Subjectivity Analysis Using Machine Learning Algorithm

Erfan Ahmed – 13101139

Muhitun Azad - 13101073

Md. Tanzim Islam – 13101158

Md. Asad Uzzaman Sazzad – 13101152

Supervisor

Dr. Md. Haider Ali

Co-Supervisor

Samiul Islam

Department of Computer Science and Engineering

Fall 2016

BRAC University, Dhaka, Bangladesh

Declaration

We, hereby declare that this thesis is based on the results found by ourselves. Materials of work found by other researcher are mentioned by reference. This Thesis, neither in whole or in part, has been previously submitted for any degree.

Signature of Supervisor

____

Dr. Md. Haider Ali

Signature of Co-Supervisor

____

Samiul Islam

Signature of Author

____

Erfan Ahmed

Signature of Author

____

Md. Asad Uzzaman Sazzad

Signature of Author

____

Md. Tanzim Islam

Signature of Author

____

Muhitun Azad

Abstract

This paper investigates a new approach of finding sentence level subjectivity analysis using different machine learning algorithms. Along with subjectivity analysis sentiment analysis has also been shown separately in this work. Three different machine learning algorithms - SVM, Naïve Bayes and MLP have been used both for subjectivity and sentiment analysis. Moreover four different classifiers of Naïve Bayes and three different kernels of SVM have been used in this work to analyze the difference in accuracy as well as to find the best outcome among all the experiments. For subjectivity analysis rotten tomato imdb movie review [1] dataset has being used and for sentiment analysis acl imdb movie review [2] dataset has been used. Lastly, the impact of stop words and number of attributes in accuracy both for subjectivity and sentiment analysis has also been illustrated.

ACKNOWLEDGEMENT

Our deep thanks to our thesis supervisor Dr. Md. Haider Ali and to our co supervisor Samiul Islam for their generous guidance and continuous support throughout the work.

We are extremely thankful to our parents, family members and friends for their support and encouragement.

Finally we thank BRAC University for giving us the opportunity to complete our BSc. Degree in Computer Science and Engineering.

Table of Contents

	Abbreviation	**11**
1	**Introduction**	
1.1	Introduction	12
1.2	Motivation	13
1.2	Thesis Outline	13
2	**Background Research**	15
3	**Terminology**	
3.1	Subjectivity Analysis	21
3.2	Sentiment Analysis	21
3.3	WEKA	
3.3.1	Background History	23
3.3.2	Working Procedure	25
3.4	String To Word Vector	25
4	**Methodology**	
4.1	Data Collection	28
4.2	Data Formatting	28
4.3	Attribute Selection	28
4.4	Algorithm Selection	29
4.5	Work Flow	30
5	**Machine Learning Algorithms**	
5.1	Support Vector Machine	31
5.2	Naïve Bayes	35
5.3	Multilayer Perceptron	40
6	**Experiment And Result Analysis**	

6.1	Subjectivity Analysis	43
6.1.1	Experiment With SVM	43
6.1.2	Experiment With Naïve Bayes	50
6.1.3	Experiment With MLP	57
6.1.4	Comparative Analysis	60
6.1.5	Stop Word and Attribute Impact	61
6.2	Sentiment Analysis	63
6.2.1	Experiment With SVM	63
6.2.2	Experiment With Naïve Bayes	69
6.2.3	Experiment With MLP	76
6.2.4	Comparative Analysis	78
6.2.5	Stop Word and Attribute Impact	79
7	**Conclusion**	82
8	**References**	83

List of Figures

Figure No. & Name		Page No
3.1	WEKA Toolkit Graphical User Interface	24
3.2	Occurrence of ‘Amount’ in Train Set of Subjectivity Analysis	25
3.3	Mean Value of ‘Amount’	26
3.4	Occurrence of ‘mel’ in Train File	26
4.1	Attribute Selection Figure	29
4.2	Work Flow	30
5.1	Hyper Plane in Scatter	32
5.2	Hyper Plane Margins Drawing	32
5.3	Finding Exact Hyper Plane Margin	32
5.4	Creating Two Class	33
5.5	Outline in Class	33
5.6	Hyper Plane Maximum Margin	33
5.7	Solving Problem with SVM	34
5.8	Naïve Bayes Classifier Example	37
5.9	Prior Probability Using Naïve Bayes	38
5.10	Single Layer MLP	41
5.11	Multiple Layer MLP	41
6.1	Accuracy Comparison (SVM Kernels)	45
6.2	Detailed Result (Poly Kernel)	46
6.3	Detailed Result (Normalize Poly Kernel)	46
6.4	Detailed Result (RBF Kernel)	47
6.5	ROC=0.901 for Class S (Poly Kernel)	48

6.6	ROC=0.921 for Class S (Normalized Poly Kernel)	49
6.7	ROC=0.904 for Class S (RBF Kernel)	49
6.8	Accuracy Comparison (Naïve Bayes Classifiers)	51
6.9	Detailed Result (Naïve Bayes Classifier)	52
6.10	Detailed Result (Bayes Net)	52
6.11	Detailed Result (Naïve Bayes Multinomial)	53
6.12	Detailed Result (Naïve Bayes Multinomial Updatable)	53
6.13	ROC=0.9204 for class S (Naïve Bayes)	55
6.14	ROC=0.9593 for class S (Naïve Bayes Net)	55
6.15	ROC=0.974 for class S (Naïve Bayes Multinomial)	56
6.16	ROC=0.974 for class S (Naïve Bayes Multinomial Updatable)	56
6.17	Accuracy (MLP layer ‘o’)	57
6.18	Detailed Result (MLP layer ‘o’)	58
6.19	ROC=0.9283 for class S (MLP layer ‘o’)	59
6.20	Accuracy Comparison (Three Best Classifiers)	60
6.21	Accuracy Comparison (SVM Kernels)	64
6.22	Detailed Result (Poly Kernel)	65
6.23	Detailed Result (Normalize Poly Kernel)	65
6.24	Detailed Result (RBF Kernel)	66
6.25	ROC=0.948 for P (Poly Kernel)	67
6.26	ROC=0.948 for N (Poly Kernel)	67
6.27	ROC=0.9743 for P (Normalize Poly)	68
6.28	ROC=0.9743 for N (Normalize Poly)	68
6.29	ROC=0.972 for P (RBF)	68
6.30	ROC=0.972 for N (RBF)	68

6.31	Accuracy Comparison (Naïve Bayes Classifier)	70
6.32	Detailed Result (Naïve Bayes Classifier)	71
6.33	Detailed Result (Naïve Bayes Net)	71
6.34	Detailed Result (Naïve Bayes Multinomial)	72
6.35	Detailed Result (Naïve Bayes Multinomial Updatable)	72
6.36	ROC=0.9582 for class P (Naïve Bayes)	74
6.37	ROC=0.9582 for class N (Naïve Bayes)	74
6.38	ROC=0.9559 for class P (Naïve Bayes Net)	74
6.39	ROC=0.9559 for class N (Naïve Bayes Net)	74
6.40	ROC=0.9698 for class P (Naïve Bayes Multinomial)	75
6.41	ROC=0.9698 for class N (Naïve Bayes Multinomial)	75
6.42	ROC=0.9698 for class P (Naïve Bayes Multinomial Updatable)	75
6.43	ROC=0.9698 for class N (Naïve Bayes Multinomial Updatable)	75
6.44	Accuracy (MLP layer ‘o’)	76
6.45	Detailed Result (MLP layer ‘o’)	77
6.46	ROC=0.9471 for class P (MLP layer ‘o’)	78
6.47	ROC=0.9471 for class N (MLP layer ‘o’)	78
6.48	Accuracy Comparison (Three Best Classifiers)	79
6.49	Attribute VS Accuracy using Naïve Bayes Multinomial Updatable	62
6.50	Attribute VS Accuracy using Naïve Bayes Multinomial Updatable	80

List Of Tables

Table No. & Name		Page No.
1	Evaluation on Test Set (SVM Kernels)	44
2	Detailed Accuracy Using Different Kernels	48
3	Evaluation on Test Set Using Different Classifiers (Naïve Bayes)	50
4	Detailed Accuracy Using Different Classifiers of Naïve Bayes	54
5	Evaluation on Test Set using MLP (layer 'o')	57
6	Detailed Accuracy using MLP (layer 'o')	58
7	Comparative Analysis (Three Best Classifiers)	60
8	Evaluation on Test Set Using Different Kernels	63
9	Detailed Accuracy using Different Kernels (SVM)	67
10	Evaluation on Test Set using Different Classifiers	69
11 Naïve	Detailed Accuracy using Different Classifiers of Bayes	73
12	Evaluation on Test Set using MLP (layer 'o')	76
13	Detailed Accuracy using MLP (layer 'o')	77
14	Comparative Analysis (Three Best Classifiers)	78
15	Stop Words Effect on Accuracy using Naïve Bayes Multinomial Updatable Classifier	61
16	Stop Words Effect on Accuracy using Naïve Bayes Multinomial Updatable classifier	80

Abbreviations

SVM – Support Vector Machine

SMO - Sequential Minimal Optimization

MLP – Multilayer Perceptron

NLP – Natural Language Processing

S/O – Subjective / Objective

P/N – Positive / Negative

ICA - Iterative Collective Classification

ILP - Integer Linear Programming

SWSD - Subjectivity Word Sense Disambiguation

WEKA - Waikato Environment for Knowledge Analysis

GUI - Graphical User Interface

TCL – Tool Command Language

RBF – Radial Basis Function

1. Introduction

1.1 Introduction

In the recent world of information sharing the interest in the field of automatic identification and extraction of opinions and sentiments in the text has increased to a great extent. These are widely used by the entrepreneur, product manufacturer, product users, politicians and many more. The manufacturers or the companies uses these opinion based forums for reviewing their products and the customers are using them to see others review on the products they are interested in. Some important place for finding opinions are blogs, social networking sites like Facebook, Twitter, online news portal etc. But in order to fulfill the purpose proper analysis of data is very important. The term subjectivity includes emotions, rants, allegations, accusations, suspicions and speculation and sentiment analysis includes the positive and negative opinions or comments. So in order to analyze the data the most important task is to identify Subjectivity and Sentiment properly. Many approaches to subjectivity analysis rely on lexicons of words that may be used to express subjectivity. Examples of such words are the following (in bold) [2]:

(1) He is a **disease** to every team he has gone to.
(2) Converting to SMF is a **headache**.
(3) The concert left me **cold**.
(4) That guy is such a **pain**.

If the system knows the meaning of these words then it can recognize the sentiment of these sentences whether the sentences have positive or negative stance. However these key words may have both subjective and objective meaning depending on the semantic orientation and context. This is called false hit – subjectivity clues used with objective senses. False hits cause significant errors in subjectivity and sentiment analysis. The following example contains all of the key words above but these are not used as a subjective sense. These are all false hits [2]:

(1) Early symptoms of the **disease** include severe **headaches**, red eyes, fevers and **cold** chills, body **pain**, and vomiting.

To minimize this kind of errors we choose sentence level classification. As depending on the sentences the meaning of words varies (s/o) we focus on sentences rather than individual words that express subjectivity. Additionally our dataset contains only movie reviews that reduces the variety of using a single keyword in a large scale.

In this work both subjectivity analysis and sentiment analysis have been conducted separately. First subjectivity analysis with rotten tomato imdb movie review [1] dataset has been shown. Second sentiment analysis with acl imdb movie review [2] has shown. Both of the analysis were done using three different machine learning algorithms – Naïve Bayes, SVM and MLP with their different classifiers, kernels and layer accordingly. With all the results of those experiments, a comparative analysis have been shown as well. Lastly the importance of stop words in both subjectivity analysis and sentiment analysis have been presented using Naïve Bayes algorithm.

1.2 Motivation

The main motivation for this task came from seeing the present demand and interest on data mining and opinion or emotion extraction. Public review or opinion on products helps both the manufacturer and the customers to know about the pros and cons of the product. In recent times it is observed that the opinions posting on social media helped to flourish the business and public sentiment and emotions created a great impact on political and social life. For instance sentiment analysis can help the politicians to check public reviews of their speech or activity and the government to make public survey on their newly ideas that will be implemented based on public review. Moreover the entrepreneurs or the producers can also be benefited by checking the review of their products from the public review and take necessary steps to implement better ideas with the help of subjectivity and sentiment analysis. Moreover it is important for a humanoid robotic system to understand human emotion to interact with human properly and for this subjectivity analysis is must needed.

1.3 Thesis Outline

Section 2 describes the background research and basic review about the topic. Section 3 describes terminology about what subjective and sentiment analysis is. It also describes the WEKA toolkit, its graphical user interface and working procedure. This is followed by methodology in section 4, where data collection, data formatting, attribute selection, algorithm selection and work flow is described. In section 5 it describes the algorithm is used in this research, which are SVM, Naïve Bayes and MLP. Section 6 describes the experiment and result analysis for both subject and sentiment analysis. Finally we conclude in section 8 along with our future work.

2 Background Research

Definitions of subjective and objective is adopted from Akkaya C, Wiebe J, Mihalcea R. Subjective expressions are words or phrases that are used to express mental and emotional states, such as speculations, evaluations, sentiments, and beliefs. These states are generally termed as private state, an internal state that cannot be directly observed or verified by others. Polarity (also called semantic orientation) is also important to NLP applications. In review mining, we want to know whether an opinion about a product is positive or negative. [2]

Expressions may be subjective without having any particular polarity. An example given by Wilson J, Wiebe J, Hoffmann P, is "*Jerome says the hospital **feels** no different than a hospital in the states*".

In addition, benefits for sentiment analysis can be realized by decomposing the problem into Subjective or Objective(S/O) or neutral versus polar and polarity classification.

The following subjective examples are given in [4]:

His **alarm** grew.
alarm, dismay, consternation – (fear resulting from the aware- ness of danger)

=> fear, fearfulness, fright – (an emotion experienced in anticipation of some specific pain or danger (usually ac- companied by a desire to flee or fight))

What's the **catch**?
catch – (a hidden drawback; "it sounds good but what's the catch?")

=> drawback – (the quality of being a hindrance; "he pointed out all the drawbacks to my plan")

They give the following objective examples:

The **alarm** went off.
alarm, warning device, alarm system – (a device that signals the occurrence of some undesirable event)

=> device – (an instrumentality invented for a particu- lar purpose; "the device is small enough to wear on your wrist"; "a device intended to conserve water")

He sold his **catch** at the market.
catch, haul – (the quantity that was caught; "the catch was only 10 fish")

=> indefinite quantity – (an estimated quantity)

In the paper of Wiebe J, Mihalcea R it was showed how important is the interaction between subjectivity and meaning of the language. Moreover evidence was also given by them that subjectivity is a property that can be associated with word senses and word sense disambiguation can directly benefit from subjectivity annotations. To prove their hypothesis two questions were addressed, first is whether subjectivity labels can be assigned to word senses and secondly can an automatic subjectivity analysis be used to improve word sense disambiguation. To approach the first question two studies were performed, first annotators manually assign the labels subjective, objective or both to WordNet senses and secondly a method evaluates automatic assignment of subjectivity labels to word senses. An algorithm was devised to calculate subjectivity score and showed it can be used to automatically assess the subjectivity of a word sense. For the second question the output of a subjectivity sentence classifier is given as input to a word sense disambiguation system, which is in turn evaluated on the nouns from the SENSEVAL-3 English lexical sample task. In conjunction with ACL 2004 a workshop held in July 2004 Barcelona where Senseval - 3 took place in March-April 2004. Senseval-3 included 14 different tasks for core word sense disambiguation, multilingual annotations, subcategorization acquisition, logic forms, identification of semantic roles. The result of this experiment showed that subjectivity feature can significantly improve the accuracy of a word sense disambiguation system for those words that have both objective and subjective senses. The dataset used in this work was MPQA corpus having 10000 sentences from the world press annotated for subjective expressions. The MPQA Opinion Corpus contains news articles from a wide variety of news sources manually annotated for opinions and other private states (i.e., beliefs, emotions, sentiments, speculations, etc.). But the dataset were somehow seem to be worked as drawback because the annotations in the MPQA corpus works for subjective expressions in context thus the data is somehow noisy because objective senses may appear in subjective expressions [4].

In the research done by us an effective machine learning algorithms such as SVM(Support Vector Machine) and MLP(Multilayer perceptron)is used that generated more accuracy identifying subjectivity on a given context. The training dataset used is imdb rotten tomato movie review dataset. After identifying subjective sentence polarity was calculated – how much positive or negative sense they possess. Moreover for better accuracy the dataset were categorized into specific domains.

Many methods have been developed for subjectivity and sentiment analysis in previous works. Much earlier works were focused only in labeling unannotated word in a text by Church K. W, Hanks P [5] .

Another work was on automatically labeling of unannotated data done by Rilo? E, Wiebe J. First Hi-precision classifier was used by them to label unannotated data automatically that created a large training set. This training set was given to an extraction pattern learning algorithm similar to AutoSlog-TS. AutoSlog automatically builds dictionaries of extraction patterns for new domains. AutoSlog uses an annotated corpus and simple linguistic rules. A training corpus for AutoSlog must be annotated by a person to indicate which noun phrases need to be extracted from a text. *AutoSlog-TS is the new version* that generates dictionaries of extraction patterns using only preclassified texts, and does not require the detailed text annotations that AutoSlog did. The learned pattern that was obtained was used to identify more subjective sentences. However Hi-precision subjective classifier has a low recall rate which is only 31.9%. So AutoSlog-Ts won't be used by us [6].

In another work Least Common Subsumer (LCS) was used for automatically word sense labeling done by Gyamfi Y, Wiebe J, Mihalcea R, Akkaya C. The features that exploits the domain information and hierarchical structure in lexical resources was used by them such as WordNet. Moreover other types of features were also used that measure the similarity of glosses and the overlap among sets of word that are related semantically. In this paper it was suggested by them that at first identifying subjective words and then disambiguating their senses would be an effective approach. Moreover it was also suggested that a layered approach where it was suggested to classify objective or subjective first and then classify the subjective instances by polarity (positive/negative). For obtaining better result domain was reduced to increase calculation speed. However SVM were used by us [7].

In order to model a discourse scheme to imporve opinion polarity classification a design choice had been investigated by Somasundaran S, Namata G, Wiebe J, Getor L. Supervised collective classification framework and unsupervised optimization framework was used by them. For supervised framework the classifier used was Iterative Collective Classification (ICA) and for unsupervised optimization Integer Linear Programming (ILP) was used. LU and Getoor approach were also used by them that predicts the class values using global and local features iteratively. Moreover the classifiers used in this paper supervised classifier, Local, are implemented using the SVM classifier from Weka toolkit and another supervised discourse-based classifier known as ICA was also implemented by SVM due to its relational classifier. ILP was implemented by using optimization toolbox from Mathworks and GNU Linear Programming kit. The main function of this work is only polarity classification where we worked on both subjectivity and polarity classification. Therefore we didn’t use this approach [8].

Another work was Review classification done by Turney P. D. In this work whether a review is positive and negative was being investigated. An unsupervised learning algorithm, PMI-IR was presented by him. The classification of a review is predicted by the average semantic orientation of the phrases in the review containing adjectives or adverbs. To classify review a part-of-speech tagger to extract phrase containing adjective was applied first then the PMI-IR algorithm was applied to estimate the semantic orientation. But PMI-IR algorithm is not efficient with data parsing. It takes only two consecutive words to classify a review as good or bad. What if the third word changes the resultant good review into a bad one? PMI-IR method is reliance on the number of results returned by Altavista, there is the possibility of the algorithm appearing better (and simpler) than it really is by implicitly using the search algorithms of Altavista because it indexes approximately 350 million web pages (only papers that are in english) . Altavista was chosen because it has a NEAR operator. The AltaVista NEAR operator constrains the search to documents that contain the words within ten words of one another, in either order. Previous work has shown that NEAR performs better than AND when measuring the strength of semantic association between words. But the problem is Altavista (presumably for speed purposes) does not generate all documents which match a query, but attempts to select the more relevant documents, it's probable that the results of the PMI-IR algorithm rely largely on Altavista's ranking algorithms. This likely makes the actual algorithm being used much more complicated. Despite the problem Altavista cannot be used anymore as the owner of Altavista, Yahoo has shutdown the company on June 28, 2013. Moreover the limitation of this work include the time required for queries and, for some applications, the level of accuracy that was achieved. The former difficulty will be eliminated by progress in hardware. The latter difficulty might be addressed by using semantic orientation combined with other features in a supervised classification algorithm. Considering all these limitations we will not use these algorithms [9].

Similar to review classification to find strong and weak opinion clauses three machine learning algorithms were used by Wilson T, Weibe J, Hwa Rebecca. Those are boosting, rule learning and support vector regression. The algorithms were used to train the classifiers, to determine the depth of the clauses to be classified, and the types of features used. The learning algorithm were varied by them in order to explore the effect of these algorithms on the classification. For boosting BoosTexture were used, for rule learning they Ripper were used and for support vector regression SVMlight were used. The data used for the classification and regression analysis were analyzed by Support vector machine. It(SVM) a is supervised learning model with associated learning algorithms. And SVM light is the implementation of SVM in C language.These algorithms SVMLight and BoosTexture were chosen because they have successfully been used for a number of natural language processing tasks [10].

Another work relating contextual polarity recognition was done which focused on phrase-level Sentiment Analysis done by Wilson T, Wiebe J, Hoffmann P. An approach of sentiment analysis were made by them that first determines whether an expression is neutral or polar and then disambiguates the polarity of the polar expressions whether the sentiment is positive or negative. With this approach, the system was able to automatically identify the contextual polarity for a large subset of sentiment expressions, achieving results that are significantly better than baseline. An annotation scheme was introduced on the MPQA corpus to tag the polarity such as positive, negative, both or neutral. To address the contextual polarity disambiguation they approached two step solution where the first step involves in determining polar or neutral content and in second step the context marked as polar in first step are taken under consideration to identify contextual polarity. For both steps classifiers were developed by using BoosTexter AdaBoost.HM machine learning algorithm with 5000 rounds of boosting. The classifiers are evaluated in 10 fold cross-validation experiments.

This paper works on just polarity classification where in our works are classifying both subjectivity objectivity and polarity so we didn’t find this approach effective for our experiment [11].

In most recent work subjectivity word sense disambiguation (SWSD) is introduced by Akkaya C, Wiebe J, Mihalcea R.. Words were tagged with sense by them. First subjective and objective word were identified by them in a given corpora then they measure the polarity of the subjective sentences. They worked on contextual classification. The classifier used by them were Rule-based Classifier which is a sentence level classifier with high precision and low recall, Subjective/Objective Classifier which is a lexicon level classifier and Contextual Polarity Classifier which is also a lexicon level classifier. They established relation between sense subjectivity and contextual subjectivity. [2]

As our work is focused on the improvement of subjectivity and polarity classification we have used different machine learning algorithm for this purpose. First we have applied two different kernel of SVM – I) SMO poly kernel , ii) SMO normalized poly kernel. These two kernel gave us different results. After that we have applied Naive Bayes Model again with two different classifier of it – I) Multinomial naïve bayes, II) Multinomial Updatable naïve bayes. We have found significant difference using these algorithms with their different classifier and kernel selection.

Since imdb rotten tomato movie review data was used by us as our training data we believe that it will be more reliable than Altavista. As we are using SVM and Naive Bayes Model as our Subjective/Objective classifier so we believe it will be able to eliminate the possibility of bad data parsing and noticeable low recall rate.

3 Terminology

3.1 Subjectivity Analysis

Subjectivity analysis means where the feeling of the individual taking part in the analysis process determines the outcome. Subjectivity is concept that relates personhood, reality and truth of various individuals. The term subjectivity most commonly used as an explanation of the perceptions, experiences, expectations, personal or cultural understanding and beliefs specific to a person, which is based on people judgment about truth or reality. It is often used in contrast of objectivity term. Objectivity is truth or realty which is free of any individuals influence. Subjectivity is a social mode that comes through innumerable interactions within society. Subjectivity is an individual process but it is also a process of socialization. People interact with everyone around the world. Subjectivity shapes in term of economy, political, community, opinion, as well as natural world.

3.2 Sentiment Analysis

Sentiment analysis means the use of NLP, text analysis to identify and find out subjective information and express fillings. It is also known as opinion boring, finding the attitude or opinion of a speaker. Sentiment analysis tries to determine the opinion of a speaker or a writer with respect to some subject or the overall circumstantial polarity of a document. It is widely used approach in social media and many other things to identify the opinion about an application. It’s a process of analysing the number of Likes, Shares or Comments you get on a product, post, opinion, music, and video to understand how people are responding to it. Was the review of the writer positive? Negative? Sarcastic? Ideologically biased?

Turney [12] and Pang [13] worked on this topic. Turney and Pang applied different methods to analyse the polarity of product reviews and movie reviews respectively. They have worked on document level. Pang and Snydey [14] find out the polarity of a document which can classify the document on a multi way scale. Pang worked with Lee [15] who expanded the task. They have classified the data of movie review as either positive or negative. On the contrary Snydey analysed and find out an in-depth analysis of restaurant reviews. He predicted ratings for various aspects of the given reviews on restaurants. The reviews were focused on the food and atmosphere of a particular restaurant. They suggested that in most statistical classification methods, neutral texts fiction near the binary classification boundary. Three categories must be found out in every polarity problem which was suggested by several researchers and they are positive, negative and neutral. Moreover, specific classifiers such as the SVMs or the Naïve Bayes can be benefited if there is a neutral class and it will improve the overall accuracy of the classification. There are two ways for operating with a neutral class. The first option is the algorithm starts with by first identifying the neutral language. Then filtering it out and then analysing the rest in terms of positive and negative sentiments. The second option is to build a three way classification in one step. This second approach often involves probability by which we will predict an outcome over all categories. A neutral class fully depends on the nature of the data whether to use it or not or how we can use it. If the data is clearly divided into three categories like neutral, negative and positive, then it is useful and easy for the classifier it we filter out the neutral language out and only focus on positive and sentiments. It will also make the work easy for the classifiers.

A different approach to find out the sentiment of a word is the use of a scaling system. Where words are associated with having a negative, neutral or positive sentiment where they are classified into groups like highest positive to highest negative with a given associated number on a -10 to +10 scale. It gives an opportunity to adjust the sentiment of a sentence with the surroundings of its environment. When we analyse a text or sentence with natural language processing, each word is selected and given a score a range of -10 to +10 based on the sentiment positive or negative words relate to the text and their associated scores. This gives us a more refined understanding of sentiment. Words which are negate that means which can be considered as negative words but they are not negative can affect the score of the sentiment. Alternatively, if we want to find out the sentiment in a text rather than the overall polarity of the text we can give text a positive or negative sentiment [16].

3.3 WEKA

3.3.1 Background history

The full form of WEKA is Waikato Environment for Knowledge Analysis. It is worldwide popular software which is written in JAVA. It is a machine learning software. It was developed at the University of Waikato, New Zealand. It is a free software which is under the GNU General Public License. It is developed on almost machine learning algorithm to apply data mining task, by which one can find out the result easily. It is very easy to operate as it represents its own GUI (Graphical User Interface) where algorithms can easily applied directly. It also gives the option to call the algorithm from our own java code. WEKA contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization.

3.3.2 Working procedure

WEKA is a worktable [17] which is represented in a GUI that contains various type of machine learning algorithm and different type of data mining tools that can analyse data and predictive simulation. The original non-Java version of WEKA was a TCL which is high level, general purposed dynamic programming language front-end to representing algorithms implemented in other programming languages. The original version which was designed using TCL was tool to analyse data from agricultural domains [18]. But in 1997 it was shifted fully to java based version which was named WEKA 3 is now used all around the world for different applications specially for educational and research purposes.

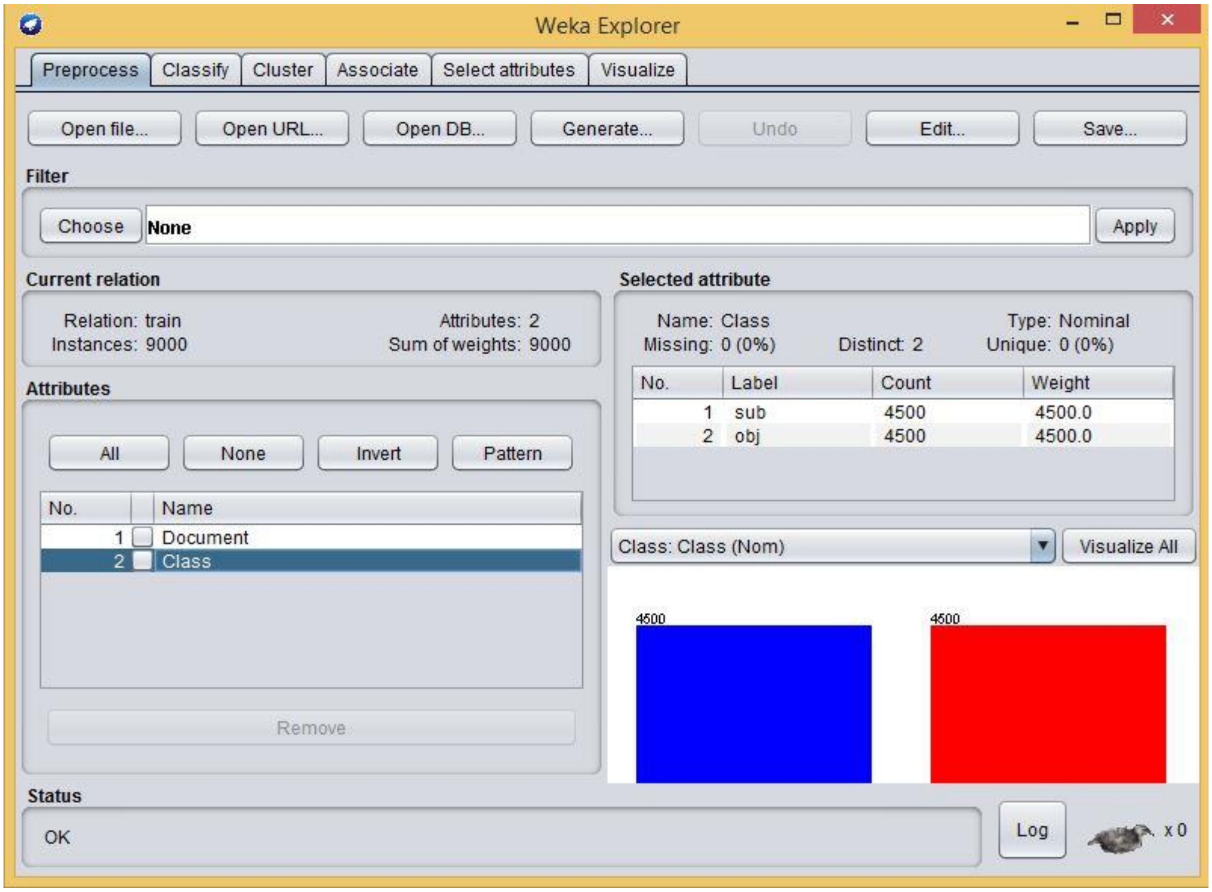


Fig 3.1: WEKA Toolkit Graphical User Interface

WEKA is supported by several machine learning algorithms and standard data mining tasks. Data pre-processing, data classification, visualization, regression, clustering and feature selection these are few of those data mining tasks that weka can do. All of WEKA's algorithms techniques are predicted by assuming that data is available as one relation. Here all the data point is described with fixed number of attributes. WEKA provides access to SQL data base servers using JAVA database connectivity and then it process the result and return it to data base query [19]. It is not capable of multi relation data mining. But there are options with separate software to convert a collection of database table and it convert it to a single table that is suitable for data processing in WEKA.

WEKA has a graphical user interface which is called Explorer is the easiest way to use it. This gives access to all of its facilities of WEKA just by selecting the proper algorithm and process by which we can see our desired output. For example, we can quickly give in a dataset through a file and build a decision tree from it. The Explorer helps us by showing every option on the user interface by only clicking on a particular option. Helpful tool tips pop up as the mouse passes over items on the screen to explain what they do. With a minimum effort we can get a result so easily but to understand the proper result how it came and what the process that generate the results are, we will have to understand those. A fundamental disadvantage of the Explorer is that it holds everything in main memory. Whenever we open a data set it automatically load everything at once. That results in that this process can be applied to small to medium sized problem. However, there are some algorithms we can operate large amount of data using those, which takes longer time but gives an output [17].

3.4 String To Word Vector

StringToWordVector is an unsupervised attribute filter built in java supported by WEKA toolkit that converts ALL the strings into a set of word vectors and choose each vector (unique word) as an attribute. We can also define the number of attributes we want to keep. By default WEKA takes 1000 attributes (form each class and selects the unique attributes among them) having higher mean value. We have conducted all the experiments with default settings. So as we get 1536 attributes from our training dataset. Among the attributes “amount” is taken as an attribute. In our training dataset “amount” - occurs 12 time and its mean value is .001 computed by StringToWordVector classifier.

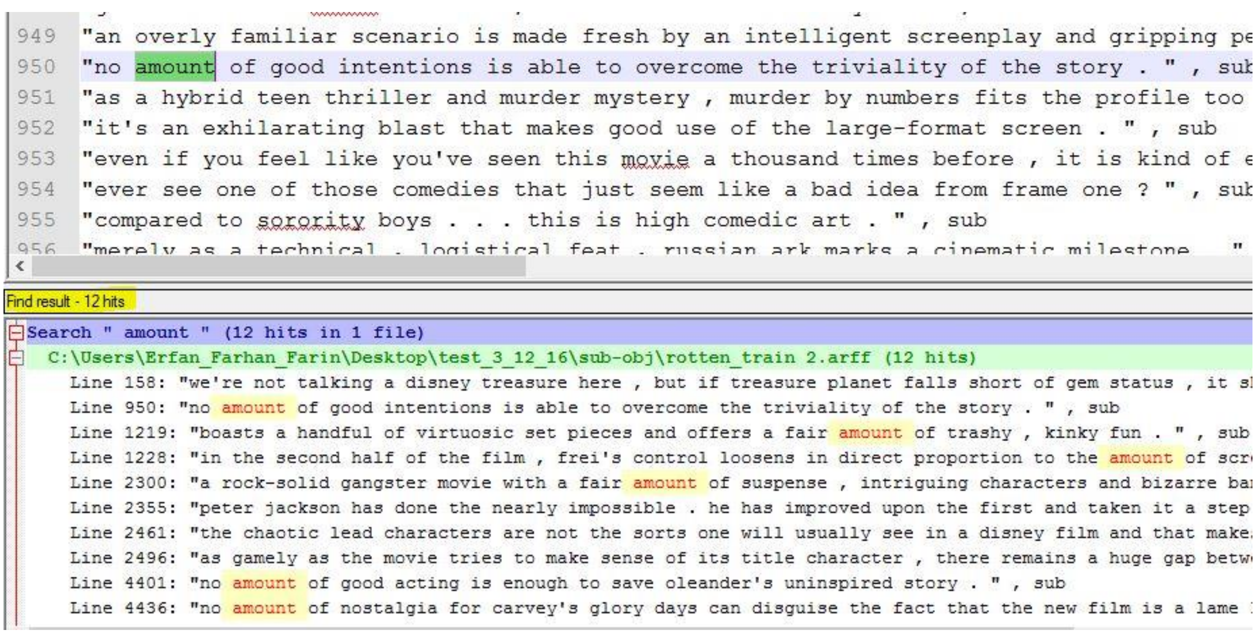


Fig. 3.2: Occurrence of “Amount” in Train Set of Subjectivity Analysis

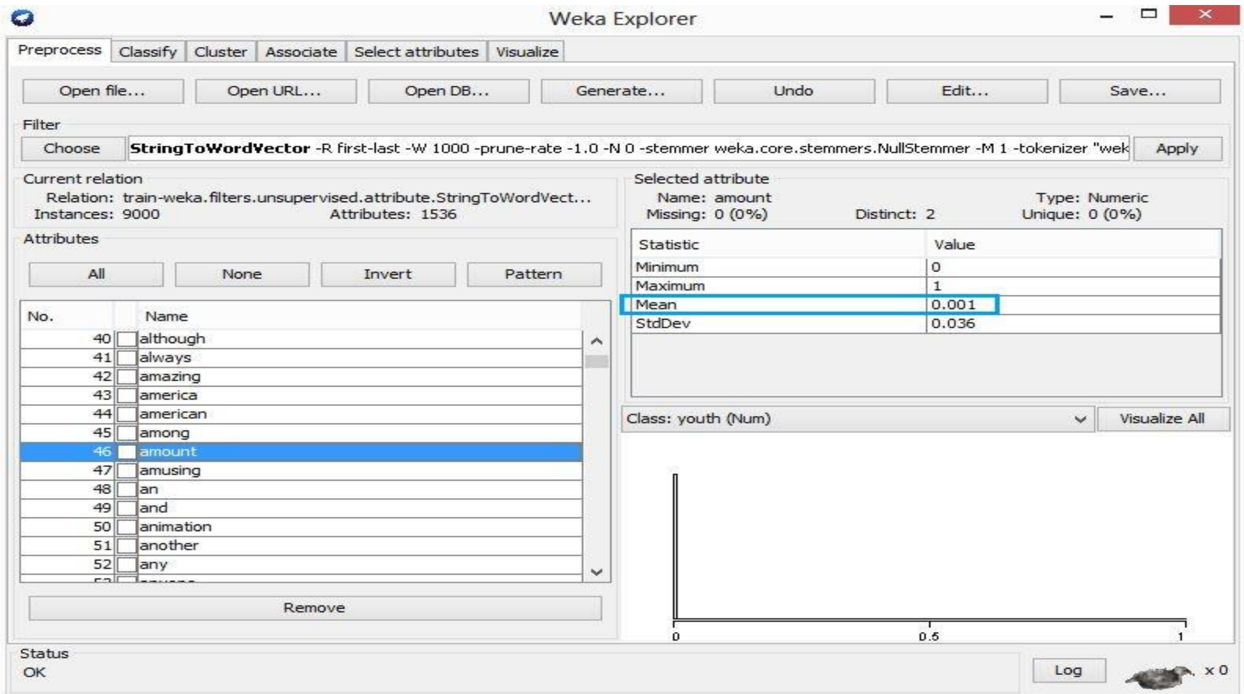


Fig.3.3: Mean Value of "Amount"

There is a word - "mel" in our train set. But this word has not been taken as an attribute because this word occurs only 6 times and has less mean value than .001.

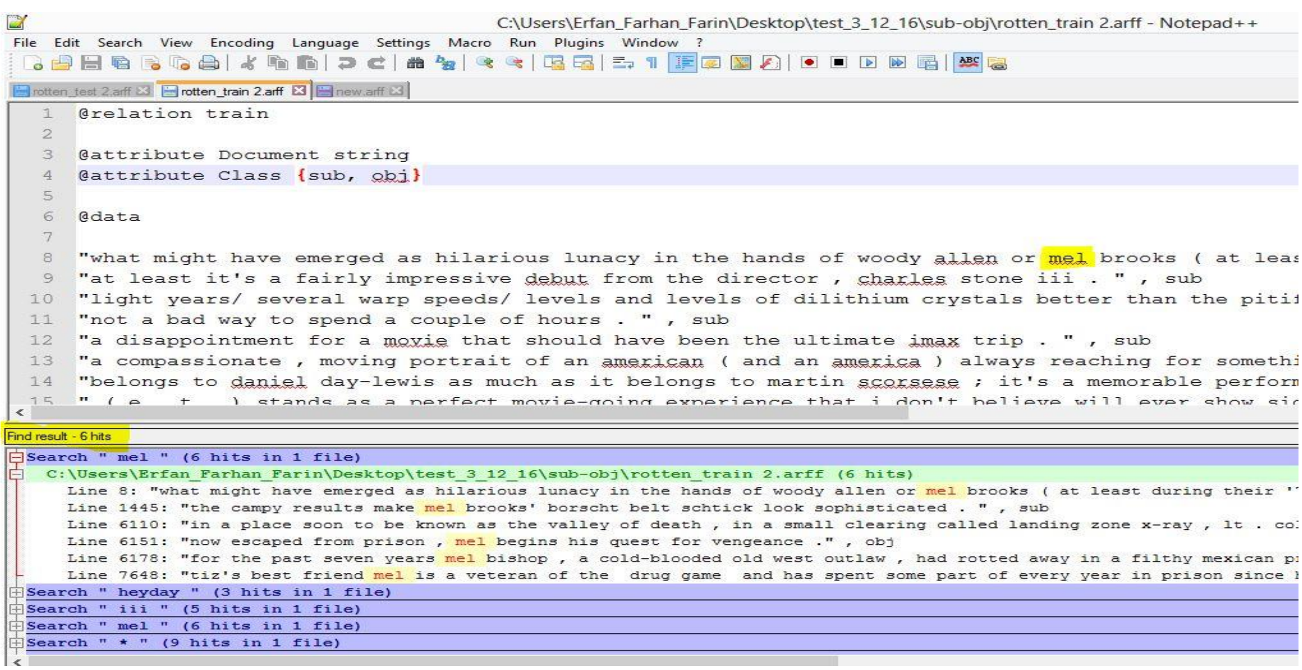


Fig. 3.4: Occurrence of - "mel" in Train File.

If we set the attribute number more than 1000 than more unique words will be chosen as attributes having lower mean value. In a nutshell StringToWordVector Converts String attributes into a set of attributes representing word occurrence (depending on the tokenizer) information from the text contained in the strings.

4 Methodology

4.1 Data collection

We have collected data from rotten tomato imdb movie review [1] for subjectivity analysis and acl imdb movie review [2] for sentiment analysis. There are 5000 subjective and 5000 objective instances separated in two text files in rotten tomato imdb movie review dataset. In acl imdb movie review dataset there are 12500 positive and 12500 negative reviews separated in two separated text file as well.

4.2 Data formatting

In our experiment we have modified the original data format and created a training and a testing dataset both in WEKA supported .arff format using Java code. First all quote (“ ”) characters, html tags were removed from the data set. Then quotes (“ ”) at the beginning and ending of each line of the dataset had been added. After that a comma (,) was put at the end of each line to separate the string and “sub” (without quote) for the subjective instances and “obj” (without quote) for the objective instances were added for the dataset of subjectivity analysis. For the dataset of sentiment analysis “pos” and “neg” were put at the end of each line of positive and negative instances respectively. Thus our training and testing dataset had been structured from the original dataset.

4.3 Attribute Selection

If “n” number of attribute is given in the WEKA GUI to be selected then what StringToWordVector does is, it takes “n” number of attributes with higher occurrence from each class. If any attributes matches it is counted as one attribute. In our case we had two class attributes. Following flow chart will give a clear view.

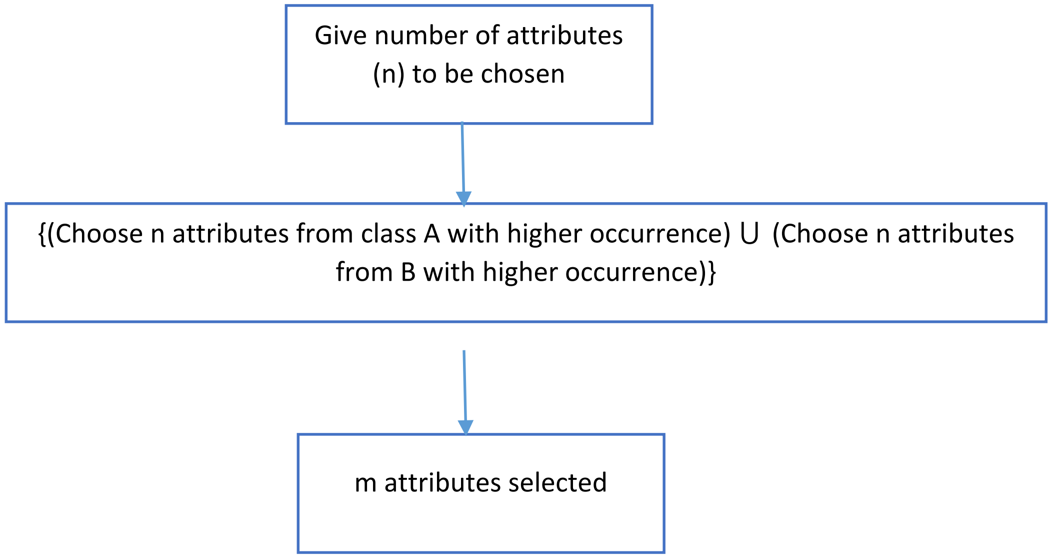


Fig 4.1 Attribute Selection Figure

4.4 Algorithm selection

There are many machine learning algorithms for text classification as described in the literature review part. After days of researching SVM and Naïve Bayes have been found providing better accuracy in the case of classifying text with the dataset has been tested with. As SVM is a binary classifier it is better suited in classifying subjectivity and polarity of sentences. Since our work differentiate between subjective/objective and positive/negative sentences which is more likely to binary classification and SVM works better for it. Using Naïve Bayes algorithm instances can be classified more than two categories. Therefore it is also even more suitable using Naïve Bayes algorithm for classifying subjectivity and polarity of instances. In previous works subjectivity and polarity was being classified considering words, phrases, and semantic orientations but in our work the entire comment has been taken as a single instances that includes one or multiple lines of sentences. Therefore actually a lot of calculations and pre-processing have been reduced. As SVM and Naïve Bayes algorithm both works with numeric values not with strings, in our work each instance has been converted into word vector using WEKA’s built in unsupervised attribute filter- StringToWordVector. Moreover SVM has multiple kernel and Naïve Bayes has different classifiers which have provided us more options to test the dataset in different ways. Moreover MLP has also been tested with the dataset but much higher time complexity has been found than that of SVM and Naïve Bayes.

4.5 Work Flow

The following flow chart is given to show the overall procedure of our work.

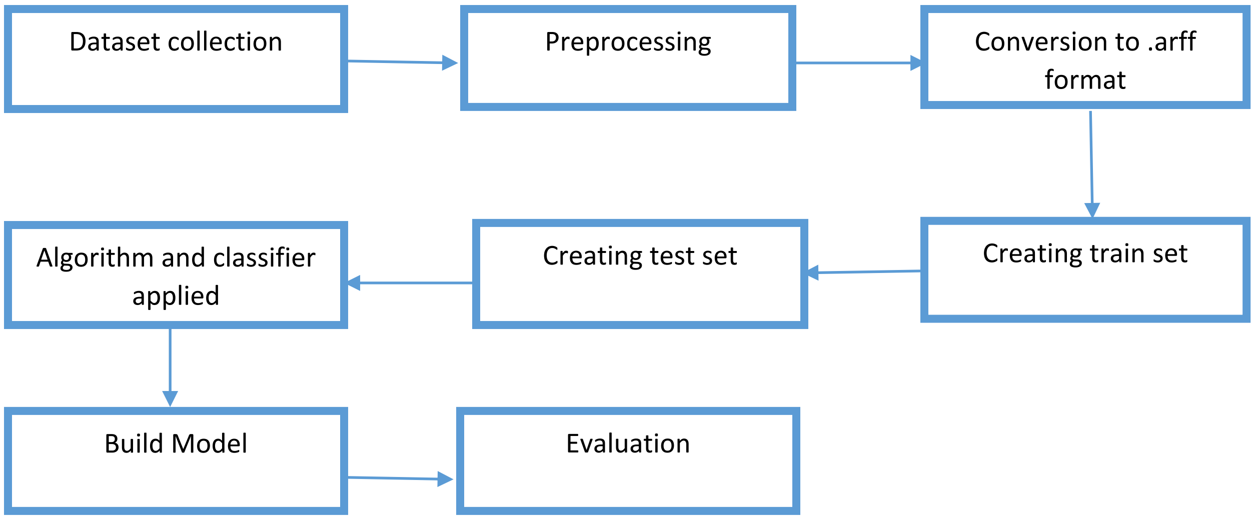


Fig 4.2: Work Flow

5 Machine learning algorithms

5.1 Support Vector Machine (SVM)

SVM (Support Vector Machine) is a machine learning algorithm. SVM is a supervised learning model which analyzes data for classification and regression analysis. SVM build a model using training algorithm that assigns new examples into one or two categories. SVM divided categories as wide as possible by creating a gap. New applications categories gap mapped into that same space or gap on which side the application fall on. The problem is when data are not properly labelled supervised learning is not possible. Then we have to follow an unsupervised learning approach to analyse, by which we can divide the data into separate groups. It follows a clustering approach which is called support vector clustering [20] and is often used in industrial applications either when data is not labelled or when only some data is labelled.

Example

Outlier: An outlier is an observation point that is distant from other observations. An observation that is well outside of the expected range of values ina study or experiment, and which is often discarded from the dataset.

Hyper plane: In geometry a hyper plane is a subspace of one dimension less than its ambient space. If a space is 3-dimensional then its hyper planes are the 2-dimensional planes, while if the space is 2-dimensional, its hyper planes are the 1-dimensional lines. This notion can be used in any general space in which the concept of the dimension of a subspace is defined.

Suppose, we have three hyper-planes (A, B and C). Now, we need to identify the right hyper-plane to classify star and circle. We need to remember a thumb rule to identify the right hyper-plane.

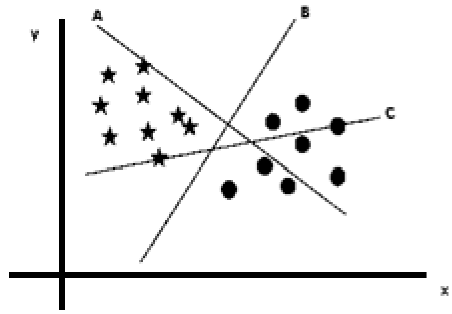


Fig 5.1: Hyper Plane in Scatter

Here, we have three hyper-planes (A, B and C) and all are in scatter possible ways. Now, how can we identify the right hyper-plane from these?

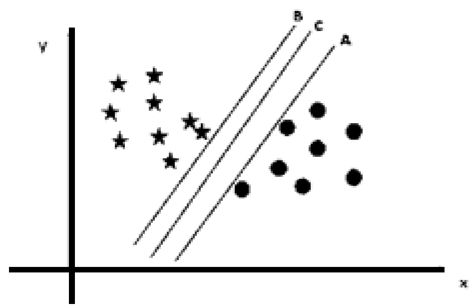


Fig 5.2: Hyper Plane Margins Drawing

Here, the distances between the nearest data point by maximizing and hyper plane will help us to decide the right hyper plane. This distance is called **Margin**.

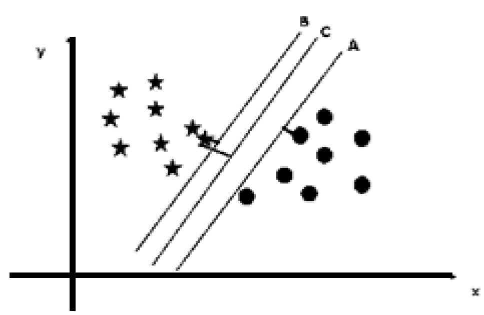


Fig 5.3: Finding Exact Hyper Plane Margin

Above, we can see that the margin for hyper-plane C is high as compared to both A and B. Hence, we name the right hyper-plane as C. Another reason we should keep in mind that we have selected the hyper-plane with higher margin is robustness. [21]. Because if we select a hyper plane having low margin then there is a high chance is that there might be a miss classification of margin.

Fig 5.4: Creating Two Class

Here we are unable to differentiate the two classes using a straight line, as one of star is in the other class as an outlier.

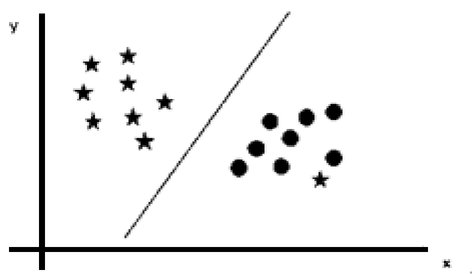


Fig 5.5: Outline in Class

One star is in circle class which is an outlier and SVM has a kind of feature that can ignore the outliers and find the hyper plane that has maximum margin. Hence, we can say, SVM is husky to outliers.

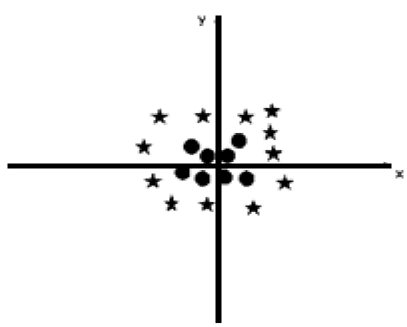


Fig 5.6: Hyper Plane Maximum Margin

Here we can’t have linear hyper-plane between the two classes. SVM solves this problem by introducing additional feature. Here, we will add a new feature z=x^2+y^2 [21].

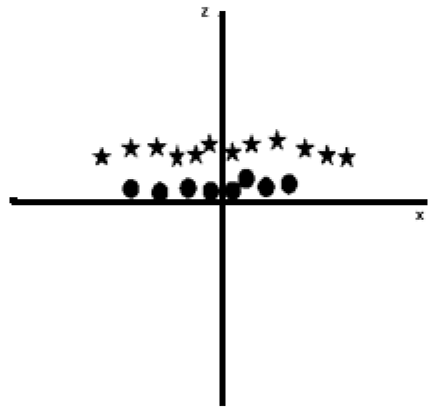


Fig 5.7: Solving Problem with SVM

SVM Applications

SVM is a tool for text classification which can reduce the need for labelled training examples in both standard inductive and tranductive settings. Image classification which is a part of image processing can also be performed using support vector machine. In the experiment and result analysis SVM achieve higher accuracy that other traditional schemes after almost just three or more round of feedback. To find out the image classification SVM follows same traditional approach as normal text analysis. The SVM algorithm has been also widely used in the biological and other sciences to find out results. SVM classifications have been used and it gives up to 90% of the compounds correctly. Support vector machine weights have also been used to consider SVM models in the past. Psthoc interpretation of support vector machine models has been used in order to identify features is a relatively new area of research with special significance in the biological sciences [22].

Sequential Minimal Optimization (SMO)

Sequential minimal optimization is a method of Support Vector Machine. It is an algorithm for solving the quadratic programming (QP) problem that arises during the training of support vector machines. SMO was invented by John Platt in 1998 at Microsoft Research. SMO is widely used for training support vector machines and is implemented by the popular LIBSVM tool, which is an open source machine learning library. After publication of SMO algorithm in 1998 it became easy to use SVM because previously used method were more complex and required quadratic programming solve.

$$\max \sum_{i=1}^{n} a_i - {}^{1}/_{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j K(x_i, x_j)\, a_i a_{j,}$$

Subject to:

$$0 \leq a_i \leq C, \text{ for i = 1,2,…,n, } \sum_{i=1}^{n} y_i a_i = 0$$

5.2 Naïve Bayes

In machine learning, naïve Bayes classifier is a simple probabilistic classifier which is based on Bayes theorem. It is a very popular method to categorize test, where the problem of judging text documents to one or more category with word frequencies as the feature. It is a machine learning algorithm which is with proper pre-processing it can be competitive methods like support vector machine. It can be also applicable for automatic medical diagnosis. Naïve Bayes classifiers are highly scalable, which requires linear number of variables. Maximum likelihood training can be done only by evaluating expressions taking linear amount of time. Other classifiers use expensive iterative approximation. Naïve Bayes is also called as Bayesand independent Bayes and many other different names. These names are the reference of the use of Bayes theorem in a classifier, but naïve Bayes is not one of the Bayesian methods. Naïve Bayes is a classifier method which uses a simple technique of constructing a classifier which represent as a vector feature values. In this case class labels are drawn from finite set. All naïve Bayes classifier assume that the value of a particular feature that is independent of any other feature. Thus Naïve Bayes is a full bunch of algorithm based on some common principles rather than a single algorithm.

Naive Bayes is a conditional probability model. If we give a problem instance it will be represented by a vector $\boldsymbol{x} = \boldsymbol{x_{1}}_{,....,}\boldsymbol{x_n}$ representing some n features, it assigns to this instance probabilities for each of K possible outcomes or classes C_k. [23]

$$(C_k|x_1, \dots \dots, x_n)$$

But there is a problem with the above formula. The Problem is that if the number of features n is large or if a feature can take on a large number of values, then founding probability of this kind of table is difficult. We therefore reformulate the model to make it more feasible. Using Bayes Theorem, the conditional probability can be break down as

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)}$$

WE can also write the Bayesian theorem as:

$$posterior = \frac{prior\ \times likelihood}{evidence}$$

But denominator does not depend on C the values of the features Fi are given, so that the denominator is constant. The numerator is equivalent to the joint probability model

$$p(C_{k,}x_{1,......,}x_n)$$

We can also write the equation as the definition of conditional probability:

$$p\left(C_{k,}x_{1,......,}x_n\right) = p(x_1, \dots \dots, x_n, C_k)$$

$$= p(x_1|x_2, \dots . x_n, C_k)\, p(x_2, \dots \dots, x_n, C_k)$$

$$= p(x_1|x_2, \dots . x_n, C_k)\, p(x_2|x_3, \dots . x_n, C_k)\, p(x_3, \dots \dots, x_n, C_k)$$

$$= \dots \dots$$

$$= p(x_1|x_2, \dots . x_n, C_k)\, p(x_2|x_3, \dots . x_n, C_k) \dots\ p(x_{n-1}|x_n, C_k)\, p(x_n|C_k)\, p(C_k)$$

Now assume that each feature Fi in conditionally independent of every other feature Fj for j != i , given the category C. This means that

$$p(x_i|x_{i+1},\dots.x_n,C_k) = p(x_i|C_k)$$

Thus, the joint model can be expressed as

$$p(C_k|x_1,\dots,x_n) \propto p(C_k,x_1,\dots,x_n)$$

$$\propto p(C_k)p(x_1|C_k)p(x_2|C_k)p(x_3|C_k)\dots\dots$$

$$\propto \mathrm{p}(C_k)\prod_{i=1}^{n} p(x_i|C_k)$$

This means that under the above assumptions, the conditional distribution over the class variable C is :

$$p(C_k|x_1,\dots\dots,x_n) = \frac{1}{Z}p(C_k)\prod_{i=1}^{n} p(x_i|C_k)$$

Where the evidence is Z = p(x) a scaling factor dependent only on $x_1,\dots,x_n$, that is, a constant if the values of the feature variables are known.

Example Of Naïve Bayes

The Naive Bayes Classifier technique is based on the Bayesian technique. It is very suitable when the dimensionality of the inputs is high. It is a very simple method. But Naïve Bayes can perform elegant classification methods.

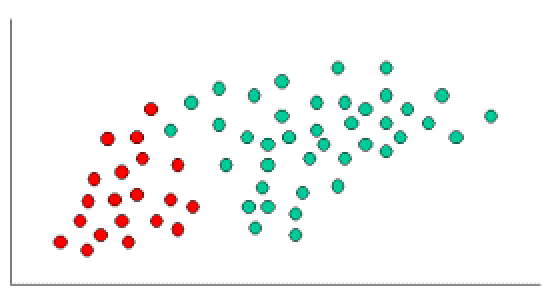


Fig 5.8: Naïve Bayes Classifier Example

Naïve Bayes Classification can be described by above figure. It indicates that the objects can be either GREEN or RED. This task is to find out which class they belong based on currently existing objects above.

Since there are twice as many GREEN objects as RED, it can possibly happen that a new class will have more GREEN than RED. In the Bayesian analysis it is called prior probability. Prior probabilities are often based on previous experience. It often can predict outcome before it actually happens.

Thus, we can write:

$$Prior\ probability\ for\ GREEN \propto \frac{Number\ of\ GREEN\ Object}{Total\ Number\ of\ Object}$$

$$Prior\ probability\ for\ RED \propto \frac{Number\ of\ RED\ Object}{Total\ Number\ of\ Object}$$

Since there is a total of 60 objects, 40 of which are GREEN and 20 RED, our prior probabilities for class membership are:

$$prior\ Probability\ for\ GREEN\ \propto \frac{40}{60}$$

$$Prior\ Probability\ for\ RED\ \propto \frac{20}{60}$$

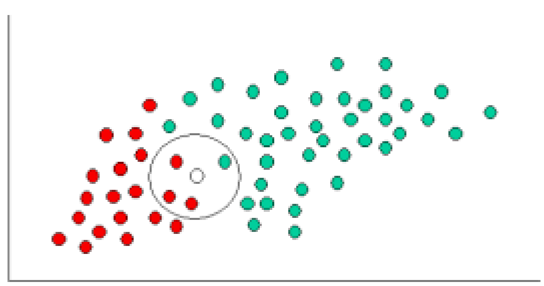


Fig 5.9: Prior Probability Using Naïve Bayes

Now we have a prior probability and now we can classify by adding a new object which is a WHITE Circle. These objects are well defined and we can assume that new object belong to a particular colour which is GREEN according to prior probability. To measure this likelihood, we draw a circle around X which includes a number of points irrespective of their class labels. Then we can calculate the number of points in the circle belonging to each class label. From this we calculate the likelihood:

$$Likelihood\ of\ X\ given\ GREEN\ \propto \frac{Number\ of\ GREEN\ in\ the\ vicinity\ of\ X}{Total\ Number\ of\ GREEN\ cases}$$

$$Likelihood\ of\ X\ given\ RED\ \propto \frac{Number\ of\ RED\ in\ the\ vicinity\ of\ X}{Total\ Number\ of\ RED\ cases}$$

From the above observation, it is clear that Likelihood of X given GREEN is smaller than Likelihood of X given RED, since the circle include only 1 GREEN object and 3 RED ones. Thus:

$$Probability\ of\ X\ given\ GREEN\ \propto \frac{1}{40}$$

$$Probability\ of\ X\ given\ RED\ \propto \frac{3}{20}$$

The prior probabilities indicate that X may belong to GREEN as there is twice as much GREEN than RED. But the likelihood indicates that the class membership of X is RED as the vicinity of RED is higher than the vicinity of GREEN. The final classification is produced by combining both sources of information, like the prior and the likelihood, to form a probability using the so-called Bayes' rule in Bayes Theorem. The probabilities are :

$$Posterior\ Probability\ of\ X\ being\ GREEN \propto Prior\ Probability\ of\ GREEN\ \times$$
$$Likelihood\ of\ X\ given\ GREEN \qquad = \frac{4}{6} \times \frac{1}{40} = \frac{1}{60}$$

$$Posterior\ Probability\ of\ X\ being\ RED\ \propto Prior\ Probability\ of\ RED\ \times Likelihood\ of\ X\ given\ RED = \frac{4}{6} \times \frac{1}{40} = \frac{1}{60}$$

Finally, we classify X as RED since its class membership achieves the largest probability [24].

5.3 Multilayer Perceptron (MLP)

Back propagation algorithm

Back propagation is a common method for training artificial neural network. It calculates gradient of loss function with respect to all the weight in a network. Each propagation implements in two steps forward and backward propagation.

MLP

A multilayer perceptron is an artificial feed forward neural network model. It maps sets of input data onto a set of appropriate outputs. It is a multiple layers of nodes directed graph where each layer is connected to the next one. The hidden nodes and the output notes are the processing elements with nonlinear activation function. Multilayer perceptron use back propagation algorithm [25]. Single propagation technique was invented by Rosenblatt in 1958. Multilayer perceptron performs generate a single output from multiple inputs by forming a linear combination. This linear combination based on input weights. [26]. Where $\boldsymbol{W}$ denotes the vector of weights, $\mathbf{x}$ is the vector of inputs, b is the bias and ø is the activation function.

$$y = \emptyset\left(\sum_{i=1}^{n} w_i x_i + b\right) = \emptyset(W^T x + b)$$

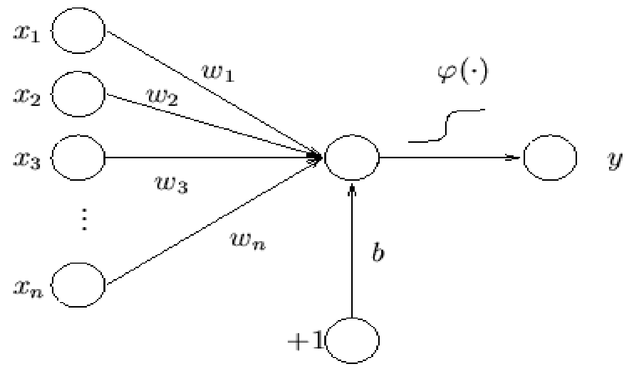
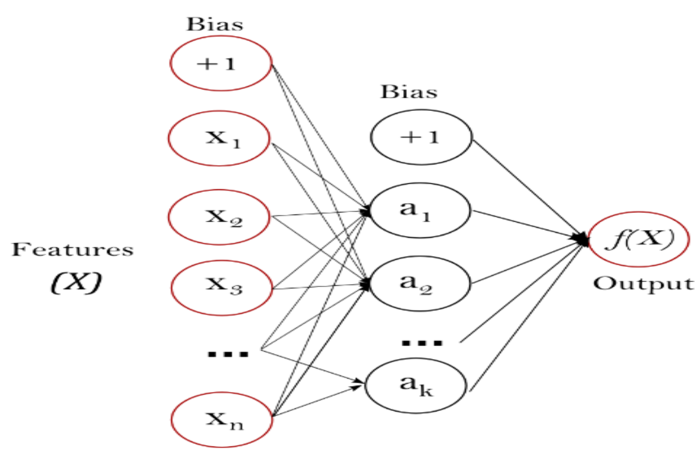


Fig 5.10: Single Layer MLP

A single perceptron where there is only a single layer is not very useful because of its limited mapping ability. Single perceptron uses different activation functions but it only able to represent an oriented ridge like function. A normal multilayer perceptron algorithm consists of a set of source nodes which form the input layer, one or more hidden layers of computation nodes, and an output layer of nodes. The input signal propagates layer-by-layer through the network [26].



5.11: Multiple Layer MLP

MLP network with one hidden layer can perform several other tasks. But they represent a rather limited kind of mapping. As Hornik and Funahashi showed in 1989 [27], such networks are capable of approximating any continuous function $f: R^n \rightarrow R^m$ to any given accuracy.

In supervised learning problems MLP are typically used. The supervised learning problem of the MLP can be solved with the back-propagation algorithm. The algorithm consists of two steps the forward and the backward pass. In forward pass, input we evaluate to determine the outcome.

But in the backward pass, parameters are propagated back through the network weight. The network weights can then be adapted using any gradient-based optimisation algorithm. The whole process is iterated until the weights have converged [26]. The MLP network can also be used for unsupervised. Unsupervised learning can be done by setting the same values for both input and output networks. The sources emerge from the values of the hidden neurons [28]. The MLP network has to have at least three hidden layers for any reasonable representation and training such a network is a time consuming process.

6. Experiment & Result Analysis

The results obtained from three machine learning algorithms with different classifiers and kernels are based on their accuracy, precision, recall, ROC area.

Recall is how many of the correct hits are found and Precision is how many of the returned hits are true positive means how many of the found are correct hits.

Precision is calculated using the formula, $\frac{tp}{tp+fp}$

Recall is calculated using the formula, $\frac{tp}{tp+fn}$

Where tp stands for true positive (actual and test data is correctly classified), fn stands for false negative (actual data is correct but predicted as incorrect), fp stands for false positive (actual is incorrect but predicted as correct).

F-measure is used to measure a test's accuracy. F-measure can be interpreted as a weighted average of the precision and recall. F-score reaches best at 1 and worst at 0.

F-measure formula, $2 \cdot \frac{precision \cdot recall}{precison + recall}$

Receiver Operating Characteristic (ROC) or ROC curve is a graphical plot that illustrates the performance of a binary classifier system as its discrimination threshold is varied. The curve is created by plotting the false positive rate (FPR) along x-axis against the true positive rate (TPR) along y-axis at various threshold settings. Accuracy is measured by the area under the ROC curve. An area of 1 represents the perfect test and close to 1 is excellent test.

6.1 Subjectivity Analysis

9000 movie reviews containing 4500 subjective and 4500 objective instances for training set and 1000 movie reviews containing 500 subjective and 500 objective instances for test set was taken for subjectivity analysis.

6.1.1 Experiment with SVM

As previously mentioned SMO classifier with three different kernels; Poly Kernel, Normalized Poly Kernel and Rbf Kernel was used for the experiment with SVM. Table 1 describes evaluation on test set using three different kernels of SVM. Figure 6.2, 6.3 and 6.4 was taken from the result window of WEKA which respectively represents three different kernels poly, normalize poly and rbf kernels output.

Algorithm	Classifier	Kernel	Trained data	Test data	Correctly classified instances	Incorrectly classified instances	Accuracy	Time to build model(s)
SVM	SMO	poly kernel	9000	1000	901	99	90.1	66.95
SVM	SMO	normalized poly kernel	9000	1000	921	79	92.1	126.14
SVM	SMO	rbf kernel	9000	1000	904	96	90.4	98.38

Table 1: Evaluation on Test Set (SVM Kernels)

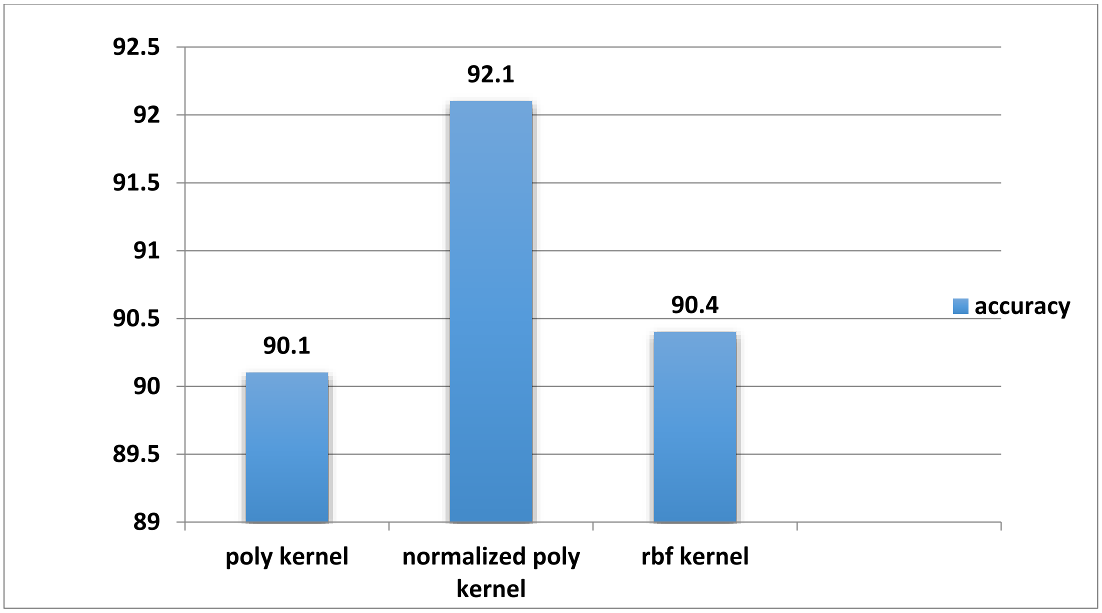


Fig 6.1: Accuracy Comparison (SVM Kernels)

In the above table 1, using poly kernel accuracy was achieved 90.1% where 901 instances were classified correctly and 99 instances classified incorrectly from 1000 test data. Then again using normalized poly kernel for the same test set accuracy increased 2 % from 90.1% to 92.1% where 921 instances were correctly classified and 79 instances were incorrectly classified. Changing kernel to RBF kernel for the same test set accuracy again decreased 1.7% from 92.1% to 90.4% than normalized poly kernel but increased only 0.3% from 90.1% to 90.4% than poly kernel where 904 instances were correctly classified and 96 instances were incorrectly classified. Though time taken to build model is highest in normalized poly kernel than two other kernels shown in table 1 but as this experiment is more concerned about accuracy so normalized poly kernel is the most successful than two other kernels used for the experiment with SVM. Figure 6.1 shows accuracy comparison using three different kernels.

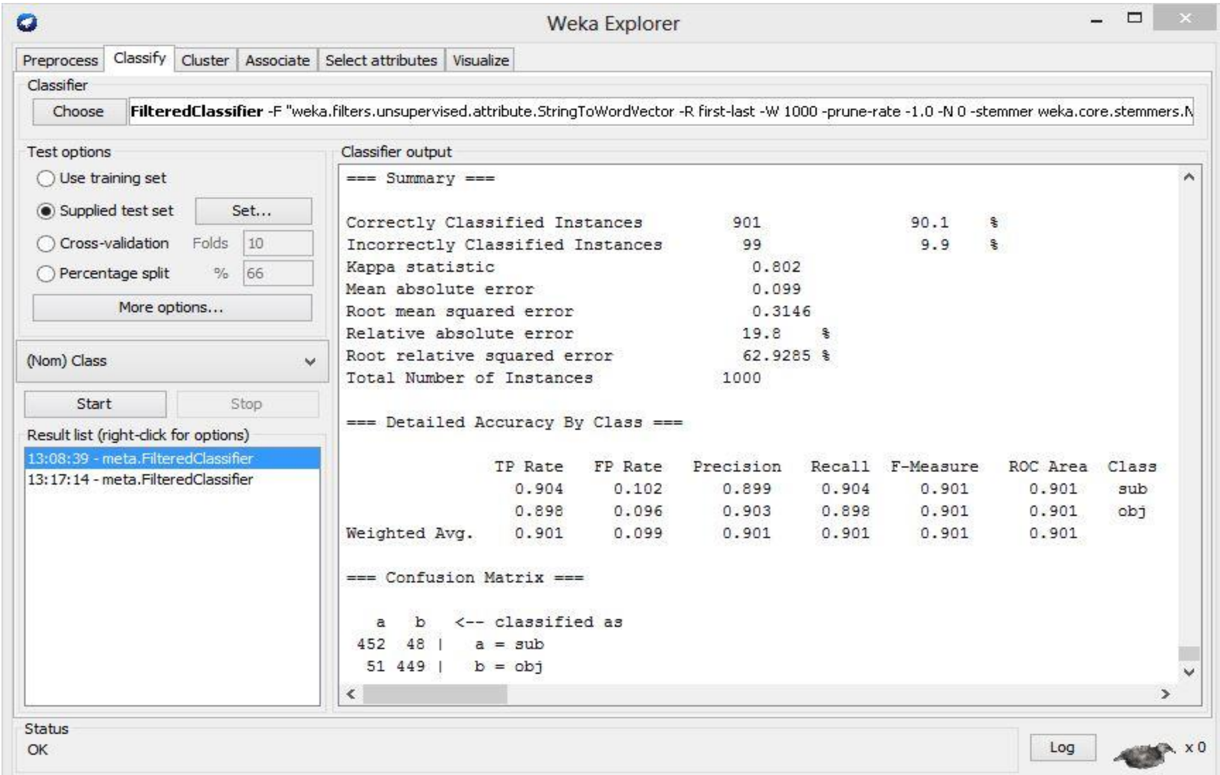


Fig 6.2: Detailed Result (Poly Kernel)

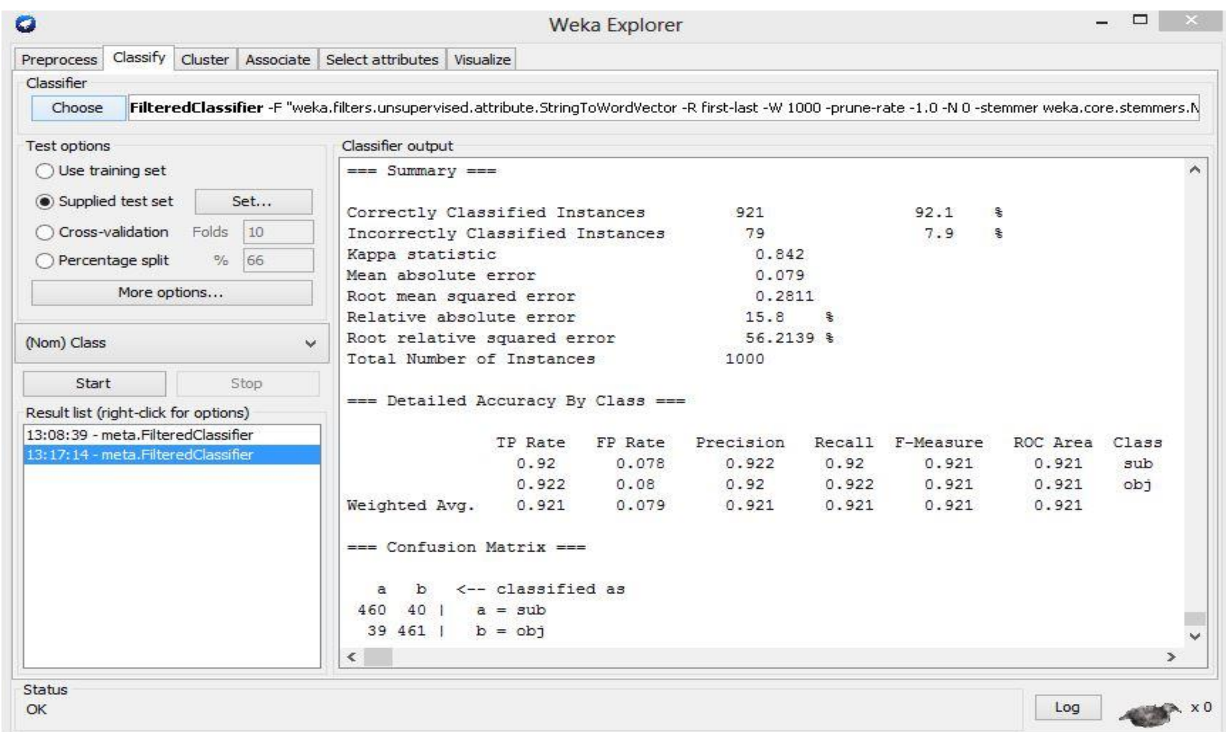


Fig 6.3: Detailed Result (Normalize Poly Kernel)

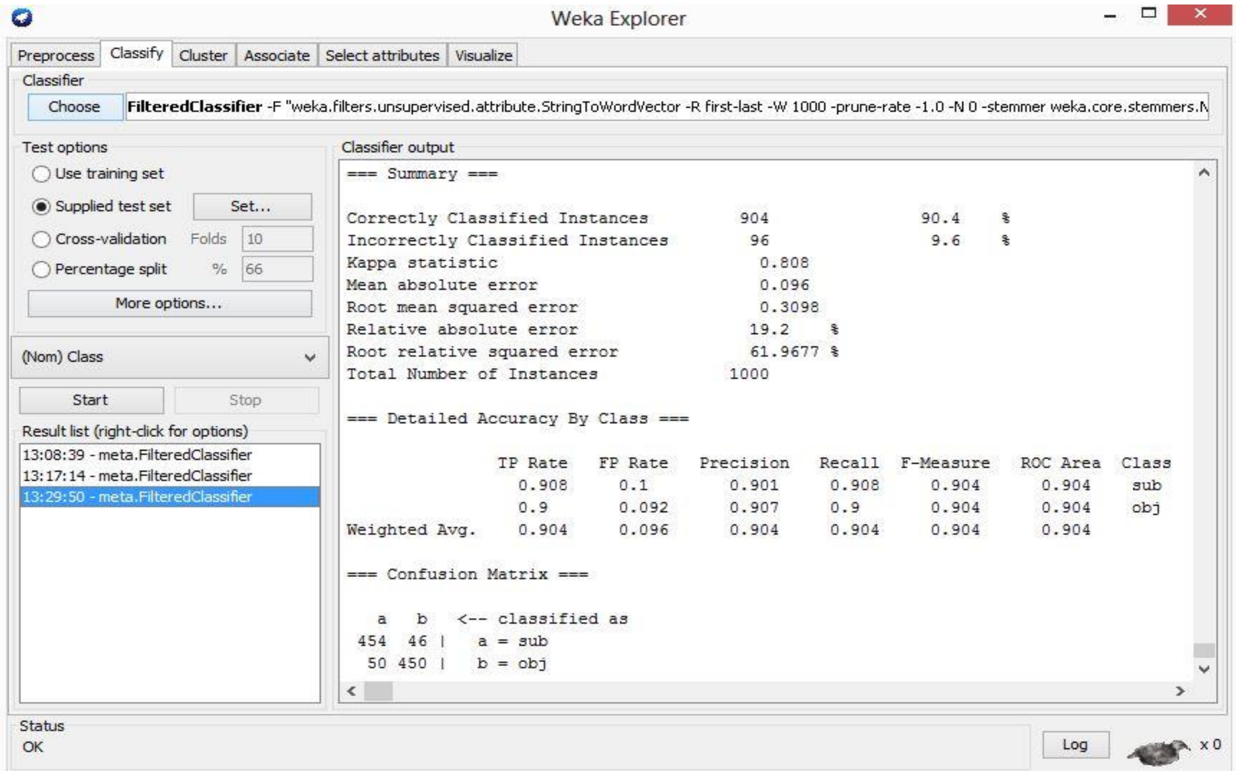


Fig 6.4: Detailed Result (RBF Kernel)

Table 2 describes the detailed accuracy using three different kernels where only weighted average of subjective and objective classes for different ratio is shown. In table 2, among all three kernels tp rate 0.921 is the highest which is in normalized poly kernel and fp rate 0.079 is also the lowest in normalized poly kernel. Precision, recall, f-measure and ROC area 0.921 is also highest in normalized poly kernel comparing to other two kernels. Here in table 2, area under the ROC curve 0.921 is the highest that means among all three kernels of SVM that was used to test, normalized poly kernel gives more accuracy to correctly classify the test set between two classes subjective and objective. Figure 6.5, 6.6 and 6.7 respectively represents the ROC curve of three different kernels poly, normalize poly and rbf which shows the ROC curve for subjective class. All these figures were taken from WEKA classifier visualize: threshold curve window where x-axis denotes false positive rate and y-axis denotes true positive rate.

Kernel	TP rate	FP rate	Precision	Recall	F-Measure	ROC Area
poly kernel	0.901	0.099	0.901	0.901	0.901	0.901
normalized poly kernel	0.921	0.079	0.921	0.921	0.921	0.921
rbf kernel	0.904	0.096	0.904	0.904	0.904	0.904

Table 2: Detailed Accuracy Using Different Kernels

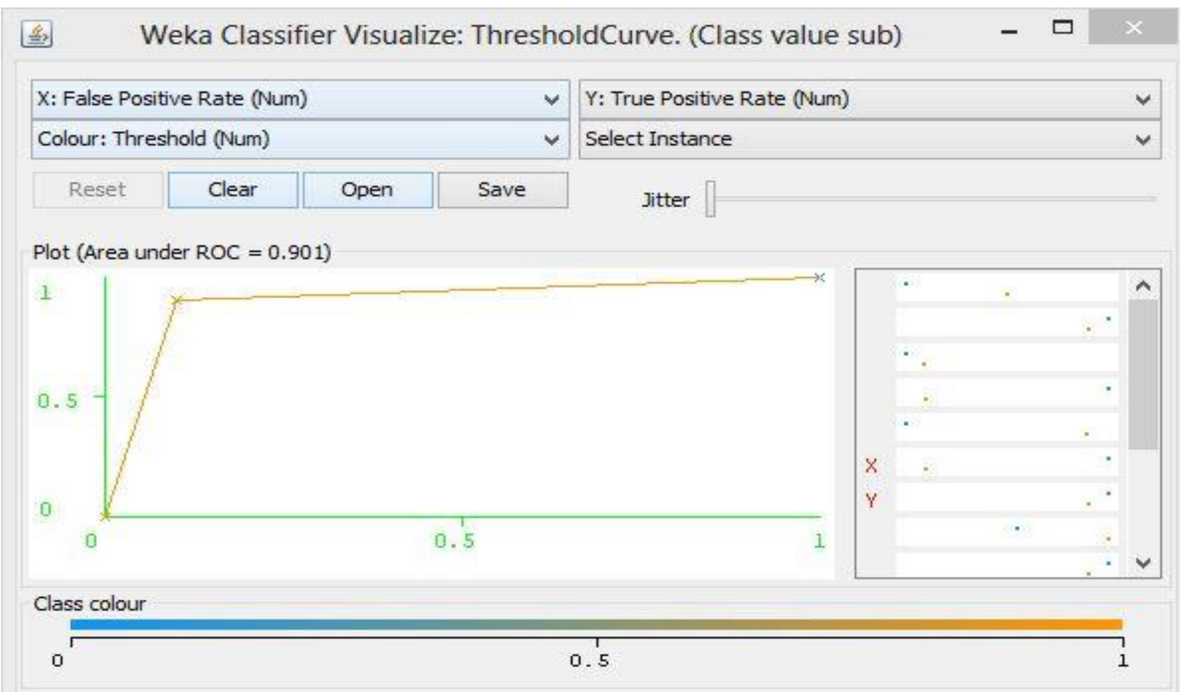


Fig 6.5: ROC=0.901 for Class S (Poly Kernel)

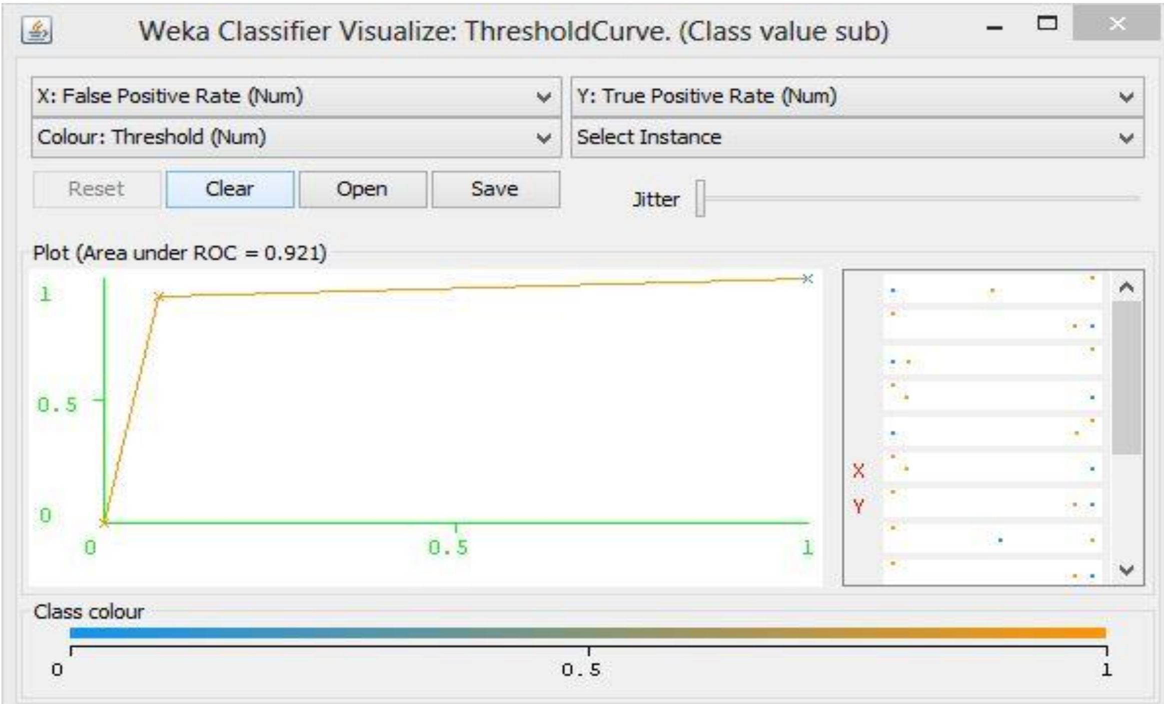


Fig 6.6: ROC=0.921 for Class S (Normalized Poly Kernel)

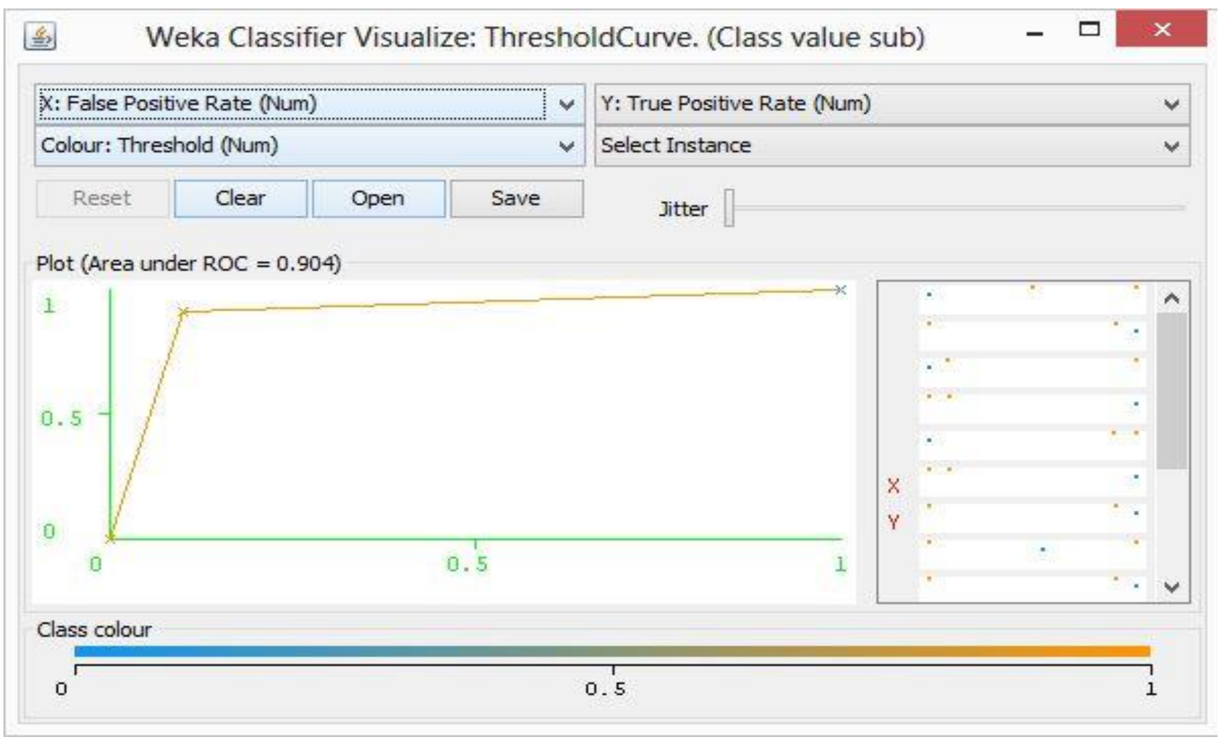


Fig 6.7: ROC=0.904 for Class S (RBF Kernel)

6.1.2 Experiment with Naïve Bayes

For Naïve Bayes experiment 4 different classifiers were used; Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable. Table 3 describes evaluation on test set using four different classifiers of Naïve Bayes and figure 6.8 shows the bar chart comparing accuracy of four different classifiers. Figure 6.9, 6.10, 6.11and 6.12 was taken from the result window of WEKA which respectively represents four different classifiers Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable outputs.

Algorithm	**Classifier**	**Trained data**	**Test data**	**Correctly classified instances**	**Incorrectly classified instances**	**Accuracy**	**Time to build model(s)**
Naïve Bayes	Naïve Bayes	9000	1000	849	151	84.9	6.51
Naïve Bayes	Bayes net	9000	1000	897	103	89.7	8.56
Naïve Bayes	Naïve Bayes multinomial	9000	1000	926	74	92.6	0.52
Naïve Bayes	Naïve Bayes multinomial updatable	9000	1000	926	74	92.6	0.45

Table 3: Evaluation on Test Set Using Different Classifiers (Naïve Bayes)

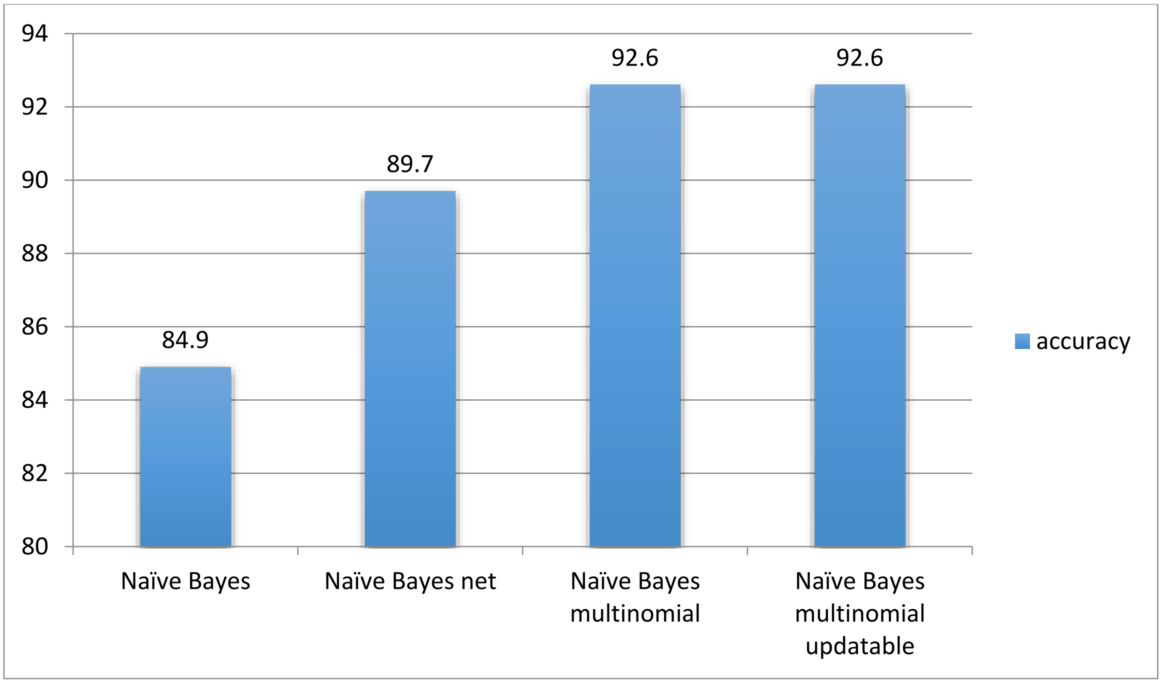


Fig 6.8: Accuracy Comparison (Naïve Bayes Classifiers)

In the above table 3, using Naïve Bayes classifier accuracy achieved 84.9% where 849 instances were classified correctly and 151 instances were incorrectly classified. Then using Bayes net classifier accuracy increased from 84.9% to 89.7% where 897 instances were classified correctly and 103 instances were incorrectly classified. Naïve Bayes multinomial and Naïve Bayes multinomial updatable gave the same and highest accuracy of 92.6% which is 2.9% more accurate than previous best of Bayes net 89.7%. Here 926 instances were correctly classified and 74 instances were incorrectly classified for both classifiers Naïve Bayes multinomial and naïve Bayes multinomial updatable. Though accuracy is same but time taken to build model in Naïve Bayes multinomial updatable is less than Naïve Bayes multinomial which is 0.45s in Naïve Bayes multinomial updatable and 0.52s in Naïve Bayes multinomial. As this experiment is more concerned with accuracy so from above table 3 it clearly shows that among all the classifiers Naïve Bayes multinomial updatable gives the best accuracy.

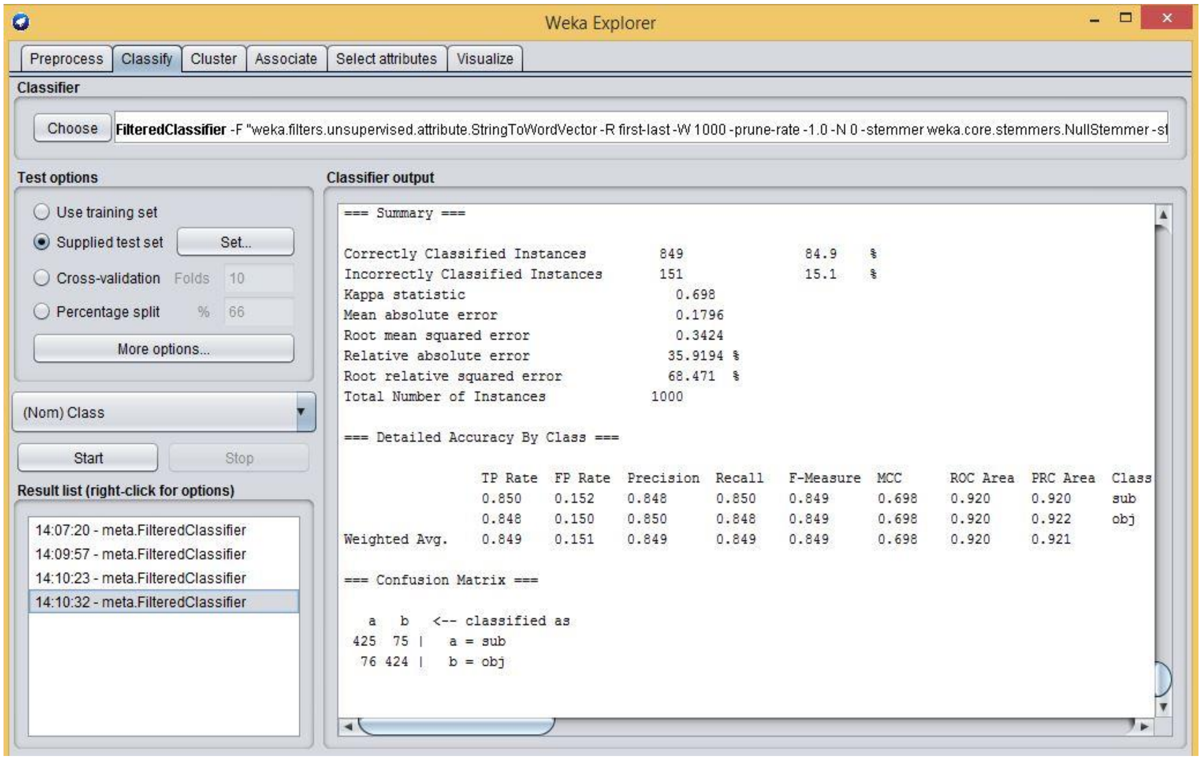


Fig 6.9: Detailed Result (Naïve Bayes Classifier)

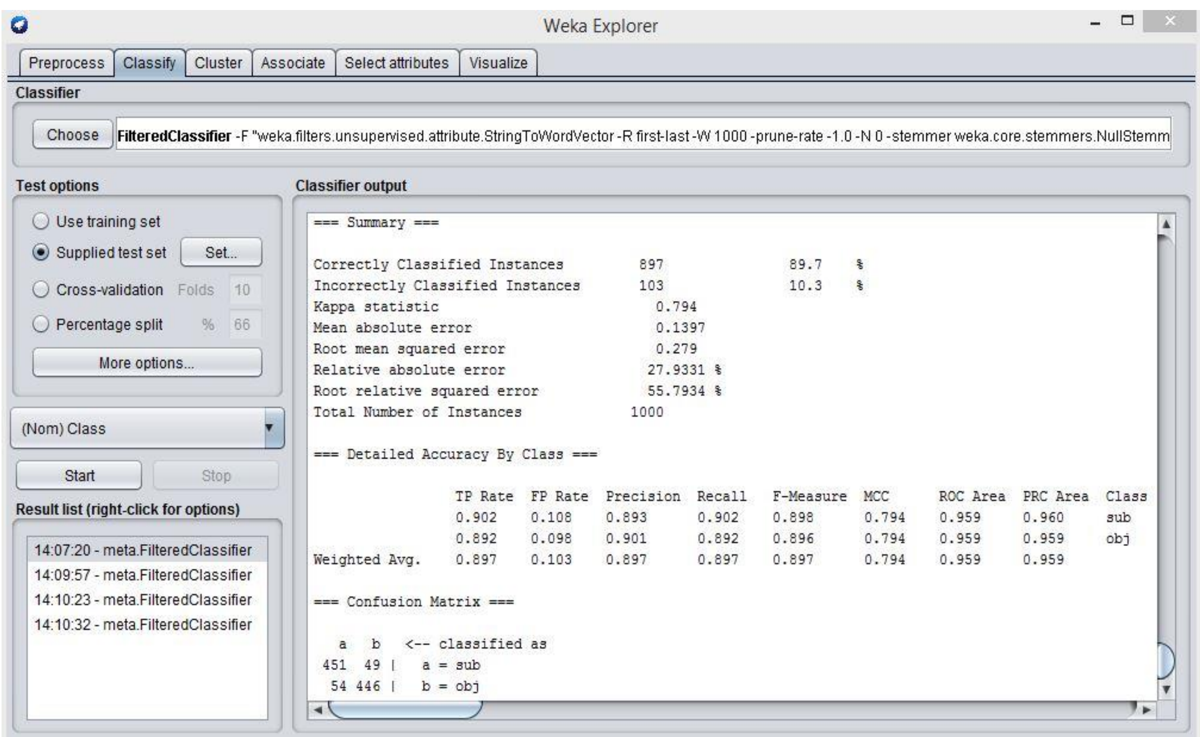


Fig 6.10: Detailed Result (Bayes Net)

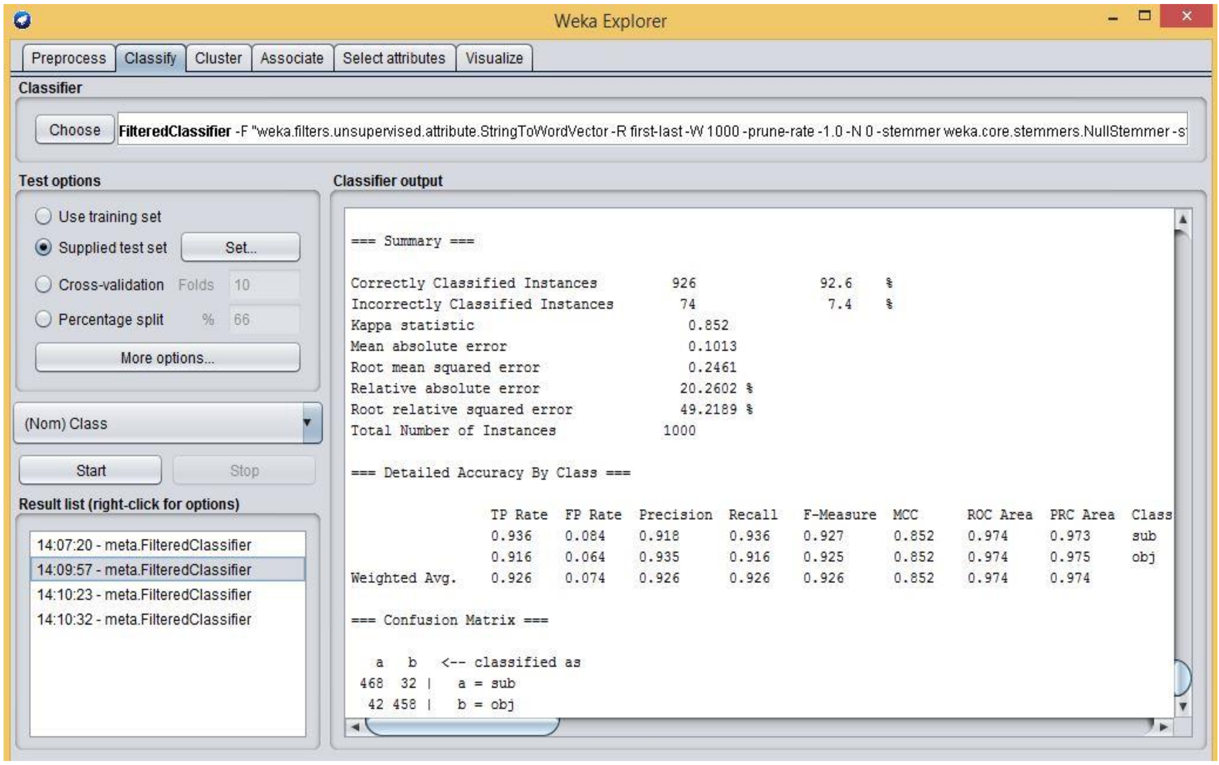


Fig 6.11: Detailed Result (Naïve Bayes Multinomial)

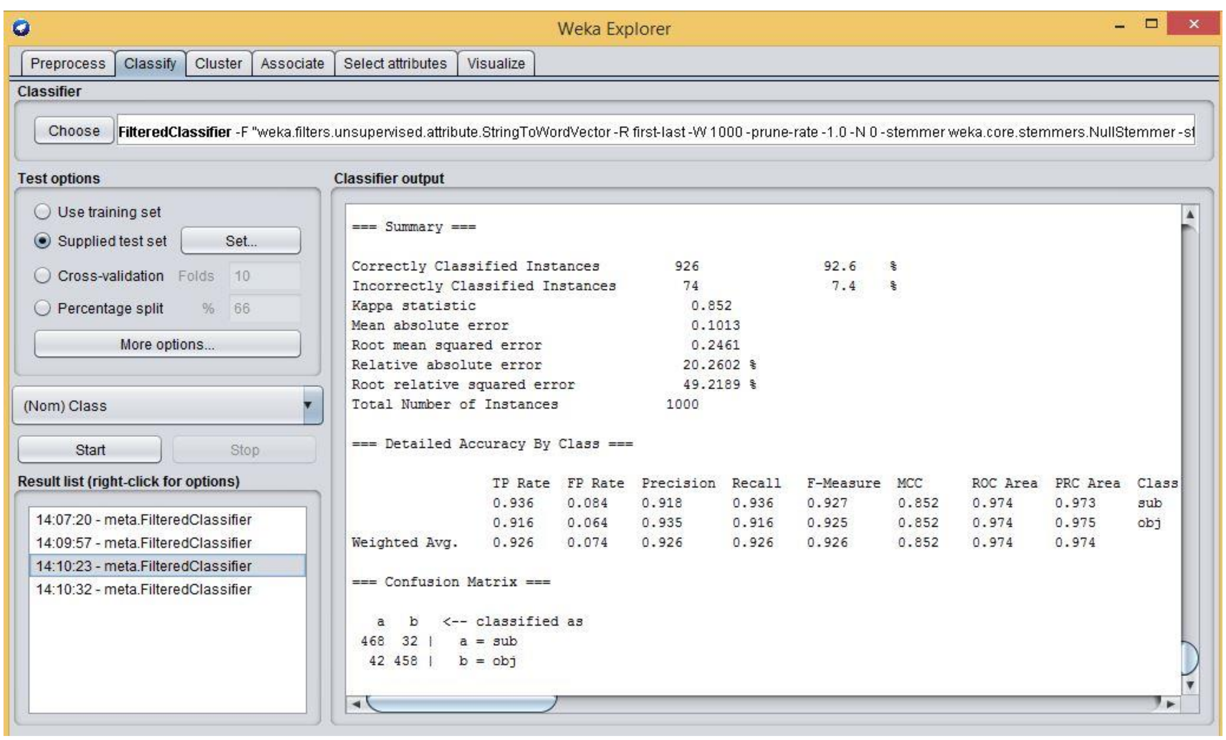


Fig 6.12: Detailed Result (Naïve Bayes Multinomial Updatable)

Table 4 describes detailed accuracy using four different classifiers of Naïve Bayes model where weighted average for subjective and objective classes of different ratio is shown.

classifier	TP rate	FP rate	Precision	Recall	F-measure	ROC area
Naïve Bayes	0.849	0.151	0.849	0.849	0.849	0.920
Bayes net	0.897	0.103	0.897	0.897	0.897	0.959
Naïve Bayes multinomial	0.926	0.074	0.926	0.926	0.926	0.974
Naïve Bayes multinomial updatable	0.926	0.074	0.926	0.926	0.926	0.974

Table 4: Detailed Accuracy Using Different Classifiers of Naïve Bayes

In table 4, among all classifiers of Naïve Bayes tp rate 0.926 is highest and fp rate 0.074 is lowest in Naïve Bayes multinomial and Naïve Bayes multinomial updatable classifiers. Precision, recall, f-measure value 0.926 is highest among all classifiers and also same in both these classifiers. Area under the ROC curve 0.974 is also highest in both these classifiers which means these two classifiers gives more accuracy among all other classifiers used for Naïve Bayes to correctly classify the test set between two classes subjective and objective. Figure 6.13, 6.14, 6.15, 6.16 respectively represents the ROC curve of subjective class with ROC value for four different classifiers Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable.

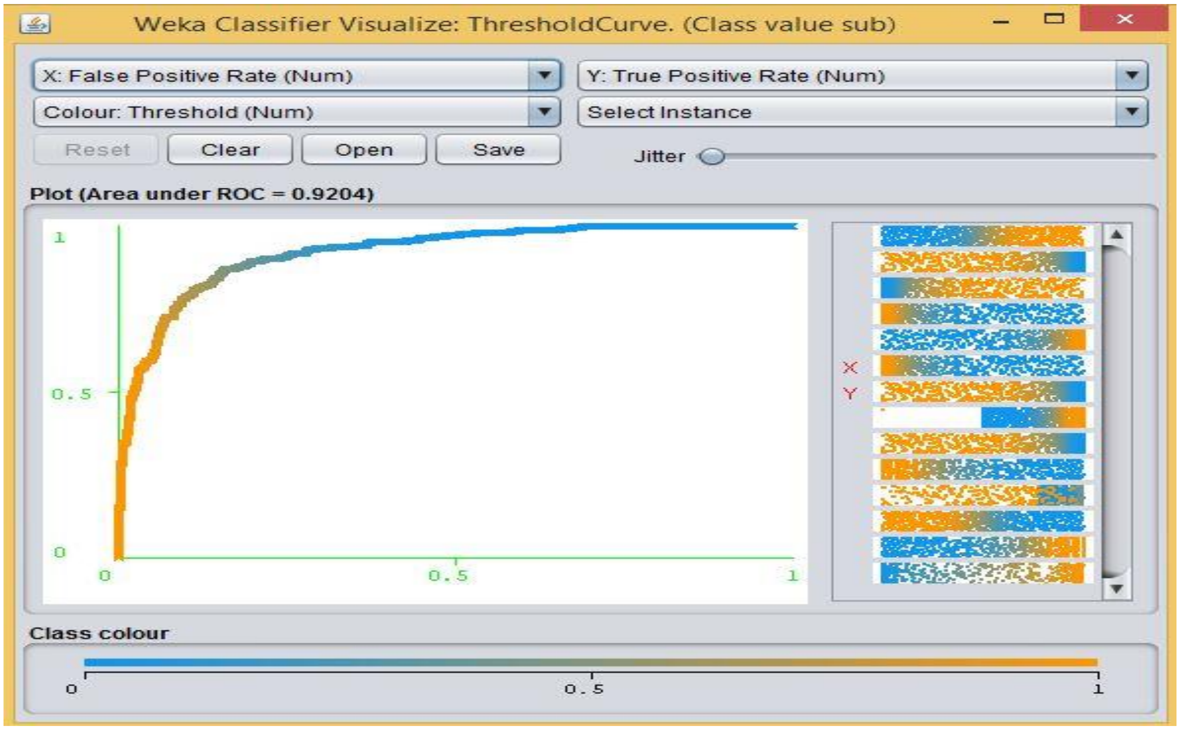


Fig 6.13: ROC=0.9204 for class S (Naïve Bayes)

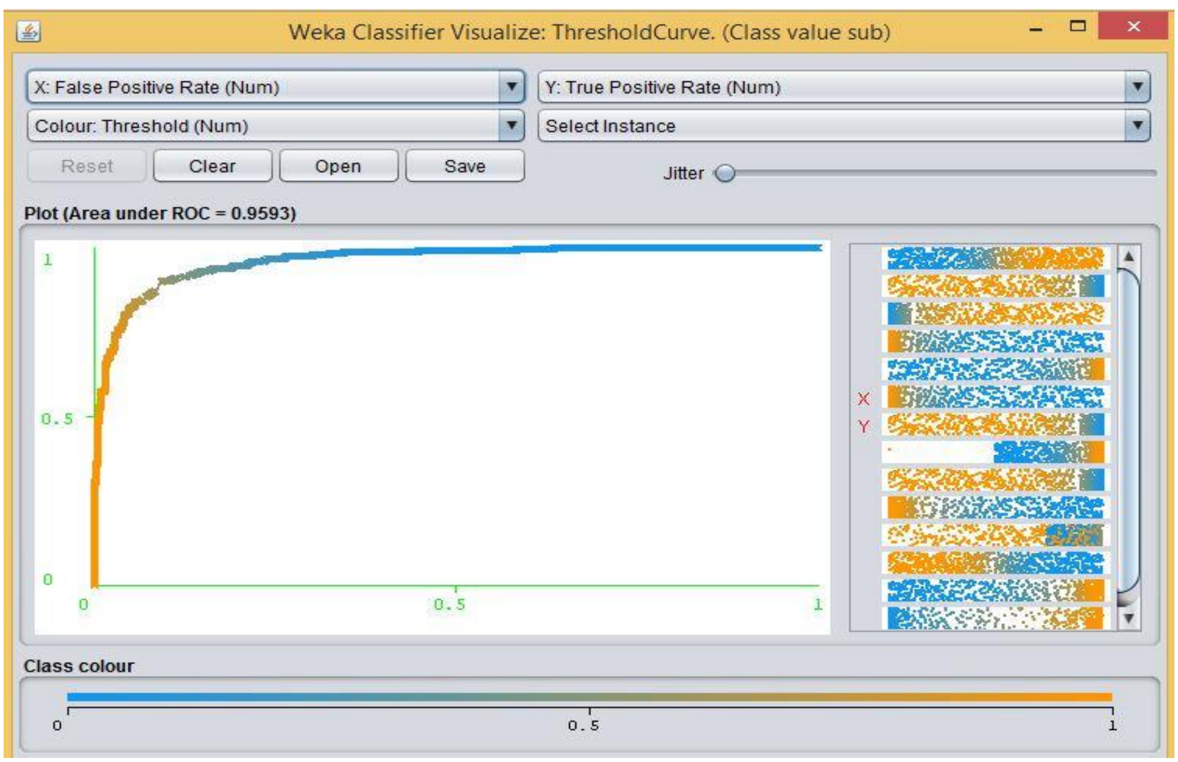


Fig 6.14: ROC=0.9593 for class S (Naïve Bayes Net)

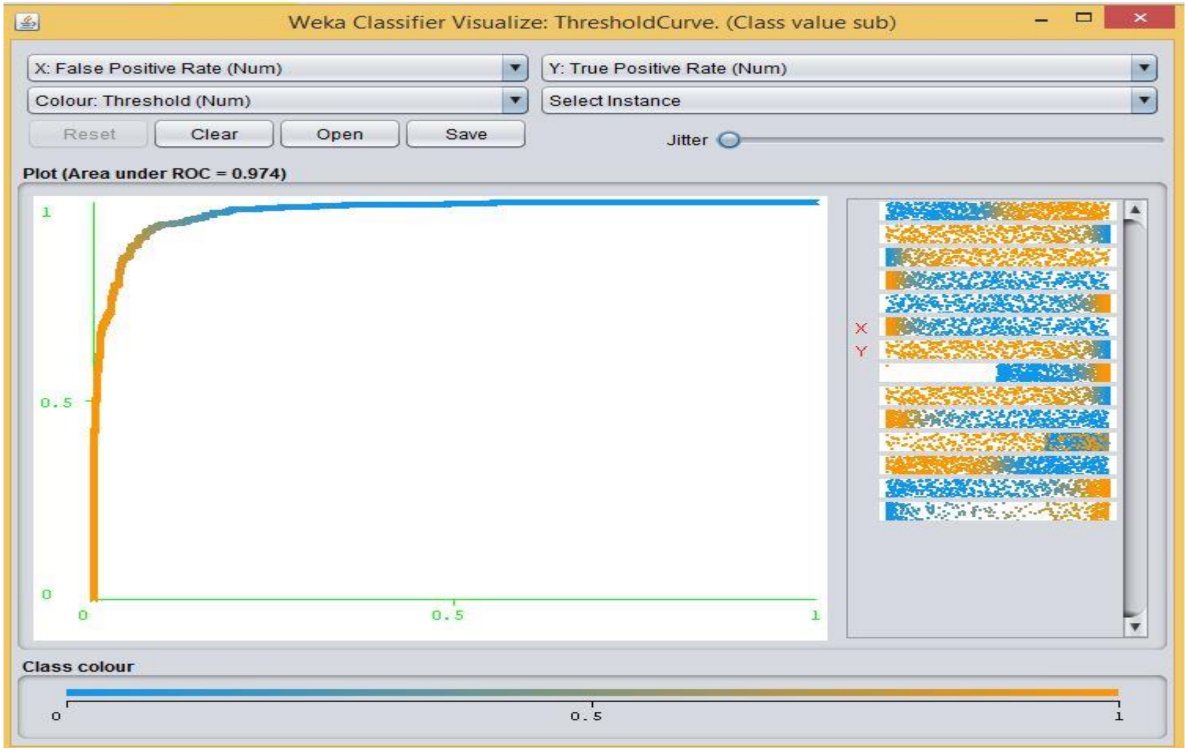


Fig 6.15: ROC=0.974 for class S (Naïve Bayes Multinomial)

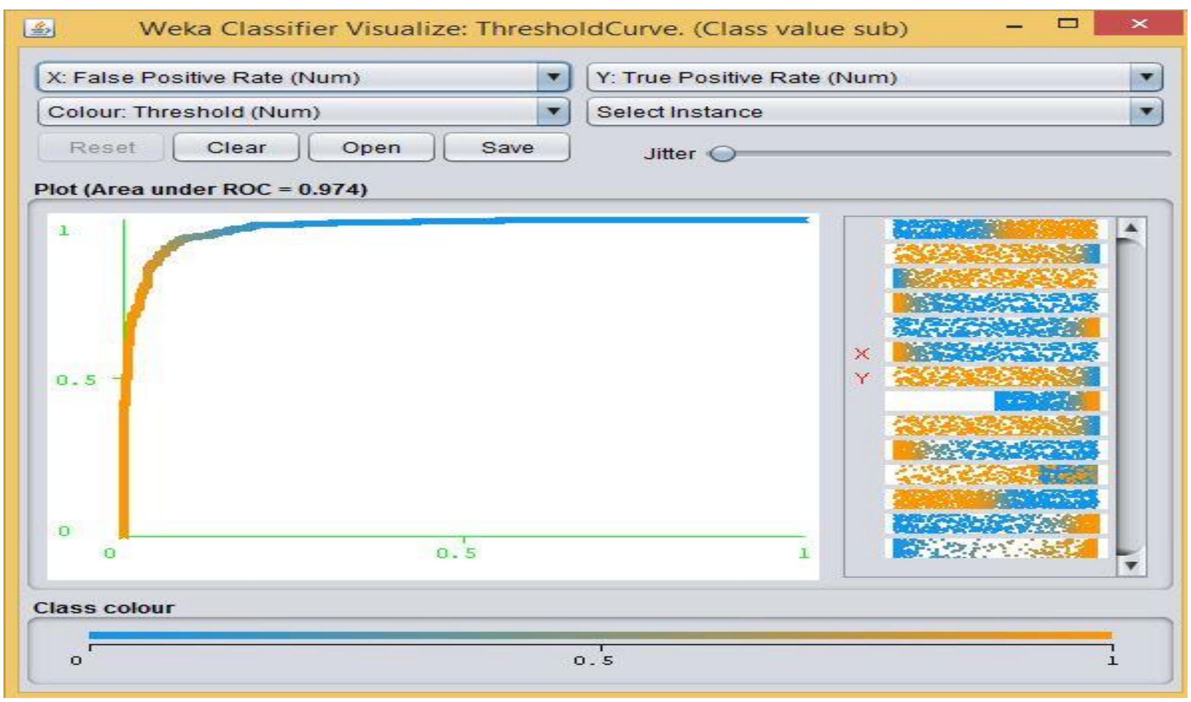


Fig 6.16: ROC=0.974 for class S (Naïve Bayes Multinomial Updatable)

6.1.3 Experiment with MLP

WEKA supports the following layers- 'a' = (attributes + classes) / 2, 'i' = attributes, 'o' = classes, 't' = (attributes + classes) for wildcard values, default = a. Hidden layer ‘o’ was used for the experiment with MLP. As there are two classes- subjective and objective in our dataset using hidden layer “o” means applying two layers. Table 5 describes evaluation on test set using MLP hidden layer ’o’ and figure 6.17 shows bar chart of accuracy.

Algorithm	Layer	Trained data	Test data	Correctly classified instances	Incorrectly classified instances	Accuracy	Time taken to build model(s)
MLP	‘o’	9000	1000	870	130	87%	1636.32

Table 5: Evaluation on Test Set using MLP (layer ’o’)

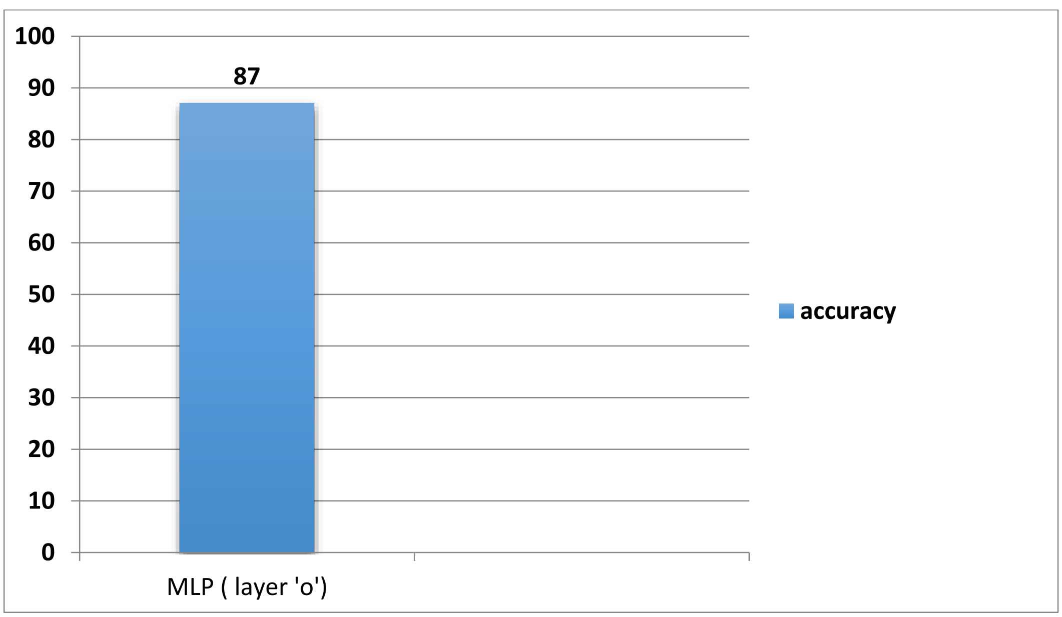


Fig 6.17: Accuracy (MLP layer ‘o’)

In the above table 5, accuracy was achieved 87% using MLP hidden layer ’o’ where 870 instances were correctly classified and 130 instances were incorrectly classified. But time taken to build model was 1636.32s which is the longest time among all the other models tested for the experiment. It means MLP takes more time to build model than other models. Figure 6.18 was taken from the result window of WEKA which represents the output using MLP hidden layer ‘o’ to test data. Fig 6.17 shows bar chart of accuracy using MLP (layer ‘o’).

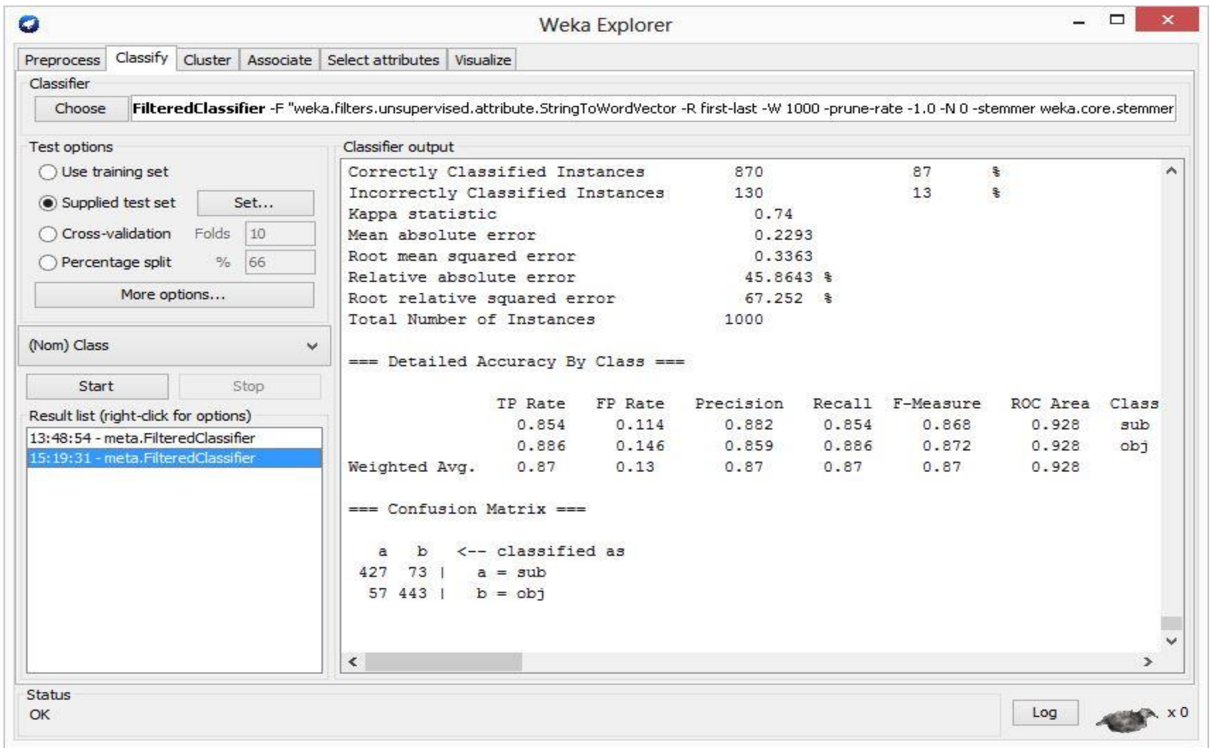


Fig 6.18: Detailed Result (MLP layer ‘o’)

layer	**TP rate**	**FP rate**	**Precision**	**Recall**	**F-measure**	**ROC area**
‘o’	0.87	0.13	0.87	0.87	0.87	0.928

Table 6: Detailed Accuracy using MLP (layer ’o’)

Above table 6 describes the detailed accuracy using MLP hidden layer ‘o’ where weighted average of subjective and objective classes for different ratio is shown. Here tp rate is 0.87, fp rate is 0.13, precision, recall and F-measure is 0.87 and ROC area is 0.928. Figure 6.19 shows the ROC curve of subjective class.

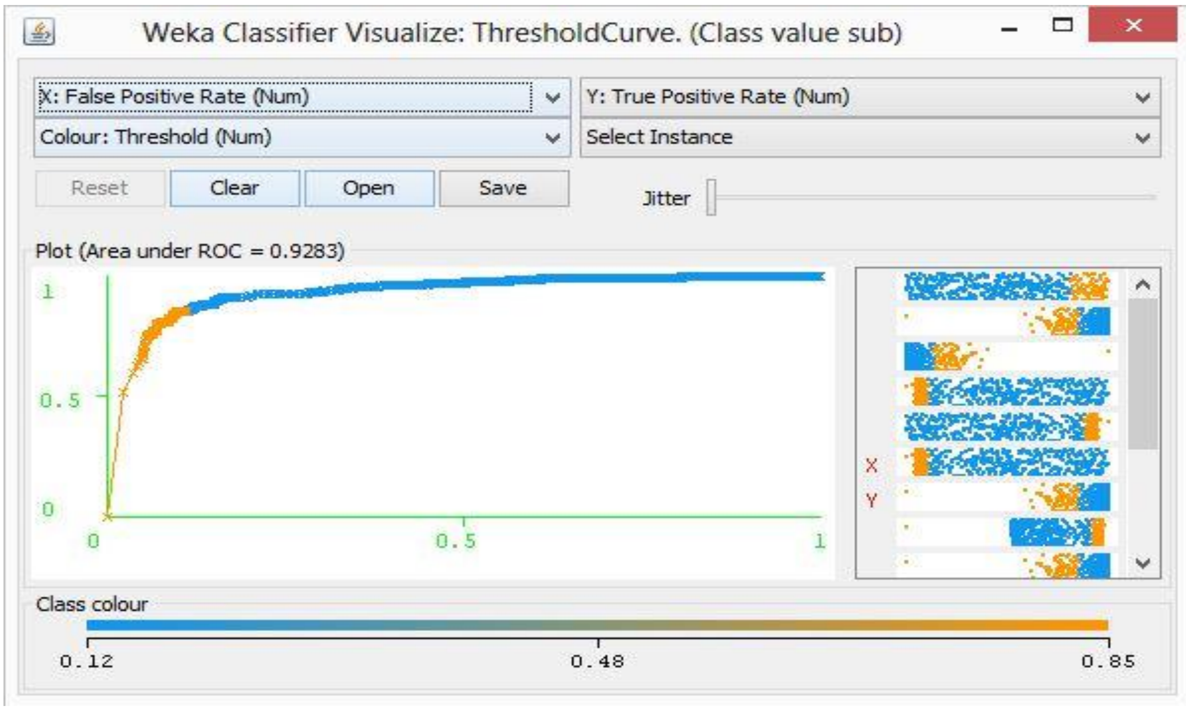


Fig 6.19: ROC=0.9283 for class S (MLP layer ‘o’)

6.1.4 Comparative analysis:

Based on highest accuracy choosing the best three classifiers from all the algorithms used for subjectivity analysis table 7 compares them below:

Algorithm	Classifier (if any)	Kernel (if any)	Accuracy	Time taken to build model(s)
SVM	SMO	Normalized poly kernel	92.1%	126.14
Naïve Bayes	Naïve Bayes multinomial		92.6%	0.52
Naïve Bayes	Naïve Bayes multinomial updatable		92.6%	0.45

Table 7: Comparative Analysis (Three Best Classifiers)

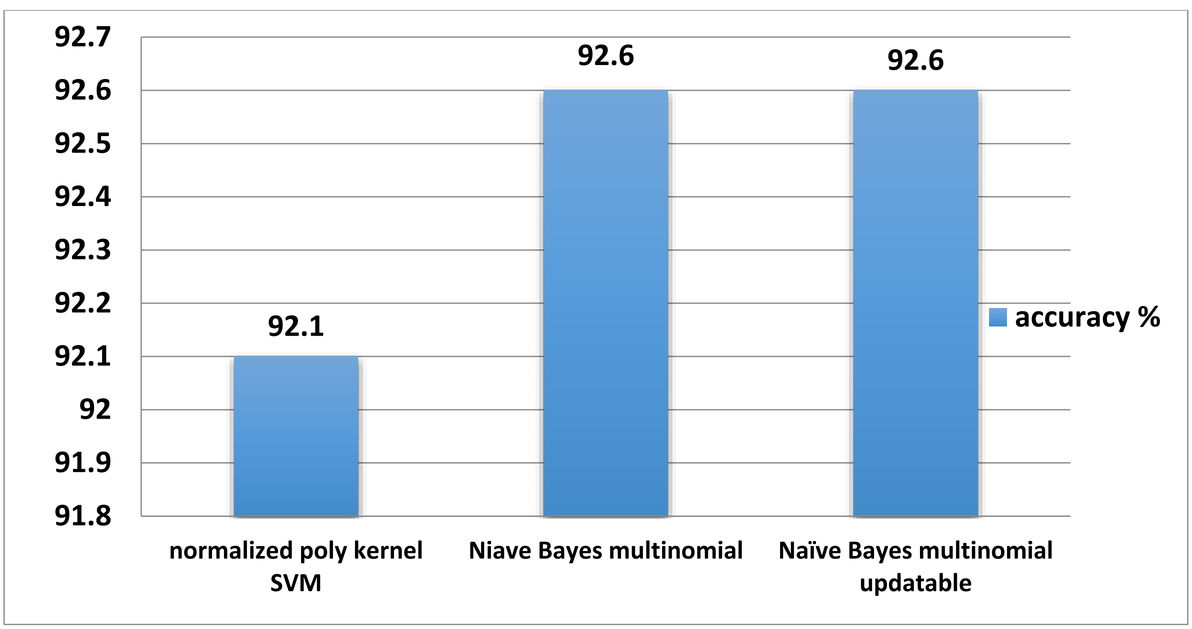


Figure 6.20: Accuracy Comparison (Three Best Classifiers)

From table 7 and fig 6.20 it clearly shows that among the three best classifiers chosen from all algorithms, Naïve Bayes multinomial and Naïve Bayes multinomial updatable gives the best and same accuracy which is 92.6 %. As time taken to build model is little bit low in multinomial updatable so it can be said that Naïve Bayes multinomial updatable performed as best classifier for subjectivity analysis.

6.1.5 Stop Word and Attribute Impact

The following movie review has been taken from the test set of subjectivity analysis that has been used in the experiment. If stop words were not ignored then the predicted output was correct. If stop words were ignored then the predicted output was incorrect. With stop word the probability of subjective was higher that probability of objective which gives correct output but without stop word the probability of being objective of that review was higher than the probability of subjective therefore it results in incorrect output.

"in the affable maid in manhattan , jennifer lopez's most aggressive and most sincere attempt to take movies by storm , the diva shrewdly surrounds herself with a company of strictly a-list players . " , sub

Instance no	Actual	Predicted	Error	Subjective probability	Objective probability	Use Stop Word
18	sub	sub		*0.729	0.271	False
18	sub	obj	+	0.021	*0.979	True

Table 15: Stop Words Effect on Accuracy using Naïve Bayes Multinomial Updatable Classifier

Moreover if the number of attributes changes the accuracy percentage changes. As it is stated earlier that all the above mentioned experiments were conducted using default attribute number which is 1000. Now the following figure will show how the changes in attribute number and stop word effect accuracy of subjectivity.

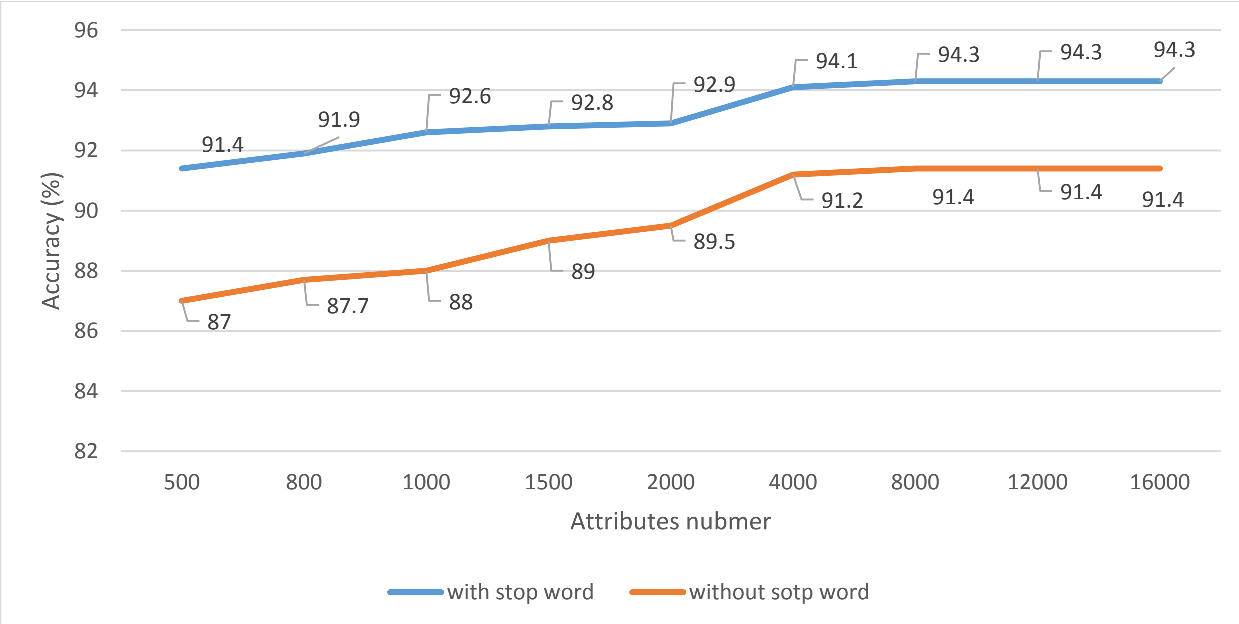


Fig 6.49.: Attribute VS Accuracy using Naïve Bayes Multinomial Updatable

The figure shows that if the attribute number increases the accuracy also increase for subjective / objective classification. When the attribute number max then the accuracy is fixed. Here we see from 8000 attribute the accuracy remains fixed for both case of stop word. This means the dataset contains maximum 8000 unique attributes. Now if we look at figure it is clearly seen that the blue one contains higher accuracy than the orange one. Where blue line represents accuracy gained having/without ignoring stop words and orange line represents accuracy gained for different no of attribute ignoring/without having stop words. This means without removing/ignoring stop words better accuracy has been found in sentence level subjectivity classification.

6.2 Sentiment Analysis

22000 movie reviews containing 11000 positive and 11000 negative reviews for training set and 3001 movie reviews containing 1501 positive and 1500 negative reviews for test set was taken for sentiment analysis.

6.2.1 Experiment with SVM

As previously mentioned SMO classifier with three different kernels; Poly Kernel, Normalized Poly Kernel and RBF Kernel was used for the experiment with SVM for sentiment analysis. Table 8 describes evaluation on test set using three different kernels of SVM and figure 6.21 shows the bar chart of accuracy comparison. Figure 6.22, 6.23 and 6.24 was taken from the result window of WEKA which respectively represents three different kernels poly, normalize poly and rbf kernels output.

Algorithm	**Classifier**	**Kernel**	**Trained data**	**Test data**	**Correctly classified instances**	**Incorrectly classified instances**	**Accuracy**	**Time to build model(s)**
SVM	SMO	poly kernel	22000	3001	2845	156	94.8017	8059.34
SVM	SMO	normalized poly kernel	22000	3001	2924	77	97.4342	3054.76
SVM	SMO	rbf kernel	22000	3001	2917	84	97.2009	2797.5

Table 8: Evaluation on Test Set using Different Kernels

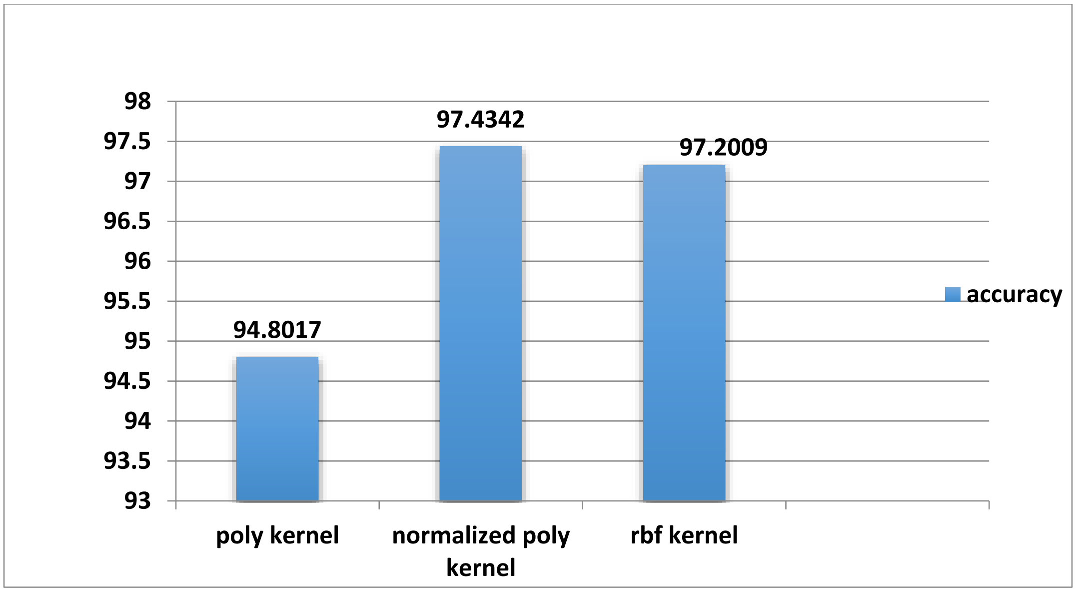


Fig 6.21: Accuracy Comparison (SVM Kernels)

In the above table 8, using poly kernel accuracy was achieved 94.8017% where 2845 instances were classified correctly and 156 instances classified incorrectly from 3001 test data. Then again using normalized poly kernel for the same test set accuracy increased 2.6325 % from 94.8017% to 97.4342% where 2924 instances were correctly classified and 77 instances were incorrectly classified. Changing kernel to rbf kernel for the same test set accuracy decreased only 0.2333% from 97.4342% to 97.2009% than normalized poly kernel but increased 2.3992% from 94.8017% to 97.2009% than poly kernel where 2917 instances were correctly classified and 84 instances were incorrectly classified. Though time taken to build model is lowest in rbf kernel than two other kernels shown in table 8 but as this experiment is more concerned about accuracy so normalized poly kernel is the most successful than two other kernels used for the experiment with SVM for sentiment analysis.

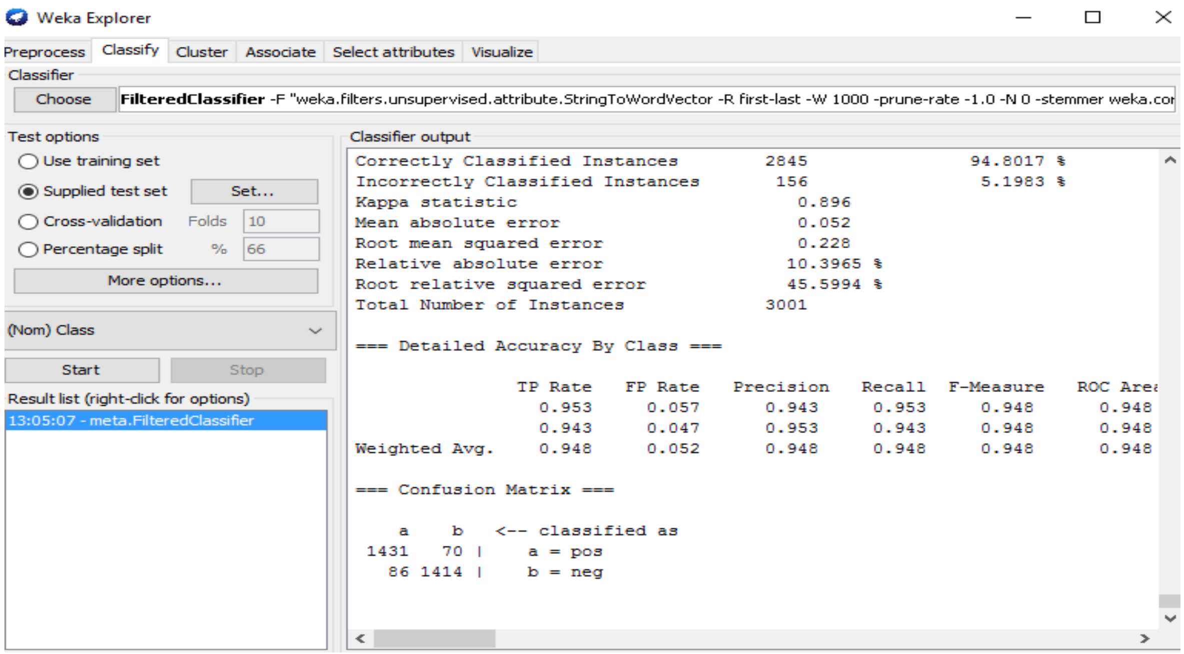


Fig 6.22: Detailed Result (Poly Kernel)

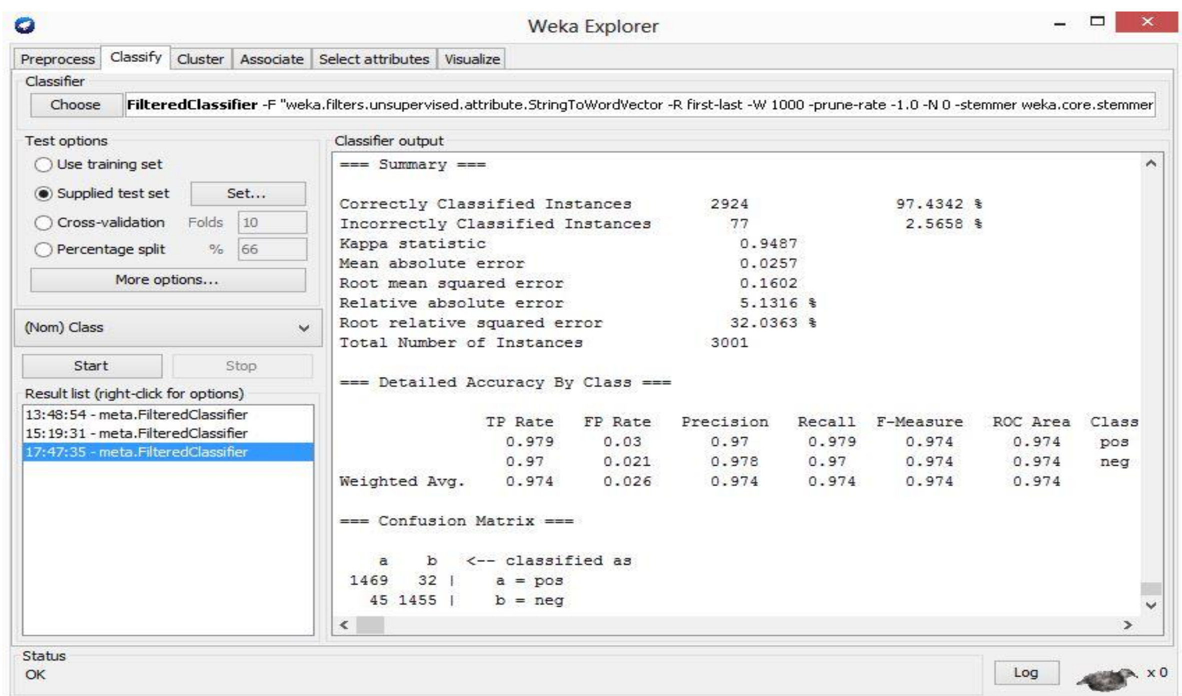


Fig 6.23: Detailed Result (Normalize Poly Kernel)

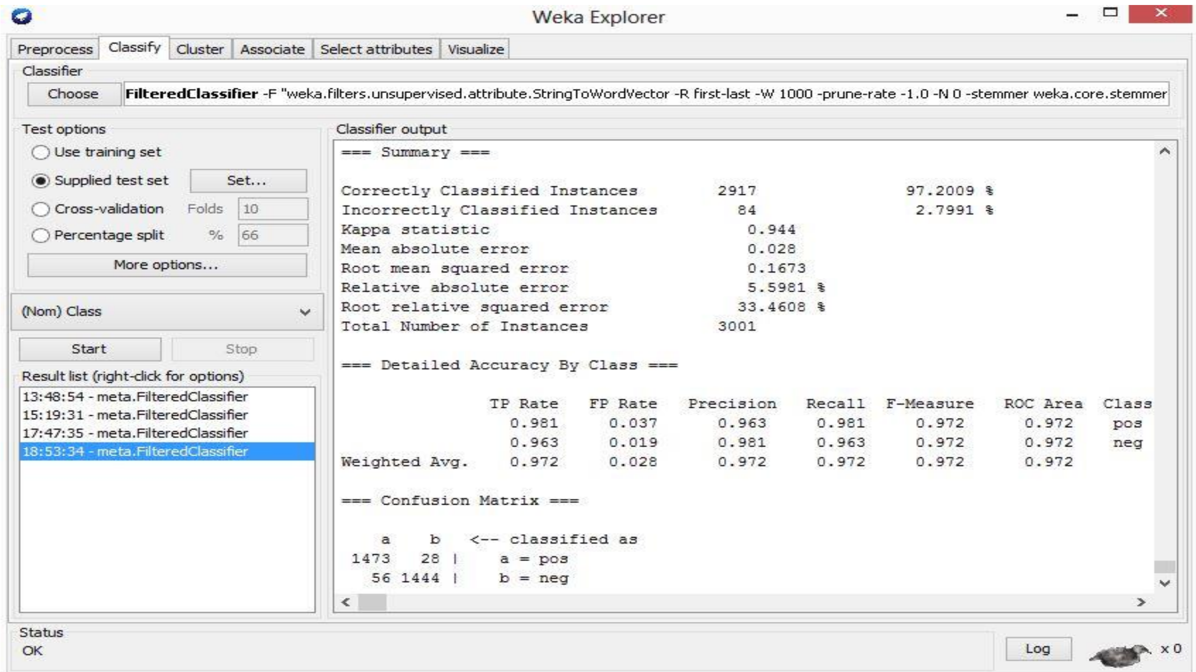


Fig 6.24: Detailed Result (RBF Kernel)

Table 9 describes the detailed accuracy using three different kernels where only weighted average of positive and negative classes for different ratio is shown. In table 9, among all three kernels tp rate 0.974 is the highest which is in normalized poly kernel and fp rate 0.026 is also the lowest in normalized poly kernel. Precision, recall, f-measure and ROC area 0.974 is also highest in normalized poly kernel comparing to other two kernels. Here in table 9, area under the ROC curve 0.974 is the highest that means among all three kernels of SVM that was used to test, normalized poly kernel is more accurate to correctly classify the test set between two classes positive and negative. Figure 6.25, 6.27 and 6.29 represents ROC curve of positive class and 6.26, 6.28 and 6.30 represents ROC curve of negative class respectively for three different kernels poly, normalize poly and rbf.

Kernel	TP rate	FP rate	Precision	Recall	F-Measure	ROC Area
poly kernel	0.948	0.052	0.948	0.948	0.948	0.948
normalized poly kernel	0.974	0.026	0.974	0.974	0.974	0.974
rbf kernel	0.972	0.028	0.972	0.972	0.972	0.972

Table 9: Detailed Accuracy using Different Kernels (SVM)

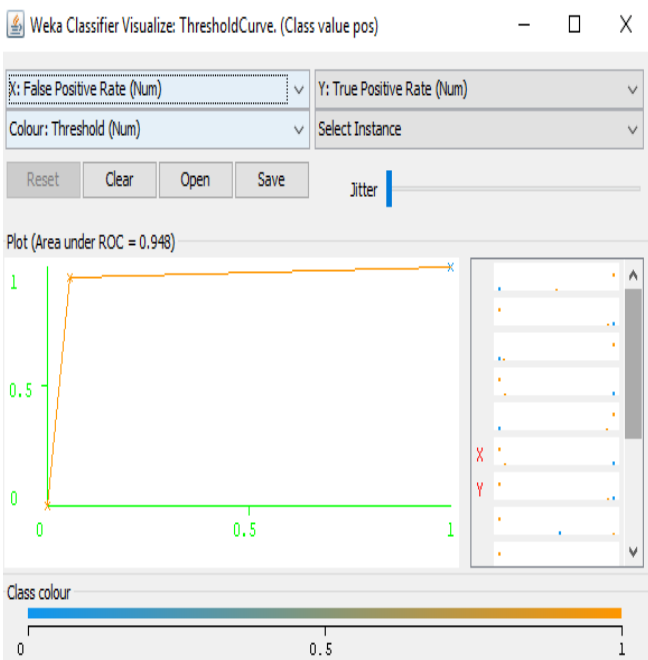


Fig 6.25: ROC=0.948 for P

(Poly kernel)

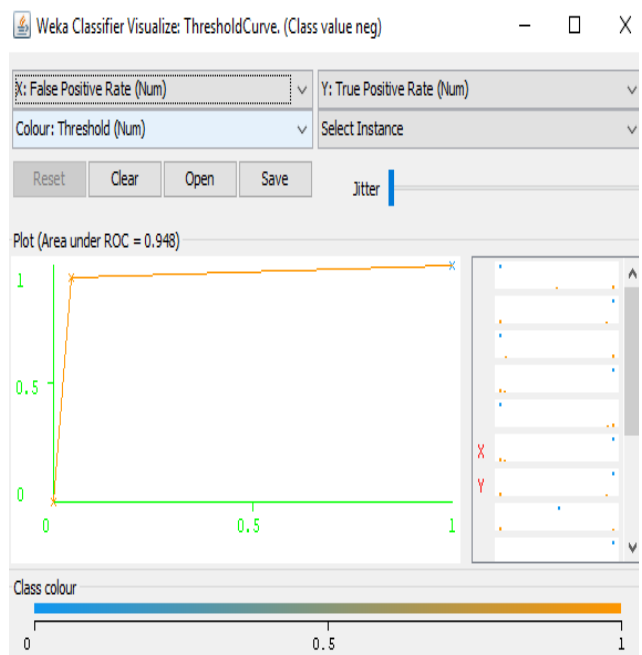
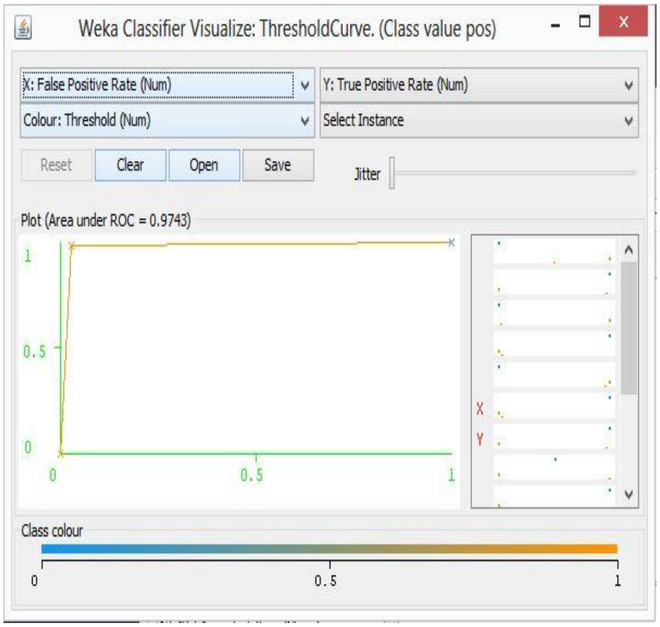


Fig 6.26: ROC=0.948 for N

(Poly kernel)



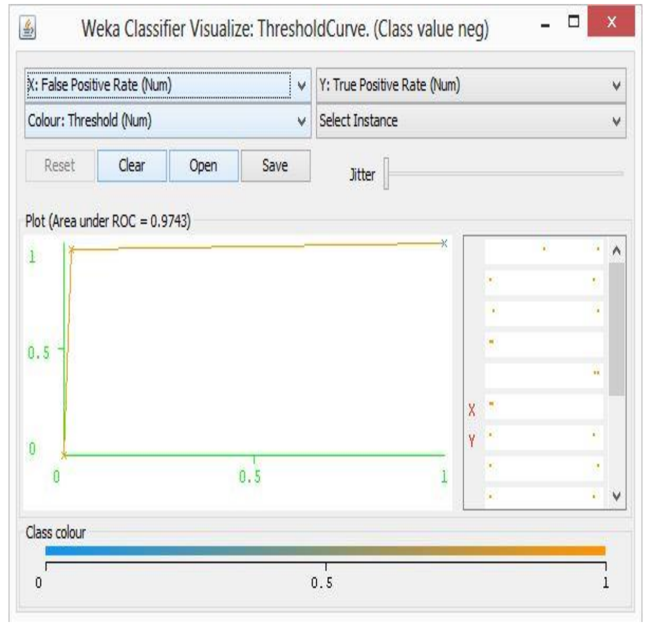
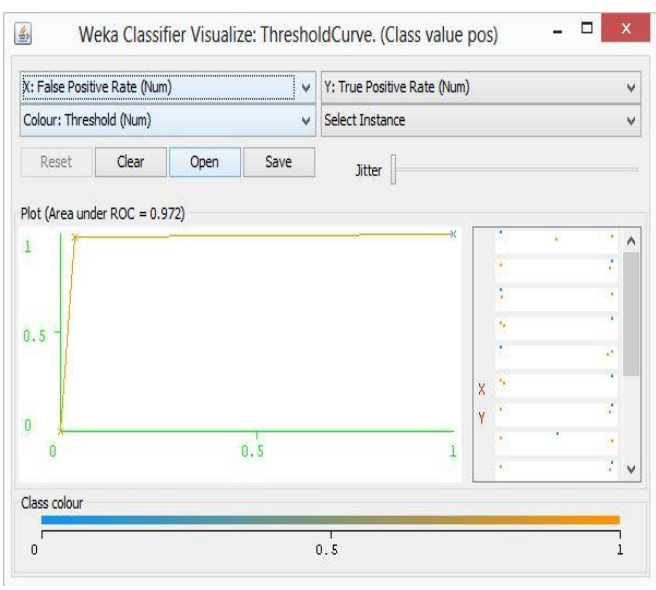


Fig 6.27: ROC=0.9743 for P

(Normalize Poly)

Fig 6.28: ROC=0.9743 for N

(Normalize Poly)



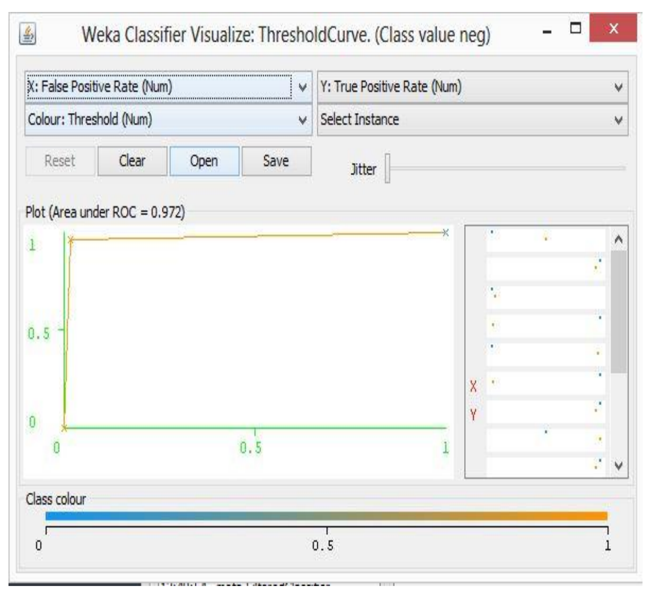


Fig 6.29: ROC=0.972 for P

(RBF)

Fig 6.30: ROC=0.972 for N

(RBF)

6.2.2 Experiment with Naïve Bayes

Like subjectivity analysis in 6.1.2, four different classifiers of Naïve Bayes; Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable was used for sentiment analysis also. Table 10 describes evaluation on test set using four different classifiers of Naïve Bayes and fig 6.31shows the bar chart of accuracy comparison. Figure 6.32, 6.33 6.34and 6.35 was taken from the result window of WEKA which respectively represents four different classifiers Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable outputs.

Algorithm	classifier	Trained data	Test data	Correctly classified instances	Incorrectly classified instances	Accuracy	Time to build model(s)
Naïve Bayes	Naïve Bayes	22000	3001	2663	338	88.7371	22.27
Naïve Bayes	Bayes net	22000	3001	2663	338	88.7371	50.76
Naïve Bayes	Naïve Bayes multinomial	22000	3001	2736	265	91.1696	10.96
Naïve Bayes	Naïve Bayes multinomial updatable	22000	3001	2736	265	91.1696	9.85

Table 10: Evaluation on Test Set using Different Classifiers

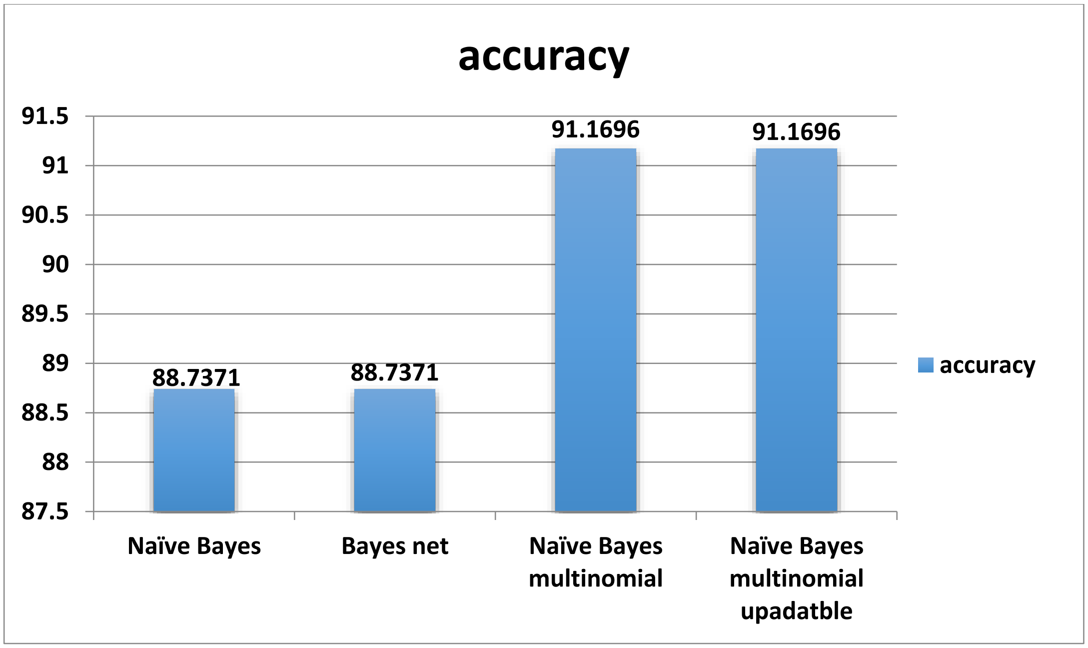


Fig 6.31: Accuracy Comparison (Naïve Bayes Classifier)

In the above table 10, using Naïve Bayes classifier accuracy achieved 88.7371 where 2663 instances were classified correctly and 338 instances were incorrectly classified. Then again using Bayes net classifier accuracy remained same. But by using Naïve Bayes multinomial and Naïve Bayes multinomial updatable for the same dataset highest accuracy obtained 91.1696% which is 2.4325% more accurate than previous best 88.7371%. Here 2736 instances were correctly classified and 265 instances were incorrectly classified for both classifiers Naïve Bayes multinomial and Naïve Bayes multinomial updatable. Though accuracy is same but time taken to build model in Naïve Bayes multinomial updatable is less than Naïve Bayes multinomial which is 9.85s in Naïve Bayes multinomial updatable and 10.96s in Naïve Bayes multinomial. As this experiment is more concerned with accuracy so from above table 10 it clearly shows that among all the classifiers Naïve Bayes multinomial updatable gives the best accuracy.

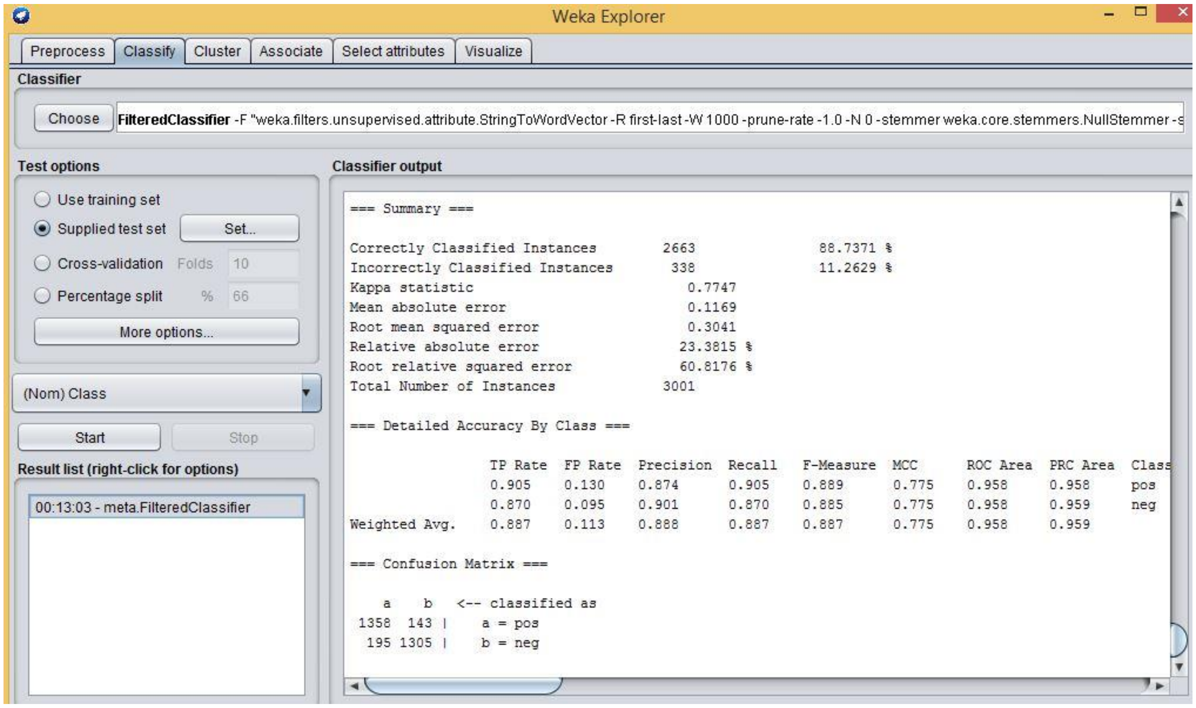


Fig 6.32: Detailed Result (Naïve Bayes Classifier)

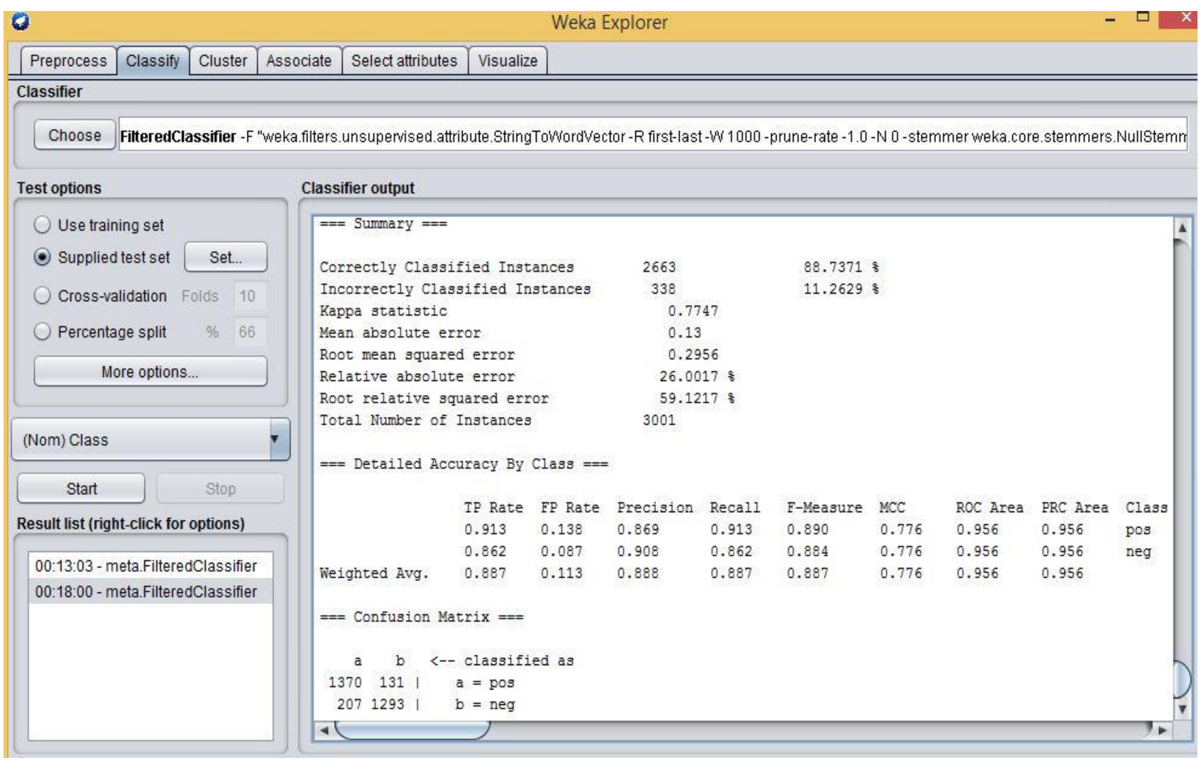


Fig 6.33: Detailed Result (Naïve Bayes Net)

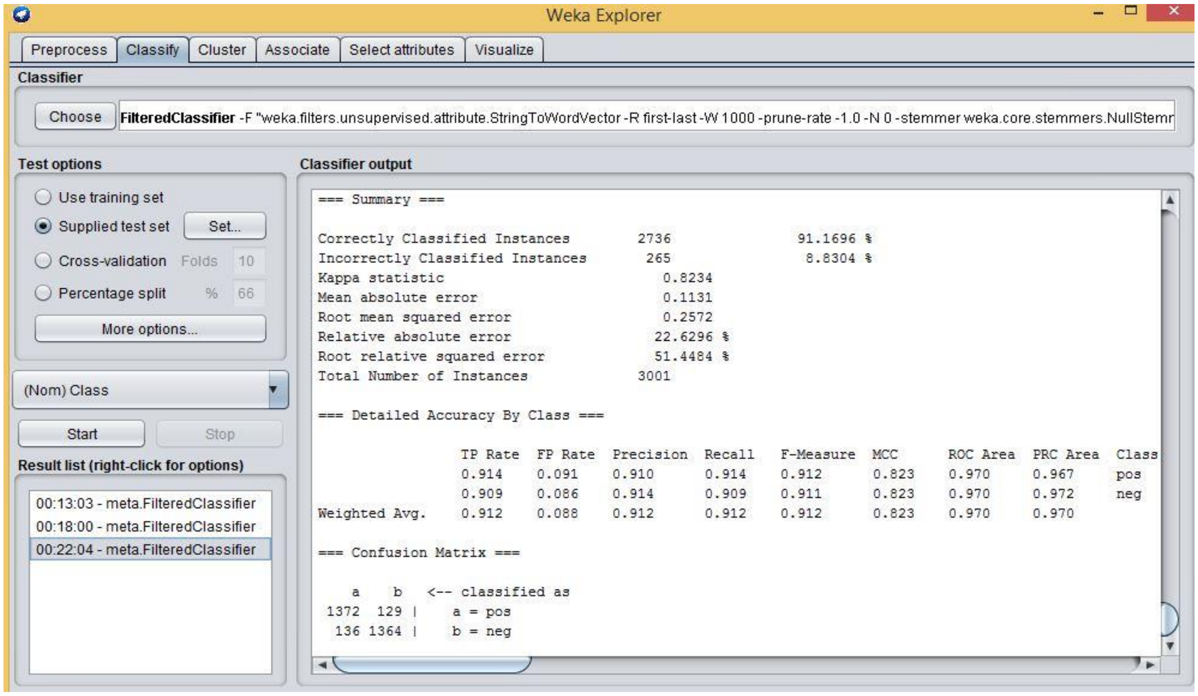


Fig 6.34: Detailed Result (Naïve Bayes Multinomial)

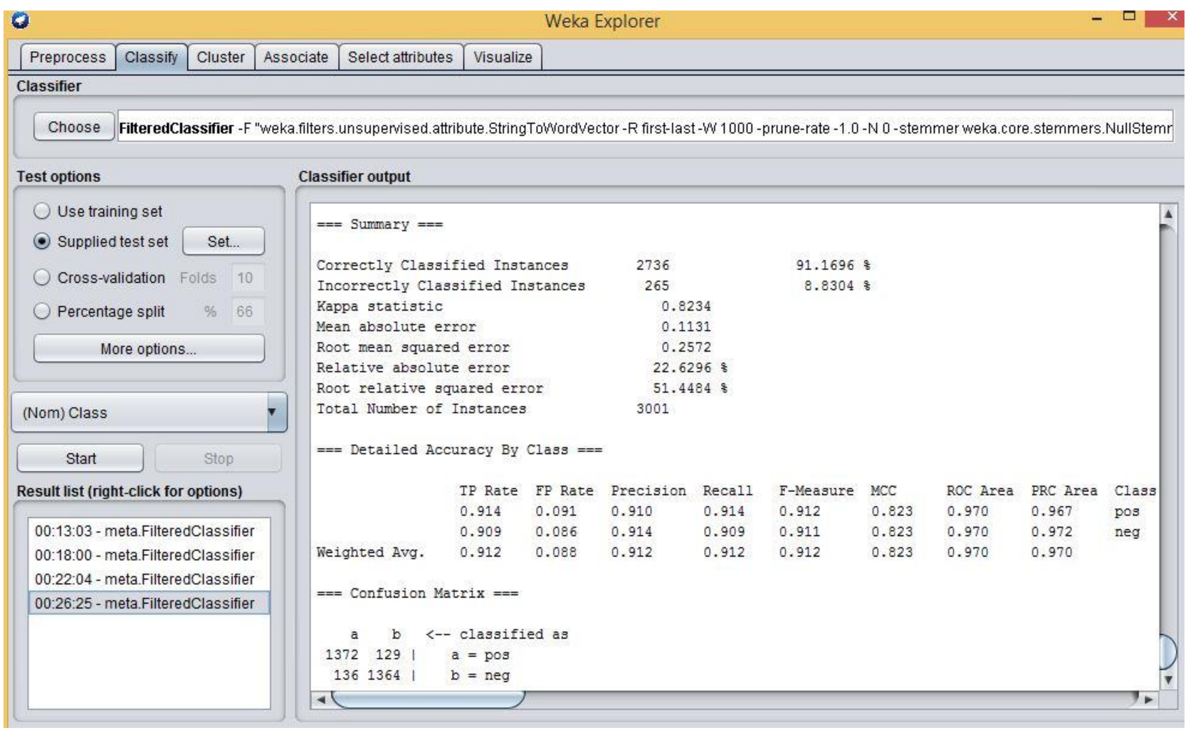


Fig 6.35: Detailed Result (Naïve Bayes Multinomial Updatable)

Table 11 describes the detailed accuracy using four different classifiers of Naïve Bayes model where weighted average of positive and negative classes for different ratio is shown.

classifier	TP rate	FP rate	Precision	Recall	F-measure	ROC area
Naïve Bayes	0.887	0.113	0.888	0.887	0.887	0.958
Bayes net	0.897	0.103	0.888	0.887	0.887	0.956
Naïve Bayes multinomial	0.912	0.088	0.912	0.912	0.912	0.970
Naïve Bayes multinomial updatable	0.912	0.088	0.912	0.912	0.912	0.970

Table 11: Detailed Accuracy using Different Classifiers of Naïve Bayes

In table 11, among all classifiers of Naïve Bayes tp rate 0.912 is highest and fp rate 0.088 is lowest in Naïve Bayes multinomial and Naïve Bayes multinomial updatable classifiers. Precision, recall, f-measure value 0.912 is highest among all classifiers and also same in both these classifiers. Area under the ROC curve 0.970 is also highest in both these classifiers which means these two classifiers gives more accuracy among all other classifiers used for Naïve Bayes to correctly classify the test set between two classes positive and negative. Figure 6.36, 6.38, 6.40, 6.42 represents ROC curve of positive class and 6.37, 6.39, 6.41 and 6.43 represents ROC curve of negative class respectively for four different classifiers Naïve Bayes, Bayes net, Naïve Bayes multinomial and Naïve Bayes multinomial updatable.

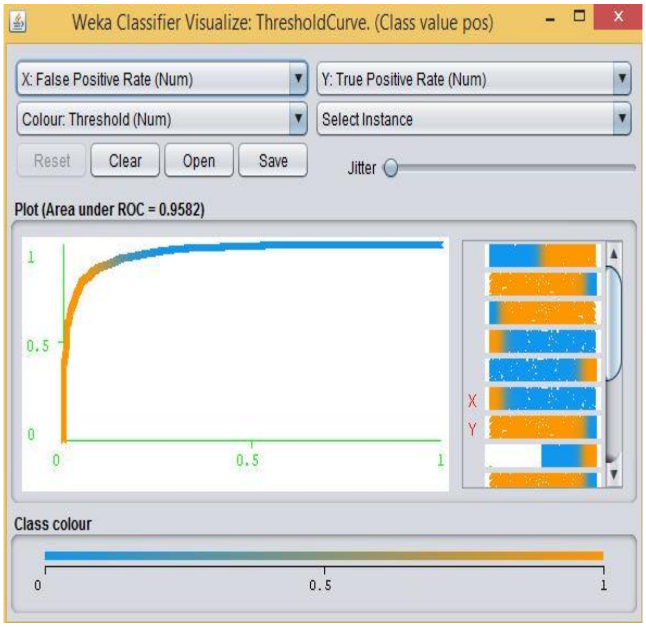


Fig 6.36: ROC=0.9582 for class P

(Naïve Bayes)

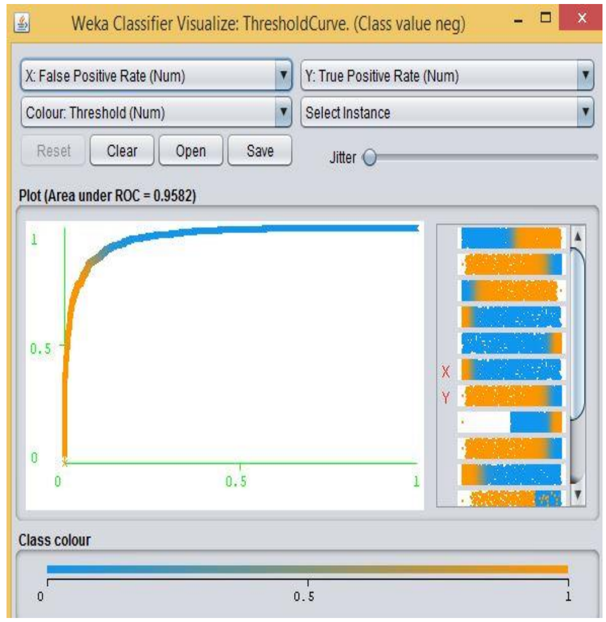


Fig 6.37: ROC=0.9582 for class N

(Naïve Bayes)

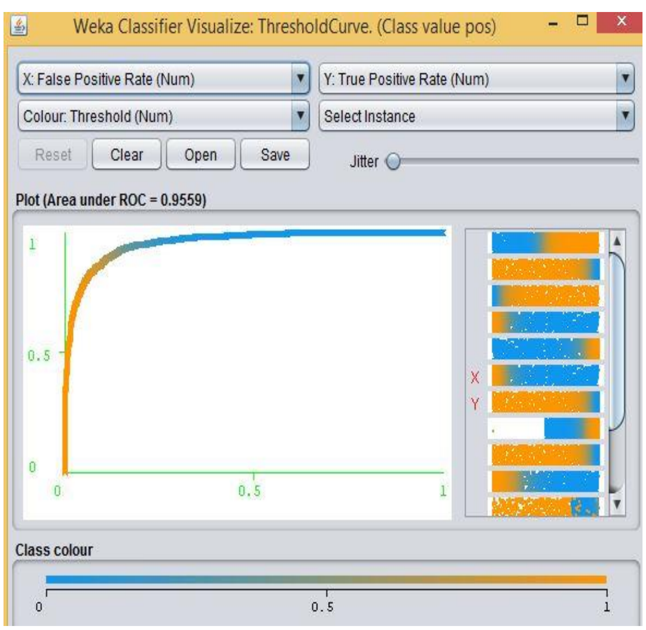


Fig 6.38: ROC=0.9559 for class P

(Naïve Bayes Net)

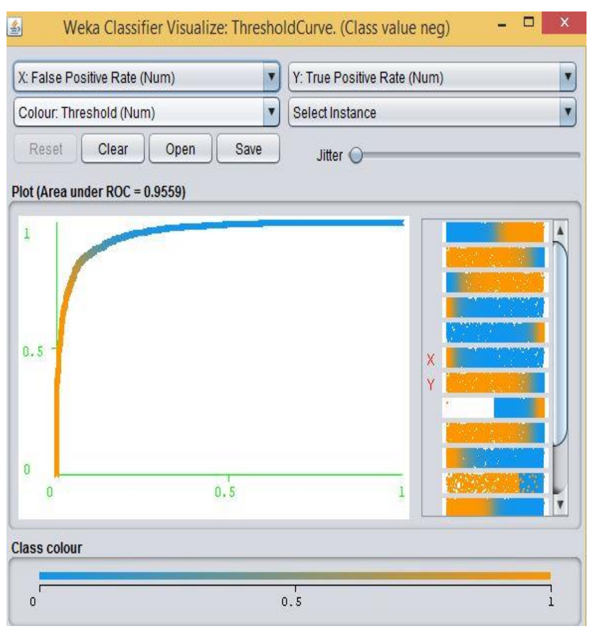
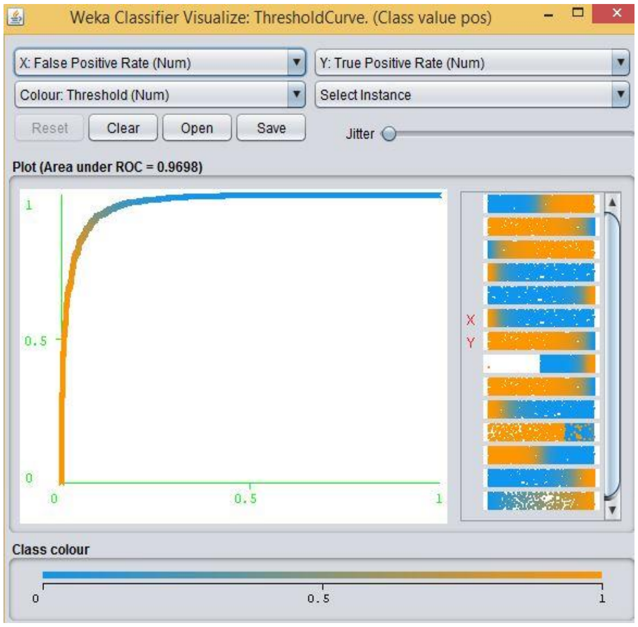


Fig 6.39: ROC=0.9559 for class N

(Naïve Bayes Net)



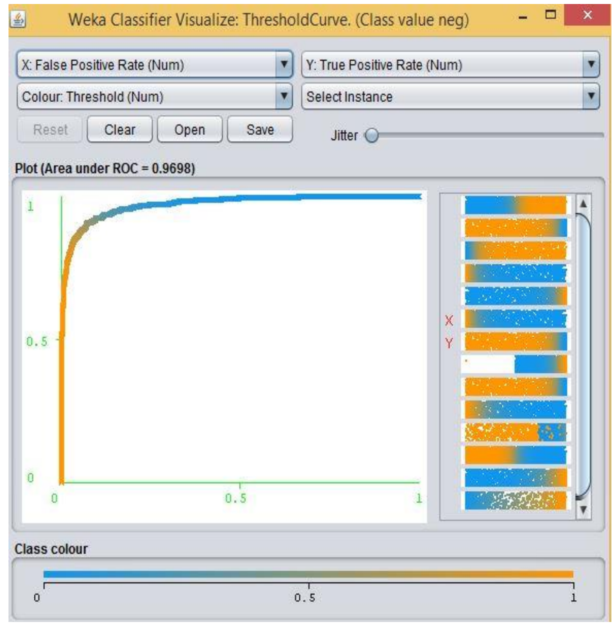
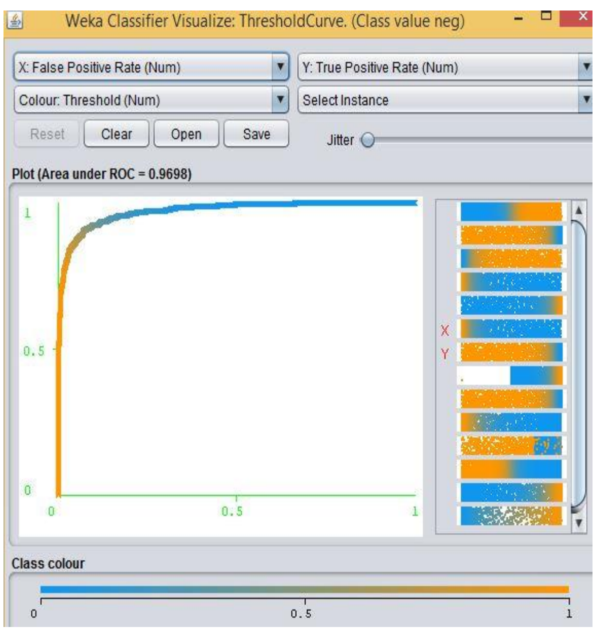


Fig 6.40: ROC=0.9698 for class P

(Naïve Bayes Multinomial)

Fig 6.41: ROC=0.9698 for class N

(Naïve Bayes Multinomial)



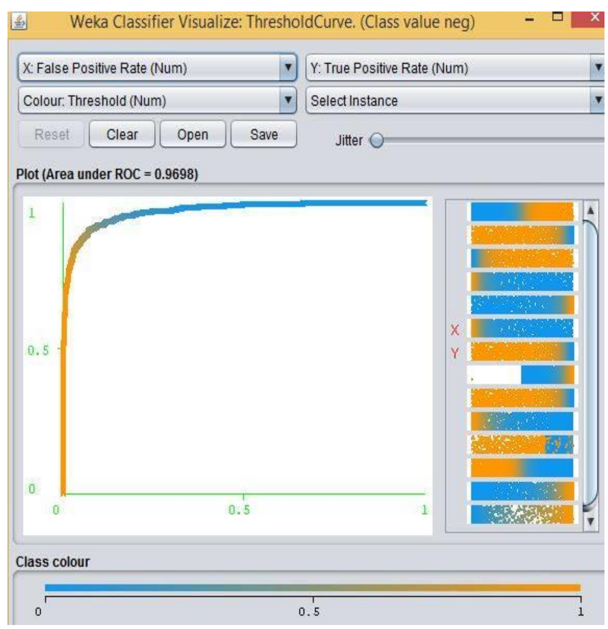


Fig 6.42: ROC=0.9698 for class P

(Naïve Bayes Multinomial updatable)

Fig 6.43: ROC=0.9698 for class N

(Naïve Bayes Multinomial updatable)

6.2.3 Experiment with MLP

Like subjectivity analysis hidden layer ‘o’ was used for the experiment with MLP where ‘o’ means classes. As there are again two classes- positive and negative in our dataset using hidden layer “o” means applying two layers. Table 12 describes evaluation on test set using MLP hidden layer ’o’ and fig 6.44 shows the bar chart of accuracy.

Algorithm	Layer	Trained data	Test data	Correctly classified instances	Incorrectly classified instances	Accuracy	Time taken to build model(s)
MLP	‘o’	22000	3001	2749	252	91.6028%	2884.42

Table 12: Evaluation on Test Set using MLP (layer ’o’)

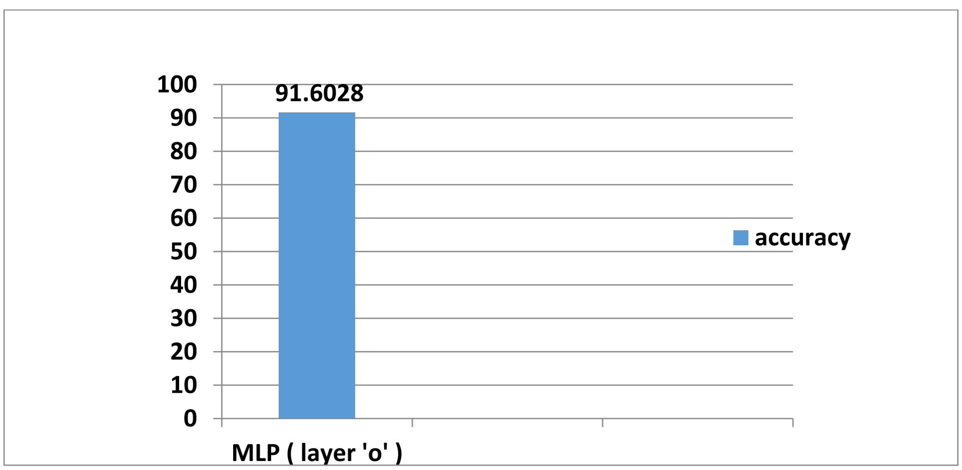


Fig 6.44: Accuracy (MLP layer ‘o’)

In the above table 12 accuracy achieved 91.6028% using MLP hidden layer ’o’ where 2749 instances were correctly classified and 252 instances were incorrectly classified and time taken to build model is 2884.42s. Figure 6.45 was taken from the result window of WEKA which represents the output using MLP hidden layer 'o' to test data.

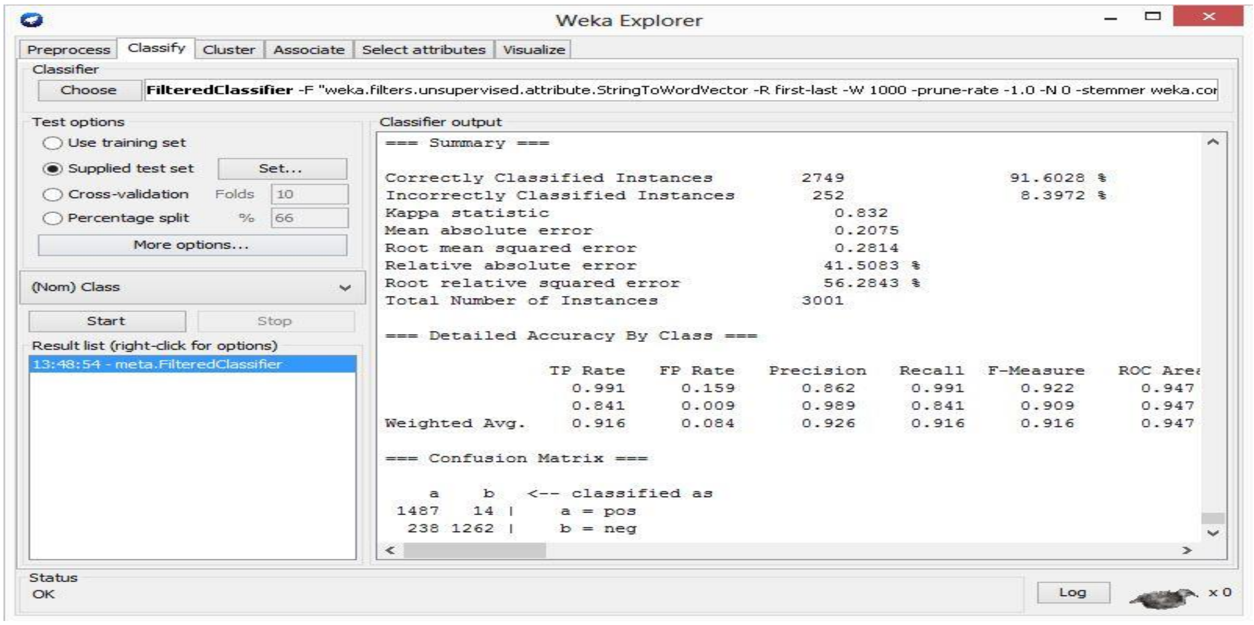
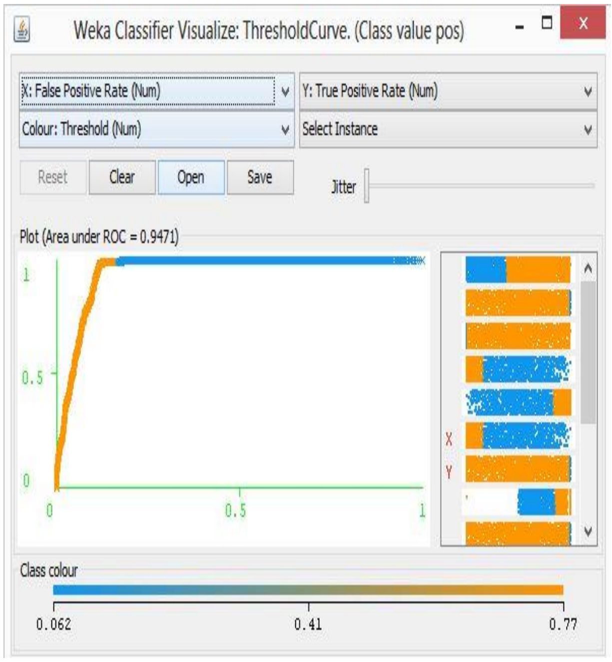


Fig 6.45: Detailed Result (MLP layer 'o')

layer	**TP rate**	**FP rate**	**Precision**	**Recall**	**F-measure**	**ROC area**
'o'	0.916	0.084	0.926	0.916	0.916	0.947

Table 13: Detailed Accuracy using MLP (layer 'o')

Table 13 describes detailed accuracy using MLP hidden layer 'o' where weighted average of positive and negative class for different ration is shown. Here tp rate is 0.916 and fp rate is 0.084. Precision is 0.926 and recall and f-measure is 0.916. Area under the curve ROC is 0.947. Fig 6.46 and 6.47 was taken from WEKA which shows the ROC curve of positive and negative class respectively.



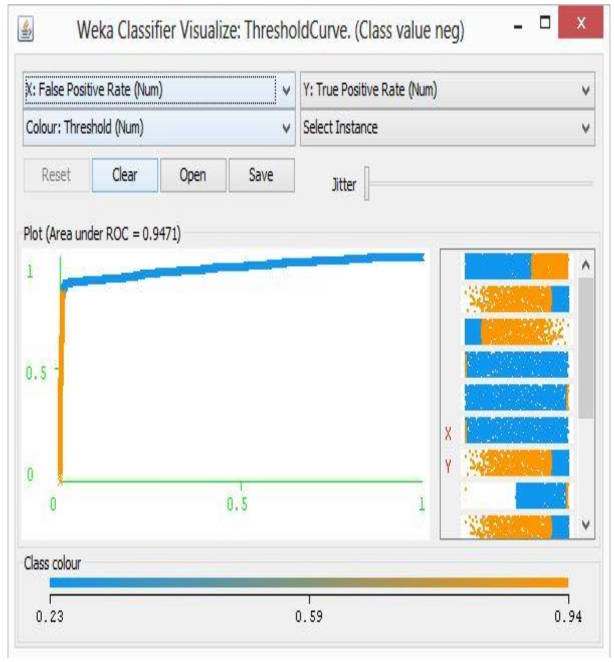


Fig 6.46: ROC=0.9471 for class P

(MLP layer 'o')

Fig 6.47: ROC=0.9471 for class N

(MLP layer 'o')

6.2.4 Comparative analysis:

Based on highest accuracy chosen the best three classifiers from all the algorithms performed table 14 compares them below and figure 6.48 shows the accuracy comparison in chart.

Algorithm	**Classifier (if any)**	**Kernel (if any)**	**Accuracy**	**Time taken to build model(s)**
SVM	SMO	poly kernel	94.8017%	8059.34
SVM	SMO	normalized poly kernel	97.4342%	3054.76
SVM	SMO	rbf kernel	97.2009%	2797.5

Table 14: Comparative Analysis (Three Best Classifiers)

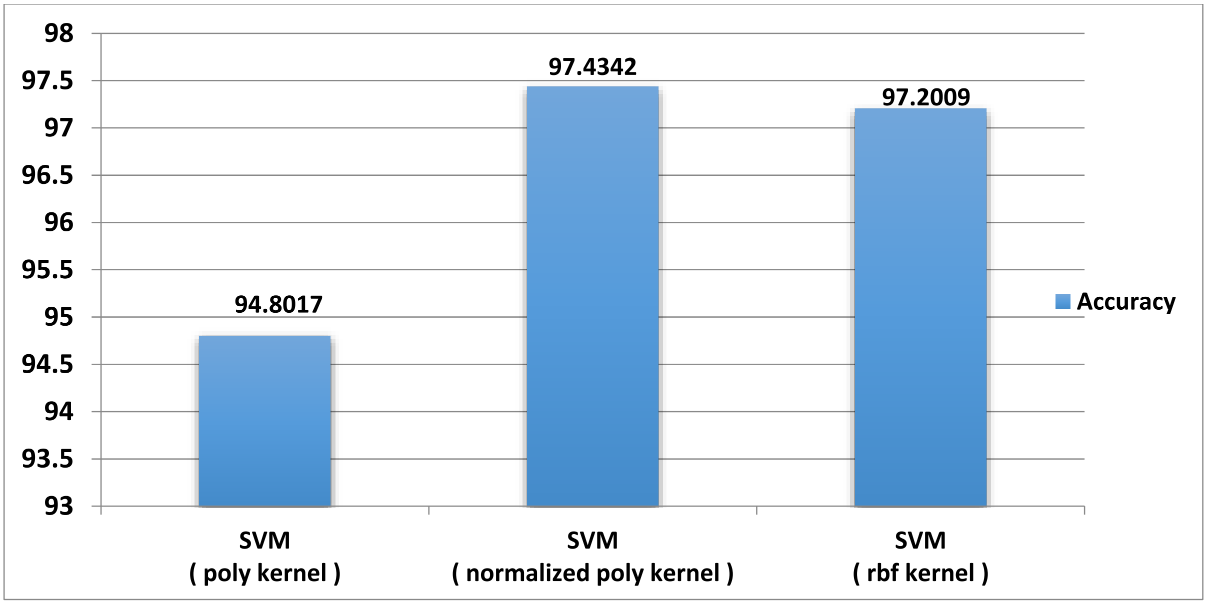


Fig 6.48: Accuracy Comparison (Three Best Classifiers)

From table 14 and fig 6.48 it can be said that SVM classifiers performed better in giving higher accuracy than other classifiers but normalized poly kernel gives the highest accuracy which is 97.4342%. So normalized poly kernel of SVM performed as best classifier in sentiment analysis for positive and negative class.

6.2.5 Stop Word and Attribute Impact

The following movie review has been taken from the test set of sentiment analysis that has been used in the experiment. If stop words were not ignored then the predicted output was correct. If stop words were ignored then the predicted output was incorrect. With stop word the probability of positivity was higher that probability of negativity which results in correct output but without stop word the probability of negativity of that review was higher than the probability of positivity therefore it results in incorrect output.

"a must see by all - if you have to borrow your neighbors kid to see this one. easily one of the best animation/cartoons released in a long-time. it took the the movies antz to a whole new level. do not mistake the two as being the same movie - although in principle the movies plot is similiar. just go and enjoy." , pos

Instance no	Actual	Predicted	Error	Positive probability	Negative probability	Use Stop Word
72	pos	pos		*0.706	0.294	False
72	pos	neg	+	0.313	*0.687	True

Table 16: Stop Words Effect on Accuracy using Naïve Bayes Multinomial Updatable classifier

Moreover if the number of attributes changes the accuracy percentage changes. As it is stated earlier that all the above mentioned experiments were conducted using default attribute number which is 1000. Now the following figure will show how the changes in attribute number and stop word effect accuracy of sentiment analysis.

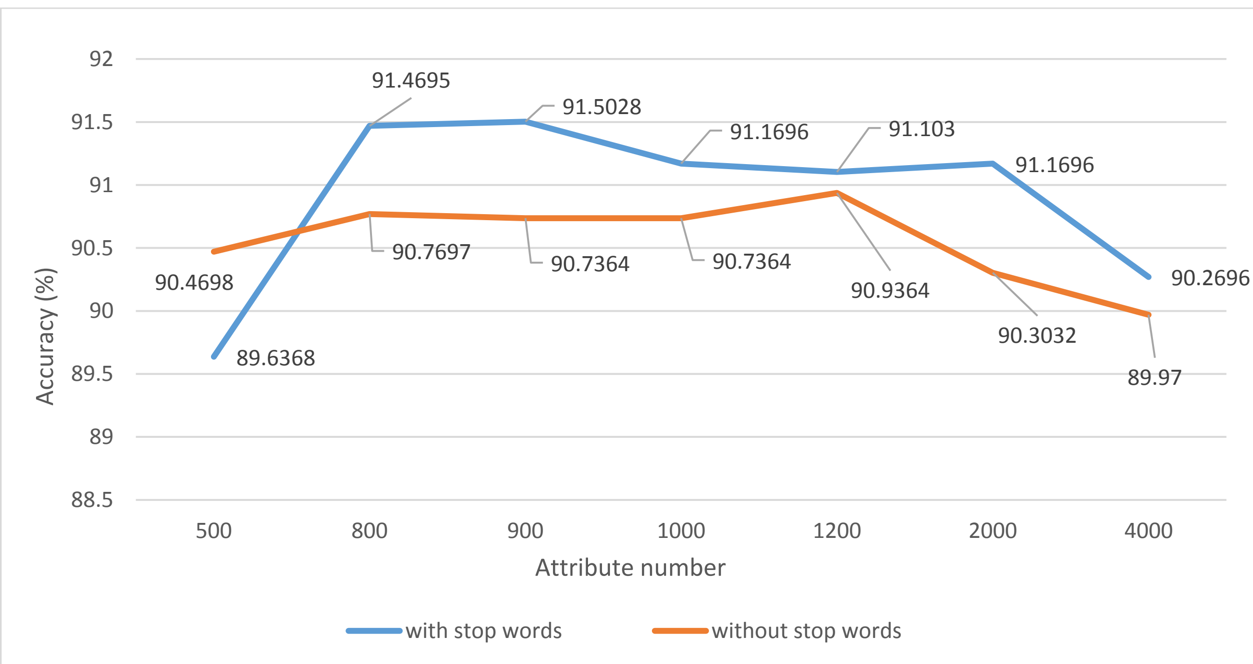


Fig 6.50. Attribute VS Accuracy using Naïve Bayes Multinomial Updatable

The orange line represents the accuracy of positive / negative classification without stop word / ignoring stop words. The blue line represents the accuracy of positive / negative classification with stop word / keeping stop words. From the figure we see except for 500 attribute in all cased blue line shows better accuracy than the orange line. Therefore it clarifies the fact that keeping stop word gives better accuracy for sentence level classification of sentiment analysis. Now if we look at the accuracy for different attributes we find the higher accuracy for 900 attributes. This is because those 900 attributes contains the most effective attributes for the dataset to classify positive/negative instance more accurately. Like subjectivity here accuracy did not increases as the attribute increases. Eventually more attributes results in poor accuracy.

7. Conclusion

This paper investigated a new approach of finding sentence level subjectivity analysis using different machine learning algorithms. We experimented with SVM, Naïve Bayes and MLP. This gave us the opportunity of comparing results among these learning algorithms. Rotten tomato imdb movie review [1] and acl imdb movie review [2] have been used as our dataset which contains only movie reviews that reduced the probability of a word to be used in multiple senses. Moreover the impact of attribute number and stop words on accuracy both for subjectivity and sentiment analysis have also shown. As there are more scope for data pre-processing and attribute selection, we are planning to do it future. Moreover we will also see if a dataset contains instances with various domains like not only movie reviews but also product, political etc. reviews then how the accuracy varies according to the variation of dataset.

8. References

[1] http://www.cs.cornell.edu/people/pabo/movie-review-data

[2] Akkaya C, Wiebe J, Mihalcea R., Subjectivity Word Sense Disambiguation, EMNLP (2009).

[3] Wilson J, Wiebe J, Hoffmann P, Recognizing contextual polarity in phrase-level sentiment analysis, In (HLT/EMNLP-2005), pages 347–354, Vancouver, Canada (2005a).

[4] Wiebe J, Mihalcea R, Word sense and subjectivity, In Proceedings of the Annual Meeting of the Association for Computational Linguistics, Sydney, Australia (2006).

[5] Church K. W, Hanks P, Word Association Norms, Mutual Information and Lexicography, Bell Laboratories Murry Hill, N.J.

[6] Riloff E, Wiebe J, Learning Extraction Patterns for Subjective Ex- pressions, International Conferene on Empirical Methods in Natural Language Processing (EMNLP-2003).

[7] Gyamfi Y, Wiebe J, Mihalcea R, Akkaya C, Integrating Knowledge for Subjectivity Sense Labeling, HLT-NAACL,2009.

[8] Somasundaran S, Namata G, Wiebe J, Getor L, Supervised and Unsupervised Methods in Employing Discourse Relations for Improving Opinion Polarity Classification, University of Pittsburg, Pittsburg, PA 15260.

[9] Turney P. D, Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews, Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL), Philadelphia, July 2002, pp. 417-424.

[10] Wilson T, Weibe J, Hwa Rebecca, Just how mad are you? Finding strong and weak opinion clauses, Intelligent Systems Program, University of Pittsburg, Pittsburg, PA 15260.

[11] Wilson T, Wiebe J, Hoffmann P, Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis, Intelligent Systems Program, University of Pittsburg, Pittsburg, PA 15260.

[12] Turney, Peter (2002). "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews", Proceedings of the Association for Computational Linguistics. pp. 417–424

[13] Pang, Bo; Lee, Lillian; Vaithyanathan, Shivakumar (2002). "Thumbs up? Sentiment Classification using Machine Learning Techniques", *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*. pp. 79–86.

[14] Snyder, Benjamin; Barzilay, Regina (2007). "Multiple Aspect Ranking using the Good Grief Algorithm", *Proceedings of the Joint Human Language Technology/North American Chapter of the ACL Conference (HLT-NAACL)*. pp. 300–307.

[15] *Pang, Bo; Lee, Lillian (2005).* "Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales", *Proceedings of the Association for Computational Linguistics (ACL). pp. 115–124.*

[16] Su, Fangzhong; Markert, Katja (2008). "From Words to Senses: a Case Study in Subjectivity Recognition" (PDF). *Proceedings of Coling 2008, Manchester, UK.*

[17] *Ian H. Witten, Eibe Frank, Mark A. Hall (2011), "Data Mining: Practical machine learning tools and techniques, 4th Edition", Morgan Kaufmann, San Francisco. Retrieved 2011-01-19.*

[18] *G. Holmes, A. Donkin, I.H. Witten (1994), "Weka: A machine learning workbench" (PDF). Proc Second Australia and New Zealand Conference on Intelligent Information Systems, Brisbane, Australia*. Retrieved *2007-06-25*

[19] P. Reutemann; B. Pfahringer; E. Frank (2004). "Proper: A Toolbox for Learning from Relational Data with Propositional and Multi-Instance Learners", *17th Australian Joint Conference on Artificial Intelligence (AI2004)*. Springer-Verlag. Retrieved 2007-06-25.

[20] Ben-Hur, Asa, Horn, David, Siegelmann, Hava, and Vapnik, Vladimir; "Support vector clustering" (2001) Journal of Machine Learning Research, 2: 125–137

[21] https://www.analyticsvidhya.com/blog/2015/10/understaing-support-vector-machine-example-code/

[22] John C. Platt, Microsoft Research. Microsoft Way , Redmond , WA 98052 USA. http://www.research.microsoft.com/~jplatt

[23] Narasimha Murty, M.; Susheela Devi, V. (2011), *Pattern Recognition: An Algorithmic Approach,* ISBN 0857294946

[24] StatSoft, Inc. (2013). Electronic Statistics Textbook. Tulsa, OK: StatSoft. WEB: http://www.statsoft.com/textbook/, (Printed Version): Hill, T. & Lewicki, P. (2007). STATISTICS: Methods and Applications. StatSoft, Tulsa, OK.

[25] Rosenblatt, Frank. x. Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms, Spartan Books, Washington DC, 1961

[26] SimonHaykin. *Neural Networks - A Comprehensive Foundation, 2nd ed.* Prentice - Hall, Englewood Cliffs, 1998.

[27] Kurt Hornik, Maxwell Stinchcombe, and Halbert White, Multilayer feedforward networks are universal approximators, *Neural Networks*, 2(5):359-366, 1989.

[28] Sepp Hochreiter and Jürgen Schmidhuber, Feature extraction through LOCOCODE. ,*Neural Computation*, 11(3):679-714, 1999.