Sentence Level Sentiment Analysis in the Presence of Conjuncts Using Linguistic Analysis

Arun Meena and T.V. Prabhakar

Department of Computer Science and Engineering,
Indian Institute of Technology, Kanpur
208016 Kanpur, UP, India
{arunm, tvp}@iitk.ac.in

Abstract. In this paper we present an approach to extract sentiments associated with a phrase or sentence. Sentiment analysis has been attempted mostly for documents typically a review or a news item. Conjunctions have a substantial impact on the overall sentiment of a sentence, so here we present how atomic sentiments of individual phrases combine together in the presence of conjuncts to decide the overall sentiment of a sentence. We used word dependencies and dependency trees to analyze the sentence constructs and were able to get results close to 80%. We have also analyzed the effect of WordNet on the accuracy of the results over General Inquirer.

Keywords: Sentiment analysis, favorability analysis, text mining, information extraction, semantic orientation, text classification.

1 Introduction

In recent years, there has been a rapid growth of web-content, especially on-line discussion groups, review sites and blogs. These are highly personal and typically express opinions. To organize this information, automatic text categorization and identification of sentiment polarity is very useful. Most work done in this field has been focused on topic based categorization, which is sorting the documents according to their subject content.

Sentiment classification is a special case of text categorization problem, where the classification is done on the basis of attitude expressed by the authors. Sentiment analysis requires a deep understanding of the document under analysis because the concern here is how the sentiment is being communicated. Previous attempts in solving this problem, for example [2], [4] focused on the use of machine learning methods (N-gram, etc.), ignoring the importance of language analysis which is being used to communicate sentiments. Therefore, we need to find new methods to improve the sentiment classification exploring the linguistic techniques.

Our work differs from earlier work in four main aspects: (1) our focus is not on classifying each review as a whole but on classifying each sentence in a review. (2) We give more consideration/importance to the language properties of the sentence and in understanding the sentence constructs, for each sentence we recognize the subjects of the feeling and the feature being described. (3) We concentrate on the effects of conjunctions and sentence constructions which have not been researched for

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sentiment analysis. (4) Our method does not need a training set since it depends on linguistic analysis.

2 Previous Work

The cornerstone on sentiment analysis is Pang and Lee's 2002 paper [2]. The authors of that paper compare Naive Bayes, Maximum Entropy, and Support Vector Machine approaches to classify sentiment of movie reviews. They explain the relatively poor performance of the methods as a result of sentiment analysis requiring a deeper understanding of the document under analysis. Document level sentiment classification assumes the whole document to have a single overall sentiment [1], [9], [11], [15].

In [14] the authors assigned sentiment to words, but they relied on quantitative information such as the frequencies of word associations or statistical predictions of favorability. A number of researchers have also explored learning words and phrases with prior positive or negative polarity (another term is semantic orientation) [1], [10]. Although we use a similar technique we don't limit ourselves to any limited word list, instead we use WordNet to find the semantic orientation of the words which are not found in the General Inquirer word list.

An approach similar to ours is taken by Matsumoto, et al. in [3]. The authors of that paper recognize that word order and syntactic relations between words are extremely important in the area of sentiment classification, and therefore it is imperative that they are not discarded. They construct a dependency tree for each sentence and then prune them to create subtree for classification.

Our work is most close to this work but still has a great deal of difference as we are not training on the trees - we use POS-tagging and dependency trees to analyze the sentence constructs. We analyze the effects of conjunctions in detail on the overall semantic orientation of the sentence. Our analysis is not confined to adjectives and verbs as we have also dealt with nouns, adverbs, conjunctions and prepositions which act as feeling words or affect the sentiment of the phrase.

3 Sentiment Analysis

The essential issue in sentiment analysis is to identify how sentiments are expressed in texts and whether the expressions indicate positive (favorable) or negative (unfavorable) opinions towards the subject. Thus, sentiment analysis involves identification of sentiment expressions, polarity and strength of the expressions and their relationship to the subject.

Often times, two words that are syntactically linked in a sentence are separated by several words. In these cases, small N valued N-gram models would fail at extracting a correlation between the two words, but we have used typed dependencies and dependency tree to deal with Non-Local Dependency Problem.

Another problem is The Word Sense Disambiguation Problem, consider two sentences ***I love this story***, ***this is a love story,*** the first sentence is communicating positive sentiment, whereas the second sentence is an objective statement with neutral sentiment**.** By looking at the typed dependencies of the words *(love, story)* in the first sentence, one can identify that they have a direct object relation {***dobj(love-2, story-4)***} which identifies it as a sentence with a sentiment, while in the second sentence {***nn(story-5, love-4)***} *love* just acts as an noun modifier to the word *story*, stating that the story is a love story identifying it as an objective sentence.

Role of Conjunctions: A conjunction is a word that links words, phrases, or clauses, and it may be used to indicate the relationship between the ideas expressed in a clause and the ideas expressed in rest of the sentence. They play a vital role in deciding the overall polarity of a sentence. They often change the sentiment into the opposite orientation or add in the strength of the sentiment.

For example, The Pacifica is exceptionally quiet most of the time, but it suffers some engine blare under hard acceleration. If we only consider the word exceptionally, we will mistake the sentiment for positive. However, the word but in the sentence changes its sentiment orientation, actually it is negative. The difficulty with conjunctions is that they can occur almost anywhere in the structure of a sentence and therefore demands a thorough analysis of the sentence construct as we need to find the main clause in a sentence in order to decide the sentence level polarity.

4 Sentiment Classification (Evaluation)

Step1 does the POS-tagging, generates the dependency tree and gives the typed dependencies of the words, for this the *"Stanford Lex-Parser"* [7] is used. We then select the feeling words (a feeling word is anchored by some substantive meaning and describes an author's attitude towards the subject). In Step 2 and 3, we determine the presence of a conjunction and if present we identify all the individual phrases containing sentiments. Step 4 calculates the polarity of individual phrases using the default polarity calculation method with the help of the general inquire word list [13] or WordNet to get the semantic orientation of the words.

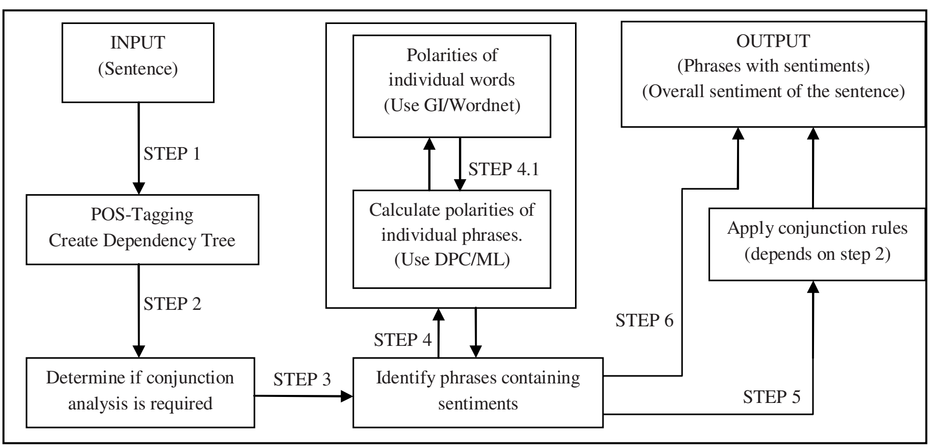

Fig. 1. Steps in the process of sentiment classification using our system

If a conjunction is found, Step 5 applies a rule (which we created with a very comprehensive list of conjunctions) to the sentence depending upon the type of conjuncts. The rules help in deciding the main clause of the sentence, i.e. the phrase that will decide the overall polarity of the sentence. If no conjunction is found, then the default method for finding the polarity of sentiment expression is used. Finally, in Step 6 the total polarity of the sentence is decided.

4.1 Conjunction Analysis

Full syntactic parsing plays an important role to extract sentiments correctly, because the local structures obtained by a shallow parser are not always reliable [8]. We start by passing the current sentence to the lex-parser, the output of the lex-parser is the dependency tree with POS tagging and the typed dependencies of the words.

Example: Following example explains the process of sentiment classification with the help of dependency tree and the typed dependencies of the words in a sentence. The tagset used is the penn-tagset, where JJ=adjective, NN=noun, VP=verb phrase etc.

Example 1. Supergirl is definitely a terrific DVD package, but a very lousy movie

```
(ROOT
 (S
  (NP (NNP Supergirl))
  (VP (VBZ is)
   (ADVP (RB definitely))
   (NP
    (NP (DT a) (JJ terrific)
     (NNP DVD) (NN package))
    (, ,)
    (CC but)
    (NP (DT a) (RB very) (JJ lousy)
     (NN movie))))
  (. .)))
```

```
nsubj(package-7, Supergirl-1)
cop(package-7, is-2)
advmod(package-7, definitely-3)
det(package-7, a-4)
amod(package-7, terrific-5)
nn(package-7, DVD-6)
det(movie-13, a-10)
advmod(movie-13, very-11)
amod(movie-13, lousy-12)
conj_but(package-7, movie-13)
```

In this example, if we just analyze the whole sentence with the default polarity calculator the result will be ***{+1 (terrific, package); -1 (lousy, movie)}***. (The word *lousy* is not present in the GI word list, so the semantic orientation of this word will be searched using the WordNet as described in the section 4.3). Therefore the total polarity of the sentence is ***{+1 -1 = 0} neutral***, but from the sentence it is clear that the author didn't like the movie so the orientation should be negative.

Now, as we have incorporated the effects of conjunction in the sentiment analysis, the analysis will be somewhat different. The individual polarities of both the phrases will be as above, but the two phrases are connected by a conjunction *but* joining *(terrific package, lousy movie*), which are *(NP, NP)*. Comparing the tags and the conjuncts with the rules from the rule file, it's clear that the second phrase is the main clause and therefore it will be used to decide the overall polarity of the sentence which is negative ***(-1)***.

4.2 Conjunction Rules

We have compiled rules to analyze the effects of more than 80 conjunctions (including all types of conjunctions) with 10 rules on average for each conjunction. A sample rule is given below:

Table 1. Rules for usage and effects of the conjunction *but*

```
<conjunction id="but" class="CC" subClass="ADVERSATIVE">
        <rule LC="NN" RC="NN" result="!RC" />
        <rule LC="JJ" RC="JJ" result="RC" />
        <rule LC="S" RC="S" result="RC" />
        ………………..
</conjunction>
```

The rule is for the conjunction *but*, it also shows the class and subclass of the conjunction. Each *rule* tag describes a rule for different conjuncts, according to the first rule if the left clause and right clause of the conjunction are NN; for example *everyone/NN but/CC John/NN is/VBZ present/JJ,* the polarity for the right NN will be opposite of the polarity of the left NN. Therefore, as the sentence is positive towards *everyone* so it is negative toward *John*, this is what the rule describes. Similarly we can conclude for other rules.

4.3 Default Polarity Calculation (DPC)

We start the polarity classification by identifying the Positive and Negative words using the General Inquirer (GI) [13]. While determining the orientation of a word, if a word is not found in the GI list, we search that word in the WordNet dictionary and all the synonyms are searched for semantic orientation in the GI word list (as synonyms generally have same semantic orientation) which helps us in determining the polarity of the word. While calculating polarity of a word we have also considered effects of ***negations*** (*good* is positive, while *not good* is negative) [12]. Further effects of words like *very, little, rather* etc. which intensifies or decreases the polarity of a word have been analyzed.

One problem with the method of counting positive and negative terms is that we may need to remove the suffix of a given term in order to see if it exists in our list of terms. To do this we are using the stemming algorithm of *“Stanford Lex-Parser”* [7].

4.4 Overall Sentiment Determination

Once we get the individual polarities of the phrases, we decide the polarity of the sentence as described earlier. The product review analysis is also possible with this Sentiment Analyzer; you can even provide specific subject or subjects to find the polarity.

Example 2. An example explaining how conjunctions change the whole sentiment of the sentence

[INPUT]
The notchy gear box was a worry and needed some time getting used to, but today with a three month old Aveo I can safely say it was no problem.

[OUTPUT]
Finding Polarity:
notchy: -1 {gear box}
worry: -1 {gear box}
Conjunction Found [and]: Current Polarity = -2
Conjunction Found [but]: Current Polarity= 0
problem: -1 (preceding *no* found) : +1 {gear box, worry}
Total Polarity: [-1 and 0 but +1]
and(-1, 0) = -1
but(-1, +1) = +1
Final Polarity: +1

Once each sentence in a given text is evaluated, combining sentence level ratings to a global score is still a tough problem.

Summarization of the results depends on the query type, i.e you may want to have all the phrases containing the sentiments or you may need the polarity of the entire sentence then the polarities of individual phrases will be combined together using conjunction analysis to find the overall sentiment of the sentence.

5 Experimental Results

Our experiments use car reviews as the dataset, compiled from different car review sites like http://www.motortrend.com, http://wardsautoworld.com, etc. The dataset contains more than 10,000 pre-labeled sentences, 5000 positive and 5000 negative.

We will first look at the results of the machine learning algorithms. There were more than 60% (40,000/64,000) sentences in the movies review dataset with one or more than one conjunction and as expected the results were very poor (less than 40%). It is clear from the results that the algorithm trained on the documents can't be used for the sentence level analysis; further the machine learning can't be efficiently used for sentences with conjunction(s).

Table 2. Results of learning algorithm (Naïve Bayes) in presence of one or more conjunctions

Tested on sentences with	Trained with No Conjuncts	Trained with Conjuncts
No Conjunction	70%	73%
Conjunction(s)		
1 Conjunction	51%	58%
More than 1 Conjunctions	40%	55%

Our system gave a poor result with the movie dataset i.e. just 39%, as the reviews were labeled at document level. There were many sentences with overall negative polarity in the positive reviews and vice-versa.

For the evaluations, we check whether the polarity of the sentiment is appropriately assigned to the given subject in each input in terms of the sentiment expression in the output, and calculated the precision and recall.

Table 3. Accuracy of the various classification algorithms considered in this paper

	Machine Learning	**DPC**		**Conjunction Analysis**	
		GI	GI with WordNet	GI	GI with WordNet
Sentences with No Conjuncts	72%	54%	66%	…	…
Sentences with Conjuncts	56%	39%	51%	62%	78%

6 Conclusions and Future Work

From Table 3, we can observe that use of WordNet substantially enhances the accuracy of the sentiment analysis. We can also see that conjunction analysis improves the sentiment classification by more than 25% and it is clear from the results that Machine learning algorithm is superior to DPC. Performing *base level* sentiment analysis using a learning algorithm and employing conjunct analysis for combing these phrase level sentiments to sentence level sentiments appears will result in better accuracy.

Our current system requires manual development of sentiment lexicons, and we need to modify and add sentiment terms for new domains, so automated generation of the sentiment lexicons in order to reduce human intervention in dictionary maintenance will also be our priority. This will improve precision and recall for new domains.

We believe that our major challenge is in the conjunction rules; we need to find a way of dealing with situations for which there is no rule specified. In addition we can implement named identity tagging for domain specific information and it should help remove objective sentences to a greater extent.

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