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Weighted Sentiment Score Formulation Using Sentence Level Sentiment Density for Opinion Analysis

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Abstract

This paper focuses on one of the classical research domain in natural language processing: Sentiment analysis that is, identifying the view or opinion in textual data. The paper explores the Sentiment analysis problem of movie review categorization into positive or negative review using Lexicon and Machine learning based approaches. Sentiment of the document is decided via the formulated sentiment score using these approaches. The lexicon based approach uses SentiWordNet dictionary as a lexical resource to get the polarity score of the word. The machine learning approach uses Naïve Bayes classification algorithm applied to tokenized sentences from movie review at sentence level rather than document level. A notion of sentiment density is introduced as a weighing mechanism to model the contribution of a classified sentence in formulating overall sentiment score of the document. The best case accuracy achieved is 88% for classifying negative reviews using this modified version of machine learning approach.

Keywords: Sentiment analysis, Naïve Bayes, Lexical analysis, Machine learning, sentiment density, sentiment score

INTRODUCTION

With the increase in the volume of data generated online every day, it is difficult for humans to extract information from the raw data and derive meaningful inferences. The advent of technology has made it possible for the research community to make information retrieval, processing, and analysis easier for humans by making computers do the same task as humans do. One such task is to extract opinion from text often termed as opinion mining or sentiment mining. Work in this field is mostly done on reviews (movie, customer and product reviews), articles, blogs and tweets to identify opinion expressed in them. For our work, we have used the Movie Reviews Dataset made available by Pang and Lee first used in [1]. Opinion extracted can either be divided into two categories: positive and negative, or multiple categories: Good, Very good, Bad, Very bad etc. Another way may be to define a numerical score between -1 and 1, -1 being the negative extreme and 1 being the positive extreme. In this paper, only two categories are considered for sentiment classification: positive and negative. A modified Machine Learning approach for sentiment score generation is proposed to decide if the document is positive or negative based on this score. Modeling the sentiment of a document using a Sentiment Score rather than just sentiment classification using Machine learning algorithms like Naïve Bayes, SVM and maximum entropy gives more clarity as to how positive or negative the document is.

In this paper, we have investigated two widely used techniques used in sentiment analysis: Machine Learning Sentiment classification and Lexical analysis. In our work, the machine learning approach is modified for document level sentiment analysis. Instead of classifying the whole document as positive and negative (using any classification algorithm) we have tokenized the document into sentences and have applied Naïve Bayes classification algorithm to classify the sentences into two classes: positive or negative. Once the classification is done at sentence level, all the sentences are combined to calculate the overall sentiment score of the document. A concept of sentiment density is introduced at the sentence level which is the ratio of the feature word to the total number of words in a sentence. Sentiment density is used as a weighing mechanism for the contribution of a sentence in overall sentiment of the document. An approach that exploits the Lexicon polarity score taken from SentiWordNet dictionary is also explored.

PREVIOUS WORK

Sentiment analysis or opinion mining is one the emergent research fields in Natural language processing. Analyzing user behaviour via sentiment analysis is of importance for companies to predict the popularity of their products. Several product based software and web services have been designed to carry out sentiment analysis of online and offline text reviews as discussed in [2]. Most of the early work in the field is done by Pang and Lee [1, 3, 4] and Turney [5].Pang and Lee [6] presented a survey of more than 300 papers that encompasses several sentiment analysis tasks, challenges and applications. In [7] and [8] different approaches and techniques to sentiment analysis are reviewed. Predominantly, the researchers have approached the sentiment analysis problem using supervised machine learning and Lexicon based techniques. In supervised Machine learning approach a classification algorithm like Naïve Bayes and Support Vector Machine is trained on annotated text to build a classifier model for sentiment classification.

Pang et al. [4] investigates Sentiment classification problem on movie reviews dataset and outlines how it differs from topic based classification. Their results suggest that Naïve Bayes, Maximum Entropy and SVM that performs very well on topic based categorization tend to give less accuracy for Sentiment categorization. However, their experiments to improve sentiment categorization suggest the use of feature presence than feature frequency, negation handling and unigram over bigrams. Turney [5] in his paper has presented an unsupervised learning algorithm for sentiment analysis of reviews based on the semantic orientation of phrases. However in their work the accuracy achieved for movie review dataset is only 66%.

In [9] it is pointed out that Machine Learning techniques for sentiment classification are domain-dependent and demonstrated that including emoticons for sentiment analysis task can help reduce this dependency. Lexicon based methods [10] on the other hand is domain independent since it relies on a lexical resource like SentiWordNet dictionary [11] that provides an opinion strength of a word as a valence score. Such dictionary based approaches are independent of the domain wherein the valence score of feature word is same in any context as investigated in the paper [12]. Authors have also discussed about binary sentiment classification over multi-domain dataset for document level sentiment classification using Rule-based and machine learning approach. The rule-based approach has used SentiWordNet dictionary as a lexical score that remains common across all domains. Results indicate that machine learning classifier performs better than rule-based approach since the classifier can adapt to the attributes of the domain.

Sentiment analysis is mainly done at 3 levels: document level, sentence level and Aspect level [7]. M. khan et al. in [8] discusses the challenges encountered at all these levels. Most of the work at document level sentiment analysis is done with reviews particularly with Movie reviews dataset made available by Pang and Lee [1]

To achieve better results to sentiment analysis problems, various other approaches combined with Machine Learning sentiment classification have been experimented. Appel et al. in [13] presents a hybrid approach to sentiment analysis problem where besides machine learning classification polarity is also modeled using fuzzy sets. To strengthen the hybrid approach author incorporates the use of semantic rules like Negation handling and clause level punctuation. Sentiment Lexicon approach is also being carried out using SentiWordNet dictionary. Farra et al. [14] has proposed a methodology for sentence and document level sentiment analysis of Arabic text wherein authors adopted a document chunking approach for finding the sentiment of the document. The overall sentiment of the document is governed by the class of chunked sentences post sentiment classification. As per their experiments, they found out that dividing the document into chunks of four gives the best result. Aftab et al. in [15] uses random forest classifier to classify customer reviews takes from Amazon.com. Authors have improved the training procedure of the classifier using Term frequency variance method that takes into count the informative terms that belong to only one category.

DATASET

For the purpose of this paper, we have taken the Movie reviews dataset made available by Pang and Lee [1].Movie reviews are considered to be one of the most difficult domain for sentiment classification because they are an opinionated text written by individuals in varying writing style as opposed to the reportage news articles that follow a structured writing style. This linguistic randomness makes it difficult to exploit semantic rules of the language in case of movie reviews. Also, all the opinions in movie review may not always be about the movie. A sentence like “The movie X was amazing but Y(actor) failed to do justice to his character” expresses a positive opinion ‘amazing’ about the movie but negative opinion ‘failed’ about the actor of the movie. These conflicting opinion words need to be taken care of while investigating the sentiment of the whole document. This problem requires context resolution to be carried out as a Pre-processing step before determining the sentiment of the text. The occurrence of slangs and sarcasm are amongst the other important challenges while working with the Movie review dataset.

The original dataset consists of 1000 positive and 1000 negative review documents. Each document is a review that holds an opinion about a movie. We have used 300 positive and 300 negative reviews for our training set. In our proposed method we have considered sentence level sentiment classification that contributes to the overall sentiment of the document, therefore, the training set review documents are tokenized into sentences for training the Naïve Bayes algorithm. We have taken 8000 positive and 8000 negative sentences obtained after sentence tokenization of 300 positive and 300 negative reviews respectively. As per our intuition, the assumption is that the sentences tokenized from the positive review are positive and that from negative review are negative. The sentences taken for the learning process are at least 10 words in length. This ensures that the sentence given to the training classifier is long enough for it to learn.

PROBLEM FORMULATION AND OBJECTIVES

The objective of this work is to classify a document as positive or negative while addressing the issues encountered when sentiment analysis is done at the document level. Directly applying any supervised Machine learning technique to classify the document as positive or negative does not achieve desirable accuracy. Therefore in our work we have tried to accomplish this task at sentence level wherein the document is subdivided into sentences and sentiment classification of these sentences contributes to decide the overall polarity of the document. The objectives of this paper can be briefly summarized as follows:

- Categorizing the sentences in a document as Positive and Negative by using Naïve Bayes classifier. It is trained on 8000 negative and 8000 positive sentences tokenized from the Movie Review Dataset of positive and negative reviews.

- Formulating an overall Sentiment Score of a document using supervised machine learning sentiment classification at sentence level. The concept of Sentiment density is proposed as the weighing mechanism for modeling the contribution of each sentence to the overall polarity of the document.
- Lexical analysis of the document where the valence score of each feature word is taken from the SentiWordNet dictionary as a lexical resource.

METHODOLOGY

In this section, we have discussed two widely used approaches for sentiment analysis- Machine learning approach and Lexical approach. A method to formulate the sentiment score of the document is presented using both approaches.

Feature extraction

In any text analysis and classification, features are distinct words present in the text. For our Sentiment analysis problem, feature set will consist of opinion carrying words. In English language, Adjectives are a part of speech that bears an opinion. In [16] Benamara et al. suggest the use of Adjectives as well as Adverb as a feature set. In our study, we have experimented with both Adjectives and Adverb together and with Adjectives alone. We have worked only with Unigrams. However, Bigrams and Trigrams can also be explored in the future work.

Modified machine learning approach

In this approach, a machine learning classifier is used to categorize a text into classes or categories as shown in Fig. 1. Commonly used supervised classification algorithms for the sentiment analysis task are Support vector machine, Naïve Bayes and K-nearest neighbours. However, the definition of best algorithm is highly debatable for sentiment classification.

We have used Naïve Bayes classification algorithm for our work. It is a supervised Machine learning algorithm based on the bag of words model which is simple and easy to implement. It takes an annotated text also known as the training set as input and builds a Naïve Bayes classifier model over it that categorize our text into the corresponding classes. Theoretically, it suffers from underlying assumption of conditional independence of features. For text classification task, the features considered are words which are unrelated to other co-occurring words. Even after this disadvantage Naïve Bayes algorithm accounts for high accuracy in text classification. [17]

In this paper, we have attempted binary sentiment classification into two classes: positive and negative. It can be easily extended to include a third class as Neutral by incorporating a training dataset for Neutral movie reviews. One direct way of using Naïve Bayes for document level sentiment classification is to input the whole document as a single entity in the training set which accounts for low accuracy. In our approach, we have presented a two-stage model for sentiment classification. It is based on a basic assumption that if a majority of sentences in a document are positive then the document carries an overall positive opinion.

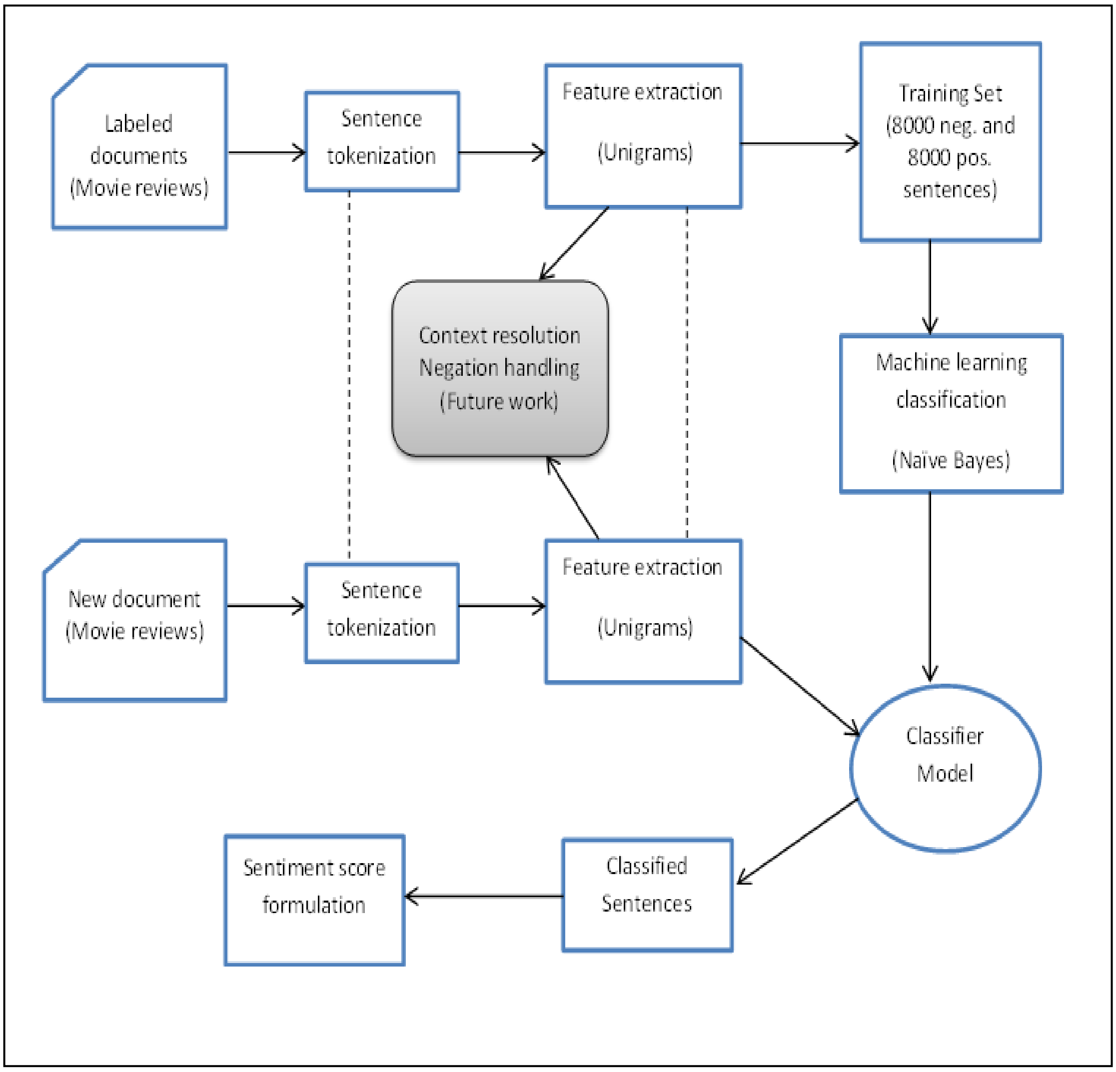

Figure 1: Architecture diagram for Machine learning based approach

In the first stage, the document is subdivided into sentences and Naïve Bayes classifier is trained on positive and negative sentences. The sentiment classification is then carried out at sentence level. To find the polarity of the new test document, tokenized sentences are passed to a Naïve Bayes classifier model that classifies them into positive or negative.

In the second stage, the classified sentences of the first stage are used to determine the overall polarity of the document. Not all sentences contribute to the document polarity equally. N. Farra et al. in [6] concluded that in movie reviews the opinionated sentences are predominantly in the beginning and at the end of the review. To model this hypothesis we have introduced the concept of sentiment density in our work as discussed in detail in the next subsection.

Sentiment density

Sentiment density of a sentence governs the weight of each sentence in determining the overall sentiment of a document. It is used as a weighing mechanism to model the impact of each sentence. For this paper, we define sentiment density of a sentence as the ratio of feature words to the total number of words present in it. The value of sentiment density lies between 0 and 1.Let W be the set of all words in a sentence, F be the set of all the feature words in the sentence where $F \subset W$ and f_j denotes the weight of j^{th} feature word (that can be obtained from SentiWordNet dictionary) present in F then Sentiment density for the i^{th} sentence denoted by SD_i is defined as:

$$SD_i = \sum_{j=1}^{|F|} f_j \Big/ |W| \quad (1)$$

In our work, we have taken a uniform weight of one for all the feature words. Steps followed for sentiment density calculation can be explained with the help of an example as follows:

Input: “The movie is hilarious with surprising climax supported by the solid script”

Step1: Word tokenization: After Word tokenization of the sentence the set W is as follows: W={'The', 'movie', 'is', 'hilarious', 'with', 'surprising', 'climax', 'supported', 'by', 'solid', 'script'}

Step2: POS tagging: After Parts of Speech Tagging the sentence is as follows: [('The', 'DT'), ('movie', 'NN'), ('is', 'VBZ'), ('hilarious', 'JJ'), ('with', 'IN'), ('surprising', 'JJ'), ('climax', 'NN'),('supported', 'VBN'), ('by', 'IN'), ('solid', 'JJ'), ('script', 'NN')]

Step 3: Feature extraction: The feature words consist of the opinion carrying words expressed by Adjectives (POS tag starts with J) and Adverbs (POS tag starts with R).After Feature word extraction and stop word removal the set of feature words F is as follows: F={‘hilarious’, ‘surprising’, ‘solid’}

Therefore Sentiment density of the above sentence= 3/11 =0.27273

Score formulation

Using the machine learning approach described above we can formulate the Sentiment Score of a document using a two-stage model. We define a classifying factor to quantify the sentiment classification of i^{th} sentence as follows:

$$CF_i = \begin{cases} 1, & if\ i\ is\ positive \\ -1, & if\ i\ is\ negative \end{cases} \tag{2}$$

Overall sentiment score of the document D is defined as:

$$\text{D} = \sum_{i=1}^{|D|} (CF_i \ * SD_i) / |D| \tag{3}$$

Where |D|> 0 is the total number of sentences in the document.CF is the classifying factor and SD_i is the sentiment density that lies between 0 and 1. So the value of D lies between -1 and 1. Likewise, the score can be calculated for all the documents using the above mentioned approach as shown in Fig. 2.

Lexical approach

In this approach, Lexicons that are words with some opinion sense are used to find the sentiment in a text. A lexicon is then searched in a lexical database to find its opinion sense. The lexical database used in our work is SentiWordNet dictionary via which a polarity score is assigned to a feature word. It is used as a lexical resource for opinion mining that gives a degree of an opinion carrying word. It assigns a valence score for each synset (set of synonyms) existing in WordNet dictionary. A triplet score for positivity, negativity and objectivity is assigned. The sum of all the three score is always 1. The entire feature words score is then combined to find the overall sentiment score of the document as explained in the following subsection.

Score formulation

Let V (f_i) denote the valence score of f_i feature word in the feature set F. The feature set F consist of set of words with positive valence words denoted by P and set of all negative valence words denoted by N such that F=P ∪ N. Let p and n denotes the overall positive and negative sentiment score of the document such that:

$$\text{p} = \frac{\sum_{i=1}^{|P|} V(f_i)}{|P|} \quad where\ f_i \in P \tag{4}$$

$$\text{n} = \frac{\sum_{i=1}^{|N|} V(f_i)}{|N|} \quad where\ f_i \in N \tag{5}$$

The overall sentiment score of document D is given by D =p-n that lies between -1 and 1.

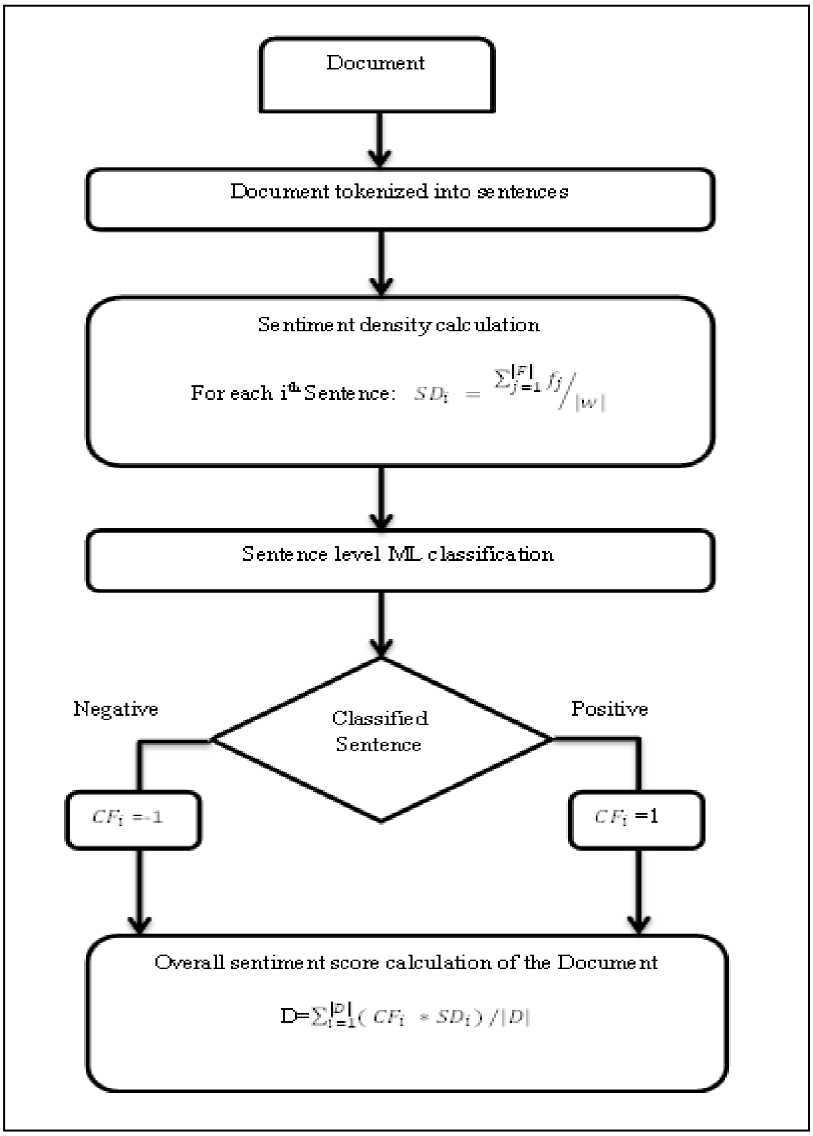

Figure 2: Flow diagram for sentiment score calculation of a document using weighted sentence level machine learning classification.

EXPERIMENT AND RESULTS

We investigated the two widely used methodologies for sentiment analysis to generate the sentiment score of a document as described in section in section 6. In both the methods a sentiment score of the document is generated that lies between -1 and 1. Our results show that the score obtained by our modified machine learning approach is more accurate than Lexical based approach. We have used confusion matrix also known as an error table to represent our results. It comprises actual and predicted class information of our binary classification task. The data in the matrix is used in evaluation of different performance measures as shown in next subsection.

In Lexical approach, a positive and negative score of feature words are taken from SentiWordNet dictionary and an overall document score is calculated using it. To check if the generated score is in correspondence with the document polarity class, we tested it on 100 positive and 100 negative movie reviews. The results obtained are shown in table 1 and 2 with Adjectives and Adjectives + Adverbs as features words respectively. The score obtained by this method is more accurate for positive reviews than negative reviews.

Table 1: confusion matrix for lexical approach with adjectives as feature word.

Lexical approach with adjective		**PREDICTED**	
		Negative	***Positive***
ACTUAL	***Negative***	TN: 64	FP: 36
	Positive	FN: 32	TP: 68

Table 2: confusion matrix for lexical approach with adjectives + adverbs as feature word.

Lexical approach with adjective + adverb		**PREDICTED**	
		Negative	***Positive***
ACTUAL	***Negative***	TN: 58	FP: 42
	Positive	FN: 29	TP: 71

We also experimented with the modified machine learning approach as shown in Fig. 2. We used Naïve Bayes classification algorithm trained on 600 movie reviews at the sentence level. Using the terminology of sentiment density an overall sentiment score is calculated. Based on the score, a document can be classified as positive or negative. The score also gives a degree of polarity in the document. The trained classifier model is tested with 100 positive and 100 negative reviews. Table 3 and table 4 shows the results achieved by this technique for Adjective and Adjectives + adverb as the feature set respectively.

Table 3: confusion matrix for modified ML approach with Adjectives as feature words.

Modified ML approach with Adjective		**PREDICTED**	
		Negative	***Positive***
ACTUAL	***Negative***	TN: 80	FP: 20
	Positive	FN: 26	TP: 74

Table 4: confusion matrix for modified ML approach with Adjectives + Adverbs as feature words.

Modified ML approach with adjective + adverb		**PREDICTED**	
		Negative	***Positive***
ACTUAL	***Negative***	TN: 88	FP: 12
	Positive	FN: 30	TP: 70

It is evident from table 4 that the technique is more accurate for negative reviews than positive reviews. Intuitively it supports the idea that a positive statement is more close to the neutral statement than a negative one.

Table 5: Performance measures evaluation table.

	FEATURE	**ACCURACY**	**PRECISION**	**RECALL**	**F1 SCORE**
MODIFIED MACHINE LEARNING APPROACH	Adjectives	0.770	0.787	0.740	0.762
	Adjectives + Adverbs	0.790	0.853	0.700	0.768
LEXICAL APPROACH	Adjectives	0.660	0.653	0.680	0.666
	Adjectives + Adverbs	0.645	0.689	0.710	0.699

Evaluation

Sokolova et al. [18] in their review paper have discussed various performance measures to evaluate binary and muti-class text classification. We have used the following four indexes for the evaluation of our approaches:

- Accuracy= (TP+TN)/(TP+TN+FP+FN)
- Precision= TP/(TP+FP)
- Recall= TP/(TP+FN)
- F1 Score= (2*Precision*Recall)/(Precision + Recall)

Table 5 illustrate these measures in case of Modified Machine Learning approach as well as Lexical approach for both the feature sets: Adjectives and Adjectives + Adverbs.

DISCUSSION

The results obtained from modified machine learning approach are better than dictionary based lexical approach. We introduced the concept of sentiment density that led to opinion quantification at the sentence level. This modified machine learning approach worked well for negative reviews giving a maximum accuracy of 88% while it gives a maximum of 74% in case of positive reviews. This is intuitive with an idea that a negative review is more negative than a positive review is positive. The accuracy of our modified machine learning approach does not directly depend on the accuracy of Naïve Bayes classifier because the Naive Bayes classification is done at the sentence level while the sentiment analysis is done at the document level.

However, sentiment score generated from lexical approach are not very convincing. The maximum accuracy reached is 71% in case of positive reviews. We do not have the valence score of every feature word in SentiWordNet dictionary. This leads to omitting of these words in overall document score calculation resulting in low accuracy. Also, the score taken from SentiWordNet is context-free, however, sentiment weight of each word is different when used in different contexts. This approach also assumes the use of unigram for sentiment analysis. A more concrete formulation of Lexical analysis is required to overcome these disadvantages and assumptions.

In our work the formulated sentiment score not only provides a way to classify the document as positive and negative but at the same time quantifies the sentiment of every document. We can also use sentiment score for bias analysis and finding sentiment correlation between documents. Both the experimented approaches can also be combined to form a hybrid method for sentiment score generation.

CONCLUSION AND FUTURE SCOPE

In our work, we have carried out sentiment analysis using Lexical and machine learning approaches. A score is generated using both the approaches that quantify document polarity between -1 and 1.Lexical analysis is a dictionary based approach where SentiWordNet dictionary is used as a lexical resource. Using the valence score of the feature word from SentiWordNet dictionary, the overall sentiment score is modeled. This approach is identical across all domains since the valence score of the word is independent of its usage in the sentence. It is applicable only for unigram based analysis. On the other hand machine learning approach adapts to the distribution of features across the training set. In our work, we attempted the document level sentiment analysis at sentence level. We formulated a sentiment score of the document via Sentiment density of the document along with naïve Bayes Sentiment classification.

All sentiment analysis tasks were carried out on movie review dataset. Sarcasm and contextual ambiguity are some of the challenges encountered in movie review domain that can be resolved in the future work. Context can be established using any co-reference resolution method like Stanford coreference resolver. Throughout our work, we have worked with unigrams and the features words considered for both the approaches are Adjectives and Adjectives + Adverbs. Bigrams and trigrams along with other parts of speech can be explored in the future work. Negation handling and modeling punctuation are other improvements to be included in future work.

REFERENCES

[1] B. Pang, and L. Lee, 2004 “A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts,” Proc. of Meeting of the Association for Computational Linguistics, p.271.

[2] Jesus Serrano-Guerrero, Jose A Olivas, Francisco P Romero, and Enrique Herrera-Viedma, 2015, “Sentiment analysis: a review and comparative analysis of web services,” Information Sciences, Vol. 311, pp. 18-38.

[3] B. Pang, and L. Lee, 2005, “ Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales,” Proc. 43rd Annual Meet.of ACL,No. 1, pp. 115–124.

[4] B. Pang, L. Lee, and S. Vaithyanathan, 2002, “Thumbs up?: sentiment classification using machine learning techniques,” Proc. of the ACL-02 conference on Empirical methods in natural language processing, Vol. 10, pp. 79-86.

[5] P. D. Turney, 2002, “Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews,” ACL '02 Proc. of the 40th Annual Meeting on Association for Computational Linguistics, pp. 417-424.

[6] B. Pang, and L. Lee, 2008, “Opinion Mining and Sentiment Analysis. – Foundations and Trends in Information Retrieval,” Vol. 2, 2008, pp. 1-135.

[7] W. Medhat, A. Hassan, and H. Korashy, 2014, “Sentiment analysis algorithms and applications: A survey,” Ain Shams Eng. J., Vol. 5, No. 4, pp. 1093–1113.

[8] M. T. Khan, M.Durrani, A. Ali, I. Inayat, S. Khalid, and K. H. Khan, 2016, “Sentiment analysis and the complex natural language,” Complex Adaptive Systems Modeling, Vol. 4, No. 1, p. 1.

[9] J. Read, 2005, “Using Emoticons to reduce Dependency in Machine Learning Techniques for Sentiment Classification,” Proc. of ACL Student Research workshop,pp. 43-48.

[10] M. Taboada, J. Brooke, M. Tofiloski, K. Voll, and M. Stede, 2011, “Lexicon-Based Methods for Sentiment Analysis,” Computational Linguistics, Vol. 37, No. 2, pp. 267–307.

[11] AEsuli, and F. Sebastiani, 2006, “SENTIWORDNET: A Publicly Available Lexical Resource for Opinion Mining,” Proc. of the 5th Conference on Language Resources and Evaluation, pp. 417–422.

[12] K. Denecke, 2009, “Are SentiWordNet scores suited for multi-domain sentiment classification?,” Proc. 4th International Conference of. Digital. Information. Management,pp. 32–37.

[13] A. Mukwazvure, and K. P. Supreethi, 2015, “A Hybrid Approach to Sentiment Analysis of News Comments,” Proc. 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions), IEEE.

[14] N. Farra, E. Challita, R. A. Assi, and H. Hajj, 2010, “Sentence-level and document-level sentiment mining for Arabic texts,” Proc. IEEE International. Conference on. Data Mining workshops, pp. 1114–1119.

[15] Md. Aftab Alam, A.A. khan, Jameel Hashmi, and Dr. M. Daiyan, 2016, “Sentiment classification using supervised method,” International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 6, No 1, pp. 45-49.

[16] F. Benamara, S. Irit, C. Cesarano, N. Federico, and D. Reforgiato, 2007, “Sentiment Analysis : Adjectives and Adverbs are better than Adjectives Alone,” Proc of International Conference of Weblogs Social Media, pp. 1–4.

[17] P. Gamallo,and M. Garcia, 2014, “Citius: A Naive-Bayes Strategy for Sentiment Analysis on English Tweets,” Proc. Of 8th International Workshop on Semantic Evaluation, pp. 171–175.

[18] M. Sokolova, and G. Lapalme, 2009, “Systematic analysis of performance measures for classification tasks,” Information Processing and Management, Vol. 45, No. 4, pp. 427–437.