***Handling Polarity Shift For Opinion Mining***

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*Abstract*— **Opinion mining or sentiment analysis is the study of people’s opinion, sentiments, attitudes and emotions expressed in written language. It is one of the most active research programs in natural language processing and text mining. Though sentiment analysis has been a trending research program in the community of natural language processing, the Bag Of Words based machine learning approach is state-of-the-art for this task. However, BOW model does not focus much on polarity shift which may create a different overall impact. Polarity shift handling is one of the major problems in performing sentimental analysis of any text or sentence. Earlier work has been done on handling the polarity shifts focused on detecting polarity shift with limited scope. Some works also included training of the classifier either by reversing of the original reviews or extracting the features based on patterns. This study aims to handle polarity shift. Sentiment classification will be performed in 2 major steps i.e. Tokenization and Polarity shift handling. A model is proposed to handle explicit negation with a larger scope. Unlike traditional negation modifiers, our aim is to negate the related terms even if it does not immediately follow negation modifier. Apart from modification and polarity shift handling, other tasks for sentimental classification such as pre-processing, tokenization will be performed in a traditional way. Proposed model will be evaluated on Kaggle’s “Bag of Words meets Bag of Popcorn” which is a balanced dataset consisting of 25000 positive and negative reviews in total. For the proposed model, partial data-set have been used. Ten-fold cross validation technique will be used for evaluation of proposed model. Proposed model will be compared and analyzed with the existing state-of-the-art model such as PSDEE.**

***Keywords—tokenization, polarity shift, explicit negation, PSDEE, Bag-Of-Words.***

# Introduction

With the recent trend of online shopping, social network analysts found that about 2.5 quintillion bytes of data is generated every day; with such a huge amount data being generated everyday it has been attracting many developers and this has leads to development of new branches like data mining and big data [1]. This data being generated has been influencing many people in some or the other way so there is a need to analyse the data forming a sub-branch better known as sentimental analysis. Sentiments can be said as thoughts, views or ideas expressed by an individual towards the product. In the same way many users express their views for the product leading to generation of large amount of data. Sentimental analysis is the process of analysing the sentiments of the review which can be positive or negative or both. Sentimental analysis is also referred as opinion mining, which is used to extract useful information or data from the set of data. Opinion mining is the process of extracting the opinion provided by the customer or user. It is used to identify and aggregate the sentiments or opinion.

Extracting sentiments from these reviews is the first major task to be performed for analyzing. While extracting these sentiments, the challenge faced is handling polarity shifts of those reviews. Polarity of a review is termed as the presence of the positive or negative words in the review. Polarity shift occurs when the sentence consists of the words like not, don’t, but, although, and soon that shifts the polarity of the sentence i.e from positive to negative or vice versa.The biggest challenge is detection of such terms and handling them appropriately according to amount of positivity and negativity. Three types of polarity shifter have been proposed in earlier work and they are explicit negation, explicit contrast and sentimental inconsistency [2]. Explicit negation occurs when negative words or negators occurs in a statement and contribute to the polarity shift. Explicit contrast are the contrasting words in which user express opposite ideas and Sentimental inconsistency is the one in which the user expresses many ideas which may be opposite to each other and may lead to inconsistency of statement. In the proposed approach, main aim is to handle negation occurring in the reviews which covers maximum part of the polarity structure.

## REVIEW OF LITERATURE

There have been various methods and systems proposed for handling polarity shifts. Each proposed system gave certain accuracy in providing results by established algorithms. At present, numerous researchers have used many methods such as SVM, PSDEE model.

Table 1: Comparative analysis of different systems

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sr. No** | **Reference. No** | **Title** | **Authors** | **Datasets** | **Approach** | **Performance**  **(accuracy)** | **Precision** | | **Recall** | |
| 1. | [8] | Fuzzy Logic Based Sentiment Analysis of Product Review Documents | Indhuja K. | SFU review corpus | Sentiment classification | 85.58% | 84.86% | | 86.92% | |
| 2. | [4] | Sentiment Classification using Enhanced Contextual Valence Shifters | Vo Ngoc Phu  Phan Thi Tuoi | Internet movie dataset | Combination of Term counting and enhanced Contextual valence shifter method | 84% | P  77.44% | N  61.10% | P  66.54% | N  72.95% |
| 3. | [7] | Frame based detection of opinion holders and topics: A model and a tool | Aldo Gangemi  Valentina Presutti | MPQA corpus  Europarl corpus | Heuristic graph mining approach | 78% | 72% | | 64% | |
| 4. | [9] | Associating Sentimental orientation of Chinese Neologism in social media data | Xi Liu  Vincent Ng | 3 million micro blogs posted by 2695 micro blog users | Metcalf’s approach | 33% | 50.95% | | 92% | |
| 5. | [10] | An approach based on Tree Kernel for opinion mining of online product review | Peng Jiang,  Chunxia Zhang | Customer review data | Support Vector Machine, KNN, Perceptions model | 89.56% | 91.53% | | 93.1% | |
| 6. | [11] | A syntactic approach for aspect based opinion mining | Chinsha TC, Shibily Joseph | Restaurant review from trip advisor | Approach to aspect level opinion mining using SentiWordNet. | 78.04% | 83% | | 89.25% | |
| 7. | [5] | Extracting aspects and mining opinions in product review using supervised learning. | A Jeyapriya, C.S. Kanimozhi Selvi | Customer review dataset  (amazon,cnet,opinions) | Dynamic adaptive Support Apriori uses Naïve Bayes, Maximum entropy class, SVM | 86.365% | Aspect extraction: 75% | | 85.71% | |
| Sentiment orientation: 90% | | 94.74% | |

Xia and Feng Xu proposed dual sentiment analysis method for in which they trained the classifier and then the system would predict the sentiment [3]. They first created the reviews which would be sentimentally opposite to the original reviews; such reviews were called as reversed reviews.

Then for training the classifier, they gave the pairs of these reversed and original reviews as input to the classifier. Phan Thi Tuoi and Vo Ngoc Phu mainly focused on classifying the sentiments using Term-counting and Hui Song and Xiaoqiang Liu in their word proposed a system to extract the features from the reviews based on patterns [5]. The patterns of Part of speech tags and features from training corpus were extracted and applied into a pattern matching algorithm which then extracted the titles and opinion words from the reviews. The system created these patterns by splitting the sentences of the reviews (in their work: Chinese reviews) into sub-sentences based on punctuation for getting word segmentation and POS tags. Then from the POS patterns extracted, it would choose the best effective pattern to create pattern set. Their system achieved accuracy of 80% for extracting features. Takeru Yokoi and Roliana Ibrahim proposed a method of extracting the emoticons for representing the sentiment intention [6]. This emoticon extraction method was based on eye characters and string symmetry of emoticons where the target emoticons were classified into three categories; eastern emoticon (face with horizontal line), western emoticon (face with vertical line) and Japanese emoticon (multiple lines on the face). Valentina and Diego proposed a Sentilo model for detecting holders and topics of opinion sentences [7]. But this model was based on an assumption that the events and situations in the reviews would be the primary entities of an opinion which then was used for mapping the holder, topics and sub-topics.

Indhuja K in her work demonstrated Fuzzy logic for sentimental analysis of product reviews, which was used to compute fuzzy score of given reviews [8]. The logic involved the representation of sentences in form of parse trees using Stanford parser. The output of this parse tree was then fed into the fuzzy opinion mining model for obtaining the score. Then, based on the score, the reviews were classified as- very positive, positive, neutral, negative, very negative.

Li-Feng and Xi Liu focused on Chinese neologisms in the social media data in their work where neologism discovery methods were used for detecting neologisms [9]. After detecting the neologisms, their system determined the sentiment orientation based on TF-IDF method. But in their method, they achieved a very poor accuracy of 33% as they labeled many unknown words as “neologism” by mistake.

Rui Xia proposed a PSDEE model for handling polarity shifts. This model showed a different approach of modeling the polarity than the term counting method, i.e., it proposed a three stage model of first detecting polarity shifts, second eliminating the polarity shifts in negation and finally a polarity shifts ensemble model [2]. The system first divided the sentences into sub-sentences based on different types of polarity shift elements (in their work: negation, contrast, sentiment inconsistency), then their system would eliminate the negator from the negation sentences and then reviews would be ensemble. Compared to previous work, our system applies the method of pre-processing the reviews, and then using sentiment classifier, classify the reviews into positive and negative.

Negation and contrasts cover 60% of the polarity structure [2]. Thus, for obtaining effective results and accuracy in sentimental analysis, it became important for handling the above mentioned polarity shifts. There are various works carried out by researchers earlier.

S. Das and M. Chen proposed an approach wherein their system would append the polarity word occurring in the sentence with “\_n” (Example: good 🡪 good\_n), thus forming a whole new term in the term document matrix [12]. We observed that this approach increased the overall dimensionality of term document matrix thus affecting the accuracy.

S. Li, Y. Chen in their work of handling the negation assumed that the combinations occurring frequently in a sentence would be polarity unshifted, whereas those occurring rarely would be polarity shifted reviews[13]. This approach led to creation of four different terms document matrices (tdm); viz positive shifted tdm, positive unshifted tdm, negative shifted and negative unshifted tdm, which could lead to confusion and error in the results.

R. Xia and C. Zong proposed a method of finding the appropriate antonyms of the polarity words occurring in the reviews (Example: good 🡪 bad) [14]. The problem in this method we observed was that not all the words have appropriate antonyms (Example: surprising). In such cases, this approach might fail in providing accurate result.

S. Padmaja extended the scope of negation modifiers while handing the negation occurring in the sentence (Example: The movie is not very good) [15]. But this method worked only when the polarity word (“good” in this case) was at the proximity of two places from the polarity shifters (“not” in this case).

R. Xia and F. Xu proposed a three stage model for detecting and eliminating the polarity shifts occurring in the reviews [2]. This was the most effective method in handling the negations except that this approach worked only if the polarity word was present right after the polarity shifter.

### PROPOSED MODEL

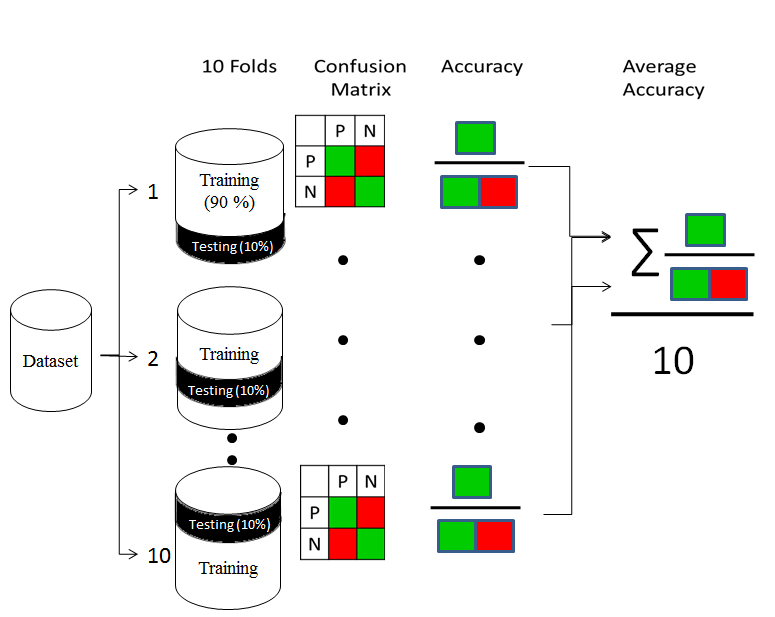
# CONTEXT BASED NEGATION HANDLING

A typical sentiment classifier consists of Induce and Deduce model. In which HTML tags are removed, HTML tags are the unwanted tags which carry no meaning and just add weightage to the data. Followed by removal of punctuation and stop-words, Punctuation are unwanted symbols which must be removed, Stop-words are the frequently occurring terms which are irrelevant and finally tokenization is done in which the tokens are extracted and sentiments are classified. But still the problem of polarity shift remains unsolved. In this paper aim is to handle this Polarity Shift using Context Based Negation Handling Model to handle negation irrespective of its proximity from the Governor word.

1. NEGATION HANDLING

The presence of negative terms like not, don’t, never, neither, nor and so on, in the sentences lead to the occurrence of Negation in a statement. There are four common types of Negation i.e. explicit negation, implicit negation, Affixal negation and Non-verbal negation. But main focus is on explicit negation as it is the most common type of negation which is the major reason for the occurrence of polarity shift in a sentence. The proximity was short in terms of handling explicit negation in previous works. For example; if the review in consideration was: The movie is not at all good; then in such case, the traditionally applied algorithms failed in handling the negation as the polarity word (“good” in this case) is at a proximity of two places from the polarity shifter(“not” in this case).

**Our work:** Firstly the positive and the negative reviews from the dataset were separated i.e. 1800 reviews were divided into two parts i.e. 900 positive and 900 negative reviews. After this, Term Document Matrix for positive as well as negative reviews was created so that we can get the count of occurrence of each word in every review. Random Forest Classifier which is known for its better accuracy was being used; but the drawback of Random Forest Classifier is that if a word which is negative and its count of occurrence in positive file is higher than the negative then Random Forest Classifier considers the word as a positive word actually which is a negative word. To overcome, the Reverse Term Document Matrix was being created for which Stanford parser was used. To handle polarity shift first it is essential to determine where the negator word and the word associated with the negator is occurring in sentence for this purpose we used Stanford parser to determine the negation in sentence and the proximity of the negator with its associated word.



After getting the negation dependency of a review, the governor word extraction was carried out, which was essential for the creation of Reverse Term Document Matrix for both positive and negative reviews. After this, a negation handled Term Document Matrix which consisted of subtraction of Reverse Term Document Matrix from Term Document Matrix was created which later on was fed to the Random Forest Classifier using python.

1. Algorithm:

## INPUT

## Document = {r1, r2, r3, ……., rn}

*where r = reviews*

## Pre-processing ()

## Where, pre-processing () method consist of punctuation removal.

## Tdm [i][j] = {r1,r2,r3,……, rn}

## Where i = term list (approximately 27,000 terms)

## j = r1, r2, r3, …, rn

## Reverse\_tdm [i][j] = {r1, r2,r3,……, rn}

*(Reverse\_tdm was created after extracting the negation dependency at any proximity from the governor word)*

## Negation\_handled\_tdm[i][j] =

## Tdm[i][j ] - Reverse\_tdm[i][j]

## Negation\_handled\_tdm = {r1, r2, r3,……., rn}

*(Negation\_handled\_tdm consist of the terms printed the number of times they occur in each review)*

## Classifying sentiments as tokens.

## OUTPUT

## Review is Positive/Negative.

#### EXPERIMENT

To analyse any work, it is important to conduct experiments. For this proposed model, two sets of experiments were conducted on a dataset consisting of IMDB movie reviews.

1. DATASET

The data-set from kaggle named “Bag of Words meets Bag of Pop-corn” contained 25,000 reviews. Partial data-set consisting of 1800 IMDB movie reviews with 900 positive and 900 negative reviews each were being used. This Data-set have three attributes: Id, sentiment and review, which are classified as 0 and 1 for positive and negative respectively. Data-set does not include any neutral review and avoids any kind of biasness.

1. EVALUATION METHOD

For evaluation of results, 10 fold cross validation was used, which is one of the standard methods. In 10 fold CV data is segregated in 10 different parts and feed to model in 9:1 ratio, in which 90% is training and 10% is testing data. This cycle is repeated 10 times so that every time unbiased data can be given for testing. And then using these 10 values estimate accuracy can be found for the model using confusion matrix. Confusion matrix helps in finding true positive, true negative, false positive and false negative i.e. if the actual value is positive and using the model positive value is obtained, then it is known as true positive and if a negative value is obtained then it is known as true negative; same is in the case, false if the actual value is negative and using model positive value is obtained then it is known as false positive and a negative is obtained, then it is known as false negative.

To find the proximity of context based negation handling model, two experiments were conducted i.e. find the accuracy of model without handling negation and accuracy of model handling negation. In first experiment, basic pre-processing step of punctuation marks removal was carried out, and then the reviews were given for tokenization. Using Random forest classifier, sentiments were predicted for each review. After carrying out these steps, the average accuracy was found to be 80.16% without handling the negation.

For handling the negation, the initial steps of pre-processing remained the same. Except for the data after pre-processing was read using java for the creation of term document matrix, reverse term document matrix and finally the negation handled term document matrix. Later on the data obtained from this Negation\_handled\_tdm was fed to the Random forest classifier in a format acceptable by python. For evaluating the results, the similar technique of 10 fold cross validation was used and the average accuracy was found to be 90.88% after handling the negation.

# result

Overall two experiments were conducted in this approach. The first experiment involved finding the accuracy without handling the polarity shifts. After successfully conducting the ten-fold cross-validation for first experiment, the accuracy obtained was 80.16%. For the second experiment, we focused mainly on handling polarity shifts due to explicit negation. Standard tenfold cross validation process was used for obtaining the results. The average accuracy achieved was 90.88%. The graph below shows the accuracy obtained for each fold for both the experiments:

# conclusion

In the proposed method, the scope of explicit negation for handling polarity shifts occurring in the movie reviews have been extended and a suitable accuracy has been achieved.

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