Text Clustering and Classification Techniques using Data Mining

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***Abstract*:-** Text classification is the task of automatically sorting a set of documents into categories from a predefined set. Text Classification is a data mining technique used to predict group membership for data instances within a given dataset. It is used for classifying data into different classes by considering some constrains. Instead of traditional feature selection techniques used for text document classification. A Naive Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful for very large datasets. Automated Text categorization and class prediction is important for text categorization to reduce the feature size and to speed up the learning process of classifiers.

Keywords: *Naïve Bayesian, Clustering, Classification*

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I. Introduction

Data mining, the extraction of hidden predictive information from large databases, is a powerful new technology with great potential to help companies focus on the most important information in their data warehouses. Data mining tools predict future trends and behaviors, allowing businesses to make proactive, knowledge-driven decisions. The automated, prospective analyses offered by data mining move beyond the analyses of past events provided by retrospective tools typical of decision support systems. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations.

Text mining, sometimes alternately referred to as text data mining, roughly equivalent to text analytics, refers to the process of deriving high-quality information from text. Highquality information is typically derived through the devising of patterns and trends through means such as statistical pattern learning. Text mining usually involves the process of structuring the input text (usually parsing, along with the addition of some derived linguistic features and the removal of others, and subsequent insertion into a database), deriving patterns within the structured data, and finally evaluation and interpretation of the output. 'High quality' in text mining usually refers to some combination of relevance, novelty, and interestingness. Text mining tasks include text categorization, text clustering, concept/entity extraction, production of granular taxonomies, sentiment analysis, document summarization, and entity relation modeling (i.e., learning relations between named entities).

Text classification is the problem of automatically assigning zero, one or more of a predefined set of labels to a given segment of free text. The labels are to be chosen to reflect the “meaning” of the text. Selecting the appropriate set of labels may be ambiguous even for a human rater. When a machine is to try and mimic the human behavior, the algorithm will have to cope with a large amount of uncertainty coming from various sources. First of all, on a purely lexicographic level, human language is ambiguous per se, including words and word combinations with multiple senses which are disambiguated by the context. More importantly, the definition of meaning of a text is still vaguely defined, and a matter of debate.

One does not want to answer the question whether a computer has “understood” a text, but rather operationally whether it can provide a result which is comparable to what a human would provide (and find useful).

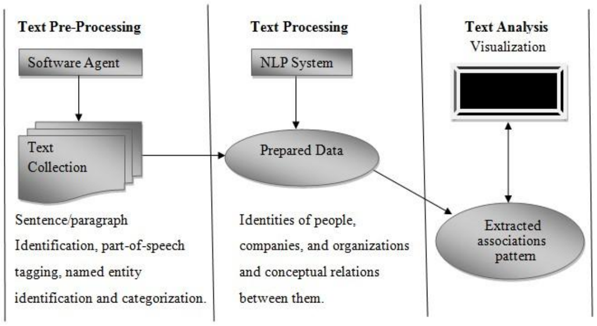

Text Pre-Processing
Software Agent
Text Collection
Sentence/paragraph Identification, part-of-speech tagging, named entity identification and categorization.
Text Processing
NLP System
Prepared Data
Identities of people, companies, and organizations and conceptual relations between them.
Text Analysis
Visualization
Extracted associations pattern

Figure 1.1 Processing in Text Mining

With the increasing availability of text documents in electronic form, it is of great importance to label the contents with a predefined set of thematic categories in an automatic way, what is also known as automated Text Categorization. In last decades, a growing number of advanced machine learning algorithms have been developed to address this challenging task by formulating it as a classification problem. Commonly, an automatic text classifier is built with a learning process from a set of pre labeled documents. Documents need to be represented in a way that is suitable for a general learning process. The most widely used representation is “the bag of words”: a document is represented by a vector of features, each of which corresponds to a term or a phrase in a vocabulary collected from a particular data set. The value of each feature element represents the importance of the term in the document, according to a specific feature measurement. A big challenge in text categorization is the learning from high dimensional data.

On one hand, tens and hundreds of thousands terms in a document may lead to a high computational burden for the learning process. On the other hand, some irrelevant and redundant features may hurt predictive performance of classifiers for text categorization.

II. Literature Review

Several text categorization and classification techniques were proposed in past. In this section I review some of the important existing text categorization and classification techniques using Naïve Bayes as follows:

- Theoretical Framework of Feature Selection
- Selecting The Maximum Discriminative Features
- Text Classification Process
- Classifiers
- A Bayesian Classifier Using Class-Specific Features For Text Categorization
- Improvement In KNN Classifier (Imp-Knn) For Text Categorization
- Feature Selection and Feature Reduction

2.1 Theoretical Framework of Feature Selection [1]

They followed the Information Theory to select feature subsets that had maximum discriminative capacity for distinguishing the samples among two or more classes. They first introduced some concepts on information measures for binary hypothesis testing (also known as “two-class” classification) and present a new divergence measure for multiple hypothesis testing (i.e., for “multi-class” classification).

2.1.1 Divergence Measures for Binary Hypothesis Testing

A Bayesian approach was presented for detecting influential observations using general divergence measures on the posterior distributions. A sampling-based approach using a Gibbs or Metropolis-within-Gibbs method was used to compute the posterior divergence measures. Four specific measures were proposed, which convey the effects of a single observation or covariate on the posterior. The technique was applied to a generalized linear model with binary response data, an over dispersed model and a nonlinear model. The purpose of feature selection was to determine the most informative features which lead to the best prediction performance. Hence, it was natural to select those features that have the maximum discriminative capacity for classification, by minimizing the classification error (i.e., maximizing the KL-divergence or the J-divergence). The J-divergence was only defined for binary hypothesis.

They were next extend the J-divergence for multiple hypothesis testing (i.e., multi-class classification). The measure of discrimination capacity may not hold. The Information Theory to select feature subsets that had maximum discriminative capacity for distinguishing the samples among two or more classes. Some concepts on information measures for binary hypothesis testing (also known as “two-class” classification) and present a new divergence measure for multiple hypothesis testing (i.e., for “multi-class” classification).

2.1.2 Jeffrey’s Multi-Hypothesis Divergence

The Jensen-Shannon (JS) divergence had the one that could be used to measure multidistribution divergence, in which the divergences of each individual distribution with a reference distribution were calculated and summed together. Unlike the J-divergence, the measure of discrimination capacity may not hold. In Sawyer presents a variant of Jdivergence with a variance-covariance matrix for multiple comparisons of separate hypotheses. The KL divergence of each detector was the measure of that discriminative capacity for discrimination; the new multi-distribution divergence was able to measure the discrimination capacity over all classes. Note that, since the JMH divergence was the sum of multiple J-divergences, it hold most properties of J-divergence. For example, JMH divergence was almost positive definite.

2.2Selecting The Maximum Discriminative Features [12]

2.2.1 Greedy Feature Selection Approach

Consider a binary (two-class) classification problem first and extend feature selection method to a general multiclass classification problem later. Unlike those existing feature selection methods which compute the score (“importance”) of features based on the feature relevance to class, goal was to select the features that offer the maximum discrimination for classification. By doing so, one could expect an improved classification performance for text categorization. For a two-class classification problem, known that the J-divergence indicated the discriminative capacity of discriminating two classes’ data under the MAP rule. To examined various values to evaluate the classification performance using those selected features. Hence, it was necessary to assign an importance score to each feature and rank the features. Here, start to propose a greedy approach to rank the features according to their discriminative capacity for naive Bayes. This approach started to determine which feature of the M features produces the maximum JMH-divergence.

The implementation of this greedy feature selection approach based on the maximum Jdivergence for two-class classification. This approach indicated that the discriminative capacity increases when more features was used for classification.

Note that the proposed greedy feature selection algorithm makes a locally optimal choice at each step to approximate the global optimal solution by selecting a feature with the maximum discriminative capacity for classification. The significance of this approach was that it started the best first feature and towards the optimal solution. This greedy approach could be considered as a wrapper approach.

However, unlike those existing wrapper approaches, this greedy approach did not need to evaluate the classification performance on a validation data set through retraining the classifier when a new feature was generated, because a closed form of KL-divergence.

However, this greedy approach still had the computation complexity.

2.3Text Classification Process [20]

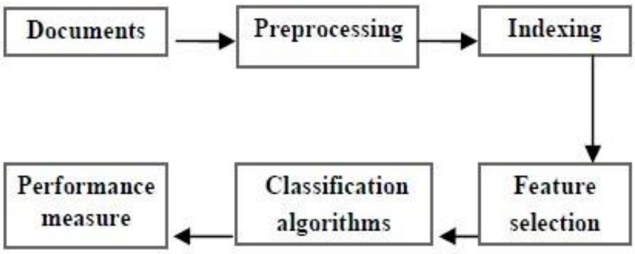
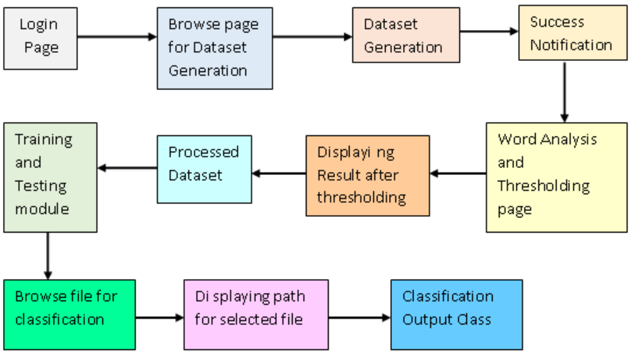


Figure 2.1 Document Classification Process

III. Proposed Approach

Below given figure shows the basic architecture of the proposed system. It mainly consists of news classification as the dataset I have chosen 20 newsgroup dataset.


Login Page
Browse page for Dataset Generation
Dataset Generation
Success Notification
Word Analysis and Thresholding page
Displayi ng Result after thresholding
Processed Dataset
Training and Testing module
Browse file for classification
Di splaying path for selected file
Classification Output Class

The proposed work is planned to be carried out in the following manner.

- System will be provided automatic text categorization using Modified Naïve Bayes algorithm.
- Text Reduction and Feature selection is done for Dataset pre-processing.
- Dataset for simulation will be 20 Newsgroups, Amazon Reviews, and Disease Detection.

The documents representation is one of the pre-processing technique that is used to reduce the complexity of the documents and make them easier to handle, the document have to be transformed from the full text version to a document vector.

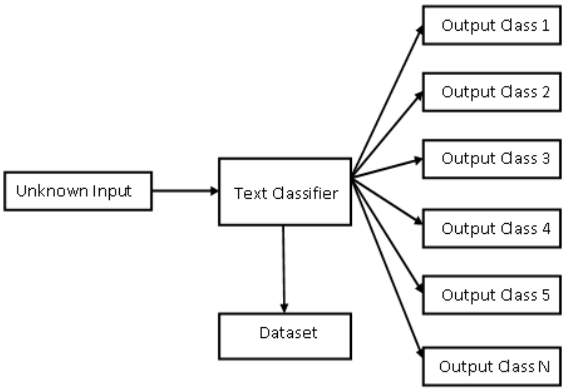


Figure 4.13(a) Sub-Architecture of Text Categorization

From the above figure, system consist of new to be classified as its input and the output will be the label to which the news probably belongs to. Classifier is the main module of the system which is the implementation of the naïve Bayes algorithm. It uses the training data as its input and classifies the input documents. Some of them are: high dimensionality of the representation, loss of correlation with adjacent words and loss of semantic relationship that exist among the terms in a document. Training data consist of large number of documents pre-processed i.e. term frequency and document frequency is calculated. Using this data the input file is classified. Usually, one has a collection of documents which is represented by word by word document Matrix.

1) Pre-processing Dataset (Apply Reduction)

The first step is to perform text reduction on dataset using text reduction technique which is used to presents the text documents into clear word format. The documents prepared for next step in text classification are represented by a great amount of features. Commonly the steps taken are:

Tokenization:A document is treated as a string, and then partitioned into a list of tokens.

Removing stop words: Stop words such as “the”, “a”, “and”, etc are frequently occurring, so the insignificant words need to be removed.

Stemming word: Applying the stemming algorithm that converts different word form into similar canonical form. This step is the process of conflating tokens to their root form, e.g. connection to connect, computing to compute. This method is used to identify the root/stem of a word. For example, the words connect, connected, connecting, connections all can be stemmed to the word “connect” [6]. The purpose of this method is to remove various suffixes, to reduce the number of words, to have accurately matching stems, to save time and memory space. In stemming, translation of morphological forms of a word to its stem is done assuming each one is semantically related.

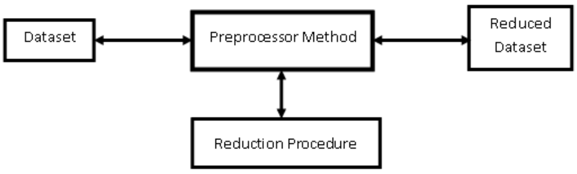


Figure 4.13(b) Pre-processing Dataset

Pre-processor processes the document words by removing:

- Symbols removal
- Stop words removal

The all symbols are removed in pre-processing step and a stop list is a list of commonly repeated features which appears in every text document. The common features such as it, he, she and conjunctions such as and, or, but etc. are to be removed.

Because they do not have effect on the categorization process. Stemming is the process of removing affixes (prefixes and suffixes) from the features. It improves the performance of the classifier when the different features are stemmed into a single feature.

2) Generating Frequencies

I have to generate dataset frequencies provided below:

- Word count
- Term Frequency
- Normalized term Frequency
- Inverse Document Frequency
- Semantic Frequent Pattern

Word Count:A word count is a numerical count of how many words a document contains. Most word processors today can count how many words are in a document for the user.Word counting may be needed when a text is required to stay within certain numbers of words. This may particularly be the case in academia, legal proceedings, journalism and advertising.

Term Frequency: Term frequency (TF) is used in connection withinformationretrievaland shows how frequently an expression (term, word) occurs in a document. Term frequency indicates the significance of a particular term within the overall document. The Naive Bayesian classifier is based on Bayes theorem with independence assumptions between predictors. This value is often mentioned in the context of inverse document frequencyIDF. The term frequency value is consulted, among other things, for the calculation ofKeywordDensity.

$$\mathrm{Tf}(t,d) = 0.5 + \frac{0.5 * f(t,d)}{\text{Maximum Occurence of Words}}$$

Normalized Term Frequency:

Document length normalization adjusts the term frequency or the relevance score in order to normalize the effect of document length on the document ranking. Term frequency normalization approaches for information retrieval involve the use of parameters. The tuning of term frequency normalization parameter(s), by measuring the normalization effect on the within document frequency of the query terms.

$$\text{Normalized Term Frequncy} = \frac{\mathrm{tf}(t,d)}{n_d}$$

Where, tf (t, d): Raw term frequency (the count of term t in document d).

Inverse Document Frequency:

The inverse document frequency is a measure of how much information the word provides, that is, whether the term is common or rare across all documents. It is thelogarithmically scaledinverse fraction of the documents that contain the word, obtained by dividing the total number of documents by the number of documents containing the term, and then taking the logarithm of that quotient.

$$\mathrm{IDF}\log(t,d) = \frac{|D|}{(\text{Number of document, term t appearns})}$$

3) Classification

Naïve Bayes Classifiers are simple probabilistic classifiers based on the Bayes Theorem. These are highly scalable classifiers involves a family of algorithms based on a common principle assuming that the value of a particular feature is independent of the value of any other feature, given the class variable. In practice, the independence assumption is often violated, but Naive Bayes classifiers still tend to perform very well under this unrealistic assumption and very popular till date. K-Nearest Neighbour Classification by is a nonparametric method for classification and is among the simplest of the classification algorithms [9]. It is a method of lazy learning because the function is locally approximated and all computation is postponed until classification, the output of the classification being a class membership. Classification of an object is done seeing the commonality among its knearest neighbours where k is a positive integer. Advantage includes easy implementation and non-parametric properties but classification process takes long time to conclude.

IV. Conclusion

The Text Classification using analytical approach project proposed a design of the application that can effectively classify text files into appropriate folder depending upon the theme of the file, using the training data to model the classifier. This application automates the text classification process otherwise would take long time doing manually the same task. Text file are appropriately classified using this application. This application allows you to select the test data, training data. A similar concept can be used for different purposes like arrange your computer, classify various documents with various applications and analyse them. Using this system I have improvised the accuracy of system to 92% which provide much better data accuracy and classification for text documents. I have used 20 newsgroup data for simulating our classification algorithm. Modified Naive Bayes Algorithm is used so that more accuracy and less time complexity can be achieved than that of Naïve Bayes algorithm.

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