VISVESVARAYA TECHNOLOGICAL UNIVERSITY

BELAGAVI – 590018, Karnataka

INTERNSHIP REPORT

ON

"Twitter Sentimental Analysis"

Submitted in partial fulfilment for the award of degree(1SG18CS022)

BACHELOR OF ENGINEERING IN
COMPUTER SCIENCE

Submitted By :-

Darshan S

1SG18CS022

Conducted By :-

Varcons Technologies Pvt Ltd

SAPTHAGIRI COLLEGE OF ENGINEERING
Hesaraghatta main road, Bengaluru-560057

2022-2023

CERTIFICATE

This is to certify that the Internship titled **"Twitter Sentimental Analysis"** carried out by **Mr.Darshan S ,** a bonafide student of abc Institute of Technology, in partial fulfillment for the award of **Bachelor of Engineering**, in **Computer Science** under Visvesvaraya Technological University, Belagavi, during the year 2022-2023. It is certified that all corrections/suggestions indicated have been incorporated in the report.

The project report has been approved as it satisfies the academic requirements in respectof Internship prescribed for the course Internship / Professional Practice (1SG18CS022)

D E C L A R A T I O N

Darshan S, final year student of Computer Science Branch, SAPTHAGIRI COLLEGE OF ENGINEERING - 560 057, declare that the Internship has been successfully com pleted, in Varcons Technologies Pvt Ltd .This report is submitted in partial fulfillment of the requirements for award of Bachelor Degree in Computer Science Branch, during the academic year 2022-2023.

Date : 25/09/2022 :

Place : Banglore

USN : 1SG18CS022

NAME : Darshan S

OFFER LETTER

Internship Offer Letter

Varcons Technologies Pvt Ltd

Date: **23rd August, 2022**

Name: **Darshan S**
USN: **1SG18CS022**

Dear Student,

We would like to congratulate you on being selected for the **Machine Learning With Python(Research Based)** Internship position with **Varcons Technologies Pvt Ltd**, effective Start Date **23rd August, 2022**, All of us are excited about this opportunity provided to you!

This internship is viewed as being an educational opportunity for you, rather than a part-time job. As such, your internship will include training/orientation and focus primarily on learning and developing new skills and gaining a deeper understanding of concepts of **Machine Learning With Python(Research Based)** through hands-on application of the knowledge you learn while you train with the senior developers. You will be bound to follow the rules and regulations of the company during your internship duration.

Again, congratulations and we look forward to working with you!

Sincerely,

Spoorthi H C
Director
Varcons Technologies Pvt Ltd
213, 2st Floor,
18 M G Road, Ulsoor,
Bangalore-560001

ACKNOWLEDGEMENT

This Internship is a result of accumulated guidance, direction and support of several important persons. We take this opportunity to express our gratitude to all who have helped us to complete the Internship.

We express our sincere thanks to our Principal, for providing us adequate facilities to undertake this Internship.

We would like to thank our Head of Dept – branch code, for providing us an opportunity to carry out Internship and for his valuable guidance and support.
We would like to thank our (Lab assistant name) Software Services for guiding us during the period of internship.

We express our deep and profound gratitude to our guide, Guide name, Assistant/Associate Prof, for her keen interest and encouragement at every step in completing the Internship.

We would like to thank all the faculty members of our department for the support extended during the course of Internship.

We would like to thank the non-teaching members of our dept, forhelping us during the Internship.

Last but not the least, we would like to thank our parents and friends without whose constant help, the completion of Internship would have not been possible.

TEAM NAME: [TEAM SAPTHAGIRI]

BHUVAN GOWDA BS (1SG18CS019)
DARSHAN S(1SG18CS022)
MUDEGOWDAR VINAY(1SG18CS058)
SAHANA R (1KT19CS075)
AKSHITHA S (1GA18IS002)

ABSTRACT

Sentiment Analysis is a technique widely used in text mining. Twitter Sentiment Analysis, therefore means, using advanced text mining techniques to analyze the sentiment of the text (here, tweet) in the form of positive, negative and neutral. It is also known as Opinion Mining, is primarily for analyzing conversations, opinions, and sharing of views (all in the form of tweets) for deciding business strategy, political analysis, and also for assessing public actions.

Enginuity, Revealed Context, Steamcrab, MeaningCloud, and SocialMention are some of the well-known tools used for the analysis of Twitter sentiment. R and Python are widely used for sentiment analysis dataset twitter. Sentiment Analysis of Twitter data is now much more than a college project or a certification program. A good number of Tutorials related to Twitter sentiment are available for educating students on the Twitter sentiment analysis project report and its usage with R and Python. You may also enroll for a python tutorial for the same program to get a promising career in sentiment analysis dataset twitter.

It may, therefore, be described as a text mining technique for analyzing the underlying sentiment of a text message, i.e., a tweet. Twitter sentiment or opinion expressed through it may be positive, negative or neutral. However, no algorithm can give you 100% accuracy or prediction on sentiment analysis.

As a part of Natural Language Processing, algorithms like SVM, Naive Bayes is used in predicting the polarity of the sentence. sentiment analysis of Twitter data may also depend upon sentence level and document level.

Methods like, positive and negative words to find on the sentence is however inappropriate, because the flavor of the text block depends a lot on the context. This may be done by looking at the POS (Part of Speech) Tagging.

Table of Contents

1. COMPANY PROFILE

A Brief History of Varcons Technologies Pvt Ltd

Varcons Technologies Pvt Ltd, was incorporated with a goal ”To provide high quality and optimal Technological Solutions to business requirements of our clients”. Every business is a different and has a unique business model and so are the technological requirements. They understand this and hence the solutions provided to these requirements are different as well. They focus on clients requirements and provide them with tailor made technological solutions. They also understand that Reach of their Product to its targeted market or the automation of the existing process into e-client and simple process are the key features that our clients desire from Technological Solution they are looking for and these are the features that we focus on while designing the solutions for their clients.

Sarvamoola Software Services. is a Technology Organization providing solutions for all web design and development, MYSQL, PYTHON Programming, HTML, CSS, ASP.NET and LINQ. Meeting the ever increasing automation requirements, Sarvamoola Software Services. specialize in ERP, Connectivity, SEO Services, Conference Management, effective web promotion and tailor-made software products, designing solutions best suiting clients requirements.

Varcons Technologies Pvt Ltd, strive to be the front runner in creativity and innovation in software development through their well-researched expertise and establish it as an out of the box software development company in Bangalore, India. As a software development company, they translate this software development expertise into value for their customers through their professional solutions.

They understand that the best desired output can be achieved only by understanding the clients demand better. Varcons Technologies Pvt Ltd, work with their clients and help them to defiine their exact solution requirement. Sometimes even they wonder that they have completely redefined their solution or new application requirement during the brainstorming session, and here they position themselves as an IT solutions consulting group comprising of high caliber consultants.

They believe that Technology when used properly can help any business to scale and achieve new heights of success. It helps Improve its efficiency, profitability, reliability; to put it in one sentence ” Technology helps you to Delight your Customers” and that is what we want to achieve.

2.ABOUT THE COMPANY

Varcons Technologies Pvt Ltd

Varcons Technologies Pvt Ltd, is a Technology Organization providing solutions for all web design and development, MYSQL, PYTHON Programming, HTML, CSS, ASP.NET and LINQ. Meeting the ever increasing automation requirements, Compsoft Technologies specialize in ERP, Connectivity, SEO Services, Conference Management, effective web promotion and tailor-made software products, designing solutions best suiting clients requirements. The organization where they have a right mix of professionals as a stakeholders to help us serve our clients with best of our capability and with at par industry standards. They have young, enthusiastic, passionate and creative Professionals to develop technological innovations in the field of Mobile technologies, Web applications as well as Business and Enterprise solution. Motto of our organization is to "Collaborate with our clients to provide them with best Technological solution hence creating Good Present and Better Future for our client which will bring a cascading a positive effect in their business shape as well". Providing a Complete suite of technical solutions is not just our tag line, it is Our Vision for Our Clients and for Us, We strive hard to achieve it.

Products of Varcons Technologies Pvt Ltd

Android Apps

It is the process by which new applications are created for devices running the Android operating system. Applications are usually developed in Java (and/or Kotlin; or other such option) programming language using the Android software development kit (SDK), but other development environments are also available, some such as Kotlin support the exact same Android APIs (and bytecode), while others such as Go have restricted API access.

The Android software development kit includes a comprehensive set of development tools. These include a debugger, libraries, a handset emulator based on QEMU, documentation, sample code, and zutorials. Currently supported development platforms include computers running Linux (any modern desktop Linux distribution), Mac OS X 10.5.8 or later, and Windows 7 or later. As of March 2015, the SDK is not available on Android itself, but softwaredevelopment is possible by using specialized Android applications.

Web Application

It is a client–server computer program in which the client (including the user interface and client- side logic) runs in a web browser. Common web applications include web mail, onlineretail sales, online auctions, wikis, instant messaging services and many other functions. web applications use web documents written in a standard format such as HTML and JavaScript,which are supported by a variety of web browsers. Web applications can be considered as a specifific variant of client–server software where the client software is downloaded to the client machine when visiting the relevant web page, using standard procedures such as HTTP. The Client web software updates may happen each time the web page is visited. During the session, the web browser interprets and displays the pages, and acts as the universal client for any web application. The use of web application frameworks can often reduce the number of errors in a program, both by making the code simpler, and by allowing one team to concentrate on the framework while another focuses on a specifified use case. In applications which are exposed to constant hacking attempts on the Internet, security- related problems can be caused by errors in the program.

Frameworks can also promote the use of best practices such as GET after POST. There are some who view a web application as a two-tier architecture. This can be a “smart” client that performs all the work and queries a “dumb” server, or a “dumb” client that relies on a “smart” server. The client would handle the presentation tier, the server would have the database (storage tier), and the business logic (application tier) would be on one of them or on both. While this increases the scalability of the applications and separates the display and the database, it still doesn‟t allow for true specialization of layers, so most applications will outgrow this model. An emerging strategy for application software companies is to provide web access to software previously distributed as local applications. Depending on the type of application, it may require the development of an entirely different browser-based interface, or merely adapting an existing application to use different presentation technology. These programs allow the user to pay a monthly or yearly fee for use of a software application without having to install it on a local hard drive. A company which follows this strategy is known as an application service provider (ASP), and ASPs are currently receiving much attention in the software industry.

Security breaches on these kinds of applications are a major concern because it can involve both enterprise information and private customer data. Protecting these assets is an important part of any web application and there are some key operational areas that must be included in the development process. This includes processes for authentication, authorization, asset handling, input, and logging and auditing. Building security into the applications from the beginning can be more effective and less disruptive in the long run.

Web design

It is encompasses many different skills and disciplines in the production and maintenance of websites. The different areas of web design include web graphic design; interface design; authoring, including standardized code and proprietary software; user experience design; and

search engine optimization. The term web design is normally used to describe the

design process relating to the front-end (client side) design of a website including writing mark up. Web design partially overlaps web engineering in the broader scope of web development. Web designers are expected to have an awareness of usability and if their role involves creating mark up then they are also expected to be up to date with web accessibility guidelines. Web design partially overlaps web engineering in the broader scope of web development.

Departments and services offered

Varcons Technologies Pvt Ltd, plays an essential role as an institute, the level of education, development of student's skills are based on their trainers. If you do not have a good mentor then you may lag in many things from others and that is why we at Varcons Technologies Pvt Ltd. gives you the facility of skilled employees so that you do not feel unsecured about the academics. Personality development and academic status are some of those things which lie on mentor's hands. If you are trained well then you can do well in your future and knowing its importance of Varcons Technologies Pvt Ltd. always tries to give you the best.

They have a great team of skilled mentors who are always ready to direct their trainees in the best possible way they can and to ensure the skills of mentors we held many skill development programs as well so that each and every mentor can develop their own skills with the demands of the companies so that they can prepare a complete packaged trainee.

Services provided by Varcons Technologies Pvt Ltd.

- Core Java and Advanced Java
- Web services and development
- Dot Net Framework
- Python
- Selenium Testing
- Conference / Event Management Service
- Academic Project Guidance
- On The Job Training
- Software Training

3.INTRODUCTION

Introduction to ML

Machine learning is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed. Machine learning focuses on the development of Computer Programs that can change when exposed to new data. In this article, we'll see basics of Machine Learning, and implementation of a simple machine learning algorithm using python.

- twitter.com is a popular microblogging website.
- Each tweet is 140 characters in length.
- Tweets are frequently used to express a tweeter's emotion on a particular subject.
- There are firms which poll twitter for analysing sentiment on a particular topic.
- The challenge is to gather all such relevant data, detect and summarize the overall sentiment on a topic.
- Sentiment Analysis is the process of 'computationally' determining whether a piece of writing is positive, negative or neutral. It's also known as opinion mining, deriving the opinion or attitude of a speaker.
- In marketing field companies use it to develop their strategies, to understand customers' feelings towards products or brand, how people respond to their campaigns or product launches and why consumers don't buy some products.
- 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 be used to predict election results as well!
- Sentiment analysis also is used to monitor and analyse social phenomena, for the spotting of potentially dangerous situations and determining the general mood of the blogosphere.

Problem Statement

- The problem in sentiment analysis is classifying the polarity of a given text at the document, sentence, or feature/aspect level.
- whether the expressed opinion in a document, a sentence or an entity feature/aspect is positive, negative, or neutral
- Sentiment analysis of in the domain of micro-blogging is a relatively new research topic so there is still a lot of room for further research in this area. Decent amount of related prior work has been done on sentiment analysis of user reviews , documents, web blogs/articles and general phrase level sentiment analysis . These differ from twitter mainly because of the limit of 140 characters per tweet which forces the user to express opinion compressed in very short text. The best results reached in sentiment classification use supervised learning techniques such as Naive Bayes and Support Vector Machines, but the manual labelling required for the supervised approach is very expensive. Some work has been done on unsupervised and semi-supervised approaches, and there is a lot of room of improvement. Various researchers testing new features and classification techniques often just compare their results to base-

line performance. There is a need of proper and formal comparisons between these results arrived through different features and classification
techniques in order to select the best features and most efficient classification techniques for particular applications.

OBJECTIVES

- To implement an algorithm for automatic classification of text into positive, negative or neutral.

- Sentiment Analysis to determine the attitude of the mass is positive, negative or neutral towards the subject of interest.

- Graphical representation of the sentiment in form of Pie-Chart.

4. SYSTEM ANALYSIS

Literature Survey:

Sentiment analysis is a growing area of Natural Language Processing with research ranging from document level classification (Pang and Lee 2008) to learning the polarity of words and phrases (e.g., (Hatzivassiloglou and McKeown 1997; Esuli and Sebastiani 2006)). Given the character limitations on tweets, classifying the sentiment of Twitter messages is most similar to sentencelevel sentiment analysis (e.g., (Yu and Hatzivassiloglou 2003; Kim and Hovy 2004)); however, the informal and specialized language used in tweets, as well as the very nature of the microblogging domain make Twitter sentiment analysis a very different task. It's an open question how well the features and techniques used on more well-formed data will transfer to the microblogging domain.

Just in the past year there have been a number of papers looking at Twitter sentiment and buzz (Jansen et al. 2009 ; Pak and Paroubek 2010; O'Connor et al. 2010; Tumasjan et al. 2010; Bifet and Frank 2010; Barbosa and Feng 2010 ; Davidov, Tsur, and Rappoport 2010). Other researchers have begun to explore the use of part-of-speech features but results remain mixed. Features common to microblogging (e.g., emoticons) are also common, but there has been little investigation into the usefulness of existing sentiment resources developed on non-microblogging data.

Researchers have also begun to investigate various ways of automatically collecting training data. Several researchers rely on emoticons for defining their training data (Pak and Paroubek 2010; Bifet and Frank 2010). (Barbosa and Feng 2010) exploit existing Twitter sentiment sites for collecting training data. (Davidov, Tsur, and Rappoport 2010) also use hashtags for creating training data, but they limit their experiments to sentiment/non-sentiment classification, rather than
3-way polarity classification, as we do.
We use WEKA and apply the following Machine Learning algorithms for this second classification to arrive at the best result:

- K-Means Clustering
- Support Vector Machine
- Logistic Regression
- K Nearest Neighbours
- Naive Bayes
- Rule Based Classifiers

In here we only use Naïve Bayes Classifiers to retrieve the Tweets from Twitter Data.

 Naive Bayes Classification:

Many language processing tasks are tasks of classification, although luckily our classes are mucheasier to define than those of Borges. In this classification we present the naive Bayes algorithmsclassification, demonstrated on an important classification problem: text categorization, the task of
classifying an entire text by assigning it a text categorization label drawn from some set of labels.

We focus on one common text categorization task, sentiment analysis, the ex-
sentiment analysis traction of sentiment, the positive or negative orientation that a writer expresses toward someobject. Are view of a movie, book, or product on the web expresses the author's sentiment toward the product, while an editorial or political text expresses sentiment toward a candidate or political action. Automatically extracting consumer sentiment is important for marketing of any sort of product, while measuring public sentiment is important for politics and also for market prediction. The simplest
versionofsentimentanalysisisabinaryclassificationtask,andthewordsofthereview provide excellent cues. Consider, for example, the following phrases extracted from positive and negative reviews of movies and restaurants,. Words like great, richly, awesome, and pathetic, and awful and ridiculously are very informative cues:

+ ...zany characters and richly applied satire, and some great plot twists

− It was pathetic. The worst part about it was the boxing scenes...

+ ...awesome caramel sauce and sweet toasty almonds. I love this place!

− ...awful pizza and ridiculously overpriced...

Naive Bayes is a probabilistic classifier, meaning that for a document d, out of all classes c∈C the classifier returns the class ˆ c which has the maximum posterior probability given the document. In Eq. 1 we use the hat notation to mean "our estimate of the correct class".

c = argmax P(c|d) where c∈C

ThisideaofBayesianinferencehasbeenknownsincetheworkofBayes(1763),Bayesian inference and was first applied to text classification by Mosteller and Wallace (1964). The intuitionofBayesianclassificationistouseBayes'ruletotransformEq.6.1intoother probabilities that have some useful properties. Bayes' rule is presented in Eq. 2; it gives us a way to break down any conditional probability P(x|y) into three other probabilities:

P(x|y) =P(y|x)P(x) /P(y)

The algoritham of sentiment analysis using Naive Bayes Classification:

function BOOTSTRAP(x,b) returns p-value(x)

Calculate δ(x)

for i = 1to b do

for j = 1to n do # Draw a bootstrap sample x*(i) of size n

Select a member of x at random and add it to x*(i)

Calculate δ(x*(i))

For each x*(i)

s ← s + 1ifδ(x*(i)) > 2δ(x)

p-value(x)≈ s b

return p-value(x)

• Many language processing tasks can be viewed as tasks of classification. learn to model the class given the observation.

• Textcategorization,inwhichanentiretextisassignedaclassfromafiniteset, comprises such tasks as sentiment analysis, spam detection, email classification, and authorship attribution.

• Sentimentanalysisclassifiesatextasreflectingthepositiveornegativeorientation (sentiment) that a writer expresses toward some object.

• Naive Bayes is a generative model that make the bag of words assumption (positiondoesn't matter)andtheconditionalindependenceassumption(words are conditionally independent of each other given the class)

• Naive Bayes with binarized features seems to work better for many text classification tasks.

The TextBlob package for Python is a convenient way to do a lot of Natural Language Processing (NLP) tasks. For example:

From textblob import TextBlob

TextBlob("not a very great calculation").sentiment

This tells us that the English phrase "not a very great calculation" has a polarity of about -0.3, meaning it is slightly negative, and a subjectivity of about 0.6, meaning it is fairly subjective.

There are helpful comments like this one, which gives us more information about the numbers we're interested in:

Each word in the lexicon has scores for:

1) polarity: negative vs. positive (-1.0 => +1.0)

2) subjectivity: objective vs. subjective (+0.0 => +1.0)

3) intensity: modifies next word? (x0.5 => x2.0)

The lexicon it refers to is in en-sentiment.xml, an XML document that includes the following four entries for the word “great”.

<word Form=”great” cornetto svnset id=”n_a-525317” wordnet id=”a-01123879” pos=”JJ” sense=”very good” polanty=”1.0” subjectivity=”1.0” intensity=”1.0” confidence=”0.9” />

<word Form=”great” wordnet id=”a-011238818” pos=”JJ” sense=”of major significance or importance” polanty=”1.0” subjectivity=”1.0” intensity=”1.0” confidence=”0.9” />

<word Form=”great” wordnet id=”a-01123883” pos=”JJ” sense=”relativity large in size or number or extent” polanty=”0.4” subjectivity=”0.2” intensity=”1.0” confidence=”0.9” />

<word Form=”great” wordnet id=”a-01677433” pos=”JJ” sense=”remarkable or out of the ordinary in degree or magnitude or effect” polanty=”0.8” subjectivity=”0.8” intensity=”1.0” confidence=”0.9” />

In addition to the polarity, subjectivity, and intensity mentioned in the comment above, there's also “confidence”, but I don't see this being used anywhere. In the case of “great” here it's all the same part of speech (JJ, adjective), and the senses are themselves natural language and not used. To simplify for readability:

Word	Polarity	Subjectivity	Intensity
Great	1.0	1.0	10
Great	1.0	1.0	1.0
Great	0.4	0.2	1.0
Great	0.8	0.8	1.0

When calculating sentiment for a single word, TextBlob uses a sophisticated technique known toMathematicians as “averaging”

TextBlob(“great").sentiment

Sentiment(polarity=0.8, subjectivity=0.75)

At this point we might feel as if we're touring a sausage factory. That feeling isn't going to go away, but remember how delicious sausage is! Even if there isn't a lot of magic here, the results can be useful—and you certainly can't beat it for convenience. TextBlob doesn't not handle negation, and that ain't nothing!

TextBlob("not great").sentiment
Sentiment(polarity=-0.4, subjectivity=0.75)

Negation multiplies the polarity by -0.5, and doesn't affect subjectivity.
TextBlob also handles modifier words! Here's the summarized record for “very” from the lexicon:

Word	Polarity	Subjectivity	Intensity
Very	0.2	0.3	1.3

Recognizing “very” as a modifier word, TextBlob will ignore polarity and subjectivity and just use intensity to modify the following word:

TextBlob("very great").sentiment

Sentiment(polarity=1.0, subjectivity=0.9750000000000001)

The polarity gets maxed out at 1.0, but you can see that subjectivity is also modified by “very” to become 0.75·1.3=0.9750.75·1.3=0.975.

Negation combines with modifiers in an interesting way: in addition to multiplying by -0.5 for the polarity, the inverse intensity of the modifier enters for both polarity and subjectivity.

TextBlob("not very great").sentiment

#Sentiment(polarity=-0.3076923076923077, subjectivity=0.5769230769230769)
polarity=−0.5·11.3·0.8≈−0.31polarity=−0.5·11.3·0.8≈−0.31
subjectivity=11.3·0.75≈0.58subjectivity=11.3·0.75≈0.58

TextBlob will ignore one-letter words in its sentiment phrases, which means things like this will work just the same way:

TextBlob("not a very great").sentiment

##Sentiment(polarity=-0.3076923076923077, subjectivity=0.5769230769230769)

And TextBlob will ignore words it doesn't know anything about:
TextBlob("not a very great calculation").sentiment
##Sentiment(polarity=-0.3076923076923077, subjectivity=0.5769230769230769)

TextBlob goes along finding words and phrases it can assign polarity and subjectivity to, and it averages them all together for longer text.

And while I'm being a little critical, and such a system of coded rules is in some ways the antithesis of machine learning, it is still a pretty neat system and I think I'd be hard-pressed to code up a better such solution.

5. REQUIREMENT ANALYSIS

SRS (Software Requirement Specification):

- Internal Interface requirement:

Identify the product whose software requirements are specified in this document, including the revision or release number. Describe the scope of the product that is covered by this SRS, particularly if this SRS describes only part of the system or a single subsystem.
Describe any standards or typographical conventions that were followed when writing this SRS, such as fonts or highlighting that have special significance. For example, state whether priorities for higher-level requirements are assumed to be inherited by detailed requirements, or whether every requirement statement is to have its own priority.
Describe the different types of reader that the document is intended for, such as developers, project managers, marketing staff, users, testers, and documentation writers. Describe what the rest of this SRS contains and how it is organized. Suggest a sequence for reading the document, beginning with the overview sections and proceeding through the sections that are most pertinent to each reader type.
Provide a short description of the software being specified and its purpose, including relevant benefits, objectives, and goals. Relate the software to corporate goals or business strategies. If a separate vision and scope document is available, refer to it rather than duplicating its contents here.The recent explosion in data pertaining to users on social media has created a great interest in performing sentiment analysis on this data using Big Data and Machine Learning principles to understand people's interests. This project intends to perform the same tasks. The difference between this project and other sentimnt analysis tools is that, it will perform real time analysis of tweets based on hashtags and not on a stored archive.

;Describe the context and origin of the product being specified in this SRS. For example, state whether this product is a ;follow-on member of a product family, a replacement for certain existing systems, or a new, self-contained product. If the ;SRS defines a component of a larger system, relate the requirements of the larger system to the functionality of this ;software and identify interfaces between the two. A simple diagram that shows the major components of the overall system, ;subsystem interconnections, and external interfaces can be helpful.

The Product functions are:

• Collect tweets in a real time fashion i.e. , from the twitter live stream based on specified hashtags

• Remove redundant information from these collected tweets.

• Store the formatted tweets in MongoDB database

• Perform Sentiment Analysis on the tweets stored in the database to classify their nature viz. positive, negative and so on.

• Use a machine learning algorithm which will predict the 'mood' of the people with respect ot that topic.

;Summarize the major functions the product must perform or must let the user perform. Details will be provided in Section 3, ;so only a high level summary (such as a bullet list) is needed here. Organize the functions to make them understandable to ;any reader of the SRS. A picture of the major groups of related requirements and how they relate, such as a top level data ;flow diagram or object class diagram, is often effective.

Identify the various user classes that you anticipate will use this product. User classes may be differentiated based on frequency of use, subset of product functions used, technical expertise, security or privilege levels, educational level, or experience. Describe the pertinent characteristics of each user class. Certain requirements may pertain only to certain user classes. Distinguish the most important user classes for this product from those who are less important to satisfy.
Describe the environment in which the software will operate, including the hardware platform, operating system and versions, and any other software components or applications with which it must peacefully coexist.

● External Interface Requirement:

We classify External Interface in 4 types, those are:
User Interface:

Describe the logical characteristics of each interface between the software product and the users. This may include sample screen images, any GUI standards or product family style guides that are to be followed, screen layout constraints, standard buttons and functions (e.g., help) that will appear on every screen, keyboard shortcuts, error message display standards, and so on. Define the software components for which a user interface is needed. Details of the user interface design should be documented in a separate user interface specification.

- **Hardware interface**:

Describe the logical and physical characteristics of each interface between the software product and the hardware components of the system. This may include the supported device types, the nature of the data and control interactions between the software and the hardware, and communication protocols to be used.

- **Software Interface**:

Describe the connections between this product and other specific software components (name and version), including databases, operating systems, tools, libraries, and integrated commercial components. Identify the data items or messages coming into the system and going out and describe the purpose of each. Describe the services needed and the nature of communications. Refer to documents that describe detailed application programming interface protocols. Identify data that will be shared across software components. If the data sharing mechanism must be implemented in a specific way (for example, use of a global data area in a multitasking operating system), specify this as an implementation constraint.

- **Communication Interface:**

Describe the requirements associated with any communications functions required by this product, including e-mail, web browser, network server communications protocols, electronic forms, and so on. Define any pertinent message formatting. Identify any communication standards that will be used, such as FTP or HTTP. Specify any communication security or encryption issues, data transfer rates, and synchronization mechanisms.

Non Functional Requirement:

● Performance Requirements:

If there are performance requirements for the product under various circumstances, state them here and explain their rationale, to help the developers understand the intent and make suitable design choices. Specify the timing relationships for real time systems. Make such requirements as specific as possible. You may need to state performance requirements for individual functional requirements or features.

● Safety Requirements:

Specify those requirements that are concerned with possible loss, damage, or harm that could result from the use of the product. Define any safeguards or actions that must be taken, as well as actions that must be prevented. Refer to any external policies or regulations that state safety issues that affect the product's design or use. Define any safety certifications that must be satisfied.

● Security Requirements:

Specify any requirements regarding security or privacy issues surrounding use of the product or protection of the data used or created by the product. Define any user identity authentication requirements. Refer to any external policies or regulations containing security issues that affect the product. Define any security or privacy certifications that must be satisfied.

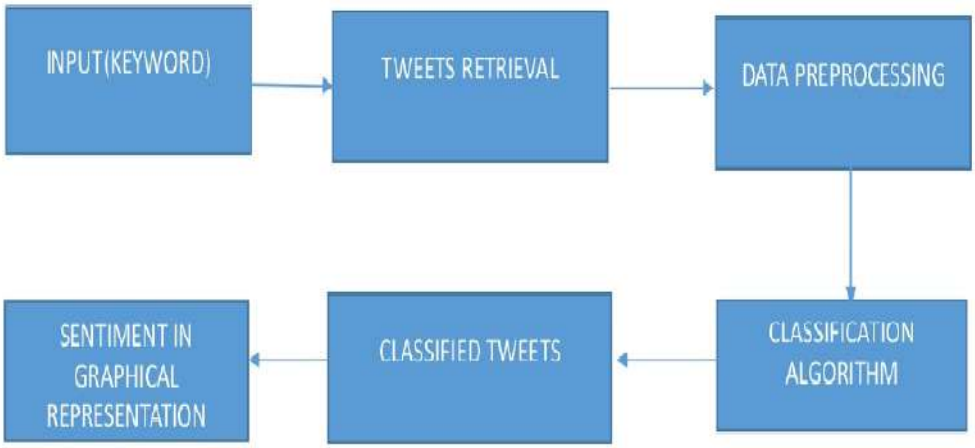
● Software Quality Attributes:

Specify any additional quality characteristics for the product that will be important to either the customers or the developers. Some to consider are: adaptability, availability, correctness, flexibility, interoperability, maintainability, portability, reliability, reusability, robustness, testability, and usability. Write these to be specific, quantitative, and verifiable when possible. At the least, clarify the relative preferences for various attributes, such as ease of use over ease of learning.

Other Requirements:

- Linux Operating System/Windows
- Python Platform(Anaconda2,Spyder,Jupyter)
- NLTK package,
- Modern Web Browser
- Twitter API, Google API

6. DESIGN & ANALYSIS



Input(KeyWord):

Data in the form of raw tweets is acquired by using the Python library "tweepy" which provides a package for simple twitter streaming API . This API allows two modes of accessing tweets: SampleStream and FilterStream. SampleStream simply delivers a small, random sample of all the tweets streaming at a real time. FilterStream delivers tweet which match a certain criteria.

It can filter the delivered tweets according to three criteria:

- Specific keyword to track/search for in the tweets
- Specific Twitter user according to their name
- Tweets originating from specific location(s) (only for geo-tagged tweets). A programmer can specify any single one of these filtering criteria or a multiple combination of these. But for our purpose we have no such restriction and will thus stick to the SampleStream mode.

Since we wanted to increase the generality of our data, we acquired it in portions at different points of time instead of acquiring all of it at one go. If we used the latter approach then the generality of the tweets might have been compromised since a significant portion of the tweets would be referring to some certain trending topic and would thus have more or less of the same general mood or sentiment. This phenomenon has been observed when we were going through our sample of acquired tweets. For example the sample acquired near Christmas and New Year's had a significant portion of tweets referring to these joyous events and were thus of a generally positive sentiment. Sampling our data in portions at different points in time would thus try to minimize this problem. Thus forth, we acquired data at four different points which would be 17th of December

2015, 29th of December 2015, 19th of January 2016 and 8th of February 2016.A tweet acquired by this method has a lot of raw information in it which we may or may not find useful for our particular application. It comes in the form of the python "dictionary" data type with various key-value pairs. A list of some key-value pairs are given below:

- Whether a tweet has been favourited
- User ID
- Screen name of the user
- Original Text of the tweet
- Presence of hashtags

- Whether it is a re-tweet
- Language under which the twitter user has registered their account
- Geo-tag location of the tweet
- Date and time when the tweet was created

Since this is a lot of information we only filter out the information that we need and discard the rest. For our particular application we iterate through all the tweets in our sample and save the actual text content of the tweets in a separate file given that language of the twitter is user's account is specified to be English. The original text content of the tweet is given under the dictionary key "text" and the language of user's account is given under "lang".

TWEETS RETRIEVAL

Tweets Retrieval:

Since human labelling is an expensive process we further filter out the tweets to be labelled so that we have the greatest amount of variation in tweets without the loss of generality. The filtering criteria applied are stated below:

- Remove Retweets (any tweet which contains the string "RT")

- Remove very short tweets (tweet with length less than 20 characters)

- Remove non-English tweets (by comparing the words of the tweets with a list of 2,000 common English words, tweets with less than 15% of content matching threshold are discarded)

- Remove similar tweets (by comparing every tweet with every other tweet, tweets with more than 90% of content matching with some other tweet is discarded)

After this filtering roughly 30% of tweets remain for human labelling on average per sample, which made a total of 10,173 tweets to be labelled.

Data Preprocessing:

Data preprocessing consists of three steps:
1) tokenization,

2) normalization, and
3) part-of-speech (POS) tagging.

Tokenization:

It is the process of breaking a stream of text up into words, symbols and other meaningful elements called “tokens”. Tokens can be separated by whitespace characters and/or punctuation characters. It is done so that we can look at tokens as individual components that make up a tweet.Emoticons and abbreviations (e.g., OMG, WTF, BRB) are identified as part of the tokenization process and treated as individual tokens.

Normalization:

For the normalization process, the presence of abbreviations within a tweet is noted and then abbreviations are replaced by their actual meaning (e.g., BRB – > be right back). We also identify informal intensifiers such as all-caps (e.g., I LOVE this show!!! and character repetitions (e.g., I’ve got a mortgage!! happyyyyyy”), note their presence in the tweet. All-caps words are made into lower case, and instances of repeated characters are replaced by a single character. Finally, the presence of any special Twitter tokens is noted (e.g., #hashtags, usertags, and URLs) and placeholders indicating the token type are substituted. Our hope is that this normalization improves the performance of the POS tagger, which is the last preprocessing step.

Part-of-speech:

POS-Tagging is the process of assigning a tag to each word in the sentence as to which grammatical part of speech that word belongs to, i.e. noun, verb, adjective, adverb, coordinating conjunction etc. For each tweet, we have features for counts of the number of verbs, adverbs, adjectives, nouns, and any other parts of speech.

Classification Algorithem:

Let's build a sentiment analysis of Twitter data to show how you might integrate an algorithm like this into your applications. We'll first start by choosing a topic, then we will gather tweets with that keyword and perform sentiment analyis on those tweets. We'll end up with an overall impression of whether people view the topic positively or not.

Step 1: Gather Tweets

First, choose a topic you wish to analyze. Inside sentiment-analysis.js, you can define input to be whatever phrase you like. In this example, we'll use a word we expect to return positive results.

```
var algorithmia = require("algorithmia");
var client = algorithmia(process.env.ALGORITHMIA_API_KEY);
var input = "happy";
var no_retweets = [];

console.log("Analyzing tweets with phrase: " + input);
client.algo("/diego/RetrieveTweetsWithKeyword/0.1.2").pipe(input).then(f
unction(output) {
 if (output.error) {
 console.log(output.error);
 } else {
 var tweets = [];
 var tweets = output.result;
 for (var i = 0; i < output.result.length; i++) {
 // Remove retweets. All retweets contain "RT" in the string.
 if (tweets[i].indexOf('RT') == -1) {
 no_retweets.push(tweets[i]);
 }
 }
}

// We will cover this function in the next step.
analyze_tweets(no_retweets);
});
```

first we use the Algorithmia API to pass our topic to the algorithm RetrieveTweetsWithKeyword(Retrieve tweets that include keyword anywhere int their text. Limited to 500 tweets per call.) as our input. This will grab tweets containing our phrase. Second, we clear out the retweets so that we don't have duplicate data throwing off our scores. Twitter conveniently includes "RT" at the beginning of each tweet, so we find tweets with that string and remove them from our data set. This leaves us with a convenient set of tweets in the array no_retweets.

Step 2: Perform Sentiment Analysis on Tweets
After gathering and cleaning our data set, we are ready to execute the sentiment analysis algorithm on each tweet. Then, we will calculate an average score for all the tweets combined.

```
var analyze_tweets = function(no_retweets) {
var total_score = 0;
var score_count = 0;
var final_score = 0;

 // Execute sentiment analysis on every tweet in the array, then calculate
average score.
 for (var j = 0; j < no_retweets.length; j++) {
client.algo("nlp/SentimentAnalysis/0.1.1").pipe(no_retweets[j]).then(functi
on(output) {
 if(output.error) {
 console.log(output.error);
 } else {
 console.log(output.result);
 score_count = score_count + 1;
 total_score = total_score + output.result;
 }
 // Calculate average score.
 if (score_count == no_retweets.length) {
 final_score = total_score / score_count;
 console.log('final score: ' + final_score);
 }
 })
 }
}
```

In the above algorithem, we iterated through each tweet in no_retweets to send that as input to the Sentiment Analysis algoritm. Then with the results from that API call, we added the output result to a total_score variable. We keep track of how many tweets we've gone through with the variable score_count, so that when it reaches the same number as the number of tweets we wanted to analyze we then calculate the final score by averaging the total_score. This final result returns a number in the range [0-4] representing, in order, very negative, negative, neutral, positive, and very positive sentimen .

Classified Tweets:

We labelled the tweets in three classes according to sentiments expressed/observed in the tweets: positive, negative and neutral We gave the following guidelines to our labellers to help them in the labelling process:

Positive:

If the entire tweet has a positive/happy/excited/joyful attitude or if something is mentioned with positive connotations. Also if more than one sentiment is expressed in the tweet but the positive sentiment is more dominant. Example: “4 more years of being in shithole Australia then I move to the USA! :D”.

Negative:

If the entire tweet has a negative/sad/displeased attitude or if something is mentioned with negative connotations. Also if more than one sentiment is expressed in the tweet but the negative sentiment is more dominant. Example: “I want an android now this iPhone is boring :S”.

Neutral:

If the creator of tweet expresses no personal sentiment/opinion in the tweet and merely transmits information. Advertisements of different products would be labelled under this category. Example: “US House Speaker vows to stop Obama contraceptive rule... http://t.co/cyEWqKlE”.

<Blank>:

Leave the tweet unlabelled if it belongs to some language other than English so that it is ignored in the training data.

Now that we have discussed some of the text formatting techniques employed by us, we will move to the list of features that we have explored. As we will see below a feature is any variable which can help our classifier in differentiating between the different classes. There are two kinds of classification in our system (as will be discussed in detail in the next section), the objectivity / subjectivity classification and the positivity / negativity classification. As the name suggests the former is for differentiating between objective and subjective classes while the latter is for differentiating between positive and negative classes.

The list of features explored for objective / subjective classification is as below:

- Number of exclamation marks in a tweet
- Number of question marks in a tweet
- Presence of exclamation marks in a tweet
- Presence of question marks in a tweet

• Presence of url in a tweet
• Presence of emoticons in a tweet
• Unigram word models calculated using Naive Bayes
• Prior polarity of words through online lexicon MPQA
• Number of digits in a tweet
• Number of capitalized words in a tweet
• Number of capitalized characters in a tweet
• Number of punctuation marks / symbols in a tweet
• Ratio of non-dictionary words to the total number of words in the tweet
• Length of the tweet Number of adjectives in a tweet
• Number of comparative adjectives in a tweet
• Number of superlative adjectives in a tweet
• Number of base-form verbs in a tweet
• Number of past tense verbs in a tweet
• Number of present participle verbs in a tweet
• Number of past participle verbs in a tweet
• Number of 3rd person singular present verbs in a tweet
• Number of non-3rd person singular present verbs in a tweet
• Number of adverbs in a tweet
• Number of personal pronouns in a tweet
• Number of possessive pronouns in a tweet
• Number of singular proper noun in a tweet
• Number of plural proper noun in a tweet
• Number of cardinal numbers in a tweet
• Number of possessive endings in a tweet
• Number of wh-pronouns in a tweet
• Number of adjectives of all forms in a tweet
• Number of verbs of all forms in a tweet
• Number of nouns of all forms in a tweet
• Number of pronouns of all forms in a tweet

The list of features explored for positive / negative classification are given below
• Overall emoticon score (where 1 is added to the score in case of positive emoticon, and 1 is subtracted in case of negative emoticon)
• Overall score from online polarity lexicon MPQA (where presence of strong positive word in the tweet increases the score by 1.0 and the presence of weak negative word would decrease the score by 0.5)
• Unigram word models calculated using Naive Bayes
• Number of total emoticons in the tweet
• Number of positive emoticons in a tweet
• Number of negative emoticons in a tweet
• Number of positive words from MPQA lexicon in tweet

• Number of negative words from MPQA lexicon in tweet
• Number of base-form verbs in a tweet
• Number of past tense verbs in a tweet
• Number of present participle verbs in a tweet
• Number of past participle verbs in a tweet
• Number of 3rd person singular present verbs in a tweet
• Number of non-3rd person singular present verbs in a tweet
• Number of plural nouns in a tweet
• Number of singular proper nouns in a tweet
• Number of cardinal numbers in a tweet
• Number of prepositions or coordinating conjunctions in a tweet
. Number of adverbs in a tweet
• Number of wh-adverbs in a tweet
• Number of verbs of all forms in a tweet

7. IMPLEMENTATION

Implementation is the stage where the theoretical design is turned into a working system. The most crucial stage in achieving a new successful system and in giving confidence on the new system for the users that it will work efficiently and effectively.

The system can be implemented only after thorough testing is done and if it is found to work according to the specification. It involves careful planning, investigation of the current system and it constraints on implementation, design of methods to achieve the change over and an evaluation of change over methods a part from planning.

Two major tasks of preparing the implementation are education and training of the users and testing of the system. The more complex the system being implemented, the more involved will be the system analysis and design effort required just for implementation.

The implementation phase comprises of several activities. The required hardware and software acquisition is carried out. The system may require some software to be developed. For this, programs are written and tested. The user then changes over to his new fully tested system and the old system is discontinued.

TESTING

The testing phase is an important part of software development. It is the Information zed system will help in automate process of finding errors and missing operations and also a complete verification to determine whether the objectives are met and the user requirements are satisfied. Software testing is carried out in three steps:

1. The first includes unit testing, where in each module is tested to provide its correctness, validity and also determine any missing operations and to verify whether the objectives have been met. Errors are noted down and corrected immediately.

2. Unit testing is the important and major part of the project. So errors are rectified easily inparticular module and program clarity is increased. In this project entire system is divided into several modules and is developed individually. So unit testing is conducted to individual modules.
3. The second step includes Integration testing. It need not be the case, the software whosemodules when run individually and showing perfect results, will also show perfect results when run as a whole.

For the following Sentiment Analysis with the help of the Survey we create a code to retrieve the data of tweeter, the code is :

```
import re
import tweepy
from tweepy import OAuthHandler
from textblob import TextBlob
import matplotlib.pyplot as plt
class TwitterClient(object):

 def __init__(self):

      consumer_key = 'jbkZ2RmduoH7eh9WBpPUQWro3'
      consumer_secret =
'RpdmaKXShnzz8NdjlBG6vad88E3CebNtx5Gb03fkEvGCst1fIo'
      access_token = '585362387-
kqPJV0ztt0Q1RVQdz77LTMhWV0CzNgk1cAJwmBHm'
      access_token_secret =
'jYfkksmxZybdn9pwpArAVWzSDpe0J4yaafU3EqQS9yJQ3'

 try:

    self.auth = OAuthHandler(consumer_key, consumer_secret)
```

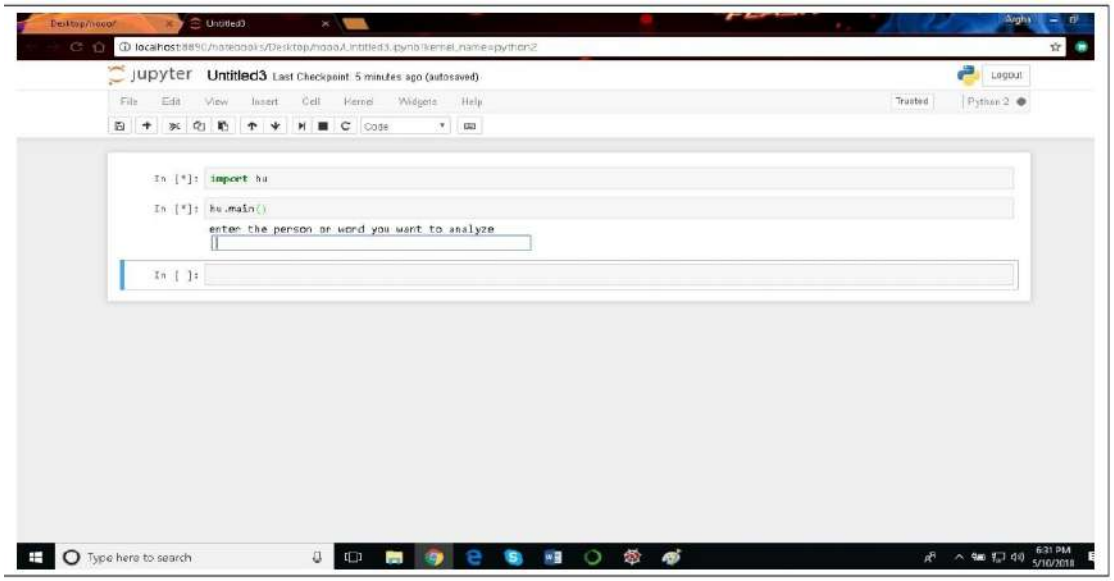
```
        self.auth.set_access_token(access_token, access_token_secret)

            self.api = tweepy.API(self.auth)
        except:
            print("Error: Authentication Failed")

    def clean_tweet(self, tweet):

            return ' '.join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z
    \t])|(\w+:\/\/\S+)", " ", tweet).split())

            def get_tweet_sentiment(self, tweet):

                analysis = TextBlob(self.clean_tweet(tweet))

                if analysis.sentiment.polarity > 0:
                        return 'positive'
            elif analysis.sentiment.polarity == 0:
                return 'neutral'
            else:
                return 'negative'

    def get_tweets(self, query, count = 20000):

        tweets = []

        try:
            fetched_tweets = self.api.search(q = query, count = count)
```

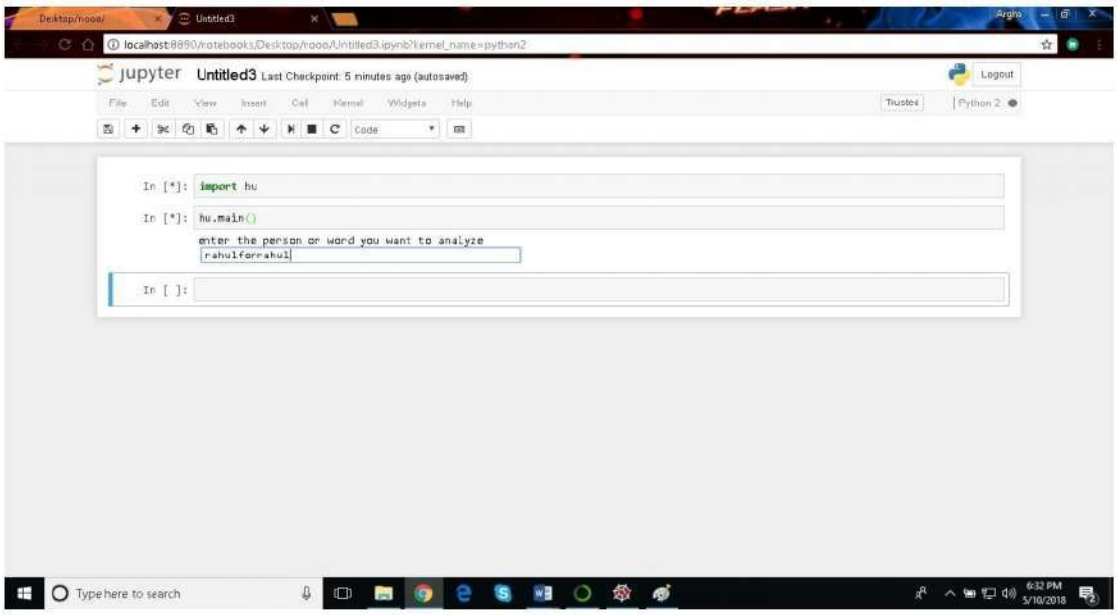
```
            for tweet in fetched_tweets:

            parsed_tweet = {}

            parsed_tweet['text'] = tweet.text

            parsed_tweet['sentiment'] = self.get_tweet_sentiment(tweet.text)

            if tweet.retweet_count > 0:

                if parsed_tweet not in tweets:
                tweets.append(parsed_tweet)
           else:
                tweets.append(parsed_tweet)

        return tweets

            except tweepy.TweepError as e:

            print("Error : " + str(e))

def plot():
    api = TwitterClient()

    tweets = api.get_tweets(query = raw_input("enter the person or word
you want to analyze\n"), count = 20000)
    ptweets = [tweet for tweet in tweets if tweet['sentiment'] == 'positive']
    pt=format(100*len(ptweets)/len(tweets))
    print("POSITIVE TWEET PERSENTAGE: ",pt)
```

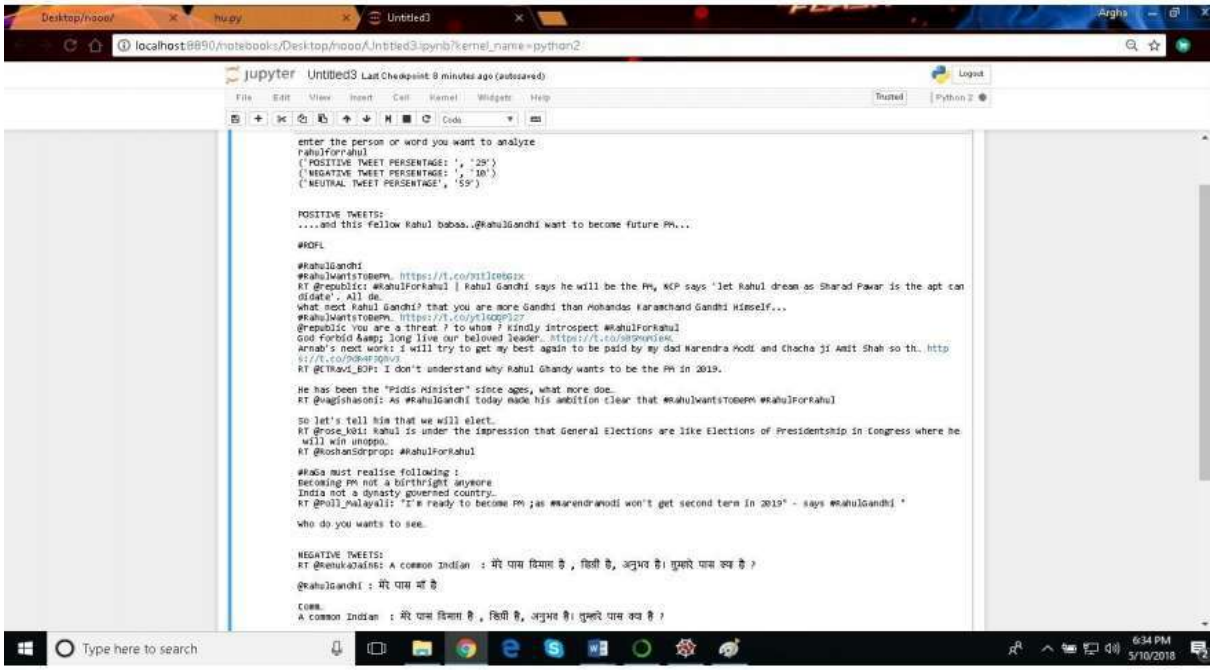
```
  ntweets = [tweet for tweet in tweets if tweet['sentiment'] == 'negative']
  nt=format(100*len(ntweets)/len(tweets))
  print("NEGATIVE TWEET PERSENTAGE: ",nt)
  nut=format(100*(len(tweets) - len(ntweets) -len(ptweets))/len(tweets))
  print("NEUTRAL TWEET PERSENTAGE",nut)
  print("\n\nPOSITIVE TWEETS:")
  for tweet in ptweets[:10]:
      print(tweet['text'])
  print("\n\nNEGATIVE TWEETS:")
  for tweet in ntweets[:10]:
     print(tweet['text'])
  choice=raw_input("PIECHART\n")
if choice=="" :
   labels = 'Positive', 'Negative', 'Neutral'
   sizes = [pt,nt,nut]
   colors = ['green', 'red', 'blue']
   explode = (0.1,0.1,0.1) # explode 1st slice
   plt.pie(sizes, explode=explode, labels=labels, colors=colors,
   autopct='%1.1f%%', shadow=True, startangle=40)
   plt.axis('equal')
   plt.show()
def main():


     plot()


 if __name__ == "__main__":


     main()
```

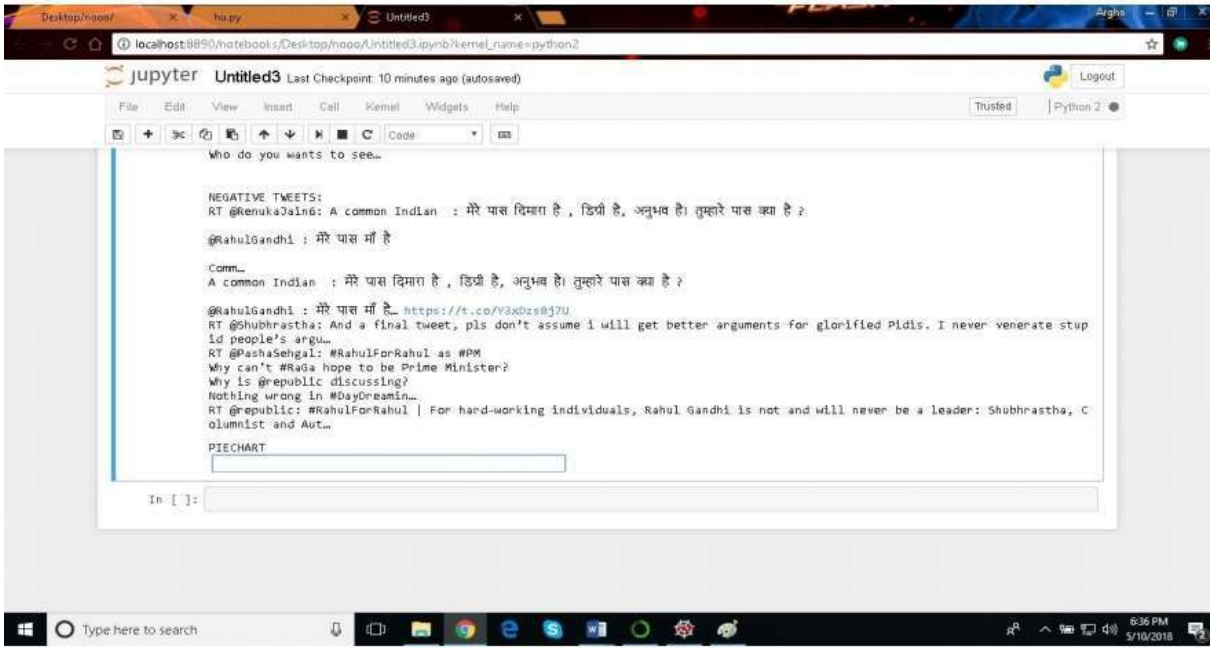
8. SNAPSHOTS

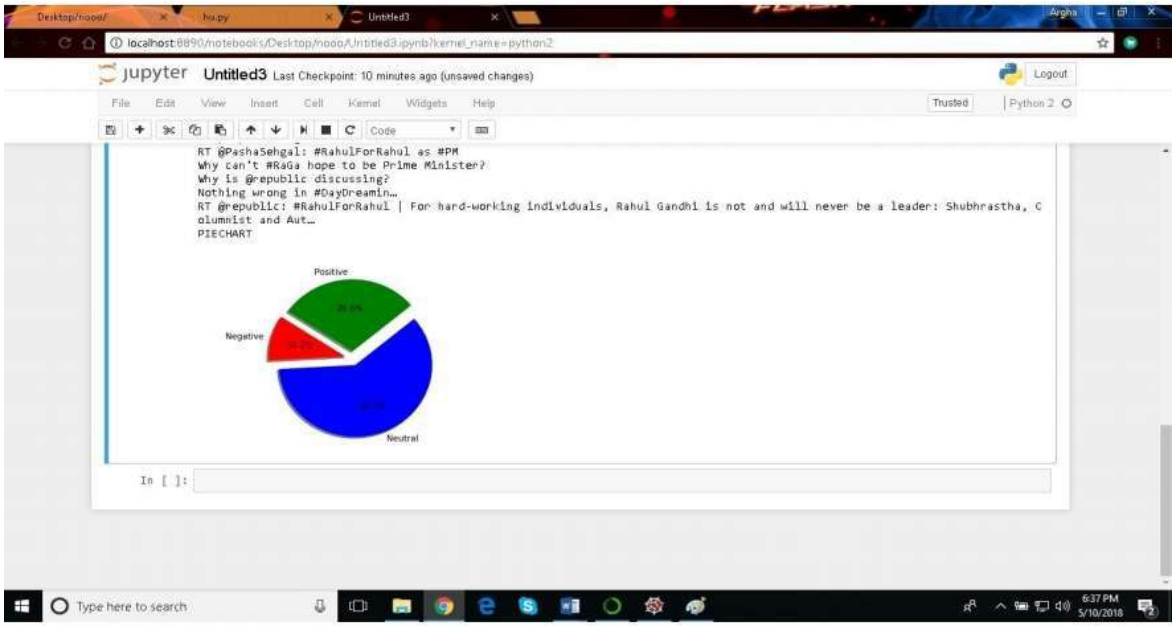
We will first present our results for the objective / subjective and positive / negative classifications. These results act as the first step of our classification approach. We only use the short-listed features for both of these results. This means that for the objective / subjective classification we have 5 features and for positive / negative classification we have 3 features. For both of these results we use the Naïve Bayes classification algorithm, because that is the algorithm we are employing in our actual classification approach at the first step. Furthermore all the figures reported are the result of 10-fold cross validation. We take an average of each of the 10 values we get from the cross validation.
we make a condition while reporting the results of polarity classification (which differentiates between positive and negative classes) that only subjective labelled tweets are used to calculate these results. However, in case of final classification approach, any such condition is removed and basically both objectivity and polarity classifications are applied to all tweets regardless of whether they are labelled objective or subjective.











If we compare these results to those provided by Wilson et al we see that although the accuracy of neutral class falls from 82.1% to 73% if we use our classification instead of theirs. However, for all other classes we report significantly greater results. Although the results presented by Wilson et al. are not from Twitter data they are of phrase level sentiment analysiswhich is very close in concept to Twitter sentiment analysis.Finally we conclude that our classification approach provides improvement in accuracy by using even the simplest features and small amount of data set. However there are still a number of things we would like to consider as future work which we mention in the next section.

9. CONCLUTION

The package was designed in such a way that future modifications can be done easily. Thefollowing conclusions can be deduced from the development of the project:

- Neutral tweets: The current classifier does not consider neutral sentiments, even though many tweets do not exhibit a clear cut positive or negative emotion, especially the ones stating a fact or news.
- Bi-grams in combination with unigrams to handle negations like “not happy”
- Semantics may be employed when sentiment of a tweet depends on the perspective of the reader.
- For example: “India lost to Australia in the semis indicates negative sentiment for India, but positive for Australia.
- Automation of the entire system improves the efficiency
- It provides a friendly graphical user interface which proves to be better when comparedto the existing system.
- It gives appropriate access to the authorized users depending on their permissions.

It effectively overcomes the delay in communications.

Updating of information becomes so easier

- System security, data security and reliability are the striking features.
- The System has adequate scope for modification in future if it is necessary.

The task of sentiment analysis, especially in the domain of micro-bloging, is still in the developing stage and far from complete. So we propose a couple of ideas which we feel are worth exploring in the future and may result in further improved performance.

Right now we have worked with only the very simplest unigram models; we can improve those models by adding extra information like closeness of the word with negation word. We could specify a window prior to the word (a window could for example be of 2 or 3 words) under consideration and the effect of negation may be incorporated into the model if it lies within that window. The closer the negation word is to the unigram word whose prior polarity is to be calculated, the more it should affect the polarity. For example if the negation is right next to the word, it may simply reverse the polarity of that word and farther the negation is from the word the more minimized ifs effect should be.
Apart from this, we are currently only focusing on unigrams and the effect of bigrams and trigrams may be explored. As reported in the literature review section when bigrams are used along with unigrams this usually enhances performance. However for bigrams and trigrams to be an effective feature we need a much more labeled data set than our meager 9,000 tweets.

Right now we are exploring Parts of Speech separate from the unigram models, we can try to incorporate POS information within our unigram models in future. So say instead of calculating a single probability for each word like P(word | obj) we could instead have multiple probabilities for each according to the Part of Speech the word belongs to. For example we may have P(word | obj, verb), P(word | obj, noun) and P(word | obj, adjective). Pang et al. used a somewhat similar approach and claims that appending POS information for every unigram results in no significant change in performance (with Naive Bayes performing slightly better and SVM having a slight decrease in performance), while there is a significant decrease in accuracy if only adjective unigrams are used as features. However these results are for classification of reviews and may be verified for sentiment analysis on micro blogging websites like Twitter.

One more feature we that is worth exploring is whether the information about relative position of word in a tweet has any effect on the performance of the classifier. Although Pang et al. explored a similar feature and reported negative results, their results were based on reviews which are very different from tweets and they worked on an extremely simple model.

In this research we are focussing on general sentiment analysis. There is potential of work in the field of sentiment analysis with partially known context. For example we noticed that users generally use our website for specific types of keywords which can divided into a couple of distinct classes, namely: politics/politicians, celebrities, products/brands,sports/sportsmen, media/movies/music. So we can attempt to perform separate sentiment analysis on tweets that only belong to one of these classes (i.e. the training data would not be general but specific to one of these categories) and compare the results we get if we apply general sentiment analysis on it instead.

10. REFERENCE

[1] Efthymios Kouloumpis and Johanna Moore,IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 4, No 3, July 2012

[2] S. Batra and D. Rao, "Entity Based Sentiment Analysis on Twitter", Stanford University,2010

[3] Saif M.Mohammad and Xiaodan zhu ,Sentiment Analysis on of social media texts:,2014

[4]Ekaterina kochmar,University of Cambridge,at the Cambridge coding Academy Data Science.2016

[5] Manju Venugopalan and Deepa Gupta ,Exploring Sentiment Analysis on Twitter Data, IEEE 2015

[6] Brett Duncan and Yanqing Zhang, Neural Networks for Sentiment Analysis on Twitter.2017

[7] Afroze Ibrahim Baqapuri, Twitter Sentiment Analysis: The Good the Bad and the OMG!,Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media.2011