while the network and database is chosen by the cloud service provider. [6]

2.5 AWS RDS

Amazon Relational Database Service (Amazon RDS) is a relational database that is hosted in the cloud. It supports a cost-effective, easy to setup alternative to the classic databases. AWS RDS is an effective database system that is compatible to several database providers like MySQL, Microsoft SQL Server and MongoDB as well[7]. In this project I have used the database instance for MySQL

Chapter 3

An insight into the components used and the approach

3.1 Choosing correct parameters in Tweets

TWEET1.csv

So, on the basis of the attached file, there are several columns. Since we were doing text analysis, we were just interested in the main tweet that was in the text format. The rest columns that is used and is helpful is the column named “IsRetweet”, It deliberately made an attempt to choose only those tweets whose “IsRetweet” was FALSE. Else the same tweet reappearing may enable fake results. Also, the “favorited” column was considered only for “TRUE” values. Since this would mean they are the popular tweets and match the opinion with many users.

3.2 Data Preprocessing techniques

1. Text data are gradually stored into dataframes and have to be decoded to a correct format. On further research it is found UTF-8 is the best format for dataframes as well as when exported to Excel.
2. Some words do not add any significance in finding the opinion of users. These words as known as stopwords like as, is, politics, science etc. These words are removed before the text analysis is done
3. Punctuations are divided into priority. So punctuations like?, ., ! are retained and other like , “”, $, # etc are removed.
4. Emoticons and expressions are an amalgamation of punctuation marks, hence these are also removed as this could be misleading at times.
5. Every tweet is followed by a URL that provides a link to the actual tweet. This is not required and removed.
6. Lemmatization is the technique of chopping words to remove their syllables and just keeping back the basic word. For example working is changed to work .Lemmatization also checks whether the chopped word exists in the dictionary or not and then saves it.

3.3 Sentiment analysis

Sentiment Analysis is the most common text classification tool that analyses an incoming message and tells whether the underlying sentiment is positive, negative our neutral. This is also described as opinion mining, since we can derive a person’s opinion or attitude who is posting.

In political field, it is used to keep track of political view, to detect consistency and inconsistency between statements and actions at the government level. It can also check whether the politics is leading to good or bad things. In other words, has there been some peaceful news or work or is it still violent and negative. It can be used to predict election results as well.

Choosing the threshold value is an important aspect of doing this analysis. In this thesis, it was maintained the basic numeric rule of 0 is the threshold for neutral tweets. However, there are other aspects that help in determining the threshold value and in turn change the analysis that is being performed.

Sentiment analysis gets more meaningful and interesting when a kind of weight is attached to every sentence. This weight helps in categorizing sentiments in a more accurate way. The weights chosen in this project was the Parts of speech tagging. Parts of speech denotes the category to which a word belongs. In English language, words can be categorized into 8 sets, namely noun, pronoun, adjective, adverb, verb, preposition, conjunction and interjection.

However, in this project NLTK is used for parts of speech tagging. The NLTK tool places words in several categories.

PARTS OF SPEECH	DESCRIPTION
CC	Conjunction, joining words
ADJ	Adjective to describe a noun
DT	Determiner
IN	Preposition
JJ	Adjective, like big
JJR	Adjective, comparative, like bigger
JJS	Adjective, superlative, like biggest
NNS	Plural noun, chocolates
NN	Singular noun, chocolate
NNP	Proper noun, like Donald Trump
PRP	Personal pronoun, I, HE, SHE
PRP$	Possessive pronoun, his, her
UH	Interjection
RB	Adverb
RBR	Comparative adverb
RBS	Superlative adverb
VB	Verb
VBD	Verb, past tense
WRB	Wh -adverb where, when

Table 3.1

On all the tags that are marked by the NLTK tool, there are some categories which would be considered as the weights for sentiment analysis. The adverb, verb, adjective and noun would be considered in this experiment and the rest will be ignored. In the categories of adverb, 3 classes are considered.

Class 1: The RB class that defines an adverb plain. For example, if the sentence is “She is looking good”

Class II: RBR this denotes a comparative degree of adverb, which means when a comparison is done between objects then this degree is used. For example, we say “She has done better in her test than him”. In this context it is clear that she has a better score and therefore will have a more weight attached. This is because it will help in signifying whether an act is more positive or negative

Class III: This is the superlative degree which denotes the highest degree for describing a verb. For example, “Her performance was the best in the class”. This signifies a even more positive or negative sentiment and has more weightage.

So, clearly it can be concluded that Case III has the highest weightage followed by Case II and case I.

In case of adjectives, a similar rulebook can be set up, where JJS has the most weightage followed by JJR and JJ

In this context, let the rest of the categories be given weightage accordingly. The existence of a verb helps in defining a sentiment in a better way than that of a noun. Similarly, then a verb will have more weightage than that of a noun.

So, if a weighted matrix is performed the list would go as,

Verb

Adverb

Noun

Adjective

3.4 Sentiment Analysis Classification: Techniques

In the Sentiment Analysis field, the biggest concern is to classify text into polarity according to opinion expression. The two classes can be either positive or negative polarity. To this an additional category can also be added, namely neutral sentiments. Sentiment Classification is mainly divided into two different approaches: the machine learning approach and lexicon- based approach.

The Lexicon-based approach uses a collection of positive, neutral and negative sentiment terms and can be divided according to a predefined corpus or dictionary. The Machine Learning approach uses classification algorithms, and Sentiment Analysis is classified similar to other text classification. The Machine learning classifiers are divided into supervised learning and unsupervised learning. In the next two sub-sections we will expand on these two approaches.

3.4.1Machine Learning Approach

The Machine Learning approach treats classification of sentiments as any other text classification problem. Text classification is based on making decisions to classify to the correct categories. [25]. It uses a set of training data to train a model that is used to predict new data that does not belong to any class. Each record is labeled to a class. When a new unlabeled record is served as an input, in this case it is a series of tweets, the model is used to predict its label class. These classes are positive, negative or neutral, however, most of the time. The classifiers do not categorize to neutral sentiments. In the Machine Learning Approach there are two different sub-approaches based on the learning method used, supervised or the unsupervised learning. The supervised learning uses a supervised classifier, which learns from training datasets and categorizes the test data into the right label. These predefined labels help in determining the opinion for the upcoming. The Supervised Learning algorithms are namely Decision Tree, Linear, Rule Based and Probabilistic Classifier.

3.4.2 Lexicon-Based Approach

Lexicon-based method is another unsupervised approach, but in this case, it uses a dictionary or corpus of words that are already classified according to sentiments. The two approaches commonly used to categorize the sentiment of a word are the dictionary-based and the corpus-based.

The Dictionary-Based approach has a strategy of manually collecting a small set of opinion words and a larger set to the remaining words are added by searching similar words and creating a WordNet. The cycle is repeated until no more words are to be found. The biggest problem of this method is that it depends on the dictionary and user may not always have all the words it requires present in the dictionary.

The Corpus-Based approach is done by finding the sentiments for a few words. Then expanding the corpus by finding synonyms and antonyms and finding their polarity. This approach has a drawback and is not as effective as the dictionary-based approach because it would need a corpus with all the English words.

Chapter 4

Data

The tweets are collected over a long period of time on many topics. The tweets were collected with the help of a cron job running on the AWS EC2 server that creates a CSV (Comma separated value) file named on that particular date(for example 12-11-1018). We consider a weekly time granularity because most machine learning algorithms work well on large sized datasets, and one month is a reasonable time period to differentiate between polarity of tweets.

4.1 Cron job

A cron job is an activity that occurs at a particular time daily, weekly or at regular intervals by the server automatically without any human intervention. This is mainly done to cary out a redundant job automatically. [8].

Each line of a crontab file represents a job, and looks like this:

```
# ┌───────────── minute (0 - 59)
# │ ┌───────────── hour (0 - 23)
# │ │ ┌───────────── day of the month (1 - 31)
# │ │ │ ┌───────────── month (1 - 12)
# │ │ │ │ ┌───────────── day of the week (0 - 6) (Sunday to Saturday;
# │ │ │ │ │                                   7 is also Sunday on some systems)
# │ │ │ │ │
# │ │ │ │ │
# * * * * * command to execute
```

Figure 4.1[36]

4.2 The raw data that is collected contains 16 types of information,

Column Name	Description
Id	The auto increment column to uniquely identify each row
Text	A string field for displaying the actual tweet written
favorited	A Boolean field to denote whether the tweet has been favorited or not
favoriteCount	A field to count the number of times the tweet is favorited
created	The date on which the tweet was created
truncated	Whether the tweet has been truncated or not

id	Id of the user who posted the tweet
statusSource	URL to the actual Twitter location of the post
screenName	The name used by user to post the tweet
retweetCount	The number of retweets posted on the original tweet
isRetweet	Whether that particular tweet is a retweet or a primary tweet
retweeted	A Boolean value to represent whether a tweet is retweeted or not
longitude	The longitude of the user tweeting
latitude	The latitude of the user tweeting

Table 4.1

As is observed from the above table, there are a lot of unnecessary and redundant information. There is a great deal of information that has to be normalized and cleaned. On extracting the tweets, the fields latitude and longitude columns were removed, as it was not adding any information required the kind of experiment were to be performed.

We also wanted to extract only those rows that are not retweets so that there were only unique rows to extract as much as text possible, later used for text mining.

CHAPTER 5

PRELIMINARY ANALYSIS

This section is dedicated to the stepping stones of this thesis. The first part of the thesis involved implementing a proof of concept to detect anomaly patterns in the datasets. The proof of concept was executed locally. Some analyses were performed before the ideation of the proof of concept.

5.1 Extraction of tweets

5.1.1. Getting Twitter API keys

We need a Twitter account that would help generate some authentication keys and tokens (i.e. API key, API secret, Access token and Access token secret) on the Twitter developer site to access the Twitter API, following these steps:

- Logging in to https://apps.twitter.com/ with proper credentials
- All the details are filled, and we submit the form
- In the next page, click on "Keys and Access Tokens" tab, and copy "API key" and "API secret" and further create my access token", and copy your "Access token" and "Access token secret".

5.1.2. Connecting to Twitter Streaming APIs

There are 2 types of API namely Streaming API and Rest API. Everyday Twitter is responsible for extracting around 600 tweets in a minute. However, Streaming data can only extract 1% of it. The REST API on the other hand helps in retrieving tweets over a certain search criterion and over a time period. Both the APIs have advantage, but for this experiment the Streaming API is chosen as live data was the input for this experiment.

There will be 4 types of uniquely identifying tokens and keys used for OAuth authentication, namely ACCESS_TOKEN, ACCESS_SECRET, CONSUMER_KEY, and CONSUMER_SECRET. [9]

5.1.3 OAuth

OAuth 2.0 is an authorization mechanism to connect to Twitter from a desktop, mobile or other interfaces..

5.1.4 Tweepy library

This provides a wrapper for the API as provided by Twitter to easily used by Python language. The functions provided in this class are listed below.

Function Name	Description
auth_handler	This decides the type of authentication handler to be used
host	The local host name
search_host	The name of the host to be searched
cache	The cache background to be used
api_root	The general API path root
search_root	The search API root
retry_count	The default number of times retry attempts can be performed
retry_delay	The number of seconds to be waited before retrying
retry_errors	The HTTP error codes generated on retry
timeout	Maximum response time
parser	The object used to parse the tweet
compression	Boolean value to denoted whether the expression is zipped or not
wait_on_rate_limit	Boolean value to denote whether tweepy should wait on rate limit
wait_on_rate_limit_notify	Boolean value to denote whether to wait when rate limit is over
proxy	URL of the HTTP proxy

Table 5.1

•

5.2 Cleaning of tweets

Cleaning of the tweets is very important to remove noise and outliers as that would greatly affect the analysis on the data done.

5.2.1 Dataframes

The extracted tweets are first read from the csv file and then converted to dataframes using the panda library. Dataframes are two-dimensional tabular datastructure that has to axes, i.e. rows and columns. [11]

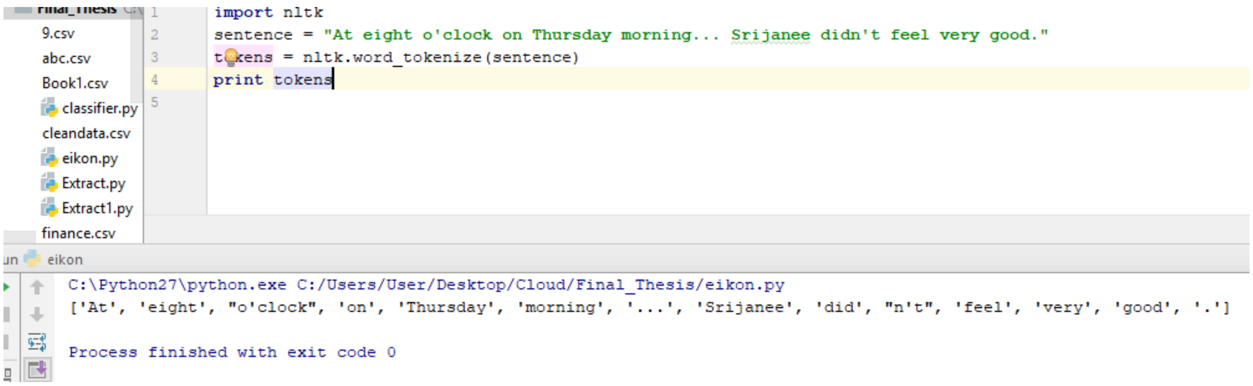
5.2.2 Pandas library

Pandas [12] is an open-source Python that is free. It not only stores a lo of data but also performs many data analytics efficiently. It includes tools for efficiently reading and writing data between in-memory data structures and different textual file formats, such as comma-separated value files, Excel, text files and many other.

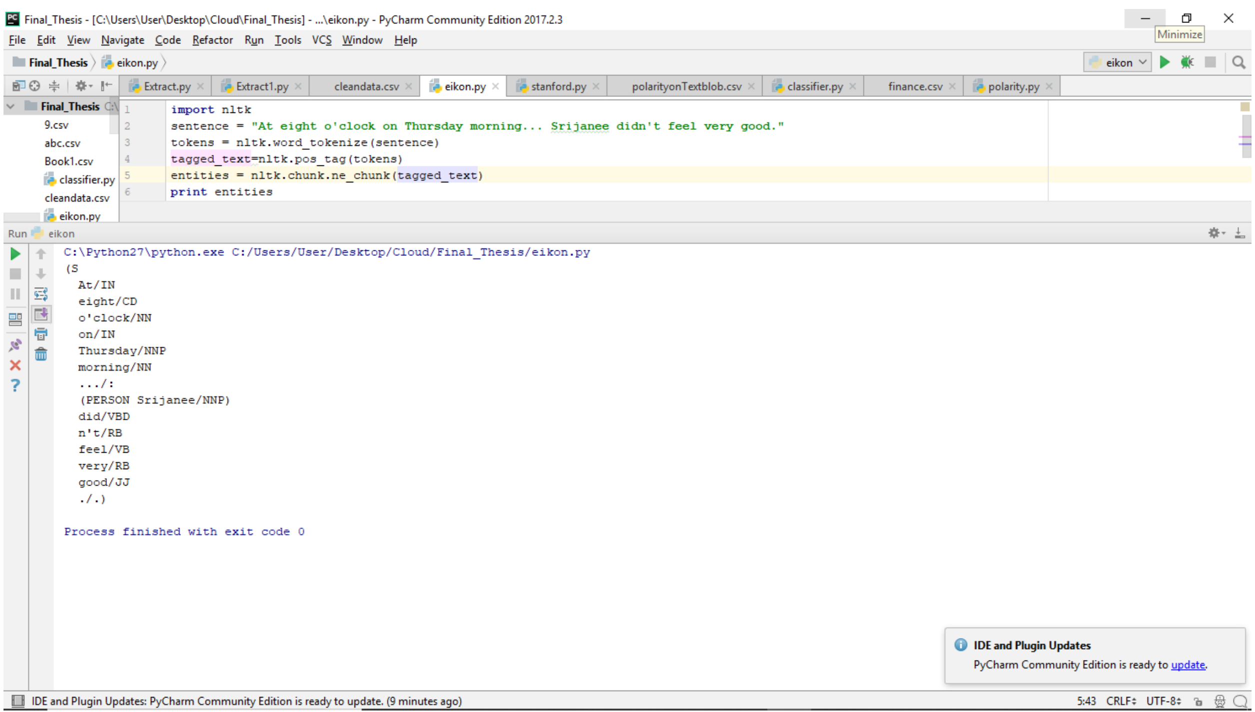
5.2.3 NLTK

NLTK (Natural Language Tool Kit) is a library used in Python that performs natural language processing.It can be used for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries. NLTK is an open-source free library. [13]

Tokenize and tag some text:



Identify named entities:



Display a parse tree:

```
from nltk.corpus import treebank
t = treebank.parsed_sents('wsj_0001.mrg')[0]
t.draw()
```

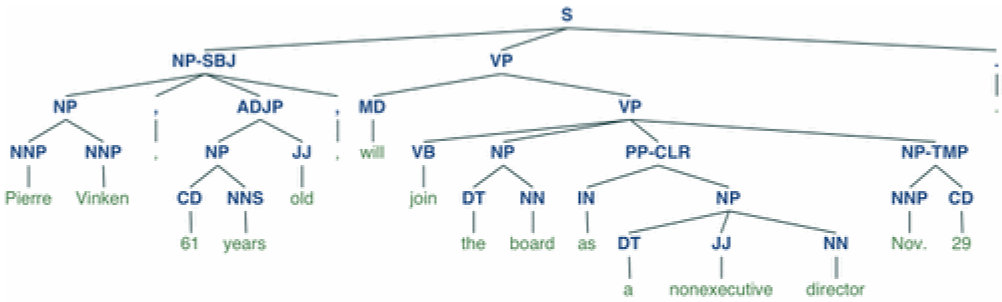


Fig 5.1

5.2.4 Data clean up

Initially all the punctuation marks, hyperlink/ URL and all the text were converted to lowercase.

The stopwords from the tweets are removed

Fig 5.2 Stopword sample for tweets collected over the topic technology

Further, the data is preprocessed with the help of stemming and lemmatization. Stemming usually refers to a process that just removes off the ends of words without any defined rule.Often it is observed that the shorter word does not have any meaning as per the English dictionary.Like ponies are transformed to poni, which does not exist in the English dictionary.

Lemmatization usually refers to remove ends of words in a more systematic manner with the use of a proper reference to a dictionary, which is referred to as a lemma. In this process, every time lemmatization occurs, it checks whether the new formed word occurs in the lemma or not. If the word is present in the lemma, then the chopping is done else the original word is returned. Linguistic processing for stemming or lemmatization is often done with the help of a particular algorithm or other external plug-ins. The algorithm used is Porter's algorithm. Porter's algorithm consists of 5 phases of word reductions, applied sequentially.

(F)	Rule			Example		
	SSES	→	SS	caresses	→	caress
	IES	→	I	ponies	→	poni
	SS	→	SS	caress	→	caress
	S	→		cats	→	cat

Further rules are applied like to checks the number of syllables to see whether a word is long enough to be described as a word or not. [14]

The clean data is then transferred to a CSV file. Now the clean data is stored in a database in the cloud, we used AWS RDS and the database instance of MySQL.

cleandata.csv

5.3 Initial Analysis

Tweets along with the fields has a lot of information embedded This could be helpful for some initial analysis that would be useful to carry out opinion mining.

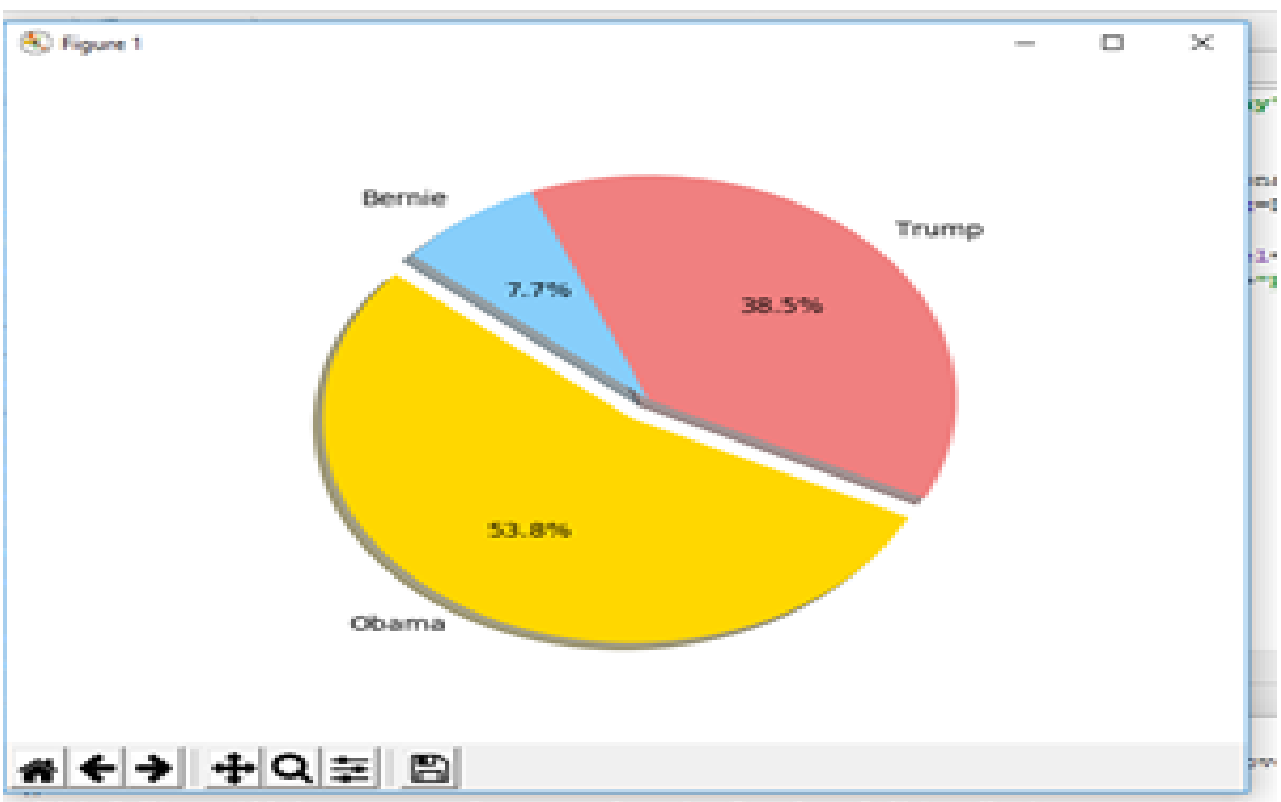


Fig 5.3

This image on the top denotes the interesting words that have come in the tweets extracted with the topic of politics. It is easily understandable; the most popular topic/person is Obama. But the question arises whether the word Obama is used to denote a negative or a positive sentiment.

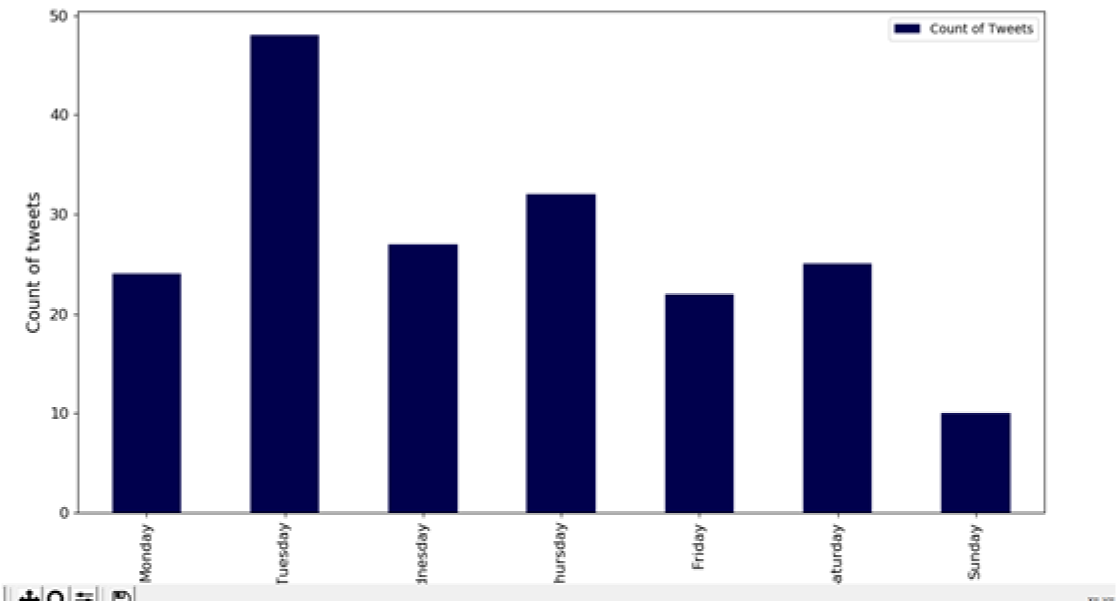


Fig 5.4

This denotes the number of tweets that are extracted over a few weeks and how the number is increased or decreased over the Weekdays.

The figure below denotes the frequency of every word used.

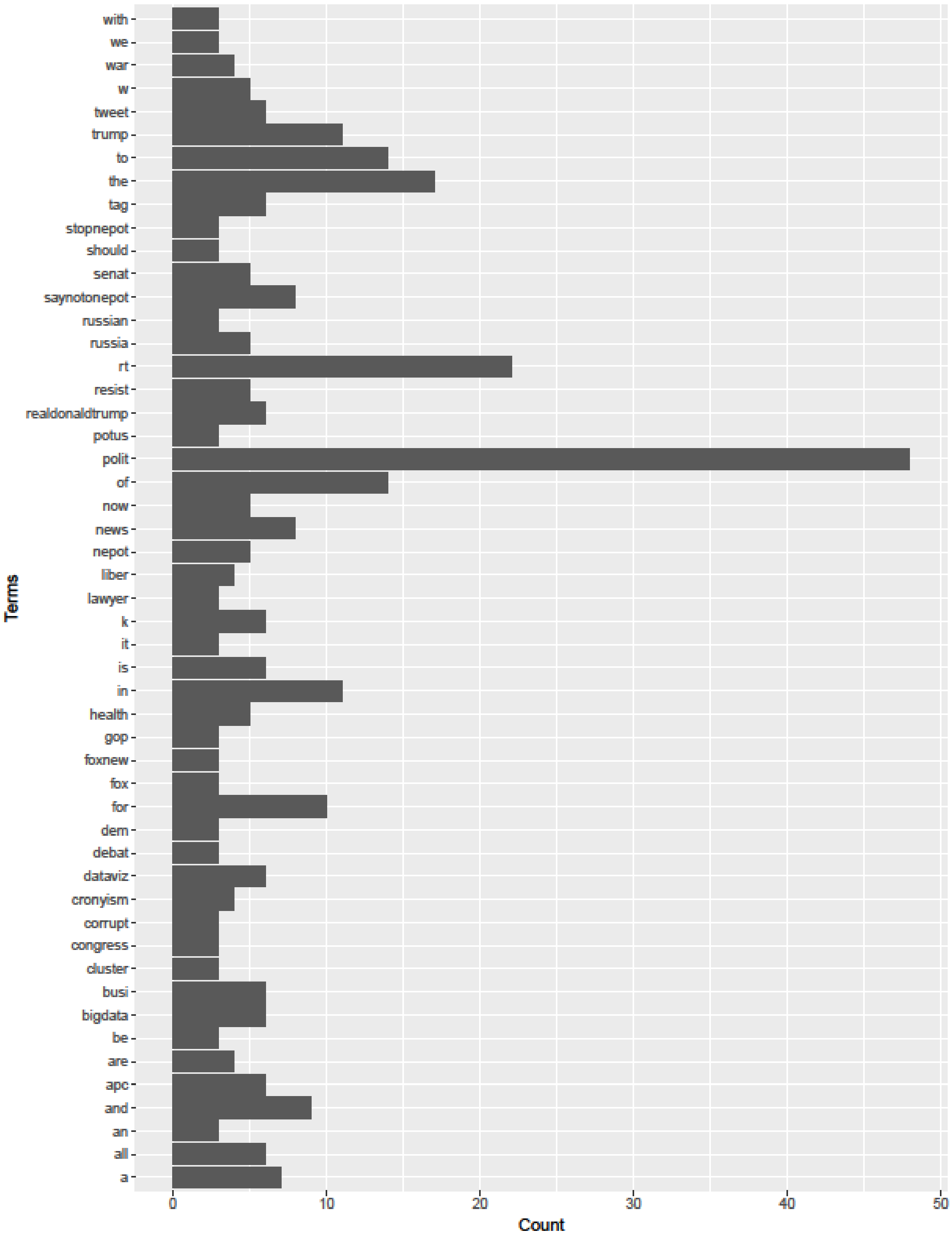

Terms
with
we
war
w
tweet
trump
to
the
tag
stopnepot
should
senat
saynotonepot
russian
russia
rt
resist
realdonaldtrump
potus
polit
of
now
news
nepot
liber
lawyer
k
it
is
in
health
gop
foxnew
fox
for
dem
debat
dataviz
cronyism
corrupt
congress
cluster
busi
bigdata
be
are
apc
and
an
all
a
0
10
20
30
40
50
Count

Fig 5.2

Chapter 6

Experiment and Analysis

On the data received, we are going to do a sentiment analysis. The objective is to class by types the tweets. We are going to distinguish 3 kinds of tweets according to their polarity score. We will have the positive tweets, the neutral tweets, and the negative tweets. We are going use several different approaches to evaluate the polarity of tweets. Then we calculate certain parameters to find the comparative report on the polarity of tweets

- First, we design a confusion matrix on the polarity of the tweets that are classified. There are two possible predicted classes: "yes" and "no". If we were predicting the presence of a person is pregnant or not, for example, "yes" would mean the lady is pregnant, and "no" would mean they are not.
- The classifier made a total of 165 predictions (e.g., 165 patients were being tested for the presence of that fetus or not).
- Out of those 165 cases, the classifier predicted "yes" 110 times, and "no" 55 times.
- In reality, 105 patients in the sample are pregnant, and 60 patients do not.

Let's now define the most basic terms, which are whole numbers (not rates):

- true positives (TP): These are cases in which we predicted yes (they are tested pregnant) and are actually pregnant.
- **true** negatives (TN): We predicted no, and they are not pregnant
- false positives (FP): We predicted yes, but they don't actually are pregnant. (Also known as a "Type I error.")
- false negatives (FN): We predicted no, but they actually are pregnant. (Also known as a "Type II error.”) [15]

N=165	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=50	FP=10	60
ACTUAL YES	FN=5	TP=100	105
	55	110	

Table 6.0

Therefore,

Accuracy=*True Positive/Total positive tweets +True Negative/Total Negative tweets*

Precision=True Positive/True Positive +False Positive

Recall=True Positive/true Positive +False Negative

=True Positive/Total Actual Positive

6.1 Sentiment analysis using Textblob

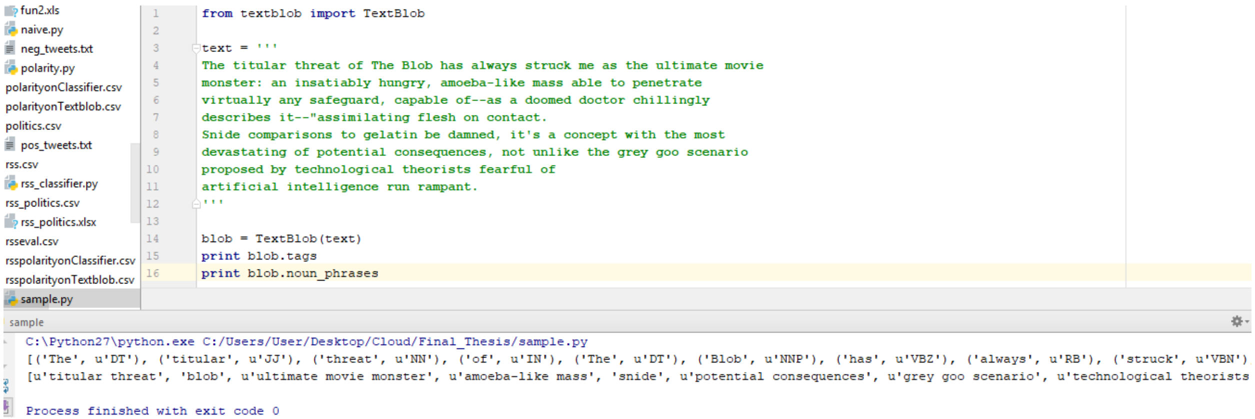
Textblob is a Python (2 and 3) library for processing textual data. This is a simple, open source API which is based on natural language processing to analyze sentiments. [16]

On evaluating text using textblob, two new results are obtained, i.e. polarity and subjectivity. For sentiment analysis, the main goal would be to classify the polarity of a given text at different levels —whether the expressed opinion in a document, a sentence or an entity feature/aspect is positive, negative, or neutral.

Subjective sentence expresses some personal feelings, views, or beliefs. For example, the statement “The sun rises on the east” this is a fact and hence it is an objective statement. However if a statement is like “I think they live at Clinton Street” is a subjective statement since this expresses someone’s belief, assumption. Subjectivity field is a float value that can take a value ranging from 0.0 to 1.0 where 0.0 is very objective and 1.0 is very subjective. [17]

The results obtained is again saved in a CSV file

polarityonTextblob.csv



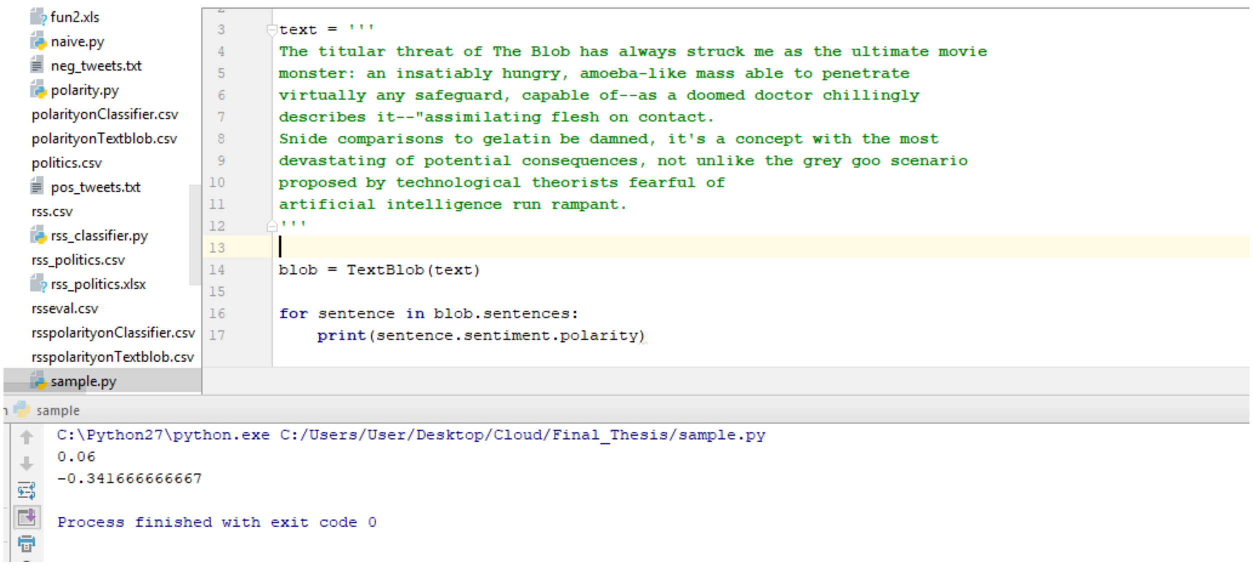


Fig 6.1

The above figure shows the different functionalities with TextBlob. TextBlob is a library that performs many natural language processing tasks quickly and with a lot more accuracy.

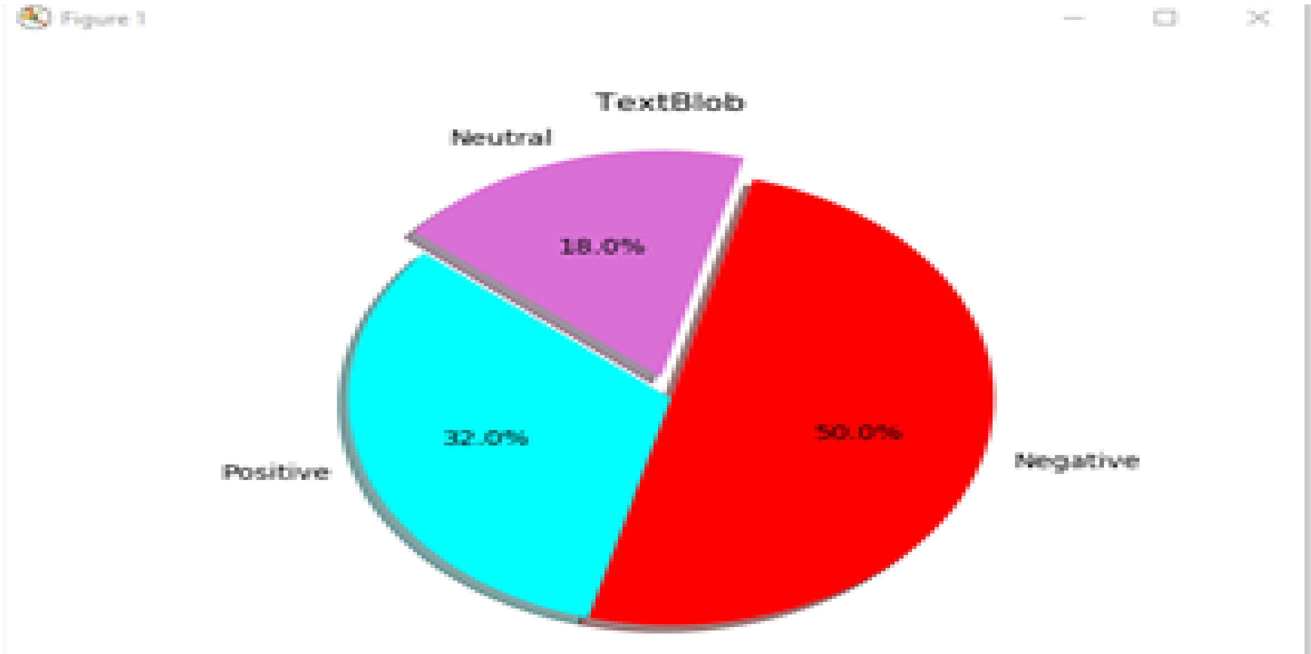


Fig 6.2

The above figure denotes a % pie chart to determine the polarity of tweets. TextBlob library is the only tool as discussed in this thesis, categorizes neutral tweets as well. The rest all tools, classifiers return only positive or negative polarity. Neutral sentiment is also useful in determining certain cases, for example “the Coffee is hot”. It is difficult to denote the polarity of this statement as some may prefer their coffee hot and some may prefer cold coffee. The third class is necessary then this method eliminates on forcibly categorizing texts into a polarity. This lexicon-based approach using TextBlob allows neutral category as well. Studies denote that addition of the third class adds more accuracy to the sentiment analysis system.

6.2 Sentiment analysis using Random forest classifier.

Random forest (RF) is a mix of several decision tree classifiers and the output is based on the result of all these classifiers. Each decision tree is constructed by using a random subset of the training data with a fixed probability distribution. The more the number of trees are constructed, the accuracy increases and the problem of overfitting does not exist. For the classification, a training set is required to train the model with two labels of positive and negative tweets. Then this prepared and learned model is used to predict the test data.

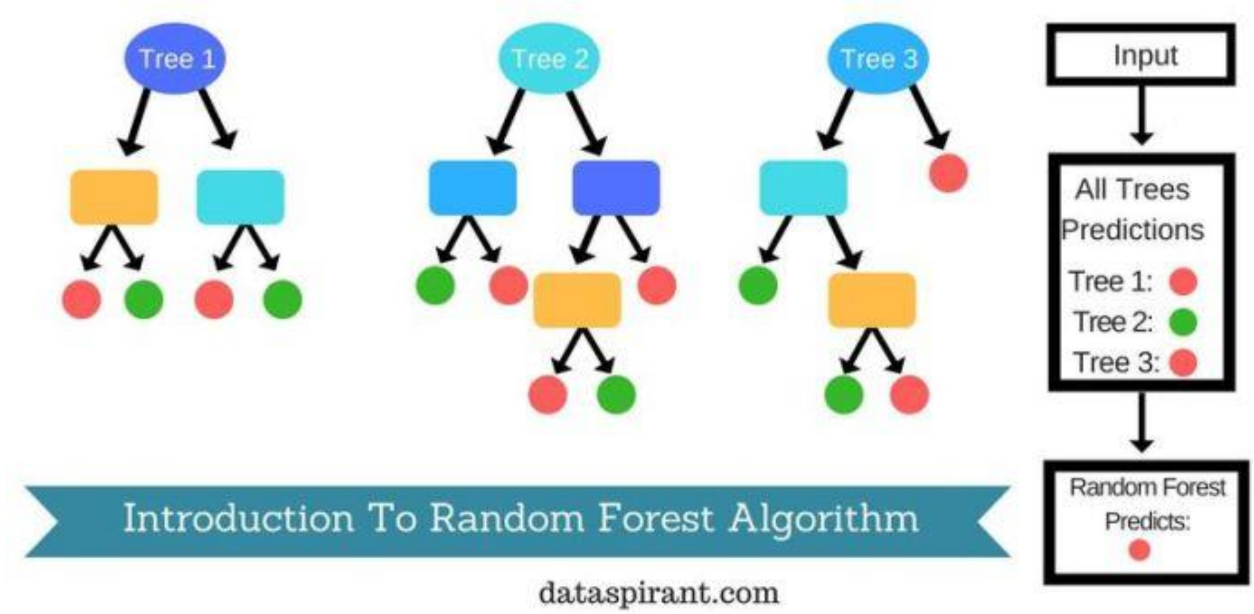


Fig 6.3 How the Random classifier works[35]

In this experiment, we divide the entire set into test and training data. First, the training data is tokenized into individual words using NLTK tokenizer and then sentiment value is determined. Based, on test data, the fit and transform function is implemented on the train data and polarity of tweets is determined, i.e. 0 for negative tweets and 1 for positive tweets. The point to be noted here as a drawback is that this classifier was bipolar in nature and was unable to categorize tweets to neutral category.

6.2.1 Sklearn library

Scikit-learn (formerly scikits.learn) is a free software machine learning library for the Python programming language. [20]

6.2.2 Count Tokenizer

Count tokenizer derived from the sklearn library uses the method of vectorization to split an entire text to individual words and find its frequency. This is termed as bag of words. [19]

The output derived is also exported to a CSV

polarityonClassifier.csv

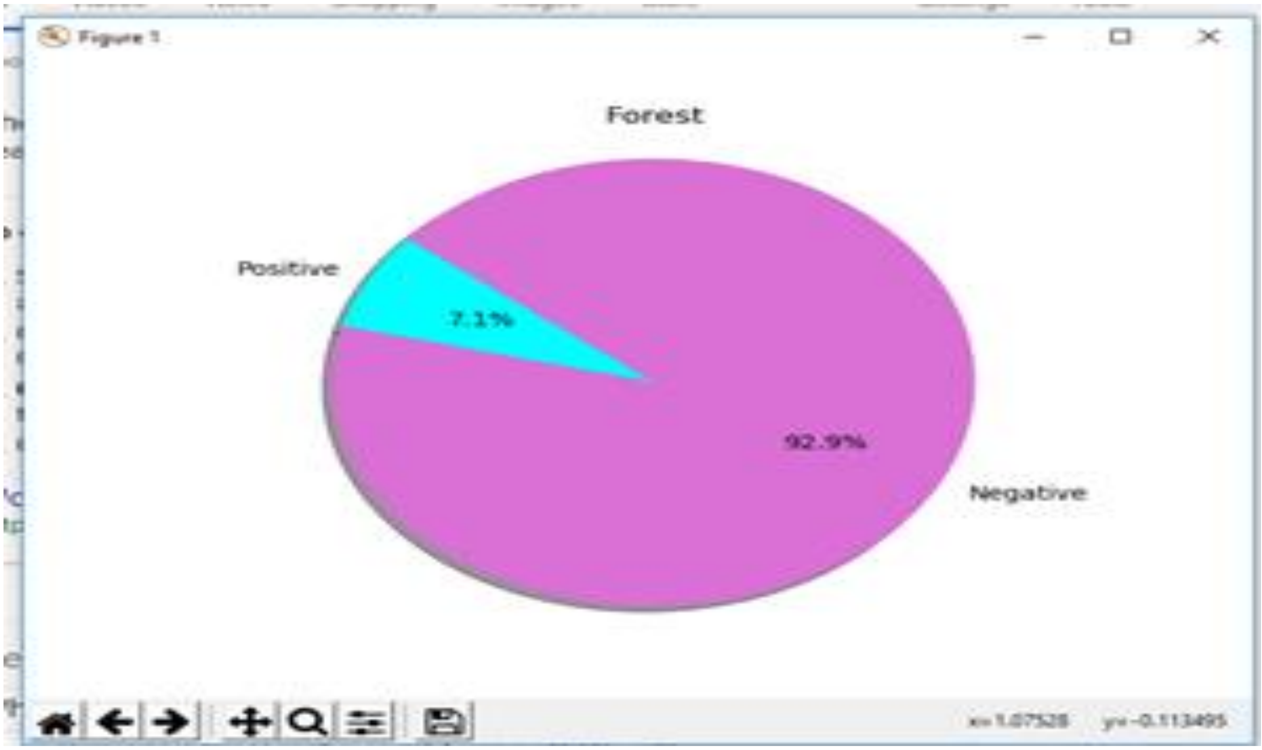


Fig 6.4

This Figure denotes the pie chart denoting polarity derived from applying Random Forest Classifier on a set of train data and based on that a fit and transform function is applied on the test data. This is a classifier-based result and return polarity only as positive and negative. The values it returns also has a value of 0=negative or 1=positive. This result is not very accurate because it all depends on the train data that have been measured first and based on that the test data is evaluated.

6.2.3 Deciding on training and test data

In data mining , the study and developing algorithms to construct a model, which eventually will make predictions on a new dataset. Such algorithms work by making predictions or decisions by working on several mathematical deductions on input data.

The data used to build the final model usually comes from multiple datasets. In particular, three data sets are commonly used in different stages of the creation of the model.

The model is initially fit on a training dataset, that is a set of examples used to fit the parameters of the model. The model (in this case a Random Forest Classifier) is trained on the training dataset. The training dataset consist of an input and the corresponding output (in this case the training set is a series of tweets and the target is polarity of each tweets). The current model is run with the training dataset and produces results, which are stored for future predictions. [26]

The fitted model is used to predict the responses for the observations in a second dataset called the training dataset. The training dataset is fitted to the model and evaluated. These sets are mainly used to evaluate the performance of a model based on the training set.

Finally, the test dataset is a dataset used to provide an unbiased evaluation of a final model fit on the training dataset.

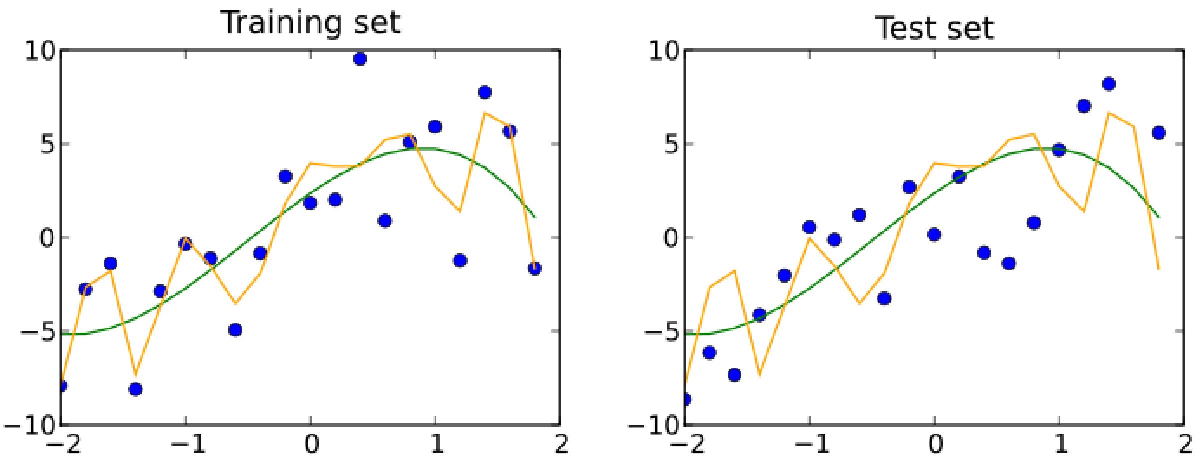


Fig 6.5 denotes the model constructed by both the training and the test data set.[33]

In this thesis, the Random Forest Classifier has also been performed with two sets of test and train data. The approach used here was that the entire tweet that was extracted at runtime was divided into a test-train ration of 60:40.

However, there are other approaches as well, one can use a separate dataset altogether that consists of a corpus of mostly all positive and negative words. These documents can then be compared to the current dataset and sentiment analysis can be done.

neg_tweets.txt

pos_tweets.txt

The above two attachments provide an example of how an example of a predefined test that that was collected on previous tweets.

Another approach is using already analyzed scripts by other tools and libraries and then using these as the test data to train the input tweets that are extracted.

6.3 Sentiment analysis using tool SentiStrength

SentiStrength is a useful tool to predict the sentiment for a text as well as find the strength of the polarity of the tweets. For negative tweets the strength ranges from -1 (not negative) to -5 (extremely negative). For positive tweets strength ranges from1 (not positive) to 5 (extremely positive)

SentiStrength analyzes text to binary polarity, to only positive and negative. This was initially developed in English but now supports various other languages.[21]

We need to input a text file where each line would represent a tweet. In this text file we just used the text field of the tweets.

TestonSentiStrength.txt

Then, the tool processes the text and gives results immediately (as it has a capacity to process 16,000 texts in 1 minute). This text is very useful as it is fast and provides polarity of every word and also gives the total negative and positive count of the tweets.

TestonSentiStrength_results.txt

6..1 Choosing SentiStrength as the tool for analyzing sentiments in this experiment

Before using SentiStrength as a tool for using in the experiment. There were a couple of testing done, where tweets were used as an input for various tools.

- **Sentiment140**: It was created by Alec Go, Richa Bhayani, and Lei Huang, who were Computer Science graduate students at Stanford University. There approach is to use machine learning based algorithms and design classifiers. Other products use a simpler keyword-based approach which may have higher precision but lower recall. There is greater transparency in the results that are given for every individual tweet, instead of as a whole. However, this tool was rejected since its accuracy was very low.

- **Chatterbox**: Chatterbox's multi-lingual sentiment analysis for social media is clever, fast, flexible & scalable. The goal of this tool is to perform sentiment analysis on textual data that are facts derived from news websites and movie rating sites. However, this tool does not work well with human written posts or blogs like Twitter or Facebook.

6.4 Sentiment analysis using Stanford NLP Tagger

Stanford also introduced its own version of NLP tagger. This tagger is also is responsible for separating individual words within a text and then categorizing it to the correct parts of speech (POS). The software is mainly a Java implementation but works with Python as a plug-in.

6.4.1 pycorenlp

This is a library used to import the Stanford NLP Tagger on a Python plug-in, since this tagger was invented and written to be compatible with the programming language Java

For this, first we save the Tagger in our local machine,

```
wget http://nlp.stanford.edu/software/stanford-corenlp-full-2018-10-05.zip
unzip stanford-corenlp-full-2018-10-05.zip
```

Then the server is started

```
d stanford-corenlp-full-2018-10-05
java -mx5g -cp "*" edu.stanford.nlp. pipeline. StanfordCoreNLPServer -timeout 10000
```

Then the library pycorenlp is installed

Pip install pycorenlp

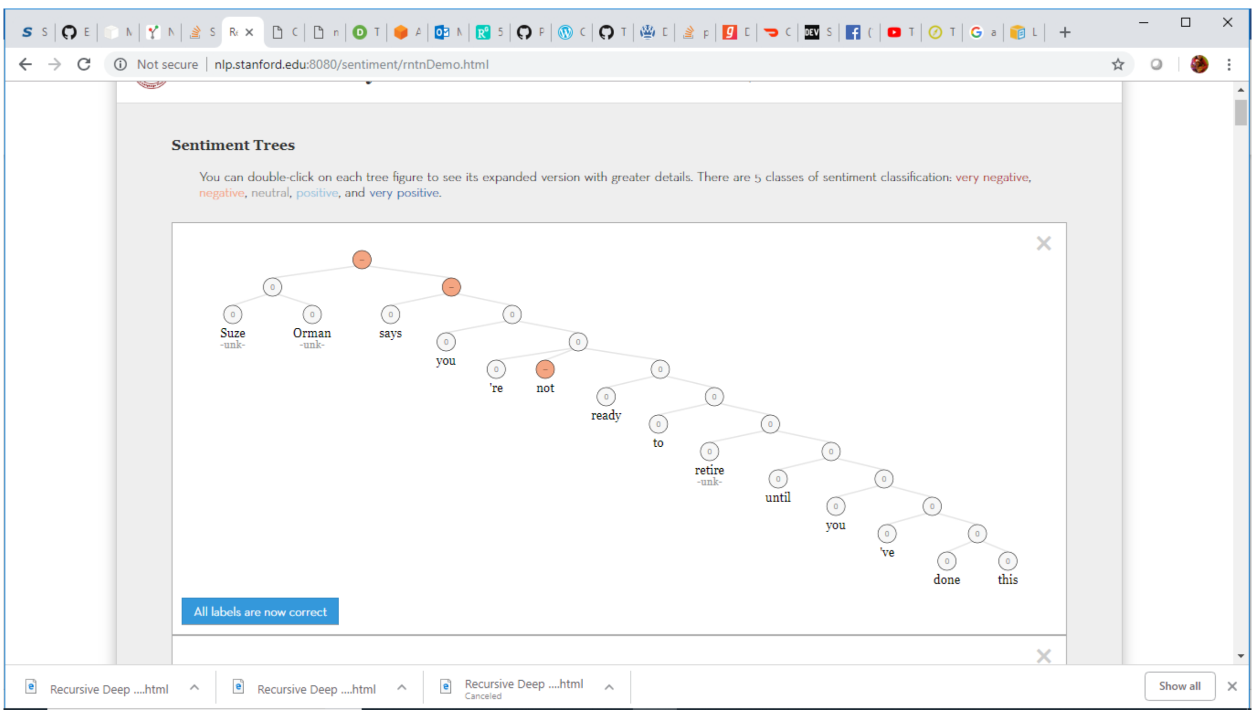


Fig 6.6 A sentiment tree as evaluated by the Stanford NLP Tagger, the root determines the polarity in this case negative

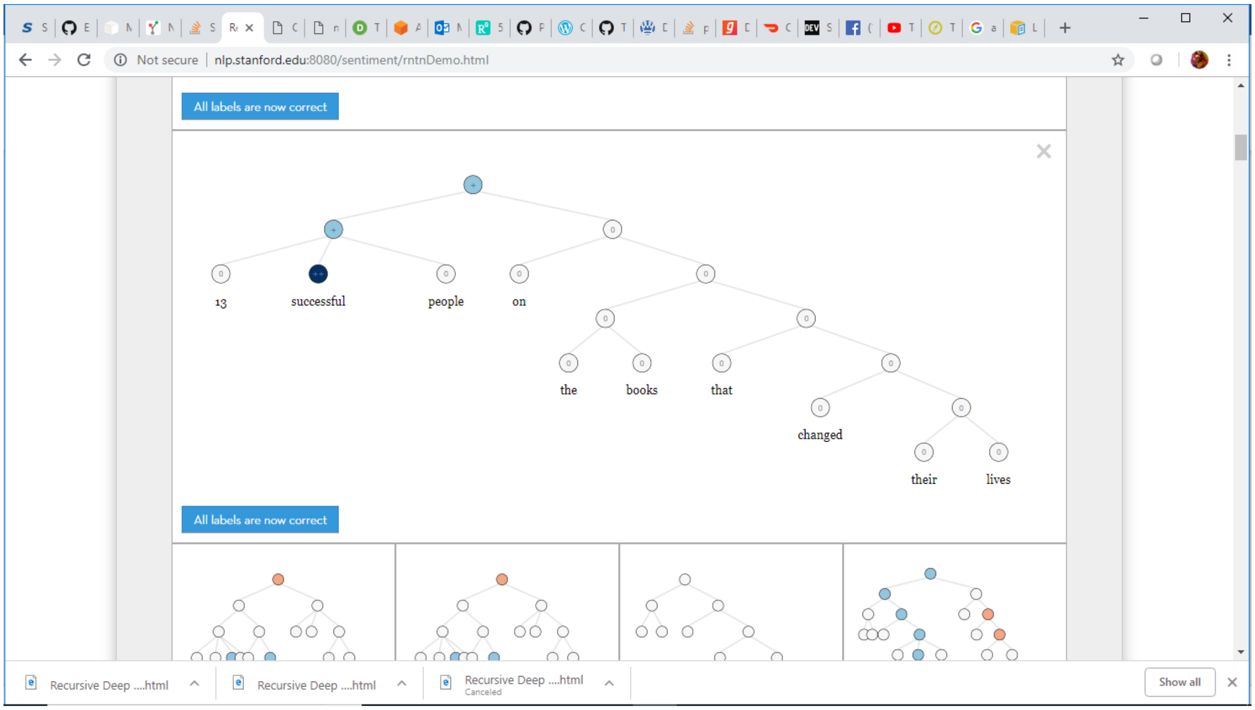


Fig 6.7 A positive analyzed tweet

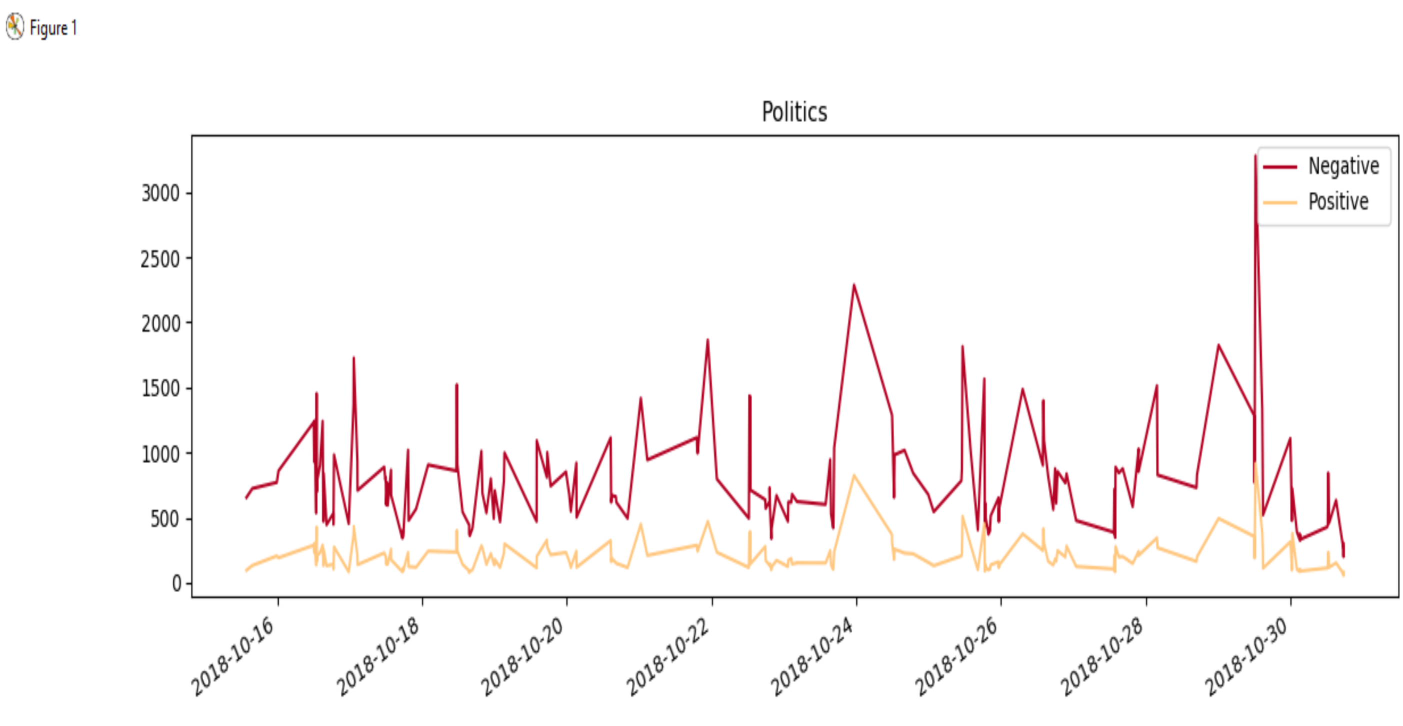


Fig 6.8

The above graph shows the plotting of the polarity of tweets over a time period of 15 days.

6.5 Evaluation

finalEvalutionFinance.xlsx

In the above figure, a comparative analysis is prepared on all the tools used for carrying out experiment.

Column 1: denotes the results obtained by the Random Forest Classifier on the test set

Column 2: denotes the text on which polarity is calculated

Column 3: denotes the polarity results obtained by textblob library. The point to be noted is that, all the rows with a polarity of “neutral” has been removed from evaluation, since the confusion matrix only comprises of positive and negative polarity.

Column 4: denotes the overall positive polarity for each text based on the tool SentiStrength

Column 5: denotes the overall negative polarity for each text based on the tool SentiStrength

Column 6: denotes the evaluation done by a user by reading the text, without the use any tools

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=2	10
ACTUAL YES	FN=3	TP=37	40
	11	39	

Table 6.1

Table 6.1 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 6 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Textblob library

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Textblob library

FP means False positive, that means the number of tweets that have been evaluated by Textblob library as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Textblob library as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=37/40+8/10

=0.9

Precision=TP/TP+FP

=37/39

=0.948717

Recall=TP/TP+FN

=37/40

=0.925

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=0	8
ACTUAL YES	FN=32	TP=10	42
	40	10	

Table 6.2

Table 6.2 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Random forest Classifier experiment

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Random forest Classifier experiment

FP means False positive, that means the number of tweets that have been evaluated by Random forest Classifier experiment as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Random forest Classifier experiment as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=10/42+8/8

=0.36

Precision=TP/TP+FP

=10/10+0

=1.00

Recall=TP/TP+FN

=10/10+32

=0.42

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=1	9
ACTUAL YES	FN=6	TP=35	41
	14	36	

Table 6.3

Table 6.3 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column3, Column 4 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the SentiStrength tool

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the SentiStrength tool

FP means False positive, that means the number of tweets that have been evaluated by SentiStrength tool as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by SentiStrength tool as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=35/41+8/9

=0.86

Precision=TP/TP+FP

=35/35+1=0.9722

Recall=TP/TP+FN

=35/35+6

=0.8536

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=3	11
ACTUAL YES	FN=4	TP=35	39
	12	38	

Table 6.4

Table 6.4denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Stanford NLP Tagger

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Stanford NLP Tagger

FP means False positive, that means the number of tweets that have been evaluated by Stanford NLP Tagger as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated Stanford NLP Tagger as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=35/39+8/11

=0.86

Precision=TP/TP+FP

=35/35+3

=0.921

Recall=TP/TP+FN

=35/35+4

=0.8974

Therefore, on evaluation of the different tools for sentiment analysis, the conclusion is derived in the table below for tweets collected on the topic of finance for 2 months.

From the table, it is concluded that Textblob gives the best accuracy while the RandomForestClassifier gives very low accuracy

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Accuracy	0.9	0.36	0.86	0.86
Precision	0.948717	1.00	0.9722	0.921
Recall	0.925	0.42	0.8536	0.8974

Table 6.5

Evaluation on tweets based on the topic “POLITICS”

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=14	FP=5	19
ACTUAL YES	FN=2	TP=29	31
	16	34	

Table 6.6

Table 6.6 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 6 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Textblob library

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Textblob library

FP means False positive, that means the number of tweets that have been evaluated by Textblob library as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Textblob library as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=29/31+14/19

=0.86

Precision=TP/TP+FP

=29/29+5

=0.852

Recall=TP/TP+FN

=29/29+2

=0.935

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=9	FP=12	21
ACTUAL YES	FN=13	TP=16	29
	21	28	

Table 6.7

Table 6.7 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Random forest Classifier experiment

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Random forest Classifier experiment

FP means False positive, that means the number of tweets that have been evaluated by Random forest Classifier experiment as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Random Forest Classifier experiment as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=16/29+9/21

=0.5

Precision=TP/TP+FP

=16/16+12

=0.571

Recall=TP/TP+FN

=16/16+13

=0.55

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=7	FP=4	11
ACTUAL YES	FN=13	TP=26	39
	20	30	

Table 6.8

Table 6.8 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column3, Column 4 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the SentiStrength tool

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the SentiStrength tool

FP means False positive, that means the number of tweets that have been evaluated by SentiStrength tool as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by SentiStrength tool as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=26/39+7/11

=0.66

Precision=TP/TP+FP

=26/26+4

=0.866

Recall=TP/TP+FN

=26/26+13

=0.666

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=5	FP=12	17
ACTUAL YES	FN=4	TP=29	33
	9	41	

Table 6.9

Table 6.9denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Stanford NLP Tagger

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Stanford NLP Tagger

FP means False positive, that means the number of tweets that have been evaluated by Stanford NLP Tagger as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated Stanford NLP Tagger as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=29/33+4/17

=0.66

Precision=TP/TP+FP

=29/29+12

=0.707

Recall=TP/TP+FN

=29/29+4

=0.87

Therefore, on evaluation of the different tools for sentiment analysis, the conclusion is derived in the table below for tweets collected on the topic of finance for 2 months.

From the table, it is concluded that Textblob gives the best accuracy while the RandomForestClassifier gives very low accuracy

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Accuracy	0.86	0.5	0.66	0.66
Precision	0.85	0.571	0.866	0.707
Recall	0.93	0.55	0.66	0.87

Table 6.10

Evaluation on tweets based on the topic “SPORTS”

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=2	10
ACTUAL YES	FN=3	TP=37	40
	11	39	

Table 6.11

Table 6.6 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 6 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Textblob library

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Textblob library

FP means False positive, that means the number of tweets that have been evaluated by Textblob library as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Textblob library as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=37/40+8/10

=0.9

Precision=TP/TP+FP

=39/41

=0.9512

Recall=TP/TP+FN

=39/42

=0.9285

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=6	FP=5	11
ACTUAL YES	FN=23	TP=16	29
	29	21	

Table 6.12

Table 6.7 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Random forest Classifier experiment

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Random forest Classifier experiment

FP means False positive, that means the number of tweets that have been evaluated by Random forest Classifier experiment as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by Random forest Classifier experiment as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=16/29+6/11

=0.55

Precision=TP/TP+FP

=16/16+5

=0.761

Recall=TP/TP+FN

=16/16+23

=0.410

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=8	FP=5	13
ACTUAL YES	FN=3	TP=34	37
	11	39	

Table 6.13

Table 6.13 denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column3, Column 4 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the SentiStrength tool

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the SentiStrength tool

FP means False positive, that means the number of tweets that have been evaluated by SentiStrength tool as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated by SentiStrength tool as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=34/37+8/13

=0.84

Precision=TP/TP+FP

=34/34+5=0.871

Recall=TP/TP+FN

=34/34+3

=0.918

N=50	PREDICTED NO	PREDICTED YES	
ACTUAL NO	TN=3	FP=3	6

ACTUAL YES	FN=2	TP=42	44
	5	45	

Table 6.14

Table 6.14denotes the evaluation of the polarity of the tweets that we have obtained with the help of a confusion matrix. The columns to be considered from the previous Excel is Column 2 and Column 1 to evaluate the values lie TN, FN, TP, FP

Here, TP means True positive, that means the number of positive tweets that have been evaluated both by the user and the Stanford NLP Tagger

TN means True Negative, that means the number of negative tweets that have been evaluated both by the user and the Stanford NLP Tagger

FP means False positive, that means the number of tweets that have been evaluated by Stanford NLP Tagger as positive but were evaluated as Negative by user

FN means False Negative, that means the number of tweets that have been evaluated Stanford NLP Tagger as negative but were evaluated as positive by user

Now, we deduce these terms and values to find accuracy, recall and precision

Accuracy=TP/ACTUAL YES+ TN/ACTUAL NO

=42/44+3/6

=0.9

Precision=TP/TP+FP

=42/42+3

=0.93

Recall=TP/TP+FN

=42/42+2

=0.95

Therefore, on evaluation of the different tools for sentiment analysis, the conclusion is derived in the table below for tweets collected on the topic of finance for 2 months.

From the table, it is concluded that Textblob and Stanford NLP Sentiment Analyzer gives the best accuracy while the RandomForestClassifier gives very low accuracy

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Accuracy	0.9	0.55	0.84	0.9
Precision	0.951	0.76	0.871	0.93
Recall	0.928	0.41	0.918	0.95

Table 6.15

From the above results, a comparison is done on the parameters of accuracy, recall, precision on the 4 tools used and on the 3 topics on which tweets are extracted

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Finance	0.9	0.36	0.86	0.86
Politics	0.86	0.5	0.66	0.66
Sports	0.9	0.55	0.84	0.9

Table 6.16 Accuracy measurement

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Finance	0.948	1.00	0.97	0.921
Politics	0.85	0.571	0.866	0.707
Sports	0.951	0.76	0.871	0.93

Table 6.17 Precision measurement

Tool	Textblob	Random forest classifier	SentiStrength	Stanford NLP Tagger
Finance	0.925	0.42	0.853	0.8974
Politics	0.93	0.55	0.66	0.87

Sports	0.928	0.41	0.918	0.95

Table 6.18 Recall measurement

The above tables denote how the value of accuracy, recall and precision differ for all the tools used on different topics.

Chapter 7

Cloud Implementation

The entire application uses Amazon Web Service as the cloud provider to implement the web interface.

7.1 Amazon Web Services EC2 instance for hosting the web application

An EC2 instance is launched for the free tier Ubuntu Operating system and a new key pair is generated

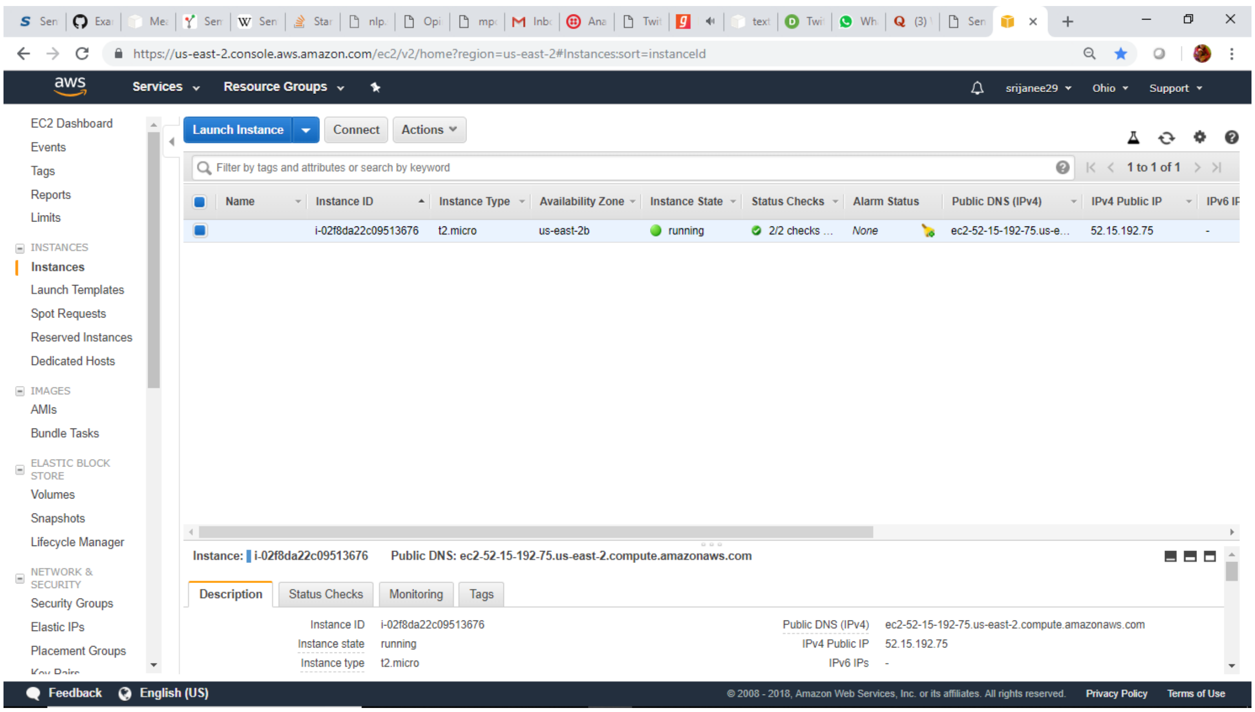


Fig 7.1

The key pair is useful for authenticated login and has to be converted into an SSL container with an extension of. pem i.e. an entire certificate chain including public key, private key, and root certificates

srijanee29.ppk

On using a Windows local host, I had to login to the ec2 instance using Putty and connected using SSH authorization with the key pair generated.

Then we added the cron job as discussed in 4 in the crontab and would check regularly if a new file was generated.

7.2 Amazon Web Services RDS instance for preserving data that has been preprocessed.

A RDS instance is launched for the free tier database instance of MySQL Server system and a new key pair is generated

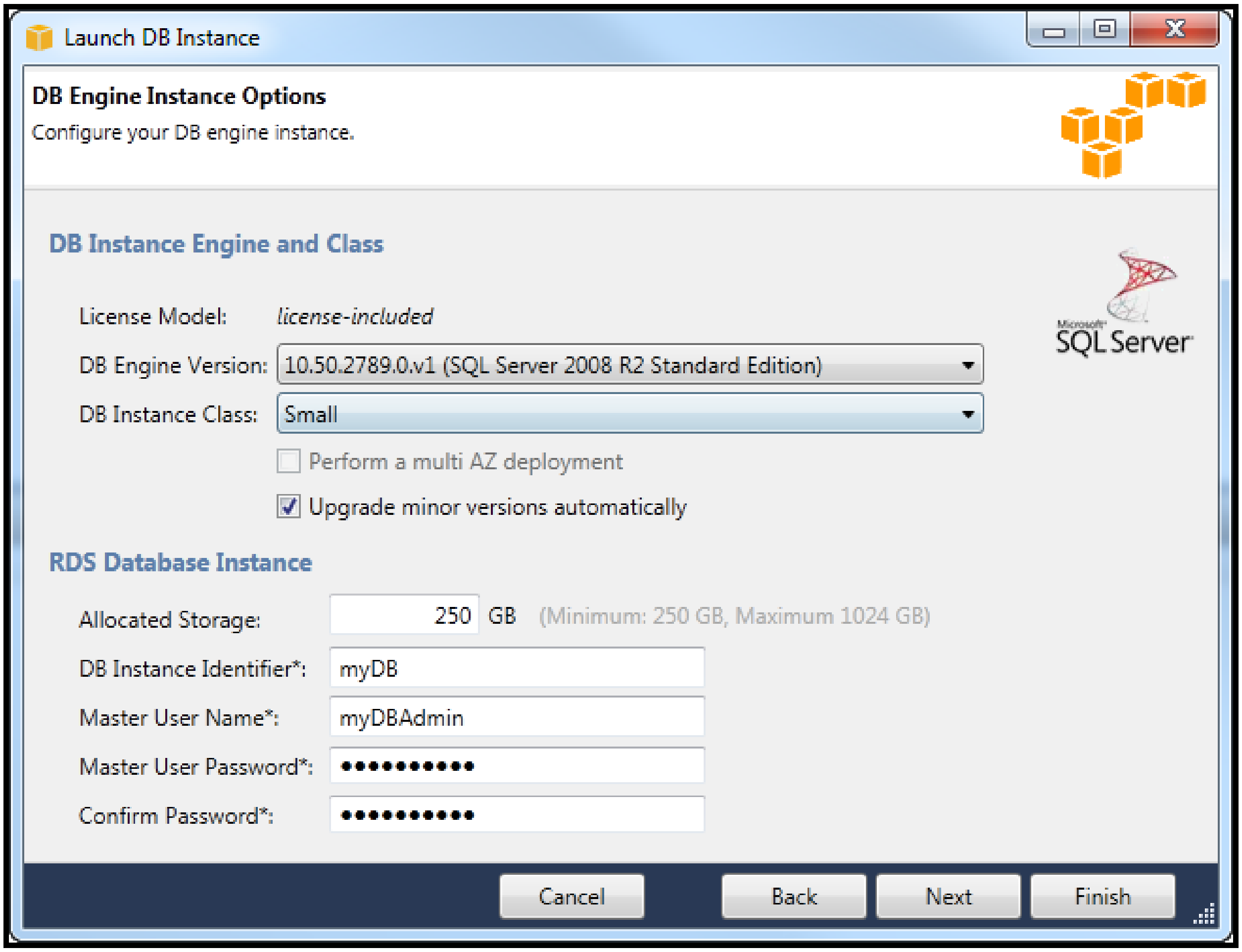


Fig 7.2

The database is a useful tool maintain all the data in a tabular form and a backup is taken at an interval of 2 days.

It is even better to maintain the database on cloud which is cost effective and elastic and can be used with “pay as you use”

7.3 Flask app

In order to python working as a backend system and able to interact with a front-end tool like JavaScript, html, d3.js etc., a flask app is used. Flask is a web application framework written in Python. Flask is based on Werkzeug WSGI toolkit and Jinja2 template engine. [22].

The input html page was created

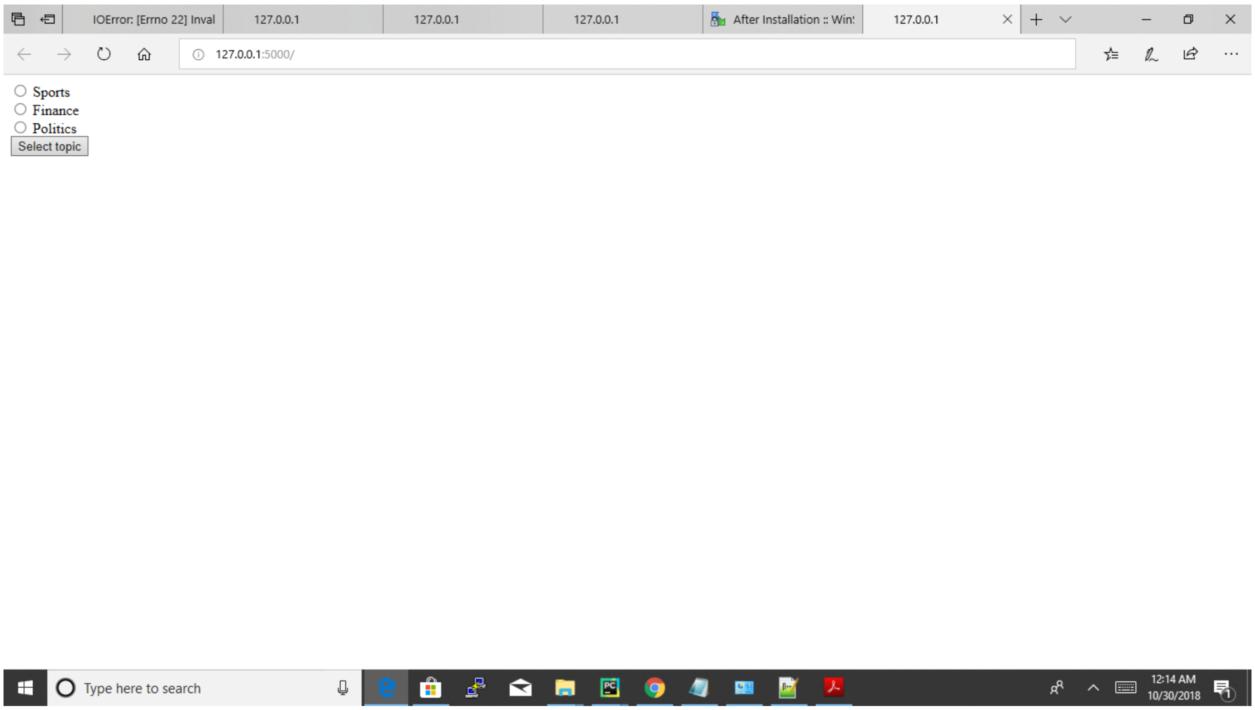


Fig 7.3

This figure provides the input page for the application where a user can select an option on the topic on which they want tweets to be recovered. The usage of radio buttons helps to select only one topic at a time.

On submission of the topic, tweets are extracted over a timeline. After that the data is preprocessed using many functions. Then polarity is found based on different methods and the final output as shown as in the figure below, shows the pie chart for every separate tool, library or classifier used.

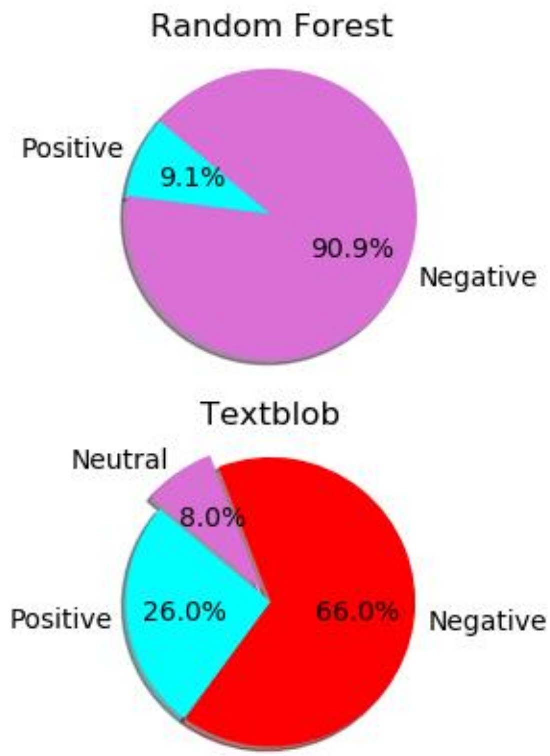


Fig 7.4

7.4 Deploying the application to AWS EC2 instance

This part was necessary to extract automatic tweets from twitter and do a live polarity comparison analysis on the extracted tweets on various topics hosted on the cloud.

There are certain steps to follow to launch an EC2 instance in the cloud.

Step 1: Choosing of a proper Amazon Machine Image (AMI).An AMI is a template that contains a combination of software, operating system, server and applications. In this case a free tier of Linux was chosen

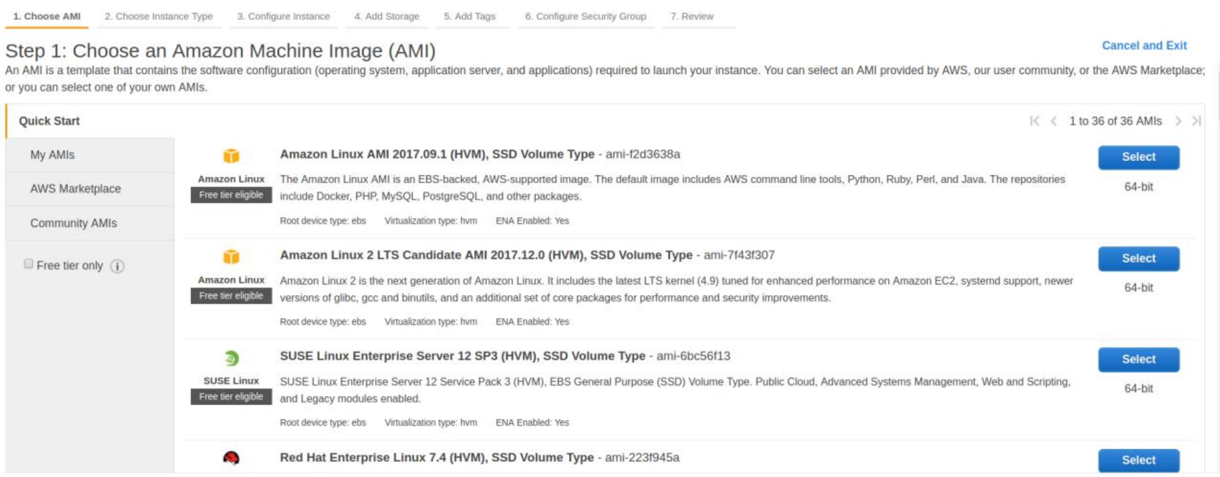


Fig 7.5

Step 2: The next steps are to configure the storage and tags. For this application, the default settings are maintained.

Step 3: This is an important step to configure the security group. Security group mainly refers to the firewall rules that are set to maintain a traffic for an instance. Generally, there is an unrestricted access for both types SSH and HTTP

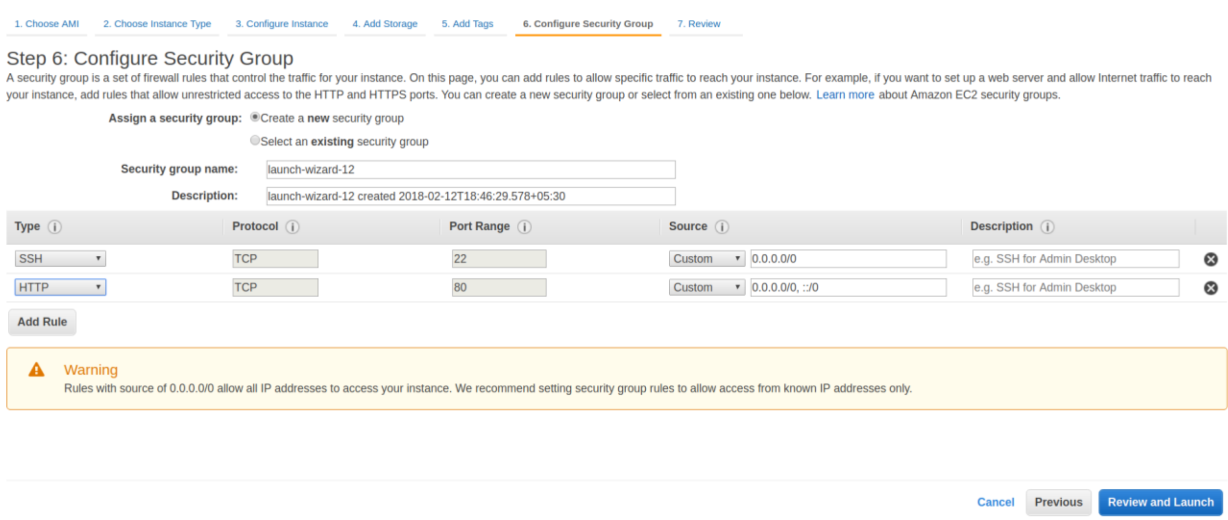


Fig 7.6

Step 4: Since a Windows machine is used for this thesis, there is a requirement of a terminal to connect to remote SSH client. In this case Putty issued. The authorization is done through SSH with the help of the. pem key pair that was generated in AWS while creating an instance.

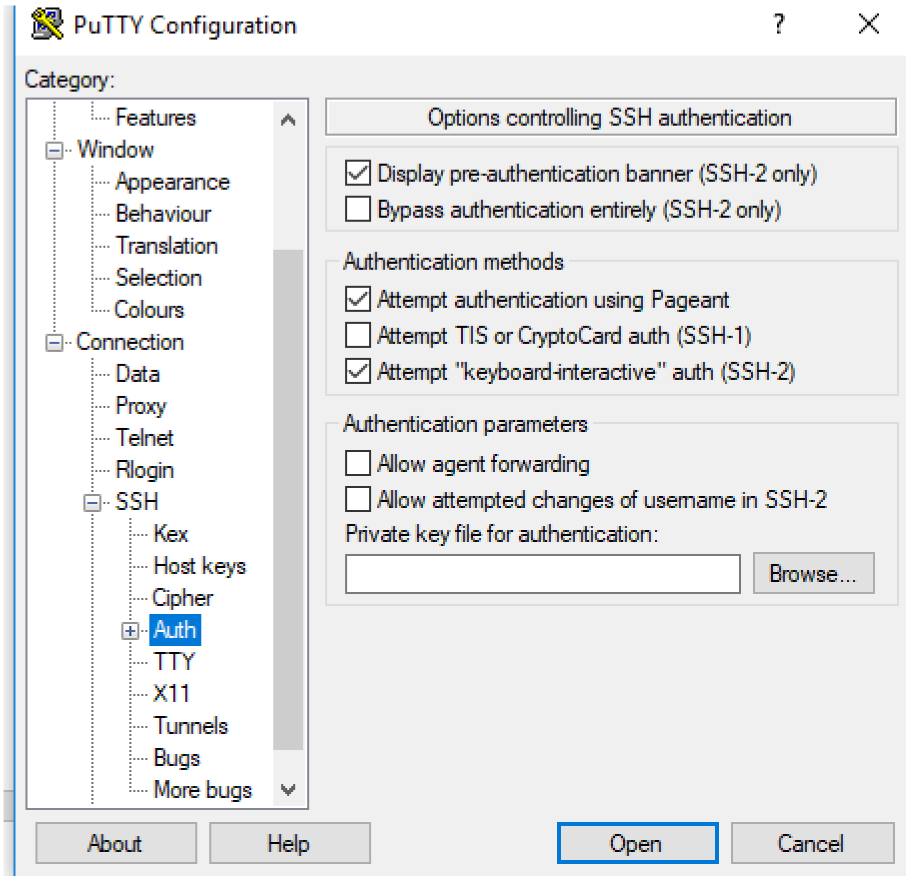


Fig 7.7

Step 5: All the dependent libraries are installed, and program files are moved to the cloud using the tool WinSCP. This tool is an open-source, free tool which works on FTP and SFTP protocol to transfer files from local machine to the cloud. It is based on the SSH protocol of Putty and the File Transfer Protocol from FileZilla.

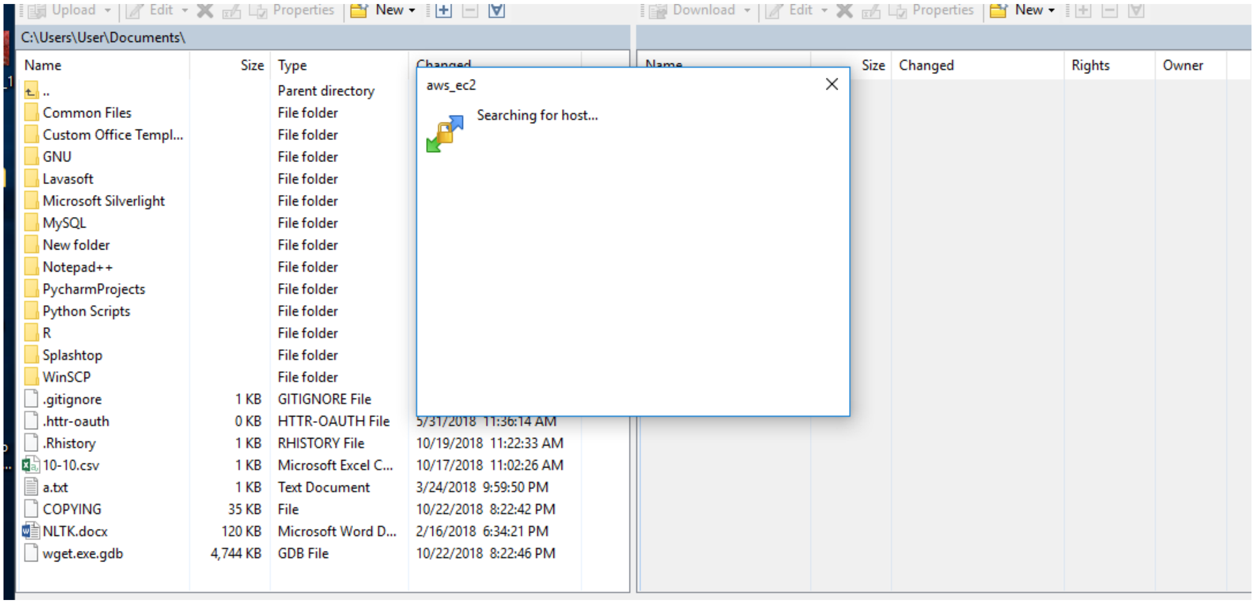


Fig 7.8

Step 6: The python file is run and output s fetched o the Public address of the ec2-instance

Chapter 8

Case Study

A case study is performed to evaluate the different tools working on different sources of text. The first chosen was news so for this case study RSS feeds were collected from the one of the most reliable news websites namely CNN. On a daily basis, this website posts news on various topics and allows user to subscribe to its feeds. For this study, the news on topics of politics was chosen. [32]

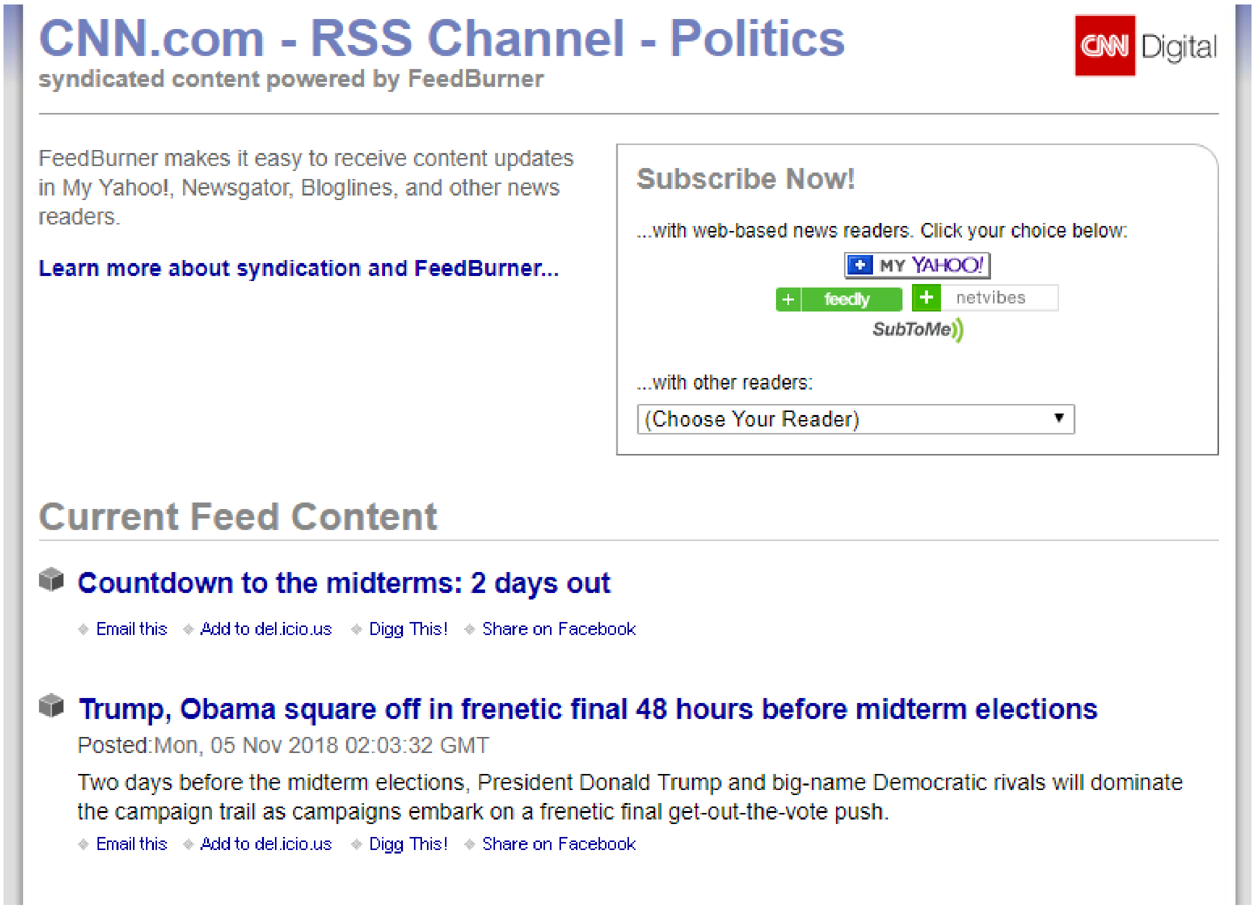


Fig 8.1

The above figure shows a sample of how the feeds are displayed on the website of CNN.

The feeds were converted into an Excel file. The CSV for is easier to read to exhibit sentiment analysis.

rss_politics.csv

8.1 RSS Feed

RSS is referred to as Really Simple Syndication. This type of feed allows users and applications to access updates of an online content in a readable format. In this experiment the feed for CNN is used where several headlines based on a particular topic like politics, current affairs, sports or similar topics. RSS supports several types of media like audio, video, text etc. An RSS document also includes full or summarized text, and metadata, like publishing date and author's name.

An XML file format ensures compatibility with many different machines/programs. RSS feeds also benefit users who want to receive timely updates from favorite websites or to aggregate data from many sites [27].

Subscribing to RSS feeds, removes the need for a user to manually check the website for new updates. Instead, their browser constantly monitors the site and informs the user for any updates. This feed is particularly useful for news, sports or weather data that have frequently keep changing.

8.2 Sentiment Analysis on RSS feeds.

The first analysis was done using the library TextBlob, which fetched the results as given below

rsspolarityonTextbl
ob.csv

The second analysis is carried out by a Random Forest Classifier, using training and test data.

rsspolarityonClassif
ier.csv

The other analysis was performed using the API SentiStrength

rss+results.txt

The other analysis was performed by Stanford NLP Sentiment Analyzer.

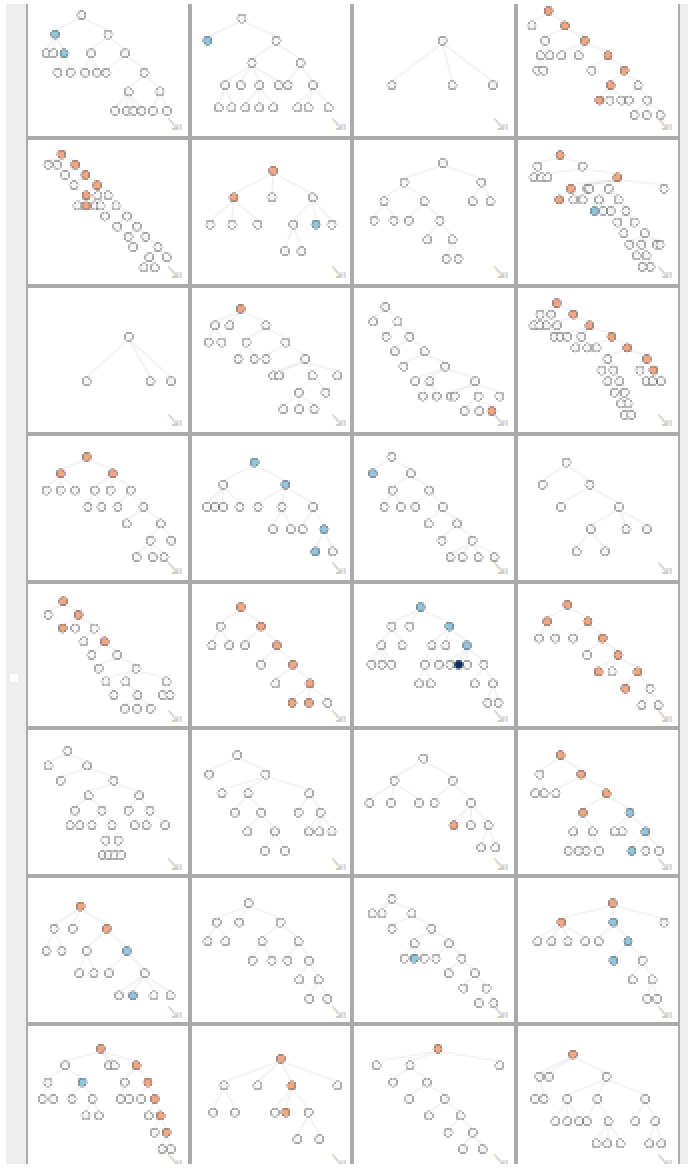


Fig 8.2

In the above figure, the analyzer shows every text in the form of binary trees and the red root denotes negative polarity, blue=positive and white denotes neutral sentiments.

On evaluation of four approaches, a final result was prepared where an expert evaluation was a also added, i.e. inputs by a user

classifier	title	textblob	SentiStrer	Stanford	Expert
0	Trump, to	0.166667	-2	0	-1
2	How Mike	0	0	0	0
0	GA Sec. of	-0.3	-3	0	-1
0	Abrams: T	-0.5	0	-1	-1
1	The Trump	0.2	0	-1	0
1	John Lege	0	0	-1	0
1	RNC chair	0.625	-2	0	1
1	Agricultur	0.15	0	-1	0
0	Utahns gri	-0.075	-3	0	-1
1	CNN Key F	0	-1	-1	1
0	Racist rob	0	-1	0	0
1	Two NY G(	0	0	-1	-1
0	How the e	0	1	-1	1
0	Trump's 2(	0	0	1	0
0	Pentagon	0	-2	1	-1
0	Michael C	0	-2	0	-1
1	GOP Sen. .	0.5	0	1	1
0	Trump vid	0	-1	-1	-1
0	Messages	0	-2	1	-1
1	Trump rai	0.5	-1	-1	0
0	A ghoulish	0	0	0	0

Table 8.1

From the above file, it shows that SentiStrength and TextBlob works similarly and is very accurate to the expert classification. The Stanford Sentiment analyzer is the close third. However, the classifier does not perform well since its bipolar and also depends on test data.

On conclusion, the above tools work very well with facts as in this case would be news from CNN as RSS feeds,

8.3 Fictional text

Fiction is any story or setting that is derived from imagination. In this case study, an excerpt from the book, The Picture of Dorian Gray by Oscar Wilde is taken as an input to conduct sentiment analysis. [24]

fiction.csv

8.4 Sentiment analysis on fiction

The first analysis was done using the library TextBlob, which fetched the results as given below fictionpolarityonTextblob.csv

The second analysis is carried out by a Random Forest Classifier, using training and test data.

fictionClassifier.csv

The other analysis was performed using the API SentiStrength

oscar wilde+results.txt

text	SentiStrer	texblob	classifier	expert
The studic	-4	0.167857	0	0
From the (	-3	0.172222	1	0
The suller	2	0.058333	1	0
In the cen	0	0.072917	0	0
As he look	0	0.066667	0	0
"It is your	1	0.246939	1	0
"I don't th	1	0.044444	1	0

Table 8.2

From the above file, it shows that SentiStrength and TextBlob works similarly and is very accurate to the expert classification. However, the classifier does perform well since its bipolar and also depends on test data. The problem is since these are fictional statements, its difficult for the expert to assign any polarity to them, hence all of them are treated as neutral polarity.

On conclusion, the above tools work not well with fiction as in this case would be parts of a story by Oscar Wilde.

8.5 Use of **spacy** for Natural language processing

SpaCy is an open source software library used for Natural language processing in a Python framework. Along with the basic NLP tasks, this library also supports deep learning algorithms and trains models using TensorFlow or Keras for forming neural networks. [29]

SpaCy performs tasks like word tokenizing and POS tagging better than NTLK. However, for sentence tokenization, NLTK works better. This is because NLTK just tokenizes the text. However, spaCy constructs syntactic trees for every sentence and deduces much more information than required. NLTK supports various languages, but spaCy has statistical models in 7 different languages, namely English, German, Spanish, French, Portuguese, Italian, and Dutch. NLTK gives an option of many algorithms to be used, however spaCy uses the best algorithm at runtime which is suited best for the given problem.

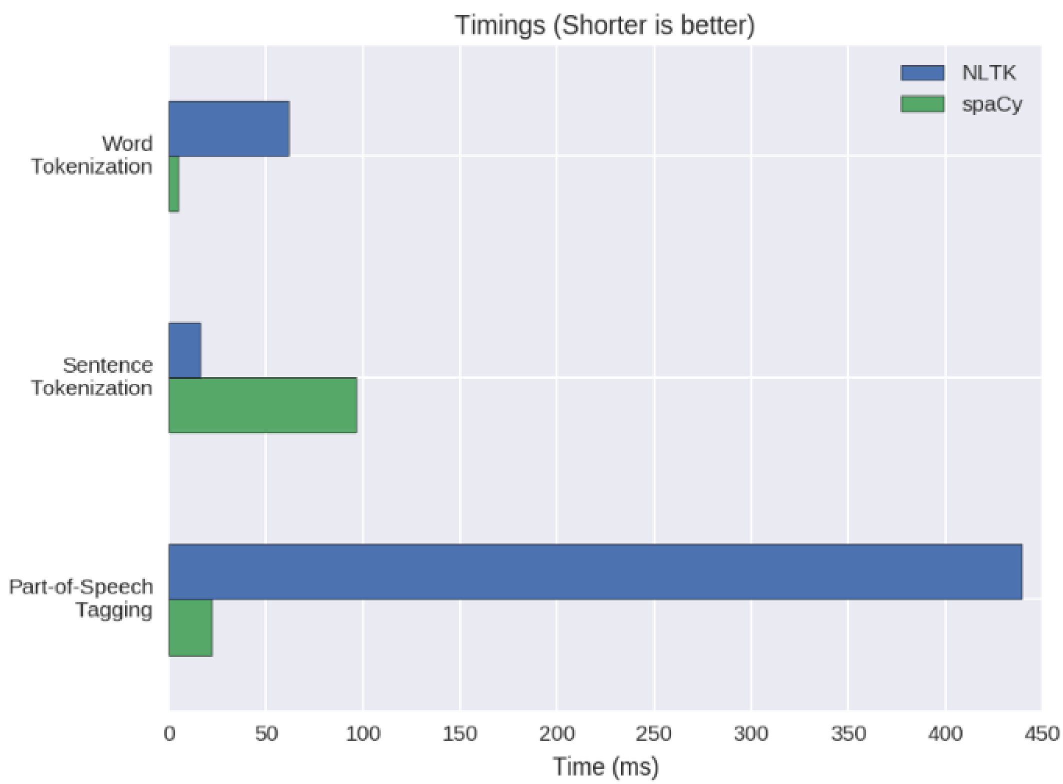


Fig 8.3[34]

The above figure shows the comparison in performance for the 2 tools in the different natural language processing activities.

8.6 Using Naïve Bayesian Classifier for classifying sentiments for tweets

The classifier is based on the Bayesian theorem for conditional probability. The theorem is based on the formula,

P(A/B) =P(A) P(B/A) P(B) [25]

Which tells us: how often A happens given that B happens, written P(A|B),
When we know: how often B happens given that A happens, written P(B|A)
and how likely A is on its own, written P(A)
and how likely B is on its own, written P(B)

For example, let us say P(Rain) means how often there is rain, and P(Cloudy) means how often we see cloudy days, then:

P(Rain|Cloud) means how often there is rain when we can see clouds

P (Cloud | Rain) means how often we can it be cloudy as well as rain

So, this can be used in the form of Bayesian Theorem,

P (Rain| Cloud) = P(Rain) P(Cloud) P(Cloud/Rain)

The Naïve Bayesian classifier is an extension of the Bayesian classifier that is responsible for creating a model using some test data and based on which the model can correctly classify any train data to the correct sentiment. This classifier uses the concept of creating word bags from the test data and training the model. On input of new data to the model, the model searches for similar words which has already been classified and evaluates the test data. This classifier is known as Naïve because it assumes the features to be unconditionally independent of each other.

For this experiment, data is divided into test and train data. Train data is a comma separated file that comprises of tweets that are collected over a large amount of time whose sentiment is already determined

Training_Set.txt

The sentences in the test dataset is tokenized into a bag of words and an NLTK Naïve Bayesian classifier is applied on the data. Then every data is classified according to sentiment and saved to a CSV file.

The output is given as

NBeval.csv

The values are divided in sentiments of either 0 or 1 where 0 determines the negative polarity and 1 is labelled as positive.

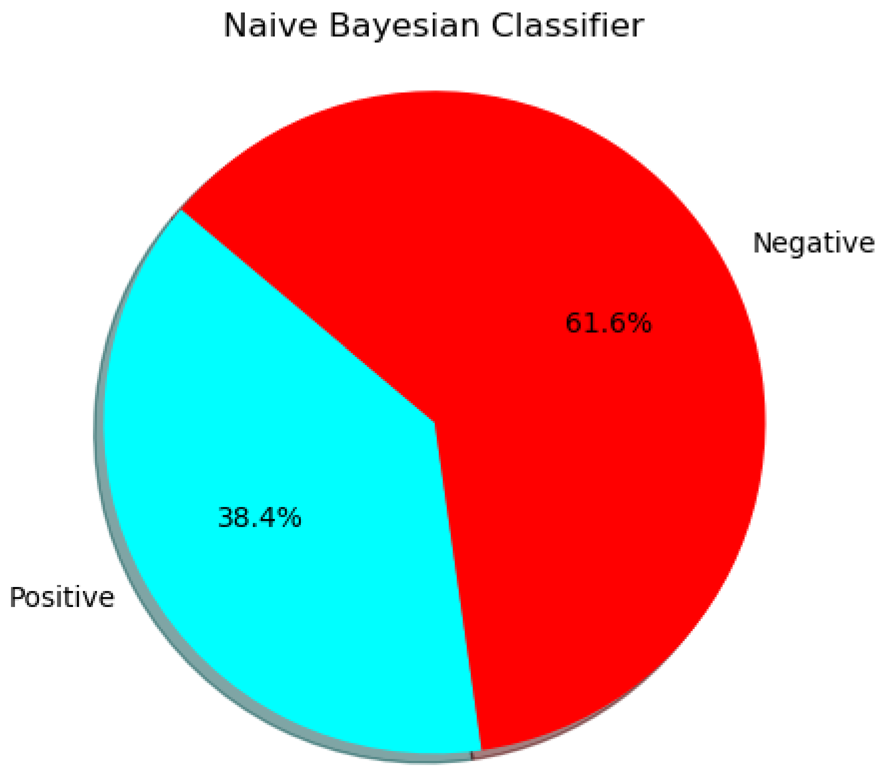


Fig 8.4

The above figure denotes a pie chart to find the percentage on negative and positive sentiments from the total number of tweets that are present in the test dataset.

On evaluation of the results it is found that the Naïve Bayesian Classifier gives a better accuracy than other classifier results. This is solely because the training set in this case is a separate document that already had previously grouped data. Much different from the kind of results deduced by the experiment with another type of classifier namely, Random forest Classifier. In the second type, a single data set was divided into test and training data and fit and transform functionalities were used on these.

So, we can conclude Naïve Bayesian proved to be accurate only by 1-2% which can be treated as negligible. This also depends on the nature of selection of choosing the training and test data as discussed above. Another factor which is greatly determining is the length of the datasets, the more the data is, it will fetch better results. Since a wider variety of data means a wider variety of words added to the corpus and hence fetches better results through classification.

8.7 Sentiment analysis on Customer reviews

Today products need, and choices are changing very fast. Customers have preferences that are easy to change. Product based companies need to stay at par with these needs and choices. Companies also need to compete with their rival companies that build similar products. For example, in the field of technology laptops and phones are never constant. Reviews from customers on websites or feedback from customers via customer support calls are important for companies to understand the growing needs of customers. Sentiment of the reviews and calls also help in determining whether products are liked by customers or there have to be made any changes. In this experiment, Amazon.com was chosen to extract customer reviews.[30]

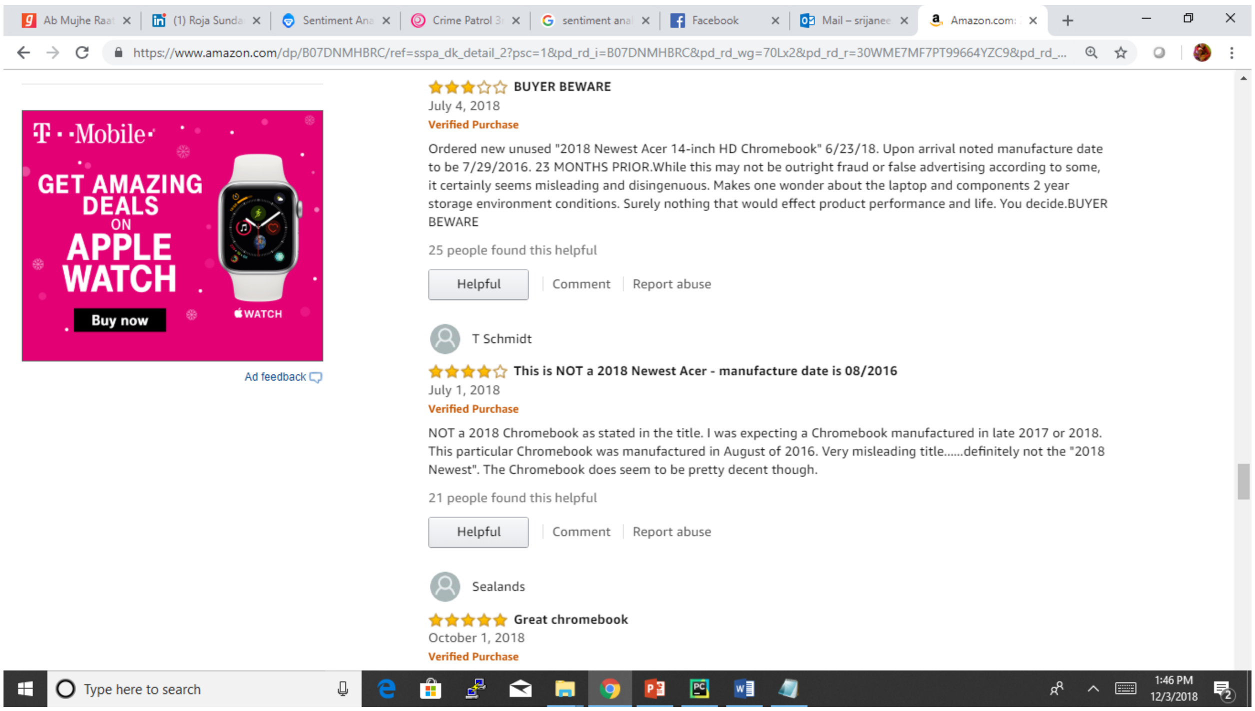


Fig 8.5

8.7.1 Web Scrapping and sentiment analysis

This is the process of extraction of data from a website and saved to a user-friendly format like saving to a file in a location or converting to json or dataframes that can be used for further analysis. Websites generally provide a lot of information that are ideal only to be viewed in the web browser. The only way to access it is to copy and paste it manually. This is a very tedious task and is not efficient at all. In such cases, web scrapping is used. This can be done by using many software or using libraries and accessing the reviews. this experiment, two Python libraries are used. Urllib is used to extract and access the data from the websites and BeautifulSoup is used to extract the data and convert them into JSON files.

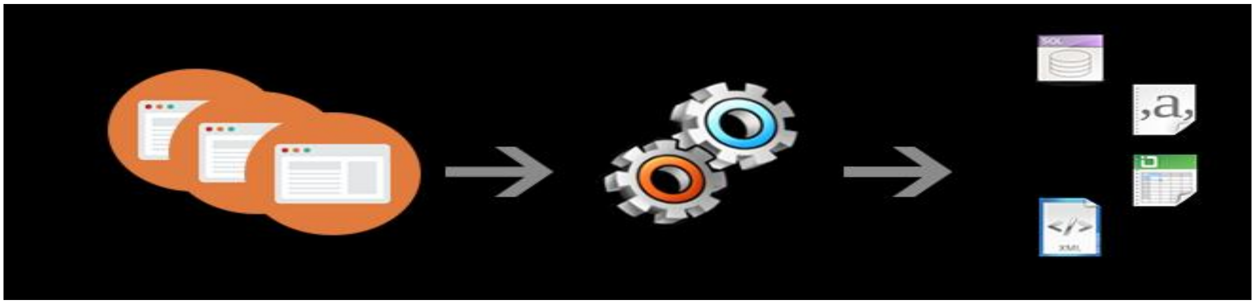


Fig 8.6[31]

amazonReviews.txt

The above attachment shows the extracted reviews from the Amazon website for the particular product

Column1	polarity	subjectivit
Ordered n	0.112662	0.628716
NOT a 201	0.096667	0.58
nice	0.6	1
Like: weig	0.244444	0.627778
What I use	0.3	0.466667
Chrome O	0	0.4
CPU: the c	0	0.4
Dislike: 13	0.5	0.5
Overall: th	0.533333	0.583333
i like its gr	0.8	0.75
What a gre	0.268519	0.412963

Table 8.3

AmazonReviewsAnalysis.xlsm

Chapter 9

Summary and Conclusion

This research started with a goal to classify tweets according to polarity. Identifying polarity on tweets is analogous to finding a needle in a haystack. Challenges involved in collecting effective data and preprocessing them so that all the text could be used. A proper method was used to extract tweets was used with the help of a cron job that ran on a daily basis and collected tweets over a time period of 2 months. Then the data was preprocessed using many methods to make the data devoid of noise and outliers. The clean data was then further preprocessed to avoid any piece of any information to be removed that was not helping in the text analysis. Amazon Web service framework was used, EC2 to host the application. This framework is also cost-effective and elastic to the needs of analysis. All these are achieved by leveraging the benefits of cloud computing.

Experiments and analyses were conducted on real datasets to find the polarity of the tweets. The different parameters chosen to measure the polarity were, TextBlob that was a library derived from Natural Language Processing. The Random Forest Classifier was used to divide the entire data set to train and test data. The third way used was using a very popular tool called SentiStrength to evaluate the polarity. Various patterns were discovered and described in the experiment These patterns aided in understanding and comparing the accuracy of every method used. The case studies demonstrated the identification of performance evaluated from different tools and how efficient they were to determine the polarity of tweets.

Opinion mining on tweets will continue to be an important area of research with the growing market on machine learning and Social media. This thesis presented a comparative analysis on sentiment analysis in a cloud based, scalable, and cost-effective data mining framework.

Chapter 10

Challenges faced on carrying the experiment

On carrying out the experiment there were many barriers met and a lot of challenges that had to be overcome.

The tone of the tweets

If two statements are considered[28]
The dress is nice
The dress is pink in color.
Most people would say that sentiment is positive for the first one and neutral for the second one, right? All *predicates* (adjectives, verbs, and some nouns) should not be treated the same with respect to how they create sentiment. In the examples above, *nice* is more *subjective* than *pink*. This means nice will have more weight than pink, however both are simple adjectives

Context and Polarity

All the tweets and statements that are generated on the basis of a context. It is uttered by someone at a particular time and space. But Twitter being a microblogging site allows only 140 characters to be written at a time. So, the context seems to be lost in some way. For example,
I support this motion.
I am not interested!
These two statements seem like an answer to a question .So the problem here is what is the question, for the first one can answer to the question Did you like the topic of the debate or one can ask did you dislike the topic .To both the above questions , the answers are valid .But the tone and opinion of the statement completely changes to a negative or positive respectively.

Irony and Sarcasm

Differences between literal and intended meaning, irony and the deeper degree of irony which is known as sarcasm usually changes positive sentiment into negative whereas negative or neutral sentiment might be changed to positive. However, detecting irony or sarcasm takes a lot of extra steps of analysis and cannot be done easily. In this experiment, this has been a drawback of not able to analyze sarcasm and irony especially in texts/tweets dealing with politics
For example, look at some possible answers to the question *Have you had a nice customer experience with us?* below.
Yes. Sure.
Assigning sentiments to any of the above statements is difficult. It sounds that an attached positive tweet is added but one can be sarcastic.

Comparisons

How to treat comparisons in sentiment analysis is another challenge worth tackling. Look at the texts below:

This book is second to none.
This is better than old choices.
This is better than nothing.
There are some comparisons like the first one above that do not need any contextual clues in order to be classified correctly.

The second and third texts are a little more difficult to classify, though seeing the word better one would immediately associate to a positive sentiment. But the question here is for the second statement, the choices that are referred to can be good or bad choices. These both statements will again create a problem to carry out a correct analysis

Emojis

There are two types of emojis according to Guibon et al.. *Western emojis* (e.g. :D) are encoded in only one character or in a combination of a couple of them whereas *Eastern emojis* (e.g. ¯ \ _ (ツ) _ / ¯) are a longer combination of characters of a vertical nature. Particularly in tweets, emojis play a role in the sentiment of texts.
The first step of preprocessing is to remove unnecessary punctuation marks that may be difficult to analyze a given text.

Defining Neutral

Categorizing statements to neutral sentiment is another challenge to tackle in order to perform accurate sentiment analysis. There are many statements that is best categorized as neutral, however some classifiers do not allow texts to be classified as a neutral category. This leads to many texts being wrongly classified.

Chapter 11
Future Work

In the future, experiments with other machine learning algorithms apart from Random Forest Classifier will be a good space to explore. With the dataset given we can now run many compute-intensive machine learning algorithms such as hierarchical clustering on the cloud. By combining the results of current experiment with the analyses by applying different algorithms that work well with our datasets will bring to light compelling results. These results might lead us to new dimensions or ways to detect polarity in a more efficient way.

Secondly, need to move forward from only text analysis to evaluate sentiments. For example, usage of smileys and other emoticons can play an important role to define the polarity of a tweet. After all, all the emoticons are denoting some kind of mood. Voice and tone analysis can be another way of identifying the polarity of a statement. Face recognition and identification of various facial expressions can also denote the sentiment of a speech and further helps in analyzing.

Thirdly, one extremely interesting part of sentiment analysis of tweets or speech which deal with sarcasm. Especially in dealing with tweets with politics, there have been several instances where one was sarcastically being positive or negative. In future, if there is a tool designed to detect the sarcasm and take that as a parameter to continue opinion mining would be great.

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