Negation Identification and Calculation in Sentiment Analysis

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Abstract—The extensive growth of user-generated content has introduced new aspects of analysis on World Wide Web data. Sentiment analysis of written text on the web is one of the text mining aspects used to find out sentiments in a given text. The process of sentiment analysis is a task of detecting, extracting and classifying opinions and sentiments expressed in texts. It includes the identification of the meaning of words within the text through natural language processing rules. While existing research presents a number of approaches for sentiment analysis, these approaches have not quite provided an appropriate and efficient way of calculating and representing the role of negation in sentiment analysis. Therefore, this paper presents a framework for automatic identification of the presence of opinion in textual data. The proposed framework includes a description of rules for negation identification and calculation. These negation rules are designed in order to improve sentiment text analysis. Main achievement of the paper is a demonstration on an approach for automatic identification and calculations of negation in opinion and sentiment analysis.

Keywords-Negation Identification; Negation Calculation; Subjectivity Analysis; Sentiment Analysis; Opinion Mining; Social Media Mining; Text Mining.

I. INTRODUCTION

The aim of sentiment analysis is to find out the positive and negative feelings, emotions and opinions written in a text. These sentiments are based on the meaning of words used in text according to different scenarios and situations. There are a variety of ways used to express the same feeling in a written text by using different grammatical rules. These grammatical rules contain negations that are very frequently used in text that completely change the meanings of words. In other words, negation identification and detecting its scope with in a sentence (text) are necessary in finding out the sentiments from a piece of text. Although negation identification is an important aspect of sentiment analysis, it is yet to be properly addressed. In general, the efforts put into sentiment analysis of sentences having negation terms in them are less efficient with respect to general sentiment analysis. Negation identification is not a simple task and its complexity increases, since negation words such as *not, nor* etc., (syntactic negation) are not the only criterion for negation calculation. The linguistic patterns - prefixes (e.g., un-, dis-, etc.) or suffixes (e.g., -less) also introduce the context of negation in textual data [24]. Similarly, word intensifiers and diminishers (contextual valence shifter) also flip the polarity of sentiments [7, 21]. It will take a lot of efforts to enlist all such words in one list. These valence shifters do not only flip the polarity but also increase or decrease the degree to which a sentimental term is positive or negative [5]. On the other hand, negation does not restrict itself to 'not'. There are terms like; *no, not, n't, never, no longer, no more, no way, nowhere, by no means, at no time*, etc. [5, 21] that also change the meaning of a sentence. However, the precision involving the negative word "*not*" is very low, at 63% [5]. Another reason is the fact that the number of negation sentences encountered is considered insignificant during the evaluation of any sentiment analysis system as compared to the level of effort required to resolve the issues related to negation. This paper is an effort towards finding an approach to handle the syntactic negation for sentiment analysis by not only using the polarity and its intensity for words but also using the dependencies, relation within the sentences and sentence structure. The negation is handled with the diminishers, intensifiers and negation terms during the process of sentiment analysis. This research mainly focuses on the identification of negation, and identification of scope of syntactic negation. It presents a proposed framework for automatic identification of opinion in textual data. The framework has been implemented and evaluated by verifying the polarity identified by prototype system with a group of participants.

The rest of the paper has been structured as follows: Section 2 presents an analysis of related work in the area of sentient analysis. This is followed by a description of the proposed framework for sentiment analysis, and the existing resources used to generate dependencies in Section 3. Section 4 presents an application of this proposed framework for negation handling in sentiment analysis. It also explains the basic rules used in this framework for handling negation. Section 5 involves an analysis of the technique used through some example illustrations together with an analysis of the results of the prototype evaluation. Section 6 provides a conclusion and the prospective extensions to this work.

II. LITERATURE REVIEW

Text based information is broadly classified into two basic types, facts and opinions. In other words, textual analysis can be understood as classification of text either positive/negative (document or sentence level sentiment classification) or subjective/objective (sentence level subjectivity classification). Sentiment analysis is a process, which deals with the detection of sentiments, opinions, emotions, appraisals and feelings towards entities, events and properties [22]. The concept of emotion, opinion or sentiment is very broad. Different researchers have identified different spectrums of emotions in different dimensions [15, 10]. However, it is believed that all these different dimensions can be mapped to either positive or negative

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emotions [25]. On the basis of this believe, research in sentiment analysis and opinion mining has considered positive and negative feelings. Most researchers in the field of opinion mining have used the lexicons and lists of words, with word as basic unit of expression of emotions in any language. Lexicon based negation i.e., negation introduced by suffix and/or prefix is easily handled with the help of a good lexical resource, i.e., dictionary, ontology, database etc. However, more emphasis on opinion analysis should be on how these words are joined and correlated with other words to give specific meanings in any language. This inter-relationship of words makes up sentences, which is why it is important to emphasis on finding the scope of negation, diminshers or intensifiers. Due to syntactic and semantic differences, it is difficult to interpret the intensity of polarity. While calculating a value of intensity of any sentence, there are always modifiers, which not only change the polarity of other words in the sentence but also affect the intensity. Negation is a complex thing as it changes the meaning (polarity and its intensity) if used within a clause. It is also difficult to identify which part of a clause a negation is changing in a sentence. The following sections II A – II D highlight different methods used for negation identification and how they affect sentiment analysis of text. Section II E discusses the State of Art for analysis of Negation.

A. *Bag of Words*

Bag of words (BOW) is a technique where each word in a document is represented by a separate variable numeric value (weight) [26]. It is the most widely used technique for sentiment analysis [3, 11]. Das and Chen [3] incorporated negation in their research for extraction of sentiments from stock market message boards. They believed that negation in a sentence reverses the meanings of the sentence. They discussed how words like "not", "never", "no", etc., serve to reverse sentence meaning. They detected negation words in sentences and tag from the sentences with negation markers [3]. In 2002, researchers in [11] adopted the same technique and added the negation word with every word until the first punctuation mark following the negation word. An example that better explains this technique is "I do not NOT like NOT this NOT new NOT Nokia NOT model" [17]. From the example above, it can be seen that this technique is not an effective way to find out the negation from a written text as negation may be based on a meaning of words, whereas understanding a scope is very necessary to determine such meanings. Another limitation of this technique is that it is based on the list of words, and lists in any language can never be complete.

B. *Contextual Valence Shifter*

Contextual Valence Shifters or modifiers are the words, which change (boost, enhance, diminish etc.) meanings [8]. Many researchers have transferred their research on sentiment analysis from BOW to Parts of Speech (POS) especially Verbs, Adjectives and Adverbs. The pioneers in giving an understanding that there is a basic polarity associated with every word were in [12]. However, lots of contextual shifters are still needed to change or modify the valance associated with words. Negatives, intensifiers or diminishers are examples of contextual shifter [12]. For example; Negatives: John is clever versus John is not clever. Intensifier: Sam is suspicious about Anna versus Sam is deeply suspicious about Anna. Diminishers: I know what to say versus I hardly know what to say. Wiegand et al. [17] believed that the effectiveness of the model believed that the effectiveness of the model could be better judged if was evaluated. Kennedy and Inkpen [6] used the same model for Contextual Valence Shifters. They enhanced their model but still kept the scope of any negation term as immediately preceding a term. There is a need for relationship finder to define the scope of negation terms [7]. Other researchers have tried to define the scope by defining lists of verbs, adjectives and adverbs and defining their relationships for sentiment analysis [16]. Lists of positive and negative terms and a set of lists for modifiers was proposed in [8] to define the scope of these modifiers as *n*- terms before and after positive or negative terms, although this *n* remained a constant. This technique is better for negation identification in comparison to the BOW technique. However, it also considered the propagation of lists as a limitation. The lists used for this technique may grow with time and can never be complete, as in any language there might be infinite number of words and ways they can be used. Therefore, there is always a need to devise some way for the system to handle words, which are not present in the lists.

C. *Semantic Relations*

Semantic relations refer to the relationship between concepts or meanings for example antonym, synonym, homonym etc. It is evident from existing research that semantic relationship is also used for negation identification. It is clear that atomic words, which can provide a misleading polarity for sentences as words can be modified (weakened, strengthened, or reversed) based on lexicon, discourse, or paralinguistic contextual operators [12]. The use of linguistic structure of sentence for sentiment analysis was proposed in [9], where the polarity of a sentence is dependent upon the polarities of its parts: noun phrases (NP), verb phrases (VP) and individual parts of speech. Negation is handled by defining different intensities of negation words. In other words, the negation of words can change the polarity of an entire sentence or only parts of it [17]. Shaikh et al. [14] has used a similar approach to calculate the sentence level sentiment analysis. They performed semantic dependency analysis on the semantic verb frames of each sentence, and apply a set of rules to each dependency relation to calculate the contextual valence of the whole sentence [14]. A two-phase process was proposed in [2] as another way of compositional semantics. They identify the polarity of words in the first phrase where all the words are classified on the basis of the level of their strength in terms of the scope in the sentence. The second phase is based on the inference rules, which identify the polarity modification feature. For example, in the sentence "They could not eliminate my doubt", the word *not* is a negater whereas *eliminate* also reverses the polarity of doubt, and not is reversing polarity of eliminate. These rules are much different as compared to the ones presented in [18] and [9, 17]. This approach is working well for simple sentences in the written text but has failed for compound sentences where a sentence may have word-based or sentence-based dependencies.

D. Relations and Dependency Based

The grammatical relationships between the words within a sentence and syntactic dependencies help in extraction of textual relations. Reschke and Anand [13] have given a context aware approach for sentiment analysis where the sentiment is evaluated towards a target entity, event, or proposition. The scope of words is defined by the clauses or phrases (noun phrase, verb phrase) in the sentence and sentiment in the sentences are understood by the heuristic rules defined to join the clauses [13]. Jai and others also tried to identify the scope of different terms by using Stanford Parser tree [27]. They used simple tree based rules by identifying the dependent terms and later used some parts of speech based tools to understand the sentimental behavior of negation [5].

There is quite an extensive research undertaken for sentiment analysis and scope of different words and their relation within a sentence and on broader sense domain. However, negation is still an over looked domain probably because of the low proportion of the number of negative sentences encountered during the evaluation of sentiment analysis. Irony is a process of using words and phrases (generally positive) that are generally different if used otherwise [1]. Therefore identification, extraction and analysis of irony are difficult.

E. Analysis of Negation

For the sentence level sentiment analysis in English language, the basic structure of English sentence and its parts: clauses and phrases are necessary to be understood. These parts further divide sentences into different types of sentences (simple, complex and compound). The sentence is made more complex by adding declarative, interrogative, exclamatory and imperative sentences. In order to further complicate the problem as the comparison, contradiction, negation and irony might also be introduced in the sentences. Negation needs to identify its scope, negation can be local (e.g., not good), or it can involve longer-distance dependencies (e.g., does not look very good) or the negation of the subject (e.g., no one thinks that it's good). It even changes its roles i.e., instead of negating and can even intensify (e.g., not only good but amazing) [18]. In order to find out the scope of the negation, the sequence of words in the sentence should be identified. On the whole, it is not simply the negation of a word but negation of the sentence [19, 21].

The expression of negation within a sentence varies a lot. It can be a verb, adverb, suffix or prefix. It might also occur more than once in a sentence and rather than cancelling each other it can give negative meaning, for example; I cannot get no satisfaction [4]. Therefore, the negation analysis has been done using many different ways: Parts of Speech, Bag of Words, and Dependency Tree. However, the best results can be found by combining these approaches. A way to understand the negation by using bag of words approach and latter resolving the scope with the help of dependency tree was proposed in [20]. The following section explains the proposed framework for sentiment analysis and the approach for negation identification and calculation that helps to solve the negation problem in sentiment analysis.

III. FRAMEWORK FOR SENTIMENT ANALYSIS

This section introduces a framework for sentiment analysis and explains how it is handling negation identification, scope of negation and calculation of sentiment on sentence level. The framework presented in Figure 1, consists of a number of detection, extraction and classification components interacting at various levels.

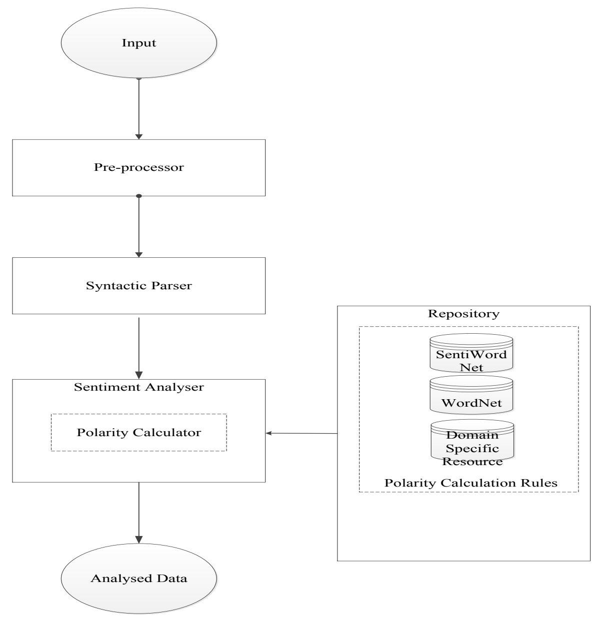

Figure 1. Framework for Sentiment Analysis

The framework shows a mixed and combined approach to lexical and syntactic analysis for sentiments. The framework uses a number of existing lexical and syntactic analysis resources for sentiment analysis. Its main components are briefly described in Sections A through C.

A. Pre-processor

The pre-processing phase of the system takes text as input and arranges all the data in required format. It splits data into sentences and forwards all the sentences to syntactic parser.

B. Syntactic Parser

The syntactic parser is an iterative parser, which uses Penn Tree Bank [30] parser to assign Parts of Speech (POS) tags to each word in the sentence. The name entities and idioms involved in a sentence are also identified in syntactic parsing. It also uses Stanford Parser [27] to identify how different words are interacting within a sentence and identifies the syntactic dependencies/relationship within a

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sentence. The syntactic parser parses each sentence iteratively with all the identified information to the sentiment analyser after classifying the sentence as a question, an assertion, a comparison, a confirmation seeking or a confirmation providing by using the rule of sentence type identification.

C. *Sentiment Analyzer*

The sentiment analyzer is basically the main part of proposed framework. It uses general resources like SentiWordNet [28], WordNet [29] and any domain specific resource to extracts the sentiment-oriented words from each sentence by using the relationship information of (dependencies within) the sentence. The Sentiment Analyzer has two sub modules, which help in calculating the polarity of sentences and documents. The Polarity Calculator (PC) calculates the polarity of a sentence and assigns a score. In order to calculate polarity, PC uses SentiWordNet [28] to identify the positive and negative words and their values assigned by the SentiWordNet [28]. In this process, PC collects the synonyms of a word if its not found in SentiWordNet [28]. The PC first uses WordNet [29] to get the synonyms. The sentiment analyzer generates frames for each sentence. A frame contains the type of sentence, subject, object/feature, sentiment oriented word(s), sentiment type (absolute or relative), sentiment strength (very weak, weak, average, strong or very strong) and polarity of sentence.

IV. USAGE OF FRAMEWORK FOR NEGATION

All the sentences having negation are forwarded from the pre-processor to the syntactic parser with other sentences. There is no specific requirement for handling the negation sentences for pre-processing. However, syntactic parser identifies the negation and POS that are involved in negation with the help of Stanford Dependency Parser [27] during the syntactic parsing phase. In the negation identification process, the kind of negation i.e., no one likes his behavior where 'no' is used to determine the behavior of one, is also identified. This process also takes care of the negation in conjunction sentences. The negation identification is very import part of syntactic parser that is used for polarity calculation by the sentiment analyzer. The following section explains how sentiment analyzer uses the negation for polarity calculation.

A. *Polarity Calculation*

Sentiment analysis identifies the semantics involved in a sentence. The words in a sentence, their meanings, alternative words, polarity of each word and intensity associated with each word are basic elements used by sentiment analyzer for sentiment identification. The polarity of sentence is usually based on the meaning of words. However, the negation (only for negation sentences) changes the meaning of the words and polarity of the sentence. In order to calculate the polarity of a sentence, some rules are defined in Table 1. These rules are defined on the basis of POS. Most negation words are classified as adverbs, suffix, prefix or verbs. However, the nouns are generally there to determine the meaning of another noun. The scope of negation will be identified by the dependency tree, which indicates how negation is interacting with other words in the sentence. This dependency will identify the scope of the negation - whether it is a single word or a phrase / clause within a sentence. In the case of a clause or phrase, the noun phrase/ clause is first calculated for the sentiment polarity before the verb phrase or clause sentiment polarity is calculated. The negation is handled in each phrase accordingly. The intensity of polarity will not exceed (+/-) 1, where + is for positive and – is for negative polarity. The intensity of a sentence is calculated as:

*Resulting Intensity = First Word/Phrase/Clause + [(1 - Second Word/Phrase/Clause) * Second Word/Phrase/Clause]*

(1)

TABLE 1. RULES SPECIFYING NEGATION

First Word /Phrase /Clause	Second Word /Phrase /Caluse	Negation	Result
Positive	Positive	True	Negative
Positive	Positive	False	Positive
Positive	Negative	True	Positive
Positive	Negative	False	Negative
Negative	Positive	True	Positive
Negative	Positive	False	Negative
Negative	Negative	True	Negative
Negative	Negative	False	Positive

The positive/negative value of words in the Equation 1 is extracted from the SentiWordNet [28] in order to calculate the polarity of a sentence. The extracted value from the SentiWordNet [28] is reversed during this process if negation is 'True' as presented in Table 1.

B. *Algorithm for Polarity Calculation*

```
Function CalculatePolarity Returns Polarity {
 Double polarity = 0
 For Each nounPhraseOfSentence {
   get SentiWordNet value of all Adjectives and Nouns of
   noun-phrase
   If (Sentence is Marked NEGATION by Syntax Parser) {
     Reverse the SentiWordNet values of related
     Nouns/Adjectives }
    For Each Noun and Adjective {
     polarity += [( 1 – Noun/Adjective) * Noun/Adjective]
     } }  For Each verbPhraseOfSentence {
   get SentiWordNet value of all Adverbs and Verbs of
   verb-phrase;
   If (Sentence is Marked NEGATION by Syntax Parser) {
     Reverse the SentiWordNet values of related
     Verbs/Adverbs  }
   For Each Verb and Adverb {
```

polarity += [(1 – Verb/Adverb) * Verb/Adverb]
} } Return polarity }

The syntax parser forwards each sentence to the sentiment parser as mentioned in Figure 1. The syntax parser identifies the 'negation' for negation sentences and also identifies the words identifying the negation before handing over the sentences to the sentiment parser. For the sentiment analysis, the sentiment parser calculates the polarity of each sentence through the above algorithm. In order to calculate the polarity of a sentence, all the noun and verb phrases are calculated. Polarity calculator gets the values of all nouns and adjectives involved in a noun phrase from the SentiWordNet [28]. These values are reversed by the polarity calculation in case of negation sentence depending on the negation scope. Similarly, polarity calculator obtains the values of all verbs and adverbs involved in the verb phrase from the SentiWordNet [28] and reversed these values in case of negation sentence. The whole process uses Equation 1 iteratively for polarity calculation while solving each noun and verb phrase.

V. ANALYSIS

The sentence polarity is calculated on the basis of the parts of a sentence. A sentence may contain either simple POS (Verb, Adverb, Adjectives, etc.) or complex parts of speech (Noun Phrase [Pronoun, Noun] or Verb Phrase [Verb, Noun Phrase], relations of possession, determiner, etc.). The following hierarchy is an example of POS in a complete sentence.

```
(Sentence
   (Noun Phrase (Pronoun, Noun))
   (Adverbial Phrase (Adverb))
   (Verb Phrase (Verb)
     (Sentence
       (Verb Phrase (Verb)
         (Noun Phrase (Noun))
       ) ) ) )
```

Sentiment polarity calculation is a nested process. This process calculates the sentiment of the most inner level first and then it calculates along with the next higher level, which is also called Sentiment Propagation [23]. This process calculates the polarity and intensity of the words and phrases. If there is a negation term the polarity will be calculated accordingly. The following three examples illustrate the whole process of polarity calculation.

A. *Example 1*

They have not succeeded, and will never succeed, in breaking the will of this valiant people.

```
(Sentence
   (Pronoun They)
   (Verb Phrase
     (Verb Phrase (have not)
       (Verb Phrase (Verb succeeded)))
     (and)
     (Verb Phrase (will)
       (Adverbial Phrase (Adverb never))
       (Verb Phrase (succeed)))
     (Prepositional Phrase (in)
       (Sentence
         (Verb Phrase (breaking)
           (Noun Phrase
             (Noun Phrase (the will))
             (Prepositional Phrase (of)
               (Noun Phrase (this valiant people)))))))))
```

The negation word 'not' is affecting the succeeded (+) whereas never is effecting succeed (+) where succeeded and succeed are joined by and (joins same polarity). Both successes are in breaking (-) the will of people who are valiant (+) people. As they have not succeeded in doing something Negative and the polarity of sentence is Positive as shown in Figure 2.

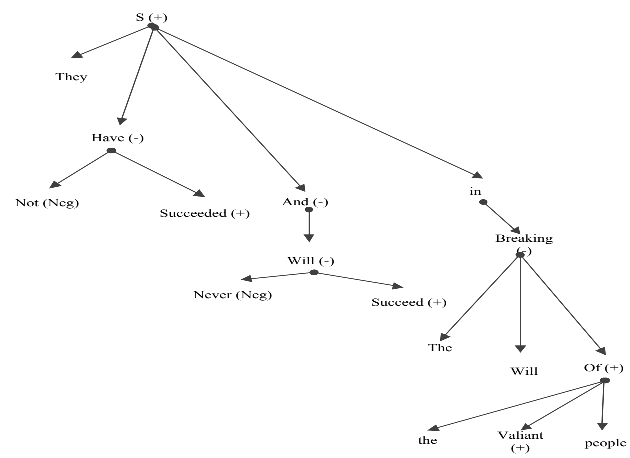

Figure 2. Dependency Tree Structure for Example 1

B. *Example 2*

Jhon is never successful at tennis.

```
(Sentence
   (Noun Phrase (Jhon))
   (Verb Phrase (is)
     (Adverbial Phrase (never))
     (Adjectival Phrase (successful)
       (Prepositional Phrase (at)
         (Noun Phrase (tennis))))))
```

Negation never is for successful (+) and this success is at tennis. This negation of positive term is a simple negation, which is presented in Figure 3.

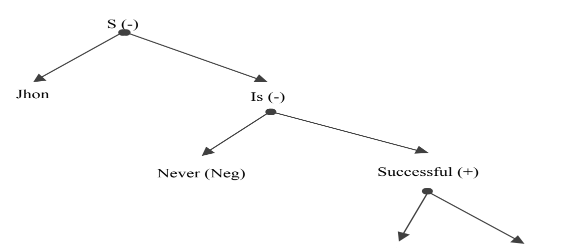

Figure 3. Dependency Tree Structure for Example 2

C. *Example 3*

The audio system on this television is not very good, but the picture is amazing.

(Sentence
(Sentence
  (Noun Phrase
    (Noun Phrase (the audio system))
    (Prepositional Phrase (on)
      (Noun Phrase (this television))))
  (Verb Phrase (is not)
    (Adjectival Phrase (very good))))
(, ,)
(Conjunction but)
(Sentence
  (Noun Phrase (the picture))
  (Verb Phrase (is)
    (Adjectival (amazing)))))

Negation not is effecting the Adjectival Phrase (very good (+)) whereas the sentence also has a conjunction of 'but' which is followed by a positive clause 'the picture is amazing (+). The conjunction 'but' diminishes the meaning of first negative and gives emphasis to following positive clause as presented in Figure 4.

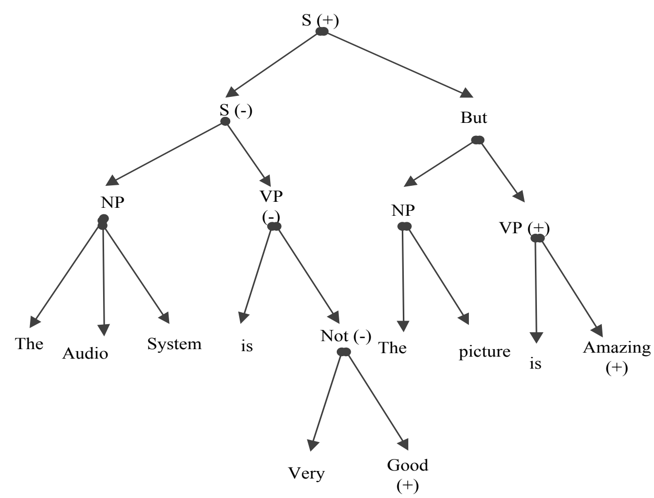

Figure 4 Dependency Tree Structure for Example 3

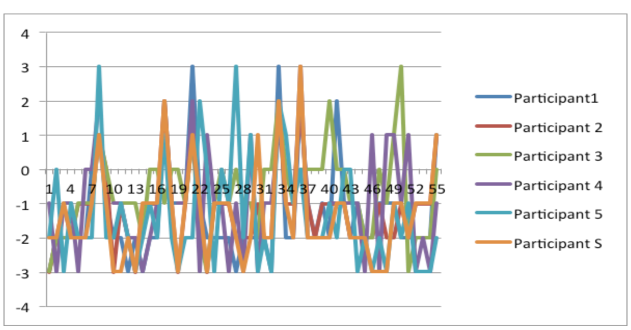

Figure 5. Graph showing Responses from Five Respondents and the Prototype System (Participant S) generated opinion scores

From the Figure 5 above, there is a clear agreement of the annotations made by all the five participants with the system with all the 55 sentences. Only two sentences (30 and 55) have more than two annotators that have given opinion polarities that are different from that of the system generated. Close analysis of these two sentences have shown why the difference.

Furthermore, the relationship between opinion polarity and intensity (as generated by the system) and all the five user generated opinion score for a sample 55 sentences was investigated using the Pearson product-moment correlation coefficient (*r*). Table 2 presents the result of the calculated multiple regression.

Table 2 Pearson Product-Moment Correlations between System and User Generated Opinion Polarity

Correlations

		Participant 1 Polarity Score	Participant 2 Polarity Score	Participant 3 Polarity Score	Participant 4 Polarity Score	Participant 5 Polarity Score	System Polarity Score
Participant 1 Polarity Score	Pearson Correlation	1	.754**	.413**	.544**	.260	.693**
	Sig. (2-tailed)		.000	.002	.000	.055	.000
	N	55	55	55	51	55	55
Participant 2 Polarity Score	Pearson Correlation	.754**	1	.412**	.342*	.329*	.872**
	Sig. (2-tailed)	.000		.002	.014	.014	.000
	N	55	55	55	51	55	55
Participant 3 Polarity Score	Pearson Correlation	.413**	.412**	1	.270	.215	.300*
	Sig. (2-tailed)	.002	.002		.056	.116	.026
	N	55	55	55	51	55	55
Participant 4 Polarity Score	Pearson Correlation	.544**	.342*	.270	1	.326*	.359**
	Sig. (2-tailed)	.000	.014	.056		.019	.010
	N	51	51	51	51	51	51
Participant 5 Polarity Score	Pearson Correlation	.260	.329*	.215	.326*	1	.327*
	Sig. (2-tailed)	.055	.014	.116	.019		.015
	N	55	55	55	51	55	55
System Polarity Score	Pearson Correlation	.693**	.872**	.300*	.359**	.327*	1
	Sig. (2-tailed)	.000	.000	.026	.010	.015	
	N	55	55	55	51	55	55

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

From the table above, we can see that the data showed no violation of normality between all the five sets. For example, *r*=.693, indicates a positive correlation between system generated polarity and opinion oriented 1, which shows a strong, positive correlation between the two variables, r=.693, n=52, p<.0005 with high levels of system generated polarity scores associated with user generated polarity scores for the sample sentences.

VI. CONCLUSION AND FUTURE WORK

Current research on sentiment analysis shows that there is a growing need to develop approaches to cope with the variety of evolving social media generated text. One aspect of research that has been identified as important, but has still received little attention is the identification of negation and its implication on the semantic understanding of sentences. This paper presents an evaluation of existing approaches to sentiment analysis and presents an approach for negation identification and calculation using a developed framework for sentiment analysis. These negation rules are designed in order to improve the sentiment text analysis.

While, there are still a number of challenges to be addressed in the field of sentiment analysis, the developed rules for negation calculation is being integrated within the general framework developed in Figure 1 within polarity

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calculation. Further work will also include the implementation of prepositional negation calculation.

The framework is not designed by keeping any specific lexical resource in mind; therefore, by improving the precision of resources the results can easily be improved.

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