IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-10, Oct 2019 E-ISSN: 2347-2693

Analyzing Sentiment and Determining Negation Scope in Political News

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DOI: https://doi.org/10.26438/ijcse/v7i10.3742 | Available online at: www.ijcseonline.org

Accepted: 12/Oct/2019, Published: 31/Oct/2019

Abstract- Automatic detection of linguistic negation in free text is a demanding need for many text processing applications including sentiment analysis. Our system uses online news archives from two different resources namely NDTV and The Hindu to predict the scope of negation in the text. In this paper, our main focus was on identifying the scope of negation in news articles for two political parties namely YSR Congress Party (YSRCP) and Alliance (which includes Jana Sena Party, Communist Party of India , Bahujan Samaj Party , Telugu Desam Party (TDP)) by using two existing namely Fixed Window Length (FWL), Dependency Analysis (DA) and one proposed methodology is Negation Sentiment Analyzer (NSA). The average F measures for each one of them were 0.61, 0.66 and 0.72 respectively. It was observed that NSA outperforms the other two. We further evaluated the results of NSA against the standard BioScope negation corpus as a benchmark, achieving 0.75 as a F1 scores.

***Keywords*:** Negation Identification, Sentiment Analysis, Natural Language Processing, Artificial Intelligence

I. INTRODUCTION

The automatic detection of the scope of linguistic negation is a problem encountered in wide variety of documents like understanding tasks, medical data mining, general fact or relation extraction, question answering, sentiment analysis and many more. This paper describes an approach to detect the scope of negation in the context of sentiment analysis, particularly with respect to sentiment expressed in online news archives. The canonical need for proper negation detection in sentiment analysis can be expressed as the fundamental difference in semantics inherent in the phrases, “this is vast,” versus, “this is not vast.” Unfortunately, expressions of negation are not always so syntactically simple. Linguistic negation is a complex topic: there are many forms of negation, ranging from the use of explicit cues such as “no” or “not” to much more profound linguistic patterns.

At the highest structural level, negations may occur in two forms: morphological negations, where word roots are modified with a negating prefix (e.g. “dis-”, “non-”, or “un-”) or suffix (e.g., “- less”), and syntactic negation, where clauses are negated using explicitly negating words or other syntactic patterns that imply negative semantics [4]. For the purpose of negation scope detection, only syntactic negations are of interest, since the scope of any morphological negation is restricted to an individual word. Morphological negations are very important when constructing lexicons, which is a separate but related research topic. Tottie also distinguishes between intersentential and sentential negation [5]. In case of intersentential negation, the language used in one sentence may certainly negate a proposition or implication found in another sentence. Rejections and supports are common examples of intersentential negation [5]. Sentential negation or negations within the scope of a single sentence is much more frequent. Thus sentential negations are the primary focus of the work presented here.

The goal of the present work is to develop a system that is built to differences in the intended scope of negation introduced by the syntactic and lexical features in each negation category. In particular, as the larger context of this research involves sentiment analysis, it is desirable to construct a negation system that can correctly identify the presence or absence of negation in spans of text that are expressions of sentiment. It so follows that in developing a solution for the specific case of the negation of sentiment, the proposed system is also effective at solving the general case of negation scope identification.

The rest of this paper is organized as follows: Section 2 presents related work on the topic of automatic detection of the scope of linguistic negations. The details of the formation of datasets extracted from online news archives and guidelines for annotations are depicted in section 3. Section 4 describes various methods of feature extraction. Stepwise implementation of negation identification using two existing and one proposed approaches are presented in section 5. Section 6 illustrates the results of the experiment performed and finally the conclusion of the work is interpreted in section 7.

II. RELATED WORK

Negation and its scope in the context of sentiment analysis has been studied in the past [6]. However, others have studied various forms of negation within the domain of sentiment analysis, including work on content negators, which typically are verbs such as “hampered”, “lacked”, “denied”, etc. [6], [7]. A recent study by Danescu-Niculescu-Mizil et al. looked at the problem of finding downward call for operators that include a wider range of lexical items, involving soft negators such as adverbs “rarely” and “hardly” [10]. With the absence of a general purpose corpus annotating the precise scope of negation in sentiment corpora, many studies incorporate negation terms through heuristics or soft-constraints in statistical models. In the work of Wilson et al.[11], a supervised polarity classifier is trained with a set of negation features derived from a list of cue words and a small window around them in the text [8]. Choi and Cardie et al. combine different kinds of negators with lexical polarity items through various compositional semantic models, both heuristic and machine learned, to improve phrasal sentiment analysis [7]. In that work [7], the scope of negation was either left undefined or determined through surface level syntactic patterns similar to the syntactic patterns from Moilanen and Pulman [6]. A recent study by Nakagawa et al. developed a semi-supervised model for sub-sentential sentiment analysis that predicts polarity based on the interactions between nodes in dependency graphs, which potentially can induce the scope of negation [9]. As mentioned earlier, the goal of this work is to compare two present and one proposed methodologies that can identify exactly the scope of negation in news articles and further comparing the better performer with the benchmark as BioScope full papers [3].

III. DATA SETS

The work described in this paper was part of a larger research to improve the accuracy of sentiment analysis in the daily political news namely The Hindu [1] and NDTV [2]. We extracted only political news pertaining to 2018 Assembly Elections for two leading parties explicitly “TDP” and “Alliance” from 1st Dec 2018 to 31st March 2019. Front page, editorial page, op–ed page and nation pages were the focus of extraction.

The gold standard annotation guidelines suggested by Alexandra Balahur and Ralf Steinberger were modified and used to decide whether the target entity (politician) is being talked about in a positive or negative light. The text snippets with multiple sentiments (Positive and Negative) or neutral (Objective) bearing sentences were discarded. According to annotator 1, in the sample of 1503 political online news articles, 15275 subjective sentences whereas according to annotator II, 15231 were subjective and 17265 were objective sentences. We considered only those sentences which were tagged by both annotators to be subjective and the count was 15175. Among 15175 subjective sentences, according to annotator 1, 9,023 were positive and 6,152 were negative sentences whereas according to annotator 2, 9,107 were positive and 6,068 were negative sentences. Cohen‘s kappa coefficient (k) was used to measure the inter annotator agreement. The possible interpretation of Kappa for the annotator agreement implied almost perfect. Thus the built training political corpus contained 15175 sentiment (Positive or Negative) bearing sentences. The obtained political news corpus was then annotated with a general principle to consider minimal span of a negation covering only the portion of the text being negated semantically and according to the following instructions:

Words of Negation
Words like “never”, “no”, or “not” in its various forms are not included in negation scope. For example, in the sentence, “It was not XYZ”, only “XYZ” is annotated as the negation span.

Noun phrases
Typically entire noun phrases are annotated as within the scope of negation if a noun within the phrase has to be negated. For example, in the sentence, “The consequence of the act was not due to YSRCP” the string “due to YSRCP” is annotated. This is also true for more complex noun phrases, e.g., “People did not expect Chandrababu Naidu to act in such a way” should be annotated with the span “expect Chandrababu Naidu to act in such a way”.

Adjectives in noun phrases
If an adjective is to be negated, instead of negating the entire noun phrase, only the negation of each term is considered separately. For instance, “Not top-drawer political party, but still wins. “top drawer” is negated, but “political party” may not, since it is still party, just not “top-drawer”.

Adverbs/Adjective phrases
Case 1: Adverbial comparatives like “very,” “really,” “less,” “more”, etc., are annotated with the entire adjective phrase, e.g., “It was not very bad” should be annotated with the span “very bad”.

Case 2: If only the adverb is directly negated, then the adverb itself is annotated. e.g., “Not only was it great”, or “Not quite as great”: in both cases the subject still is “great”, so just "only" and "quite"

1 http://www.thehindu.com/opinion/

2 http://www.ndtv.com/article/list/opinion/

should be annotated, respectively. However, there are cases where the intended scope of adverbial negation is greater, e.g., the adverb phrase "just a small part" in "Jaganmohan Reddy was on stage for the entire speech. It was not just a small part".

Case 3: "as good as X". Try to identify the intended scope, but typically the entire phrase should be annotated, e.g., "It was not as good as I remember". Note that Case 2 and 3 can be intermixed, e.g., "Not quite as good as I remember", in this case 2 is followed and just the adverb "quite" is annotated, since it was still partly "as good as I remember", just not entirely.

Verb Phrases

If a verb is directly negated, annotate the entire verb phrase as negated, e.g., "appear to be fair" would be marked in "He did not appear to be fair". For the case of verbs (or adverbs), no special instructions are made on how to handle verbs that are content negators.

For example, for the sentence "I can"t deny it was good", the entire verb phrase "deny it was good" would be marked as the scope of "can"t". Ideally annotators would also mark the scope of the verb "deny", effectively canceling the scope of negation entirely over the adjective "good". As mentioned previously, there are a wide variety of verbs and adverbs that play such a role and recent studies have investigated methods for identifying them [7], [10]. The identification of the scope of such lexical items are left for future work.

One of the freely available resources for evaluating negation detection performance is the Bio-Scope corpus [3], which consists of annotated clinical radiology reports, biological full papers, and biological abstracts. Annotations in Bio-Scope consist of labeled negation and speculation cues along with the boundary of their associated text scopes. Each cue is associated with exactly one scope, and the cue itself is considered to be part of its own scope. Traditionally, negation detection systems have encountered difficulty in parsing the full papers subcorpus, which contains nine papers and a total of 2670 sentences, and so the BioScope full papers were held out as a benchmark for the methods presented here [3].

The news article corpus is different from BioScope in several ways. First, BioScope ignores direct adverb negation, such that neither the negation cue nor the negation scope in the phrase, "not only," is annotated in BioScope. Second, BioScope annotations always include entire adjective phrases as negated, where our method distinguishes between the negation of adjectives and adjective targets. Third, BioScope includes negation cues within their negation scopes, whereas our corpus separates the two. Thus it was determined that the intended domain of application would likely contain language patterns that are significantly distinct from patterns common in the text of professional biomedical writings.

IV. EXTRACTING FEATURES

Bag-of-Words Features

Here each feature indicates the number of occurrences of a word in the document. The news for a given day is represented by a normalized unit length vector of counts, excluding common stop words and features that occur fewer than 20 times in our corpus [2].

Entity Features

As shown by Wiebe et al., it is important to know not only what is being said but about whom it is said [11]. The term "victorious" by itself is meaningless when discussing an election meaning comes from the subject. Similarly, the word "scandal" is bad for a candidate but good for the opponent. Subjects can often be determined by proximity. If the word "scandal" and "YSRCP" are mentioned in the same sentence, this is likely to be bad for "Vijayamma". A small set of entities relevant to the party can be defined priori to give context to features. For example, the entities "Sharmila," "Jaganmohan Reddy" and "Vijayamma" were known to be relevant before the assembly election. News is filtered for sentences that mention exactly one of these entities. Such sentences are likely about that entity, and the extracted features are conjunctions of the word and the entity. For example, the sentence "Vijayamma" is facing another scandal" produces the feature "Vijayamma-scandal" instead of just "scandal." Two, Context disambiguation comes at a high cost: about 69% of all sentences do not contain any predefined entities and about 8% contain more than one entity [1]. These likely relevant sentences are unfortunately discarded, although future work could reduce the number of discarded sentences using co reference resolution.

Dependency Features

While entity features are helpful they cannot process multiple entity sentences. These sentences may be the most helpful since they indicate entity interactions [2]. Consider the following three example sentences:

- Jaganmohan Reddy defeated Chandrababu Naidu in the debate.
- Chandrababu Naidu defeated Jaganmohan Reddy in the debate.
- Jaganmohan Reddy, the president of YSRCP, defeated Chandrababu Naidu in last night"s debate.

Obviously, the first two sentences have very different meanings for each candidate‟s campaign. However, representations considered so far do not differentiate between these sentences, nor would any heuristic using proximity to an entity. Three effective features rely on the proper identification of the subject and object of "defeated." Longer n-grams, which would be very sparse, would succeed for the first two sentences but not the third.

To capture these interactions, sentences were part of speech tagged, parsed with a dependency parser. The resulting parses encode dependencies for each sentence, where word relationships are expressed as parent-child links. The parse for the third sentence above indicates that "Jaganmohan Reddy" is the subject of "defeated," and "Chandrababu Naidu" is the object. Features are extracted from parse trees containing the pre-defined entities (as mentioned in subsection 4.2). Note that they capture events and not opinions.

V. IMPLEMENTATION

In the pre-processing stage, the data is cleaned to hold only what is essential for the analysis. Steps like tokenization, stop word removal, lemmatization and pos tagging were performed using NLTK and Stanford POS tagger.

Dictionary Tagging
POS tagged sentences were given as an input to the Dictionary tagger. Dictionary tagger then tags each token of every sentence with tags like positive, negative, negation (inv). SentiWordNet values were taken to tag the tokens.

Negation Scope Determination
The scope of negation detection is limited to explicit rather than implied negations within a single sentence. A lexicon of negations was created to identify the presence of negation in the sentence. Using a statistics driven approach, Klima et al. was the first to identify negation words by analyzing word co-occurrence with n-grams that are cues for the presence of negation [12]. Klima‟s lexicon served as a starting point for the present work and was further refined through the manual inclusion of selected negation cues from the corpus. The final list of cues used for the evaluation is presented in Table 1.

Table 1: Lexicon of explicit negations

uninspired	despair	doubt	nothing
hardly	lack	neither	nor
never	no	nobody	none
damage	ditch	not	n't
cannot	without	bad	evil
fail	damage	nowhere	misunderstand

The above list of lexicon serves as a reliable signal to detect the presence of explicit negations. It does not provide any means of inferring the scope of negation. To detect the scope of negation in the sentence three different approaches were implemented. The first was the Fixed Window Length (FWL) approach in which we considered a fixed length of 4 words followed by a negation keyword. Every word in a sentence was tagged as positive, negative or negation by the dictionary tagger as discussed in subsection 5.1. If the tagged sentence contains negation, then a counter was started, equal to the window size to reverse the polarity of the tokens next to negation till the size is attained and then the resultant was added to the score value.

Algorithm for Polarity Calculation
For a sentence score
If the negation tag is identified in a sentence Return {reverse the value for four consecutive scores from negation tag and then add the total scores in the sentence}
Else
Return {sum of all scores in the sentence}

The second approach was Dependency Analysis (DA). Only unigram features were employed, but each unigram feature vector is expanded to include bigram and trigram representations derived from the current token in conjunction with the prior and subsequent tokens. The distance measures can be explained as follows. Token-wise distance is simply the number of tokens from one token to another, in the order they appear in a sentence. Dependency distance was more involved, and was calculated as the minimum number of edges that must be traversed in a dependency tree to move from one node (or token) to another. Each edge was considered to be bidirectional. The number 0 implies that a token was, or was part of, an explicit negation cue. The numbers 1-4 encode step-wise distance from a negation cue, and the number 5 was used to jointly encode the concept as "not applicable". To get the parse tree of the sentences, the Stanford parser was used. The reason for that was 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 output of which was given to the nltk parse function to get the Tree object of nltk, so that traversing through the parse tree was made possible. Having determined the scope of negation cues, the sentiment scores associated with the words in the negation keywords scope can be inverted. To this end, we introduce unigram sentiment modifiers, which are initialized at a value of 1, indicating that the sentiment score retrieved from the sentiment lexicon is considered to be the true sentiment score associated with that word in the considered context. In case a word is negated, the sentiment modifier may be multiplied with an inversion factor. Initially, we assume this factor to be equal to −1. Finally, when all word scores have been determined while accounting for negation, sentences can be classified as either positive or negative. To this end, we use a sentence scoring function. If the sum of word level sentiment scores in a sentence produces a number smaller than 0, the sentence is classified as negative, else, the sentence is classified as a positive sentence. Those sentences whose score is 0 have been ignored as only two class problem are considered.

Algorithm for Polarity Calculation
For a sentence score
If the negation word is identified in the sentence Return {reverse the polarities of its parent nodes and then add the total scores in the sentence} Else
Return {sum of all scores in the sentence}

The third approach was proposed as Negation Sentiment Analyzer (NSA). It used general resources like dependency parser, SentiWordNet [13] and WordNet [12] to extract the sentiment oriented words from each sentence. The Polarity Calculator calculates the polarity of a sentence and assigns a score. In order to calculate polarity, it uses SentiWordNet [13] to identify the positive and negative words and their values assigned by the SentiWordNet [13] and collect the synonyms of a word from WordNet [12] if it was not found in SentiWordNet [13].

We observed that most negation words in the corpus were classified as adverbs, suffix, prefix or verbs. However, the nouns are generally there to determine the meaning of another noun. To identify the scope of negation again dependency parser was used which indicated how negation was interacting with other words in the sentence.

In case of a clause or phrase, the noun phrase/ clause was first calculated for the sentiment polarity before the verb phrase/ clause. The extracted value from the SentiWordNet was reversed during this process if negation was identified.

Algorithm for Polarity Calculation
For Each noun Phrase of Sentence {get SentiWordNet value of all Adjectives and Nouns of noun-phrase
If (Sentence is marked NEGATION by the Parser) {Reverse the SentiWordNet values of related Nouns/Adjectives }
For Each verb Phrase of Sentence {get SentiWordNet value of all Adverbs and Verbs of verb-phrase
If (Sentence is marked NEGATION by the Parser) {Reverse the SentiWordNet values of related Verbs/Adverbs}
Return {sum of all scores in the 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 [13].

VI. RESULTS

The evaluation metric for three different methodologies was calculated separately for both the parties. The results are as shown below:

Table 2: Results to detect comparison of negation between two existing and one proposed methods.

Metric	YSRCP			Alliance		
	FWL	DA	NSA	FWL	DA	NSA
Recall	0.59	0.68	0.72	0.65	0.72	0.77
Precision	0.53	0.61	0.69	0.59	0.69	0.79
F-Measure	0.61	0.66	0.72	0.62	0.71	0.78

As the NSA methodology was outperforming when compared to FWL and DA, the results of NSA on combined news articles (both TRS and Alliance) was further compared against Bioscope biological full paper corpora. Subsequently, the results of negation scope detection for both the Corpus are as given below.

Table 3: Results of comparison for negation scope detection by the proposed method with the benchmark.

Corpus	Precision	Recall	F-Measure
News articles	0.712	0.724	0.732
BioScope	0.733	0.741	0.753

VII. CONCLUSION

We study the concept of scope of negation (t) identification which is precisely the sequence of words affected by t. Three sets of experiments were performed to compare NSA method against other two existing methods. Experimental results show that NSA method outperforms other methods. Further the proposed approach was validated on Bioscope biological full paper corpora.

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