A DISSERTATION REPORT ON

SENTIMENT ANALYSIS USING ORIGINAL AND REVERSED REVIEWS

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE
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CERTIFICATE

This is to certify that the dissertation entitled

"SENTIMENT ANALYSIS USING ORIGINAL AND REVERSED REVIEWS"

Submitted by

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is a bonafide work carried out by him under the supervision of Prof. A. G. Phakatkar and it is submitted towards the partial fulfillment of the requirement of Savitribai Phule Pune University, for the award of the degree of Master of Engineering (Computer Engineering)

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It gives me great pleasure in presenting the dissertation report for my dissertation on "SENTIMENT ANALYSIS USING ORIGINAL AND REVERSED REVIEWS".

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Kaushik S. Hande
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ABSTRACT

The reviews and blogs obtained from social networking and online marketing sites, act as an important source for analysis and improved decision making. These reviews are mostly unstructured by nature and thus, need processing. Bag of words (BOW) model of features are used for processing in machine learning algorithms. However, BOW is not able to handle negation well because of its fundamental deficiencies. Many ways are used to handle the problem of negation. Most of them require either knowledge about language constructs or extra human interventions which eventually increases the complexity. In this work, a data expansion technique, called dual sentiment analysis (DSA), is used to address the polarity shift problem due to negation in sentiment classification. Both original and reversed reviews are used to classify the test reviews in dual sentiment analysis.

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CHAPTER 1

SYNOPSIS

1.1 DISSERTATION TITLE

Sentiment Analysis using Original and Reversed Reviews.

1.2 INTERNAL GUIDE

Prof. A. G. Phakatkar

1.3 PROBLEM STATEMENT

" To make use of the original and reversed review samples in pairs for training a statistical classifier and make predictions. "

1.4 OBJECTIVES

- To train the classifiers using reviews and actual labels.

- To predict label for test data.

- To classify test data using opposite reviews.

1.5 HYPOTHESIS

Polarity shift causes accuracy of classifier to decrease. We assume that original review and corresponding opposite review can be used together to increase the accuracy of review class label prediction and to avoid the problem caused due to polarity shift.

1.6 RELEVANT MATHEMATICS ASSOCIATED WITH DISSERTATION

1.6.1 Mathematical Model

$S = \{s, e, I, O, fmain | \phi\}$

where,

s = start state

e = end state

I = Inputs to the system

I = {x,x′,y,y′,D,D′}

where,

x = original sample

x′ = reversed sample

$y \in \{0,1\}$ = The class label of the original sample

$y' = 1 - y$ = The class label of the reversed sample

$D = (x_i, y_i)_{i=1}^{n}$ = original training set

$D' = (x_i', y_i')_{i=1}^{n}$ = The reversed training set

O = Output

O = { p(x),p(x′),p(x,x′)}

where

p(x) = Prediction for the original sample

p(x′) = Prediction for the reversed sample

p(x,x′) = Dual prediction based on a pair of sample

$f_{main} = \{f_{reverse}, f_{classifier}\}$

$f_{reverse}$ = function for reversing the corresponding each review

$f_{classifier}$ = classifier for the prediction of class of review

1.6.2 Metrics for Performance Evaluation

The parameters helpful to evaluate performance of supervised machine learning algorithm is based on the element from a matrix known as confusion matrix or contingency table. It is used in supervised machine learning algorithm to help in assessing performance of any algorithm. From classification point of view, terms such as "True Positive(TP)", "False Positive (FP)", "True Negative(TN)", "False Negative (FP)" are used to compare label of classes in this matrix as shown. True Positive represents the number of reviews those are positive and also classified as positive by the classifier, where as False Positive indicates positive reviews, but classifier does not classify it as positive. Similarly, True Negative represents the reviews which are negative also classified as negative by the classifier, where as False Negative are negative reviews but classifier does not classify it as negative.

Based on the values obtained from confusion matrix, other parameters such

as "precision", "recall", "f-measure", and "accuracy" are used for evaluating performance of the classifiers.

- **Accuracy** : It is the most common measure of classification process. It can be calculated as the ratio of correctly classified example to total number of examples.

$$\frac{TP+TN}{TP+TN+FP+FN} \tag{1.1}$$

CHAPTER 2

TECHNICAL KEYWORDS

2.1 AREA OF DISSERTATION

Natural language processing, machine learning, sentiment analysis, opinion mining.

2.2 ACM KEYWORDS

A Information Systems

  A.1 Information Retrievals

    A.1.1 Retrieval tasks and goals

      A.1.1.1 Sentiment analysis

      A.1.1.2 Clustering and classification

B Computing methodologies

  B.1 Machine learning

    B.1.1 Supervised learning by classification

      B.1.1.1 Multinomial Naive Bayes

      B.1.1.2 Support Vector Machines

CHAPTER 3

INTRODUCTION

3.1 DISSERTATION IDEA

Sentiment is an attitude, thought, or judgement prompted by feeling. Sentiment analysis is also known as opinion mining, it involves studying of peoples sentiment towards certain entities. From a perspective of a user, people are able to express their views through various social media, such as forums, micro-blogs, or online social networking sites [4].

With the advent of web 2.0 techniques, users started preferring to share their opinions on the Web. These user-generated and sentiment-rich data are valuable to many applications like credibility analysis of news sites on the web, recommendation system, business and government intelligence etc. At the same time, it brings urgent need for detecting overall sentiment inclinations of documents generated by users, which can be treated as a classification problem. Sentiment analysis includes several subtasks which have seen a great deal of attention in recent years:

1. To detect whether a given document is subjective or objective.
2. To identify whether given subjective document express a positive opinion or a negative opinion.
3. To determine the sentiment strength of a document, such as strongly negative, weakly negative, neutral, weakly positive and strongly positive.

In this work we are focusing on second subtask. Besides individuals on social media marketers also need to monitor all media for information related to their brands whether it's for public relations activities, fraud violations, or competitive intelligence. Thus, aside from individuals, sentiment analysis is also the need of companies which are anxious to understand how their products and services are perceived by the public.

The dominating text representation method in both supervised and semi supervised sentiment classification is known as the bag-of-words (BOW) model [3], which is difficult to meet the requirements for understanding the review text and dealing with complex linguistic structures such as negation [2]. Due to the polarity shift, classifiers predict polarity incorrectly. [1][7][13] .

Several approaches have been proposed in the literature to address the polar-

ity shift problem .They require either knowledge about language constructs or extra human interventions which eventually increases the complexity in classification of sentiment. Such high-level dependency on external resources makes the systems difficult to be widely used in practice. There were also some efforts to address the polarity shift problem with the absence of extra annotations and linguistic knowledge. However, results are still far from satisfactory.

3.2 MOTIVATION OF DISSERTATION

Polarity shift is a kind of linguistic phenomenon which can reverse the sentiment polarity of the text. Negation is the most important type of polarity shift [1]. For example, by adding a negation word "don't" to a positive text "I like this book " in front of the word "like", the sentiment of the text will be reversed from positive to negative. However, the two sentiment-opposite texts are considered to be very similar by the BOW representation. This is the main reason why standard machine learning algorithms often fail under the circumstance of polarity shift.

CHAPTER 4

LITERATURE SURVEY

We studied the related work on sentiment analysis and polarity shift.

4.1 SENTIMENT ANALYSIS AND POLARITY SHIFT

According to the levels of granularity, tasks in sentiment analysis can be divided into four categorizations: document- level, sentence-level, phrase-level, and aspect-level sentiment analysis.

For document and sentence-level sentiment classification, there are two main types of methods : term-counting and machine learning methods [2] [3] [4] [15]. In term-counting methods, the overall orientation of a text is obtained by summing up the orientation scores of content words in the text, based on manually-collected or external lexical resources [6] [9]. In machine learning methods, sentiment classification is regarded as a statistical classification problem, where a text is represented by a bag-of-words; then, the supervised machine learning algorithms are applied as classifier [3]. The use of ensembles of multiple base classifiers, combined with scores obtained from lexicons, can improve the accuracy of sentiment classification [15][14]. Accordingly, the way to handle polarity shift also differs in the two types of methods.

The term-counting methods can be easily modified to include polarity shift. One common way is to directly reverse the sentiment of polarity-shifted words, and then sum up the sentiment score word by word [10]. Compared with term counting methods, the machine learning methods are more widely discussed in the sentiment classification literatures. However, it is relatively hard to integrate the polarity shift information into the BOW model in such methods. For example, Das and Chen [2] proposed a method by simply attaching "NOT" to words in the scope of negation, so that in the text "I don't like this book", the word "like" becomes a new word "like-NOT". Yet Pang et al. [3] reported that this method only has slightly negligible effects on improving the sentiment classification accuracy.

4.2   GAP IDENTIFICATION THROUGH LITERATURE SURVEY

The following table shows the literature survey about different techniques of sentiment analysis used for classification.

Table 4.1: Literature Survey

No.	Reference	Techniques	Description
1	Dual Sentiment Analysis: Considering Two sides of one review [1]	Support vector machine (SVM), Naive bayes, Logistic Regression	Dual training and Dual Prediction technique is used.
2	Thumbs up? Sentiment Classification using Machine learning algorithms [3]	Learning algorithms and n-gram model	Classify the dataset using different machine.
3	Classification of sentiment reviews using N-gram machine learning approach [11]	Support Vector Machine Naive Bayes	Converting text reviews into numeric matrices using countvectorizer and TF-IDF
4	Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews [6]	Unsupervised learning algorithm for classifying a review	A specific unsupervised learning technique based on the mutual information
5	Automatic Opinion polarity Classification of movie [12]	Naive Bayes And Markov Model (MM)	Accessed overall opinion polarity(OVOP) concept using machine learning algorithm
6	Dual Training and dual prediction for polarity classification [5]	SVM and Naive Bayes	Dual training and dual prediction (DTDP)

CHAPTER 5

PROBLEM DEFINITION AND SCOPE

5.1 GOALS

- To study existing sentiment analysis approaches.

- Study of corpus based, lexical based and semantic based techniques.

- Understanding unigram, bigram, trigram and combination of them for modeling purpose.

- To train the model with naive bayes, support vector machine, maximum entropy and applying it to the test dataset.

- Evaluating the results generated by classifiers.

5.2 OBJECTIVES

Please refer Chapter 1, Section 1.7 on Page 2

5.3 STATEMENT OF SCOPE

- Preprocessing of the reviews.

- Classify reviews into two polarities.

- Evaluate the classification accuracy of each classifier.

5.4 SOFTWARE CONTEXT

5.4.1 Scikit-learn

Scikit-learn (formerly scikits.learn) is a free software machine learning library for the python programming language. It features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the python numerical and scientific libraries NumPy and SciPy.

5.4.2 NumPy

NumPy is the fundamental package for scientific computing with Python. It contains among other things:

- A powerful N-dimensional array object

- Sophisticated (broadcasting) functions

- Tools for integrating C/C++ and fortran code

- Useful linear algebra, fourier transform, and random number capabilities

It can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined. This allows NumPy to seamlessly and speedily integrate with a wide variety of databases.

5.4.3 Natural language toolkit (NLTK)

NLTK is a leading platform for building Python programs to work with human language data. It provides easy-to-use interfaces to over 50 corpora and lexical resources such as WordNet, along with a suite of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning, wrappers for industrial-strength NLP libraries, and an active discussion forum.

5.4.4 Matplotlib

Matplotlib is a python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in python scripts, the Python and IPython shell, the jupyter notebook, web application servers, and four graphical user interface toolkits. You can generate plots, histograms, power spectra, bar charts, errorcharts, scatterplots, etc. with just a few lines of code.

CHAPTER 6

DISSERTATION PLAN

6.1 PURPOSE OF THE DOCUMENT

This document specifies and estimates various risks associated with this project and states how they are handled. It also states the project plan in terms of task and their dependency.

6.2 DISSERTATION ESTIMATES

6.2.1 Reconciled Estimates

6.2.1.1 Cost Estimates

No cost is required for tools and software as open source softwares are used.

6.2.1.2 Time Estimates

Calendar time required: 11 months.

6.2.1.3 Dissertation Resources

- Software resources used are mentioned in Chapter 7, Section 7.5.1 on Page 25

- Hardware resources used are mentioned in Chapter 7, Section 7.5.2 on Page 25

6.3 RISK MANAGEMENT

This section discusses dissertation risks and the approaches used to manage them.

6.3.1 Risk Identification

For risks identification, review of scope document, requirement specifications and schedule is done. Answers to questionnaire revealed some risks. Following risk identification questionnaire has been referred.

- Are requirements fully understood by the software engineering team and its customers?

- Have customers been involved fully in the definition of requirements?

- Do end-users have realistic expectations?

- Does the software engineering team have the right mix of skills?

- Are project requirements stable?

- Is the number of people on the project team adequate to do the job?

- Do all customer/user constituencies agree on the importance of the project and on the requirements for the system/product to be built?

6.3.2 Risk Analysis

The risks for the dissertation are analyzed within the constraints of time and quality. Risk can be as follows:

- Out of memory error, while creating model and training the model.

- Review text contains unrecognized characters.

- Out of memory error, while predicting on the test dataset.

Please refer Table 6.1, 6.2 and 6.3 for detail description.

Table 6.1: Risk Table

ID	Risk Description	Probability	Impact		
			Schedule	Quality	Overall
1	Out of Memory	High	Low	High	High
2	Unrecognized characters	Low	Medium	High	Medium
3	Out of Memory	Low	Medium	High	High

Table 6.2: Risk Probability Definitions

Probability	Value	Description
High	Probability of the occurrence is	>75%
Medium	Probability of the occurrence is	26% - 74%
Low	Probability of the occurrence is	25%

Table 6.3: Risk Impact Definitions

Impact	Value	Description
Very High	>10%	Schedule impact or unacceptable quality
High	5%-10%	Schedule impact or some parts of the project have low quality
Low	<5%	Schedule impact or barely noticeable degradation in quality low impact on schedule or quality can be incorporated

6.3.3 Overview of Risk Mitigation, Monitoring and Management

Please refer Table 6.4, 6.5 and 6.6 for detail description.

Table 6.4: Risk 1

Risk ID	1
Risk Description	Out of memory error, when training model
Category	Configuration
Source	Software Requirement Specification Document
Probability	High
Impact	High
Response	Mitigate
Strategy	Changing number of features resolves this issue.
Risk Status	Occurred and Resolved

Table 6.5: Risk 2

Risk ID	2
Risk Description	Unreconized characters
Category	Configuration
Source	Software Requirement Specification Document
Probability	Low
Impact	Low
Response	Mitigate
Strategy	Convert all characters into unicode format
Risk Status	Occurred and Resolved

Table 6.6: Risk 3

Risk ID	3
Risk Description	Out of memory error, when predicting
Category	Development Environment
Source	Software Requirement Specification Document
Probability	Low
Impact	Low
Response	Mitigate
Strategy	Using sparse matrix to represent text
Risk Status	Occurred and Resolved

6.4   STAFF ORGANIZATION

6.4.1   Team Structure

- Internal Guide : Prof. A. G. Phakatkar

- Student : Kaushik S. Hande

6.4.2   Management Reporting and Communication

The progress of dissertation is reported once in a month.

6.4.3 Dissertation Task Set

Major tasks in the Dissertation stages are -

Task 1 : Requirement

1. Define problem statement
2. Identify scope, requirements
3. Related mathematical model

Task 2 : Design

1. Identifying of key objects, functional relation
2. UML diagrams and functional dependency graph
3. System design

Task 3 : Implementation

1. Import dataset
2. Classifier implementation
3. Comparison using graphs

Task 4 : Testing

1. Unit testing
2. Integration testing
3. System testing

Task 5 : Integration and Maintenance

1. Integration
2. Maintenance

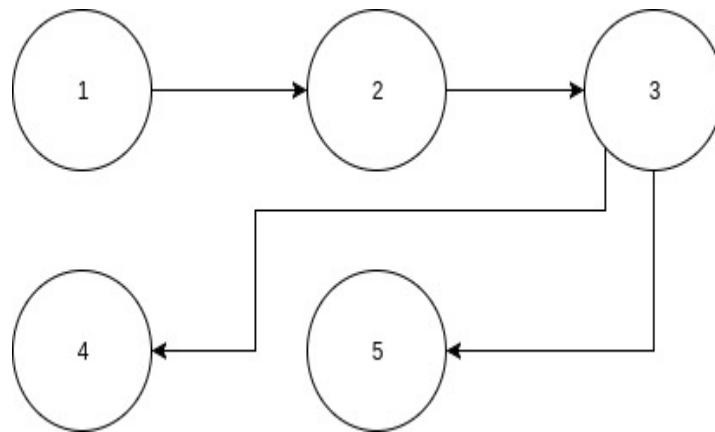Please refer figure 6.1 Task Network.

6.4.4 Task Network

Figure 6.1: Task Network

6.4.5 Timeline Chart

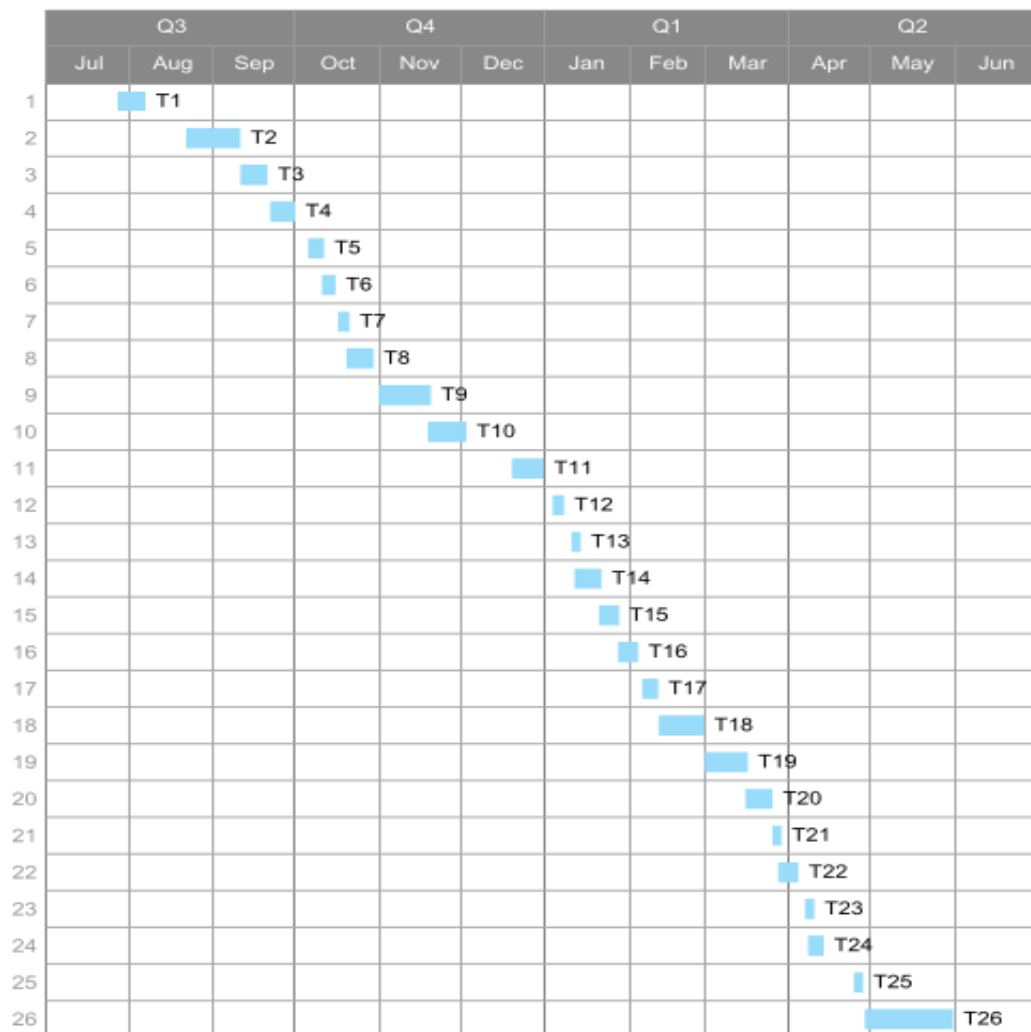Please refer Annexure B, Table B.1 on Page 62 for all Dissertation Tasks.

Figure 6.2: Timeline Chart

CHAPTER 7

SOFTWARE REQUIREMENT
SPECIFICATION

7.1   INTRODUCTION

The aim of this document is to specify the software requirements for classification of movie reviews.

7.2   PURPOSE AND SCOPE OF THE DOCUMENT

The purpose of the document is to enlist various software requirements to build the system. This document has functional and non-functional requirements for the software being developed.

7.3   OVERVIEW OF RESPONSIBILITIES OF DEVELOPER

The responsibilities of a developer includes gathering of information about the classification libraries, that can be used to design and develop the system to categorize movie reviews. The developers responsibilities include:

- Planning for dissertation (Scheduling)

- Designing of system (High Level Design Document)

- Coding of system (Implementation)

- Testing of system (Test Cases)

7.4   PRODUCT OVERVIEW

System builds classifier models for classification of reviews. Different functionality of the system are :

- Review loader : It loads the reviews into python environment.

- Stopwords remover : It removes the stopwords like is, a, an, the, was, were etc.

- Vectorizer : It converts the reviews into matrix of rows and columns where columns represents the words and rows represents each reviews. Presence of particular word in a review is shown by the values in the columns.

- Classifier : It classifies the reviews into positive and negative review.

7.5 HARDWARE RESOURCES USED

7.5.1 Software Requirements

- Python 2.7.6

- Rstudio Version 0.99.893

- R version 3.3.2

- Operating Systems:

    - Ubuntu 14.04, Ubuntu 16.04

7.5.2 Hardware Requirements

- Intel$^{®}$ Core^{TM} i7-4790 CPU @ 3.60GHz x 8 , width : 64 bits

- Memory : 8 GB DDR3

- Cores : 8

- PCI Express Gigabit Ethernet Controller, Size: 100Mbit/s, Capacity: 1Gbit/s, Width: 64 bits

- Hard Disk : 500 GB (EXT4 Primary/Logical Partition)

7.6 FUNCTIONALITY

- Download IMDB dataset of movie reviews.

- Import the movie review dataset into python environment using csv package.

- Convert the text reviews into matrix form.

- Remove the stopwords from reviews.

- Show positive and negative polarity score for test reviews.

- Compare classifiers for accuracy of classification.

7.7 INPUT

- Movie reviews with labels.

- List of stopwords.

7.8 OUTPUT

- Classification of review into positive or negative.

- Confusion matrix.

- Accuracy of classifiers.

- Comparison of classifiers.

7.9 MAJOR CONSTRAINTS

- To store movie reviews as input in csv file format.

- To execute classifiers in configured environment.

- To train the model for polarity classification.

7.10 APPLICATIONS

- Businesses and organisations which require consumer opinions to do with products they market and services they produce.

- Individuals who make decisions to purchase products or services based upon word of mouth or online reviews, or to find public opinion, e.g. concerning politics or local issues.

- Online advertising where in social media, an organisation may place an advertisement in response to a favourable review of a product, or a rival product could be advertised upon receipt of a bad review

- Opinion retrieval for general searches of opinions

- HR Analytics.

7.11   USAGE SCENARIO

A use case represents a particular functionality of a system. Hence, use case diagram is used to describe the relationships among the functionalities and their internal/external actors. This section provides various usage scenarios for the system to be developed.

7.11.1 Use Case Views

Actors of the system are user, IMDB data collector and IMDB website. IMDB data collector connects to the IMDB website and downloads the dataset. Perform text analysis on each review by using text vectorizer and sentiment analyzer. Stored results of review predictions are accessed by the user.
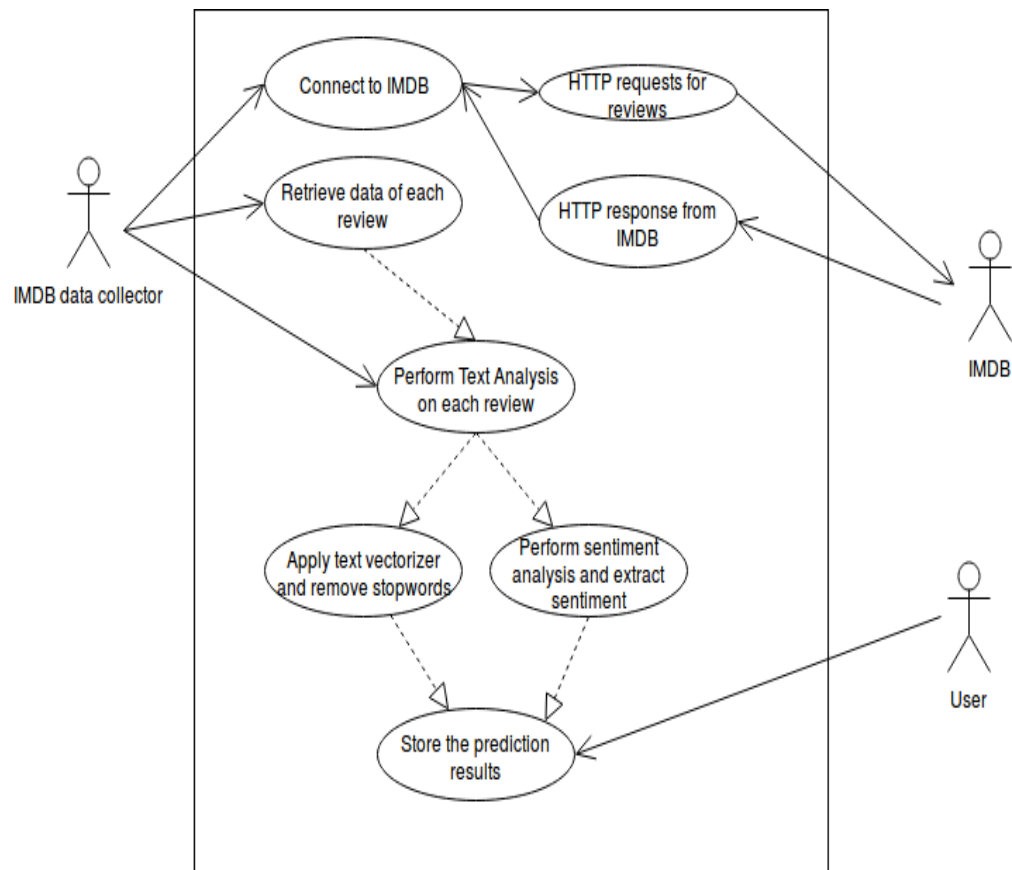
Figure 7.1: Use Case : System

7.12 MODEL AND DESCRIPTION

This section contains details about events and associated behaviour of the system which is shown using diagram below.

7.12.1 Activity Diagram

Activity diagram is a flow chart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. The control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent. The purpose of activity diagrams is to capture the dynamic behaviour of the system.

Description : As shown in figure 7.2, user downloads movie dataset. This dataset is added for processing using csv import library. Documents are preprocessed to remove stopwords and reviews are converted into matrix. Classifiers are trained after feature extraction. This trained classifiers are used on test dataset to classify.
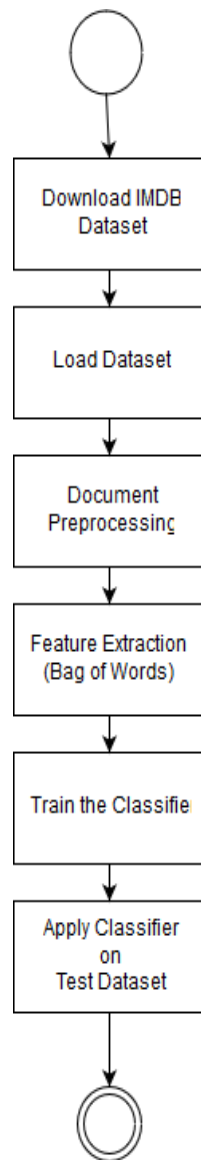
Figure 7.2: Activity Diagram

7.13   FUNCTIONAL MODEL AND DESCRIPTION

This section describes data flow diagrams (DFD) of the proposed system. There are three types of DFDs explained in the section. These diagrams explain the system in brief.

7.13.1 Data Flow Diagram

7.13.1.1 Level 0 Data Flow Diagram

In the level 0 DFD as shown in figure 7.3, downloaded reviews are loaded in sentiment analysis system. The sytem analyzes and presents report through charts to user
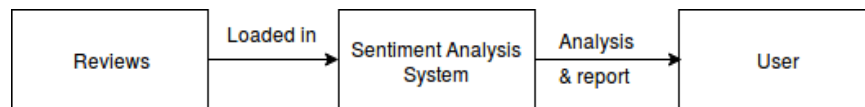

Figure 7.3: Level 0 DFD

7.13.1.2 Level 1 Data Flow Diagram

In the level 1 DFD as shown in figure 7.4, Reviews are loaded through csv file loader. Data is preprocessed and model is created. Analysis done by the system is given to the user.
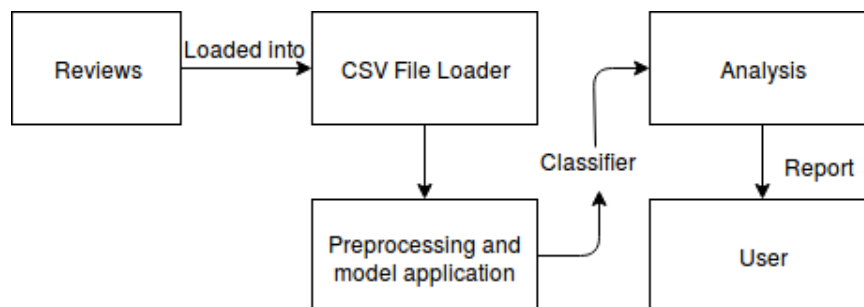
Figure 7.4: Level 1 DFD

7.13.1.3 Level 2 Data Flow Diagram

In the level 2 DFD as shown in figure 7.5, Reviews are preprocessed to give bag of words features. Classifiers are trained using this model. Classification is performed on the test dataset. Detailed analysis of results obtained by classifiers is done. It is provided to the user.
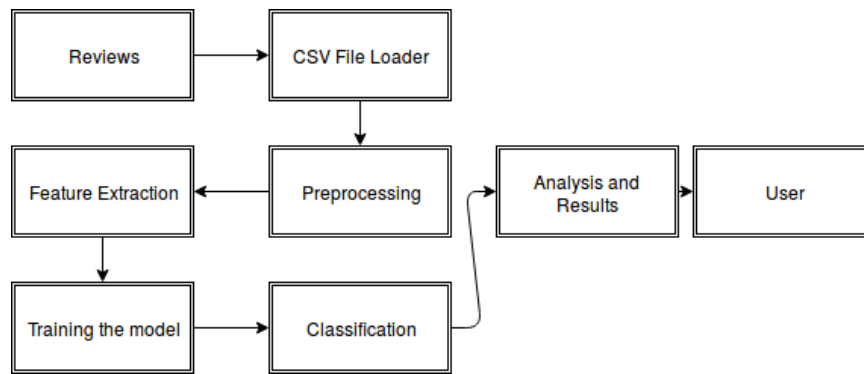
Figure 7.5: Level 2 DFD

7.14 NON-FUNCTIONAL REQUIREMENTS

7.14.1 Availability

Required libraries must be installed and loaded in the python environment with the required configurations. Dataset must be downloaded from specified URL [17].

7.14.2 Scalability

The system should be scalable to classify reviews even if the training and test data are increased. System can comfortably handle reviews dataset upto 25000 reviews.

7.14.3 Performance

The system must be interactive and delays involved must be less. There should be no immediate delays for every action and response of the system. Training time increases as the training data increases. It takes 4 to 5 seconds in training the dataset. Training time increases further when bigram and trigram models are used.

7.14.4 Usability

The system should be easy to handle and process requests efficiently. System's functions are designed to use with ease and provide results. Results are presented in the form of graphs and are easy to comprehend.

7.14.5 Reliability

The system should efficiently analyze movie reviews entirely and give correct classification result. It should be reliable to perform classification effectively on any review dataset.

7.14.6 Maintainability and Changeability

The system is made up of different independent modules that can be modified to correct faults, improve performance or other attributes, or adapt to a changed environment. System can be improved for new features and will be able to include new requirements.

CHAPTER 8

DETAILED DESIGN DOCUMENT

8.1 INTRODUCTION

This document specifies the design that is used to fetch movie reviews in CSV format, classifies individual movie review into polarity categories.

- **Polarity Categories**

    - Positive

    - Negative

IMDB movie dataset is downloaded and classified using machine learning classifier. Results obtained by various classifiers are compared with each other.

8.2 ARCHITECTURAL DESIGN

Figure 8.1 shows architectural design of proposed system. Following are important components in the system :

- Movie reviews data : It contains 1,000 positive and 1,000 negative movie reviews from IMDB.

- Preprocessing : It has stopwords removal and vectorizer.

- Training data and Test Data : Data is divided into training data and test data. Training data consists of 75% of data and test data consists of 25% of total data. Both are mutually exclusive.

- Classifier : Training data is given as a input to one of the classifier.

- Prediction system : It takes test data and applies trained model to it .

- Sentiment : It stores the end output of polarity into positive and negative classification.
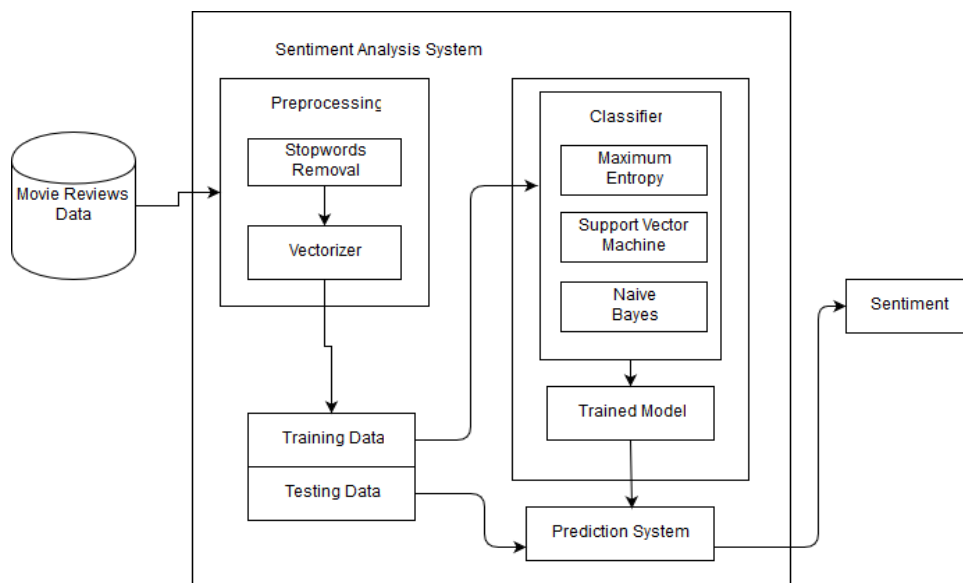
Figure 8.1: Proposed System Architecture

8.3 CLASS DESIGN

It is a static diagram that represents the static view of an application. It is not only used for visualizing, describing, and documenting different aspects of a system but

also for constructing executable code of the software application. It describes the attributes and operations of a class and also the constraints imposed on the system.

Description : In figure 8.2, modules and their relationships are shown. Document classifier used for classifying. SentimentClassification class has ClassifyReview method which predicts the polarity of review. The fit method in every classifier converts the text data into matrix of word frequency counts.
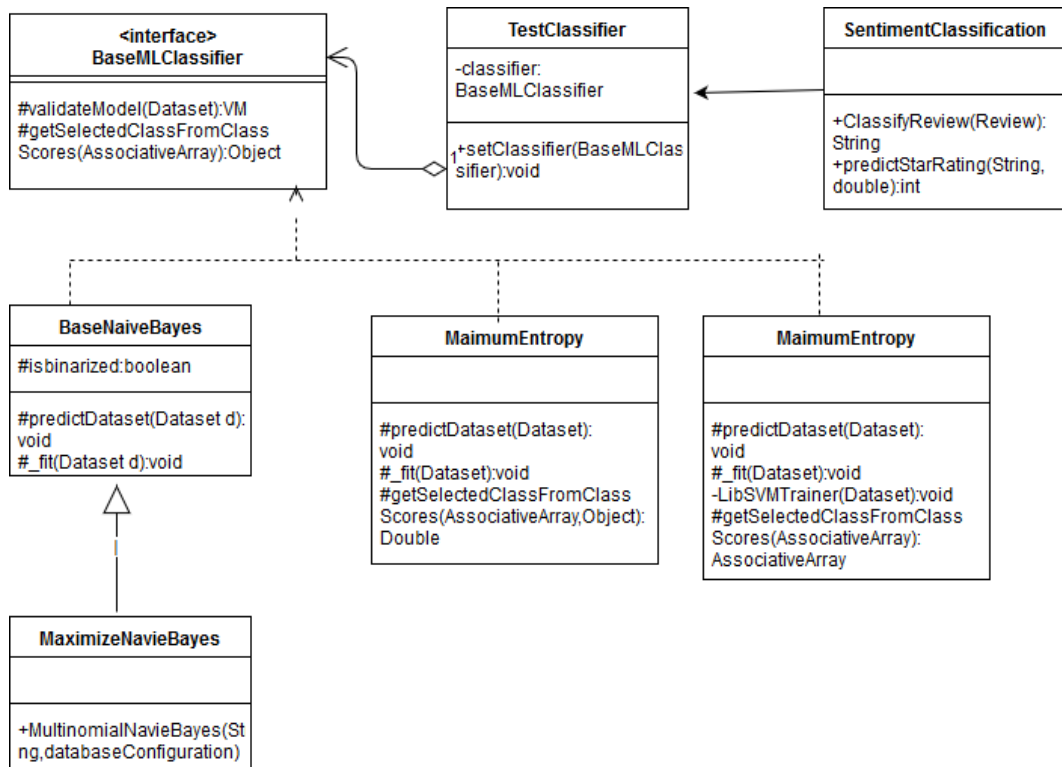

Figure 8.2: Class Diagram

8.4 COMPONENT DESIGN

It is used to model the physical aspects of a system. It is also used to visualize the organization and relationships among components in a system. It does not describe the functionality of the system but it describes the components used to make those functionalities.

Description : Figure 8.3 describes primary components of the system. Movie dataset is stored in a component which then gives to classifier system. Classifier system then preprocess the reviews and does the prediction of polority and sends the output to the console subsystem where result evaluation and comparison takes place.
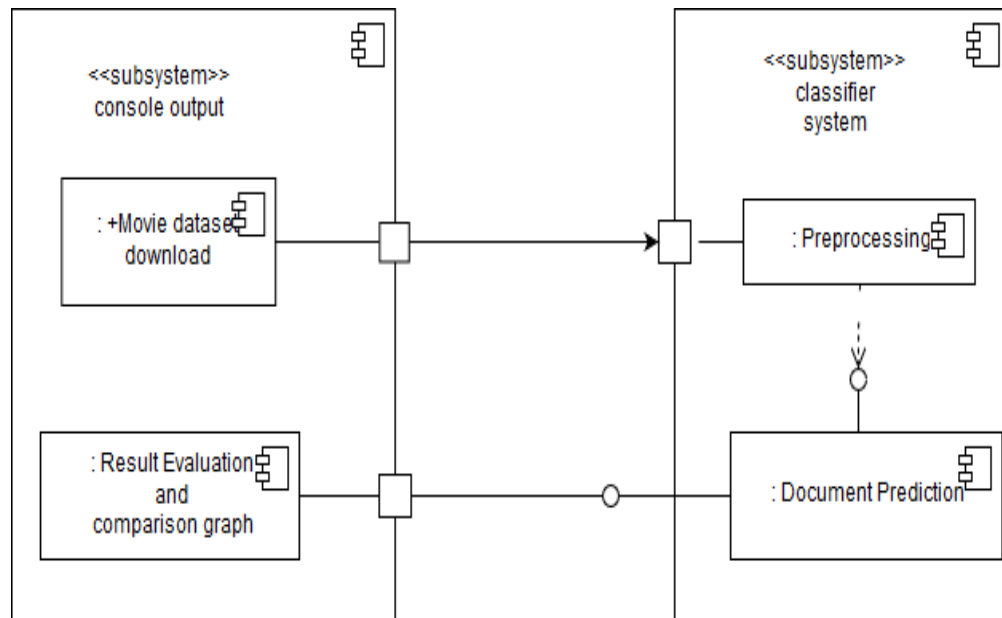
Figure 8.3: Component Diagram

8.4.1 Sequence Diagram

A sequence diagram is an interaction diagram that shows how objects operate with one another and in what order. It is a construct of a message sequence chart.

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams or event scenarios.

Description : Training data sends reviews to feature extraction module. It gives input to the classifier module. Testing data is received by learned classifier which returns the opinion type of a particular review.
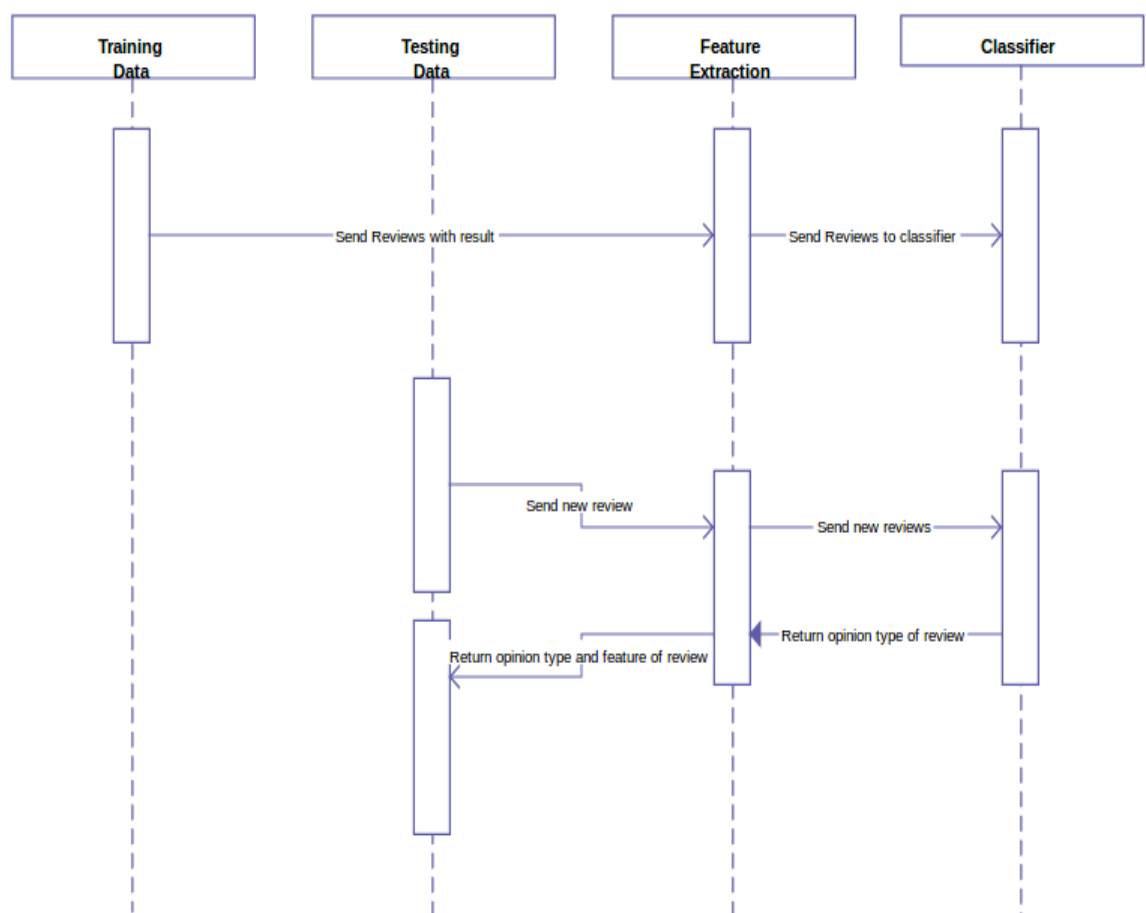
Figure 8.4: Sequence Diagram

CHAPTER 9

IMPLEMENTATION DETAILS

9.1 INTRODUCTION

This section describes implementation of the system, required libraries and dependencies needed for components of the system and use of implementation strategy.

9.2 ALGORITHM

9.2.1 Document Classification

Input : Movie review dataset in .csv file format

Output : Polarity classification

Algorithm 1 Training the model

1: **function** TRAINMULTINOMIALNB(C, D)
2:     $V \leftarrow ExtractVocabulary(D)$
3:     $N \leftarrow CountDocs(D)$
4:     *for each* $c \in C$
5:     **while** $N_c \leftarrow CountDocsInClass(D,C)$ **do**
6:        *prior[c]* $\leftarrow \frac{N_c}{N}$
7:        $text_c \leftarrow ConcatenateTextOfAllDocsInClass(D,c)$
8:        *for each* $t \in V$
9:        **while** $T_{ct} \leftarrow CountTokensOfTerm(text_c,t)$ **do**
10:          *for each* $t \in V$
11:          **while** *condprob[t][c]* $\leftarrow \frac{T_{ct}}{T_{ct}+1}$ **do**
12:            *calculate conditional probability*
13:     *return V, prior, condprob*

Algorithm 2 Testing

1: **function** APPLYMULTINOMIALNB($C, V, prior, condprob, d$)
2:     $W \leftarrow ExtractTokensFromDoc(V,d)$
3:     *for each* $c \in C$
4:     **while** $score[c] \leftarrow logprior[C]$ **do**
5:        *for each* $t \in W$
6:        *do* $score[c] += logprior[t][C]$
7:     *return V, prior, condprob*

9.3 DATASET

Pang and Lee's Movie Review Data [17] one of the first widely-available sentiment analysis datasets. It contains 1,000 positive and 1,000 negative movie

reviews from IMDB. The text is similar to movies reviews on IMDB today.

The file movie-pang02.zip contains a copy of Pang and Lee's movie review data in a csv format that can be imported directly in python. It has two categories: Pos (reviews that express a positive or favorable sentiment) and Neg (reviews that express a negative or unfavorable sentiment). For this work, we will assume that all reviews are either positive or negative; there are no neutral reviews.

For document classification, a training and testing dataset is required. Training records for polarity categories are mentioned in Table 9.1

Table 9.1: Polarity Training Dataset

Polarity	Training Records
Positive	1000
Negative	1000
Total	**2000**

9.4 SNAPSHOTS

Figure 9.1: Sample Matrix Creation with Word Counts

Figure 9.2: Sample Matrix Creation with Tf-idf

Figure 9.3: Review Classification with Negative and Positive Percentages

Figure 9.4: Three Classifiers Results (Accuracy, Recall, Precision, F-measure with Confusion Matrix)

Figure 9.5: Three Classifiers Results (Accuracy, Recall, Precision, F-measure with Confusion Matrix)

Figure 9.6: Results of Original and Opposite Reviews

CHAPTER 10

DATA TABLES AND DISCUSSIONS

10.1   RESULT TABLES

Table 10.1: Unigram Features Results

Classifier	Accuracy	Precision	Recall	F-measure
Naive Bayes	80.04	80.11	80.09	80.03
Support Vector Machine	79.02	79.24	78.91	78.93
Maximum Entropy	77.80	79.54	77.51	77.33

Table 10.2: Bigram Features Results

Classifier	Accuracy	Precision	Recall	F-measure
Naive Bayes	81.26	81.43	81.34	81.25
Support Vector Machine	80.44	80.49	80.39	80.41
Maximum Entropy	80.85	82.13	80.62	80.57

Table 10.3: Trigram Features Results

Classifier	Accuracy	Precision	Recall	F-measure
Naive Bayes	80.85	80.90	80.90	80.85
Support Vector Machine	80.04	80.34	79.92	79.93
Maximum Entropy	77.59	79.52	77.30	77.09

The above Table 10.1, Table 10.2, Table 10.3 shows accuracy, precision, recall and F-measure of three different classifiers. Three different features are used as features. First table shows results with unigram features i.e. each words is considered separate features. Second table shows results with bigram features i.e. 2 words together are considered as features. Third table shows results with trigram features i.e. 3 words combine are considered as features.

10.2 RESULT GRAPHS

Below fig. 10.1 shows comparison of accuracy scores shown in Table 10.1, Table 10.2, Table 10.3 .
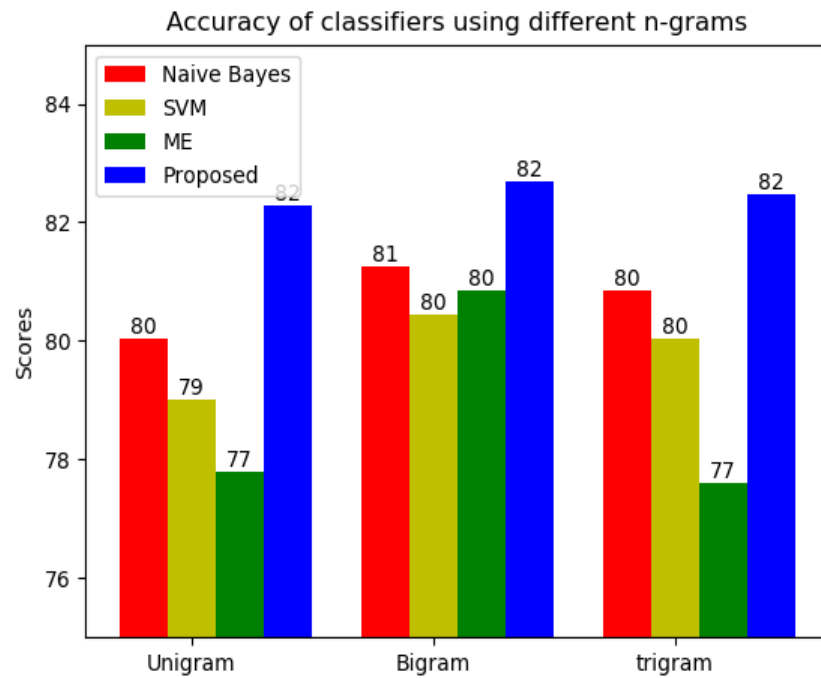
Figure 10.1: Classifiers Accuracy Score Comparison
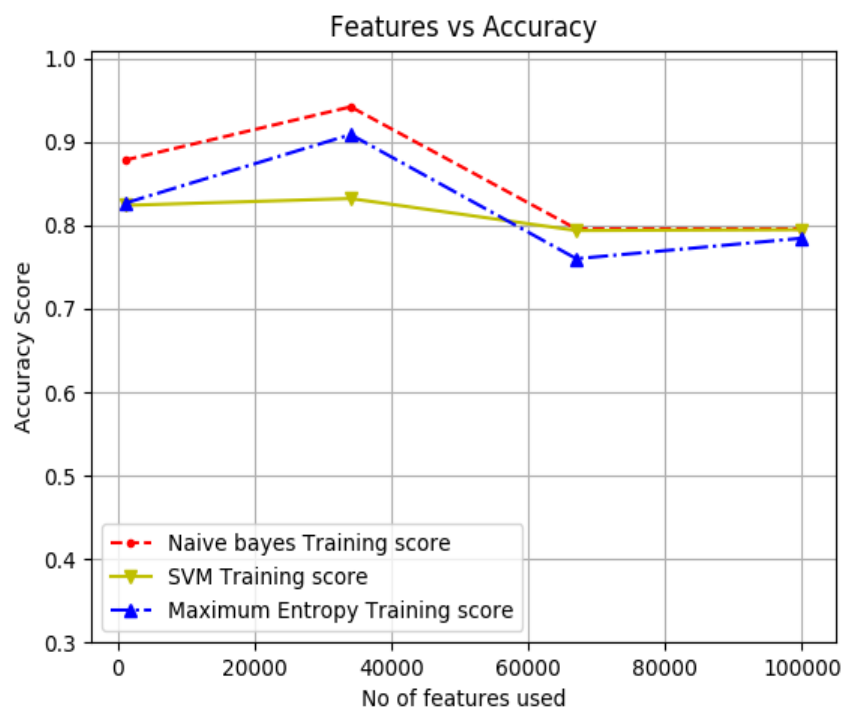
Figure 10.2: Variations in Classifier Accuracies as the no. of Features Increases

CHAPTER 11

CONCLUSION

In this work, the dual sentiment analysis technique is used to address the polarity shift problem in sentiment classification. The idea behind this is to create opposite reviews of the original reviews and used them together in bag of words model which will be the feature inputs to various machine learning algorithms such as Naive Bayes, SVM and Maximum Entropy. It performs better than the methods which were used to address the problem of polarity shift due to negation .

CHAPTER 12

FUTURE ENHANCEMENTS

The research can be extended to include the neutral reviews as well. Antonym can be obtained using words that has opposite polarity in the corpus. This corpus-based pseudo-antonym dictionary is good at obtaining more domain-relevant antonym words by learning from the corpus.

CHAPTER 13

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ANNEXURE A

PAPERS PUBLISHED

A.1 PAPER TITLE

Sentiment Analysis using Machine Learning Algorithms: A Survey

A.1.1 IJIRCCE Certification

Figure A.1: IJIRCCE Certificate

A.2 PAPER TITLE

Sentiment Analysis using Original and Reversed Reviews

A.2.1 cPGCON Certificate

Figure A.2: cPGCON Certificate

A.2.2 cPGCON Review

Sandip Foundation's Sandip Institute of Technology and Research Centre
Department of Computer Engineering
in association with Board of Studies Computer Engineering
Savitribai Phule Pune University, Pune

Evaluation Sheet for cPGCON 2017

Track ID: **T1005743**   Session No: **2**   Date: 24/09/2017

Name of the Student: **Kaushik S. Hande**   College Code: **005**   Day (1/2) 1 - Friday

Title of Paper: **Sentiment analysis using original and reversed Reviews**

Name of Session Chair: Prof. Dr. D.D. Patil, Prof. Dr. Sunil Wankhede

Evaluation by Reviewer

Sr. No	Title	Max. Marks	Marks by Reviewer
1	Relevance of Title, Abstract & Keyword	5	4
2	Adequate Literature Survey	10	7
3	Implementation Details a) Software Requirement Specification (05) **02** b) Mathematical Model & Design (05) **03** c) Implementation Status (10) **05**	20	10
4	Algorithms-Measures & Metrics a) Performance Measures Used (05) **02** b) Result Tables (10) **04** c) Comparison with similar systems (05) **01** d) Efficiency Calculation (05) **02** e) Outcome & Success definition of work (05) **02**	30	11
	Total	65	32

Evaluation by Session Chair		Max. Marks	Marks by Session Chair
5	Concluding Remarks (Result Discussion, Conclusion & Future Scope)	5	03
6	References (Journal/Conference/Recent)	5	03
7	Format, Organization of Paper, Clarity & Linguistic Quality	5	04
8	Organization of Content & Presentation Skills	5	03
9	Question & Answers	5	03
10	Contribution of Authors: To society at large /Technology/Research(Publication or Patents) /Interdisciplinary approach/ Use of modern architecture & tools	10	08
	Total	35	24
	Grand Total	Out of 100	56

Remarks/ suggestions: ____

Internal Name & sign. Prof. R.D. Pawar

External Name & sign 1. Prof. Dr. D.D. Patil Prof. Dr. S. Wankhede

Recommendation:

1. Recommended for Best paper: Yes/No   2. Recommended for Journal: Yes/No

3. Whether commercially feasible: Yes/No

Figure A.3: cPGCON Review Sheet

ANNEXURE B

DISSERTATION PLANNER

Table B.1: Dissertation Task Set

Task Title	Dissertation Task
T1	Study of Domain - Natural Language Processing
T2	Identification of problem in existing systems
T3	Review of literature
T4	Building mathematical model
T5	Report on scheme of implementation
T6	Identification of prerequisites and installation
T7	Configuring python and python package installer pip in the system
T8	Study of various machine learning algorithms
T9	Studying libraries in python required for implementation
T10	Downloading and extracting reviews from IMDB movie datasets
T11	Removing stopwords, punctuation marks, numbers etc.
T12	Report preparation
T13	Dissertation project stage I presentation
T14	Document preprocessing
T15	Creating bag of words model from movie reviews.
T16	Spliting the dataset into training and test dataset
T17	Train machine learning classifiers using bag of words model.
T18	Create unigram, bigram, trigram variations of model
T19	Train machine learning classifiers using this model.
T20	cPGCON paper presentation
T21	Predictive model construction
T22	Model testing
T23	Experimental results, analysis and validation of results
T24	Project review with demonstration
T25	Report Validation
T26	Report Submission