

Text Categorization of Movie Reviews for Sentiment Analysis

Humera Shaziya¹, G.Kavitha², Raniah Zaheer³

Assistant Professor, Department of Computer Science, Nizam College, Hyderabad, TS, India¹.

Assistant Professor, Department of Computer Science, Nizam College, Hyderabad, TS, India².

Lecturer, Department of Computer Science, Najran University, Najran, Saudi Arabia³

ABSTRACT: Text classification is an important task in many text mining applications. Text data generated from the reviews have been growing tremendously. People are participating largely in internet to give their opinion about various subjects and topics. A branch of text mining that deals with people's views about a subject is opinion mining, in which the data in the form of reviews is mined in order to analyze their sentiment. This study of people's opinion is sentiment analysis and is a popular research area in text mining. In this paper, movie reviews are classified for sentiment analysis in weka. There are 2000 movie reviews in a dataset obtained from Cornell university dataset repository. The dataset is preprocessed and various filters have been applied to reduce the feature set. Feature selection methods are widely used for gathering most valuable words for each category in text mining processes. They help to find most distinctive words for each category by calculating some variables on data. The mostly employed methods are Chi-Square, Information Gain, and Gain Ratio. In this study, information gain method was employed because of its simplicity, less computational costs and its efficiency. The effects of reduced feature set have been proved to improve the performance of the classifier. Two popular classifiers namely naïve bayes and svm have been experimented with the movie review dataset. The results show that naïve bayes performs better than svm for classification of movie reviews.

KEYWORDS: Text Classification, Opinion Mining, Sentiment Analysis, Feature Selection, Text Mining, Weka

I. INTRODUCTION

1.1 Sentiment analysis: It also called opinion mining is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes. It represents a large problem space. There are also many names and slightly different tasks, e.g., sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, review mining, etc. However, they are now all under the umbrella of sentiment analysis or opinion mining. While in industry, the term sentiment analysis is more commonly used, but in academia both sentiment analysis and opinion mining are frequently employed.

1.2 Text mining: It is the analysis of data containing natural language text. Text mining, also referred to as text data mining, roughly equivalent to text analytics, refers to the process of deriving high-quality information from text. Text mining turns the data into high-quality information or actionable knowledge. It minimizes human effort on consuming text data. It supplies knowledge for optimal decision making.

1.3 Text categorization: It refers to the task of automatically assigning documents into one or more predefined classes or categories. In recent years, there have been an increasing number of statistical and machine learning techniques that automatically generate text categorization knowledge based on training examples. Such techniques include K-nearest neighbor (KNN), naïve bayes and SVM. The documents can be classified in three ways; supervised, semi-supervised and unsupervised.

Applications of text categorization

- Automatically classify politic news from sports news

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- Recognizing spam emails
- Sentiment analysis

1.4 Supervised text categorization: when performing this task the classifier is given the classes or categories and it has to build the model based on the training data and then predict class of the test data. Fig 1 shows the process of text categorization. Initially a model is estimated from the labeled data and that model is used to determine the labels of the unobserved samples

Supervised learning

- Estimate a model/method from labeled data
- It can then be used to determine the labels of the unobserved samples

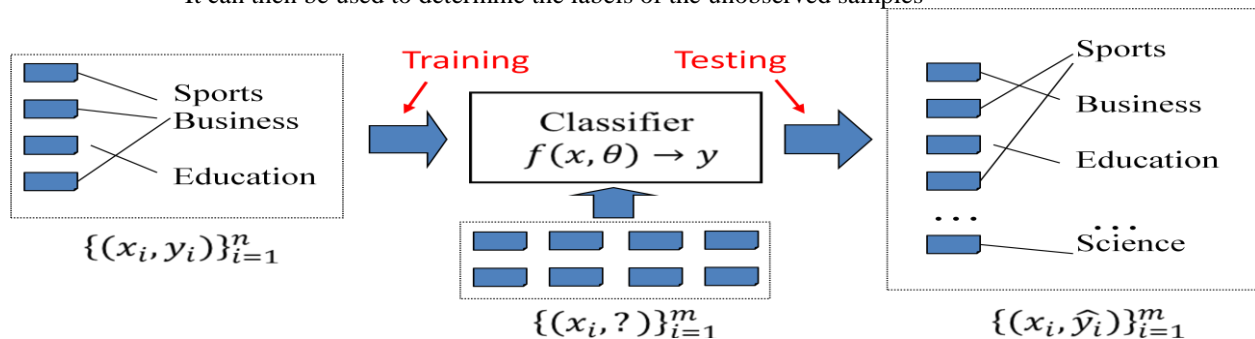


Fig 1: Supervised text categorization

1.5 Type of classification methods: There are two broad kinds of classifiers; model less classifiers and model based classifiers. Instance based classifiers belong to the category of model less that use the observation directly to classify it to a particular category. Example is K-nearest neighbor. Model based classifiers can fall into generative models or discriminative models. Generative models perform joint probability of $p(x, y)$. It specifies joint distribution for all the random variables and the dependence assumption has to be specified for $p(x|y)$ and $p(y)$. Generative models are flexible and can be used for unsupervised learning. Its example is naïve bayes. Discriminative models directly estimate the decision rule or boundary. It specifies conditional distribution and explains only the target variable. It incorporates arbitrary features for modeling $p(y|x)$. It requires labeled data and can be used for semi-supervised learning. Its example is SVM.

II. LITERATURE STUDY

Nasukawa et al , Dave et al, Coined the terms sentiment analysis and opinion mining in the year 2003. J.M. Wiebe, presents an algorithm to identify the subjective characters in fictional narrative text based on the regularities in the text. M.A. Hearst, defines a direction based text interpretation approach for text based intelligent systems to refine the information access task. J.M. Wiebe, performed extensive examination to study the naturally occurring narratives and regularities in the writings of authors and presents an algorithm that tracks the point of view on the basis of these regularities. Hatzivassiloglou and McKeown, proposed a method to find the semantic orientation of the adjectives and predicted whether two conjoined adjectives are of same polarity with 82% accuracy. L. Terveen, designed a system uses a collaborative filtering approach to recognize and reuse recommendations. J. Tatemura, developed a browsing method using virtual reviewers for the collaborative exploration of movie reviews from various viewpoints. Morinaga et al, presented a framework for mining product reputation on internet The defined approach automatically collects the user's opinions from the web and applies text mining techniques to obtain the reputation of the products. P.D. Turney, presents an unsupervised method to classify the reviews as thumbs up (recommended) or thumbs down (not recommended). It uses document level sentiment classification and Pointwise Mutual Information (PMI) to obtain the average semantic orientation of the reviews. The algorithm achieves an average accuracy of 74% for 410 reviews. Turney and Littman expanded the work by presenting an approach to find out the semantic orientation of a text by calculating its statistical association with a set of positive and negative words using PMI and Latent Semantic Analysis (LSA). The method when tested with 3596 words (1614 positive and 1984 negative) achieves an accuracy of

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82.8%. Pang et al, performed document level sentiment classification using standard machine learning techniques. They used Naïve Bayes, Maximum Entropy and SVM techniques to obtain the results for unigrams and bigrams and was able to achieve 82.9% accuracy using three fold cross validation for unigrams. Esuli and Sebastiani, presented an approach to determine the orientation of a term based on the classification of its glosses i.e. the definitions from the online dictionaries. Hu et al, derives an analytical model to examine whether the online review data reveals the true quality of the product. They analyzed the reviews from amazon. The results showed that 53% reviews had a bimodal and non-normal distribution. Ding et al, proposed a holistic approach to infer the semantic orientation of an opinion word based on review context and combine multiple opinions words in same sentence. The proposed approach also takes into account the implicit opinions and handles implicit features represented by feature indicators. A system named Opinion Observer was also implemented based on the proposed technique. Murthy G. and Bing Liu proposed a method which study sentiments in comparative sentences and also deals with context based sentiments by exploiting external information available on the web. V Suresh et al, presents an approach that uses the stop words and the gaps between stop words as the features for sentiment classification. M. Rushdi et al explored the sentiment analysis task by applying SVM for testing different domains of dataset using several weighing schemes. They used three corpora for their experimentation including a new corpus introduced by them and performed 3-fold and 10-fold cross validations for each corpus.

III. PROBLEM STATEMENT

Sentiment analysis mainly studies opinions which express or imply positive or negative sentiments. This section thus defines the problem in this context.

Opinion Definition: We use the following review about a Canon camera to introduce the problem (an id number is associated with each sentence for easy reference): Posted by: John Smith Date: September 10, 2011

“(1) I bought a Canon G12 camera six months ago. (2) I simply love it. (3) The picture quality is amazing. (4) The battery life is also long. (5) However, my wife thinks it is too heavy for her.”

From this review, we notice a few important points:

3.1 The review has a number of opinions, both positive and negative, about Canon G12 camera. Sentence (2) expresses a positive opinion about the Canon camera as a whole. Sentence (3) expresses a positive opinion about its picture equality. Sentence (4) expresses a positive opinion about its battery life. Sentence (5) expresses a negative opinion about the weight of the camera.

From these opinions, we can make the following important observation:

Observation: An opinion consists of two key components: a target g and a sentiment s on the target, i.e., (g, s) , where g can be any entity or aspect of the entity about which an opinion has been expressed, and s is a positive, negative, or neutral sentiment, or a numeric rating score expressing the strength/intensity of the sentiment (e.g., 1 to 5 stars). Positive, negative and neutral are called sentiment (or opinion) orientations (or polarities). For example, the target of the opinion in sentence (2) is Canon G12, and the target of the opinion in sentence (3) is the picture quality of Canon G12. Target is also called topic in the literature.

3.2 This review has opinions from two persons, which are called opinion sources or opinion holders (Kim and Hovy, 2004; Wiebe, Wilson and Cardie, 2005). The holder of the opinions in sentences (2), (3), and (4) is the author of the review (“John Smith”), but for sentence (5), it is the wife of the author.

3.3 The date of the review is September 10, 2011. This date is important in practice because one often wants to know how opinions change with time and opinion trends.

We are now ready to define opinion as a quadruple.

Definition (Opinion): An opinion is a quadruple (g, s, h, t) , where g is the opinion (or sentiment) target, s is the sentiment about the target, h is the opinion holder and t is the time when the opinion was expressed. This definition, although quite concise, may not be easy to use in practice especially in the domain of online reviews of products, services, and brands because the full description of the target can be complex and may not even appear in the same sentence. For example, in sentence (3), the opinion target is actually “picture quality of Canon G12”, but the sentence mentioned only “picture quality”. In this case, the opinion target is not just “picture quality” because without knowing that the sentence is evaluating the picture quality of the Canon G12 camera, the opinion in sentence (3) alone is of little use. In practice, the target can often be decomposed and described in a structured manner with multiple levels, which greatly facilitate both mining of opinions and later use of the mined opinion results. For example, “picture quality of Canon G12” can be decomposed into an entity and an attribute of the entity and represented as a pair,

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(Canon-G12, picture-quality)

Let us use the term entity to denote the target object that has been evaluated. Entity can be defined as follows (Hu and Liu, 2004; Liu, 2006 and 2011).

Definition (entity): An entity e is a product, service, topic, issue, person, organization, or event. It is described with a pair, $e: (T, W)$, where T is a hierarchy of parts, sub-parts, and so on, and W is a set of attributes of e .

IV. EXPERIMENTAL EVALUATION

For the experimental evaluation, we have used weka to perform the following tasks: convert the pre-processed text files into arff file, stemming, removal of stop words, tokenization, and feature selection and to measure the performance of the selected feature. Fig 2 depicts the model developed for the study in this paper.

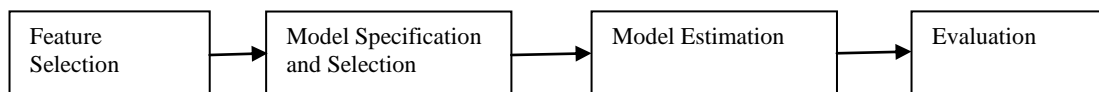


Fig 2: Steps for text categorization

4.1 Feature selection

A document is converted in Vector space representation which is a standard procedure in the representation of documents. Features in documents are in the form of N-gram, POS tags, named entities, topics. The value of feature is binary (presence/absence), Binary or TF-IDF (many variants). To select the most informative features for model training various filters are used that also reduce noise in feature representation and thus improve final classification performance. The other benefits of feature selection includes improves training/testing efficiency, less time complexity and fewer training data. Filter method Evaluate the features independently from the classifier and other features. The major activity in text mining is to classify document into the accurate category. Feature selection methods are widely used for gathering most valuable words for each category in text mining processes. They help to find most distinctive words for each category by calculating some variables on data. There are mostly employed methods such as Chi-Square, Information Gain, Gain Ratio, and Odd Ratio. In this study, two of them (information gain and chi-square) methods were employed because of their simplicity, less computational costs and their efficiency and, their formulas are shown on Eq. (1) and (2), respectively.

Information Gain : Eq. 1

$$IG = \frac{a}{N} * \log \frac{a * N}{(a + c) * (a + b)} + \frac{b}{N} * \log \frac{b * N}{(b + d) * (a + b)} + \frac{c}{N} * \log \frac{c * N}{(a + c) * (c + d)} + \frac{d}{N} * \log \frac{d * N}{(b + d) * (c + d)}$$

Chi Square : Eq 2

$$Chi\ Square = N * \frac{(a * d - b * c)^2}{(a + c) + (b + d) + (a + b) + (c + d)}$$

As known in Eq. (1) and (2): N is Total number of sample reviews, a is number of documents in the positive category which contain this term, b is number of documents in the positive category which do not contain this term, c is number of documents in the negative category which contain this term, d is number of documents in the negative category which do not contain this term. Information gain Decrease in entropy of categorical prediction when the feature is present vs absent

4.2 Model specification and selection

A model can be linear or non-linear. A linear relation specify assumptions between x and y i.e., $W^T x \rightarrow y$. Features are independent among each other. E.g. Naïve bayes and linear SVM. A Non-linear model relation between x and y i.e., $f(x) \rightarrow y$, where $f(.)$ is a non-linear function of x . Features are not independent among each other . E.g. Decision tree, Kernel SVM, Mixture model.

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4.2.1 Naïve Bayesian Classifications

Naïve Bayesian method is one of the popular techniques for text classification. It has been shown to perform extremely well in practice by many researchers. Given a set of training documents D , each document is considered an ordered list of words. Let $w_{di,k}$ denotes the word in position k of document d_i , where each word is from the vocabulary $V = \langle w_1, w_2, \dots, w_{|V|} \rangle$, where vocabulary is the set of all words we consider for classification, and let a set of pre-defined classes be $C = \langle c_1, c_2, \dots, c_{|C|} \rangle$. In order to perform classification, we need to compute the posterior probability, $P[c_j|d_i]$. Based on the Bayesian probability and the multinomial model, we have

$$P[C_j] = \sum_i P[C_j / d_i] / D$$

4.2.2 Support Vector Machine (SVM)

As explained in Dumais and Chen (2000) and Pang et al (2002). Given a category set, $C = \{+1, -1\}$ and two pre-classified training sets, i.e., a positive sample set, $Tr^+ = \sum_{i=1}^n (d_i, +1)$, and a negative sample set, $Tr^- = \sum_{i=1}^n (d_i, -1)$, the SVM finds a hyper plane that separates the two sets with maximum margin (or the largest possible distance from both sets). At pre-processing step, each training sample is converted into a real vector x_i that consists of a set of significant features representing the associated document d_i . Hence, $Tr^+ = \sum_{i=1}^n (x_i, +1)$ for the positive sample set and $Tr^- = \sum_{i=1}^n (x_i, -1)$, for the negative sample set. In this regard, for $c_i = +1$, $w \cdot x_i + b > 0$, and for $c_i = -1$, $w \cdot x_i + b < 0$. Hence, $T^+ T^- \{c_i \cdot (w \cdot x_i + b) \geq 1\}$ becomes an optimization problem defined as follows: minimize $(1/2) \|w\|^2$, subject to $c_i \cdot (w \cdot x_i + b) \geq 1$. The result is a hyper plane that has the largest distance to x_i from both sides. The classification task can then be formulated as discovering which side of the hyper plane a test sample falls into.

4.3 Model estimation

Cross validation avoid noise in train/test separation. k -fold cross-validation partitions all training data into k equal size disjoint subsets; Leave one subset for validation and the other $k-1$ for training; Repeat step (2) k times with each of the k subsets used exactly once as the validation data.

- Cross validation
 - Avoid noise in train/test separation
 - k -fold cross-validation
 - Choose the model (among different models or same model with different settings) that has the best average performance on the validation sets
 - Some statistical test is needed to decide if one model is significantly better than another

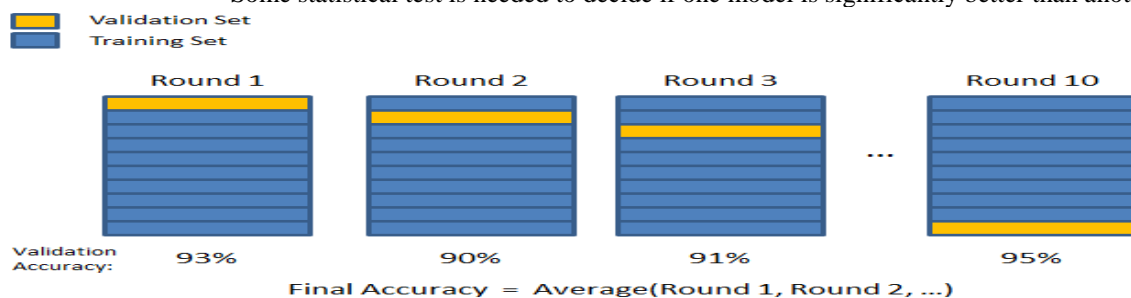


Fig 3: Cross validation

4.4 Evaluation

The performance of different methods used for opinion mining is evaluated by calculating various metrics like precision, recall and F-measure. Precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. The two measures are sometimes used together in the F score (also F-score or F-measure) is a measure of a test's accuracy.

Accuracy: The percentage of correct prediction over all predictions. Limitation is highly skewed class distribution. Accuracy is computed as $TP+TN/P+N$.

Precision: Fraction of predicted positive documents that is indeed positive. Precision calculation is $TP/TP+FP$.

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Recall: Fraction of positive documents that is indeed positive. Recall is obtained from $TP/TP+FN$.
F-Score: Harmonic mean of precision and recall computed using the equation $2PR/P+R$.

V. RESULTS AND DISCUSSIONS

To perform the analysis we use weka a commonly used machine learning software suite. The data set used in this experimental study is obtained from the Cornell university dataset repository www.cs.cornell.edu/people/pabo/movie-review-data/. The data set used is polarity dataset v2.0 that includes 2000 movie reviews of which 1000 are positive and the other 1000 are negative.

The movie review data are pre-processed text files that are 2000 in number. Out of these 1000 files are positive review files and another 1000 are negative review files. This data is loaded in weka, and using StringtoWordVector filter converted to arff file. Originally there are 47163 attributes in the data. Since large numbers of attributes are not efficient in arriving at the optimal feature set, they have been reduced by applying number of parameters to the chosen filter. Stemming is the process that identifies the root of the word and thus similar words are removed from the set of attributes. After performing stemming, the initial attributes set is reduced to 27573 which is almost 60% of the original set. Tokenization removes certain other words leaving 19244 attributes. Next pruning is done to retain only 9228 attributes in the set. The entire process of attribute reduction is depicted in the fig4.

The following chart pictorially depicts the reduction of the number of attributes

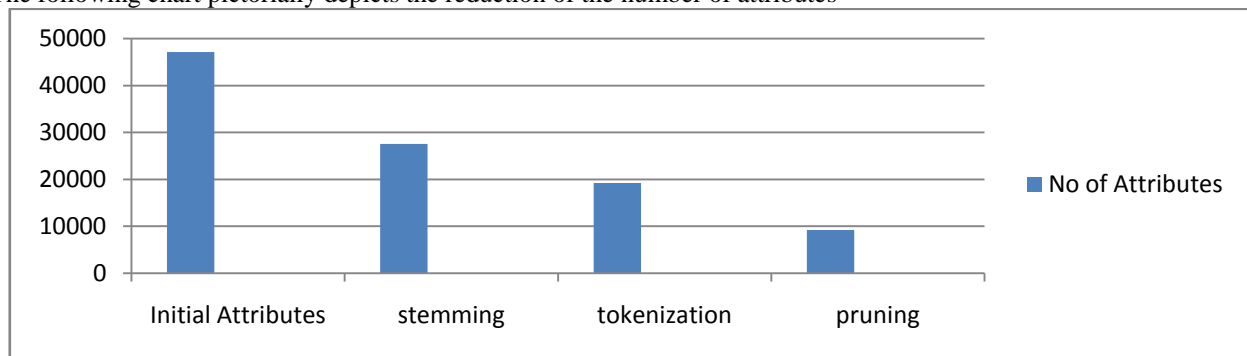


Fig 4: Attribute selection filters

Attribute selection feature of weka further reduce the number of attributes by using feature selection technique of information gain along with the ranker search mechanism. A total of 323 attributes are finally selected to perform classification task. Two classifiers in weka are used to perform classification task namely, Naïve bayes and SMO an implementation of SVM in weka. The accuracy of the classifier is measured as the number of instances correctly classified; naïve bayes correctly classifies 1702/2000 which is 85.1% whereas svm does 1691/2000 which is 84.55%. The following charts show the comparisons of naïve bayes and svm. We have worked on the dataset on two different classification algorithms i.e., naïve bayes and support vector machine. Of those, the Naïve bayes classifier had the best rate of prediction with our dataset as it better handles highly skewed data. The number of correctly classified instances is higher in naïve bayes than svm, and this is consistent with the findings in other studies. The weka software was trained to classify a review based on the characteristics of each review document, based on the reviewer's original review. The following table shows the performance results of naïve bayes and svm classifiers

Classifier	Correctly Classified	Incorrectly Classified	Accuracy	Precision	Recall	F-Score
Naïve Bayes	1702	298	85.1	86.1	84.9	84.7
SVM	1691	309	84.5	84.7	84.4	84.5

Table 1: Performance results of naïve bayes and svm classifiers

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From the experimental results obtained by executing the two most popular classification algorithms i.e., naïve bayes and svm, it is clear that naïve bayes shows better accuracy and performance compared to svm shown in table 1. The accuracy and error in terms of the number of correctly classified instances and the number of incorrectly classified instances is shown in fig 5(a). The performance results of the classifiers for precision, recall and f-score or f-measure is shown in fig 5(b). Thus both the charts of accuracy and error and performance results proves that naïve bayes performs better even for text.

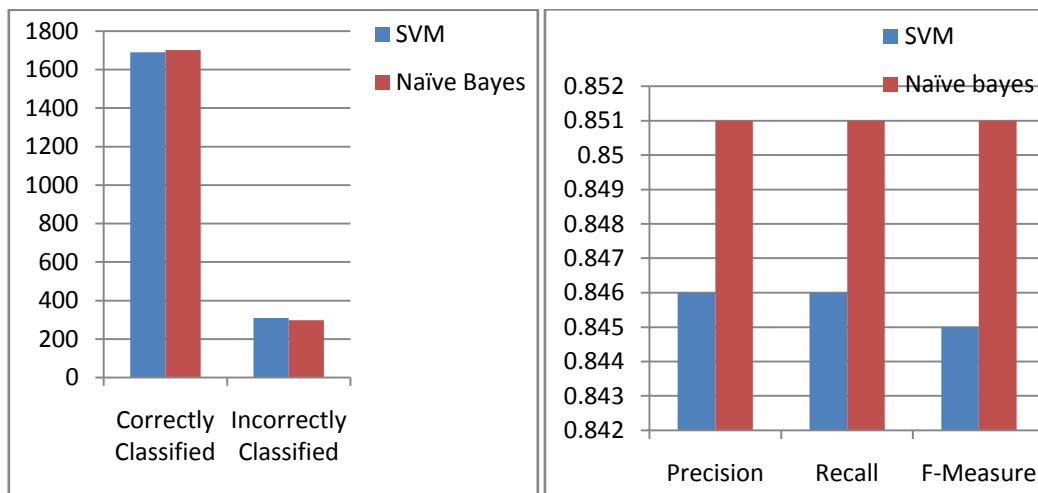


Fig 5: (a) Accuracy and error

(b) Performance results

The output from this process is called a confusion matrix, a table that cross-tabulates the actual categorizations (the rating the reviewer) with the predicted categorizations (the rating the software assigned to the movie based on the text of the review). This provides a snapshot of how well the system classifies the reviews based on the sentiment. We used Cohen's kappa, a common test for inter-rater agreement, to assess the alignment between text sentiment and the reviewer's review. The reviewer's review is treated as the first "rater" and the algorithm's classification is treated as the second "rater." The higher the level of agreement, the more accurately the algorithm was able to guess the polarity the reviewer gave the movie based solely on the content of the review text. The results of both naïve bayes and svm are almost close to one another; however naïve bayes independence assumption of words and its simplicity makes it to perform better than svm. The confusion matrix in chart form is as follows

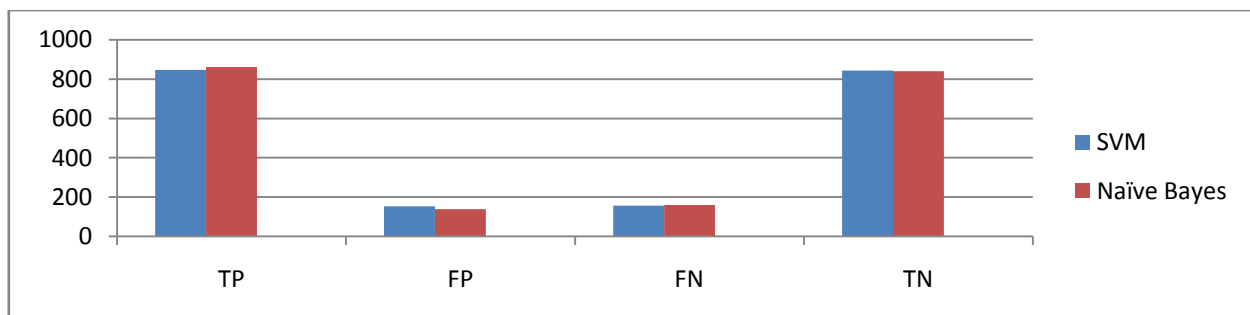


Fig 6: Confusion matrix shown as chart

As shown in the fig 6, correctly classified instances of naïve bayes is 861 which is 86.1% of the true positive result, whereas svm correctly classified 847 instances that comes to 84.7% of the true positive result. True negatives of naïve bayes are 841 which are 84.1% and of svm is 844 that is 84.4%. there is a need to cut off the false positives because the effect of false positives is more than the effects of the false negatives.

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VI. CONCLUSION

The present study deals with the problem of text classification for sentiment analysis. The most popular classification methods i.e., Naïve bayes and SVM have been experimented with movie review data set consisting of 2000 movie reviews of which 1000 are positive and 1000 are negative. Both the methods have been compared and the results show that naïve bayes outperforms SVM. Feature Selection is an essential step in a classification task which has been done in combination with classification methods.

Initially review files are preprocessed and converted to arff format, and then various filters are applied to identify the optimal feature set. Experimental results show that effect of an optimal feature selection improves the accuracy of both the classifiers. However naïve bayes proves to be better than svm with respect to accuracy of the classifier.

The model proposed in this paper is just an initial step towards the improvement in the techniques for sentiment analysis. It is worth exploring the capabilities of the model for the reviews dataset and extending the research using hybrid techniques for sentiment analysis. There is considerable scope for improvement in the creation and effective pre-processing and feature selection. The work can also be extended to improve the results using various tokenization techniques. Future researches can be carried out to generate better and fast models for higher order n-grams.

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