2014 International Conference on Advances in ICT for Emerging Regions (ICTer): 210 - 214

Enhanced Bag-of-Words Model for Phrase-Level Sentiment Analysis

Buddhika H. Kasthuriarachchy*†, Kasun De Zoysa*‡ and H.L. Premaratne*§
*University of Colombo School of Computing
Reid Avenue, Colombo 07, Sri Lanka
† buddhika.h@sliit.lk
‡kasun@ucsc.cmb.ac.lk
§hlp@ucsc.cmb.ac.lk

***Abstract*—We propose a novel rule-based model to incorporate contextual information and effect of negation that enhances the performance of sentiment classification performed using bag-of-words models. We employed morphological analysis in feature extraction to ensure feature vector contains only opinionated words in a textual review. Also it reduces the dimensionality of feature vector and, eventually improves the efficiency of the classification algorithm. Further, we consider grammatical relationships to incorporate the context of adjectives and scope of negations within a phrase, to the feature vector. This enables our model to capture contextual polarity of adjectives and impact of negation words. For the morphological analysis we mainly employ Part Of Speech taggers (POS taggers) and grammatical relationships which are obtained using typed dependency parsers. By using dependency-based rules, we relax the conditional independent assumption of bag-of-words models by way of combining adjectives and negations to identified target words and, hence obtain a sentiment classification accuracy that significantly better than baseline performance.**

***Keywords*—sentiment analysis, contextual polarity, bag-of-words**

I. Introduction

The opportunity to capture “what other people think” using social media data has raised increasing interest both in the scientific community and in the business world. However, it is a formidable task to capture opinions and emotions from ever-growing and unstructured textual data. Sentiment Analysis is a growing research area of Natural Language Processing which aims at identifying positive and negative opinions and emotions from a textual data. Presently, Sentiment Analysis research works range from document level classification [1] to sentence-level [2], phrase-level [3] or feature/aspect level analysis [4].

Much previous works on sentiment classification have focused on document-level sentiment classification, for example movie review classification by [5]. The bag-of-words models such as Naïve Bayes (NB), Support Vector Machine (SVM) and Maximum Entropy classifiers have been shown to work well in binary positive negative sentiment classification tasks on document-level datasets such as movie reviews [5]. Pang et al. found the SVM to be the most accurate classifier in [5]. However, Document-level sentiment classification incorrectly assumes that subject of all sentiment is same with the subject of a document. Similarly, even sentence level classification may suffer from the same due to sentences with mixed sentiment or multiple subjects. Since our research work is focused more towards context-aware sentiment classification, our interest mainly lies with phrase-level and aspect-level sentiment classification. Sentiment analysis at such a fine-grained level has proven very useful in tasks such as questions and answering systems and summarisation systems.

Wang and Manning in [6] have observed that simple NB and SVM variants outperform most published results on sentiment analysis datasets, sometimes providing a new state-of-art performance level. However, Application of Bag-of-Words model in a fine-grained level sentiment analysis leads to less accurate results mainly due to the absence of contextual-polarity and effect of negations. Contextual polarity aims to capture the sentiment of a term relative to the context. Also, As discussed in [7] effect of contextual information in sentiment analysis is vital. As an example, hotel reviews may contain “hot water”, which has a positive semantic orientation, whereas “hot room” has a negative orientation [8]. Thus contextual polarity plays a vital role in sentiment classification. Further, Negations terms in a sentence may reverse the sentiment of a certain word. For example consider the sentence “This movie is good” versus “This movie is not good”. In the first one good is a positive term and so this sentence is positive. When “not” is applied to the clause, “good” is being used in a negative context and so the sentence is negative [9].

The rest of the paper is organized as follows. In Section II we discuss the related work. Section III discusses the proposed method. Section IV present the experiment set-up and results. The experimental results are evaluated in Section V and Section VI concludes our work.

II. Related Work

Much work on sentiment analysis classifies documents by their overall sentiment, for example determining whether a review is positive or negative [10] [5] [1].

Phrase-level and aspect-level sentiment analysis has been of great interest from the past decade because of its practical utility. This involves extracting the aspects and the associated sentiments. Hu and Liu [11] formulated this problem and applied association mining to extract product features and used

978-1-4799-7732-1/14/$31.00 ©2014 IEEE

a seed set of adjective expanded using Wordnet synsets to identify the polarity of the sentiment words, but they do not make any attempts to relate the product features obtained into appropriate aspects.

Wu et. al [2] use phrase dependency parsing for opinion mining. In dependency grammar, structure is determined by the relation between a head and its dependents. The dependent is a modifier or complement and the head plays a more important role in determining the behaviours of the pair. The authors want to compromise between the information loss of the word level dependency in dependency parsing as it does not explicitly provide local structures and syntactic categories of phrases and the information gain in extracting long distance relations. Hence they extend the dependency tree node with phrases.

Hu et. al [3] used frequent item sets to extract the most relevant features from a domain and pruned it to obtain a subset of features. They extract the nearby adjectives to a feature as an opinion word regarding that feature. Using a seed set of labeled Adjectives, which they manually develop for each domain, they further expand it using WordNet and use them to classify the extracted opinion words as positive or negative.

Wilson et al. [3] evaluate sentence and discourse-based valence shifters. They examine 28 syntactical and linguistic features in a machine learning approach and use these features to train four different algorithms. Larger corpora yield significantly better results than the baseline.

The method proposed in [2] improves the sentiment classification of on-line customer reviews on sentence level unlike the word level lexical feature based work, by focus on sentences, this also concentrate on contextual information.

III. Proposed Method

We propose a novel rule-based model to extract information and to incorporate contextual information that enhances the performance of sentiment classification performed using bag-of-words models. We employed morphological analysis in feature extraction to ensure feature vector contains only opinionated words in a textual review. Also it reduces the dimensionality of feature vector and, eventually improves the efficiency of the classification algorithm. Further, we consider grammatical relationships to incorporate the context of adjectives and scope of negations within a phrase, to the feature vector. This enables our model to capture contextual polarity of adjectives and impact of negation words. For the morphological analysis we mainly employ Part Of Speech taggers (POS taggers) and grammatical relationships which are obtained using typed dependency parsers. By using dependency-based rules, we relax the conditional independent assumption of bag-of-words models by way of combining adjectives and negations to identified target words and, hence obtain a sentiment classification accuracy that significantly better than baseline performance.

A. Information Extraction

Initially Parts Of Speech tagging (POS tagging) is performed on each phrase to extract nouns, verbs, adjectives and negation terms. Since, we are not interested in intensity level of the sentiment, intensifiers are omitted. Also, when extracting verbs, a copula or linking verb "be" and all form of that verb are excluded. This approach helps to reduce the dimensionality of the feature space without affecting the classification accuracy, since most of the excluded words have negligible effect on a sentiment orientation.

Let P be the textual phrase to be analysed. Since we generate candidate features as sequences of nouns, verbs, adjectives that appear in phrases, we need to tokenize P and have to attach part-of-speech information to each word. We have used the Stanford POS tagger [12] for this task. Let F be the set of words extracted. Also, we obtain the dependency tree for the POS tagged phrase using Stanford Typed Dependency parser [13]. Let D be the set of all dependency-rules generated by the parser. Use of dependency rules in identifying the scope of negation and context of adjectives is discussed below.

B. Scope of Negation

We investigate the problem of determining the polarity of sentiments when one or more occurrences of a negation term such as "not" appear in a sentence. We propose a rule-based approach to identify the scope of negations to incorporate the effect to target words. Negation may be local or involve longer distance dependencies. Thus, a non-trivial methodology is required to determine it.

Algorithm 3.1: Assign Negation Target($phrase$)

$$
\begin{array}{l}
Negated \leftarrow \{\} \\
R1 \leftarrow \{\text{"advmod"},\text{"amod"}\} \\
R2 \leftarrow \{\text{"conj\_and"},\text{"conj\_or"}\} \\
mods \leftarrow \{\text{"not"},\text{"very"}\} \\
N \leftarrow \text{all negation words in } phrase \\
D \leftarrow \text{all dependency rules of } phrase \\
\textbf{for each } neg \in N \\
\textbf{do} \left\{ \begin{array}{l}
\textbf{for each } depRule \in D \textbf{ and } rel \in \{\text{"neg"}\} \\
\textbf{do} \left\{ \begin{array}{l}
\textbf{if not } (x \xrightarrow{rel} w1 \textbf{ and } rel \in R1 \textbf{ and} \\
\qquad\qquad x \in mods) \\
\textbf{then} \left\{ \begin{array}{l}
Negated \cup (neg\_ + w2) \\
\textbf{for each } (w1 \xrightarrow{rel} w2 \in D \textbf{ and} \\
\qquad\qquad rel \in R2) \\
\quad \textbf{do } Negated \cup (neg\_ + w2)
\end{array} \right.
\end{array} \right.
\end{array} \right. \\
\textbf{return } (Negated)
\end{array}
$$

Initially all the occurrences of negation terms "not","n't" and "no" in a phrase P are extracted. Then, for each negation term ***neg***, we traverse through all the grammatical rules in D searching for $neg \xrightarrow{rel} x$, where the relationship ***rel*** is "neg". All target words x identified through such grammatical relationships are considered to be influenced by the scope of the negation. As an example, the phrase "but had no delph or cutlery" contains a negation word "no" and as shown in

Figure 1, relationship between "no" and "delph" is identified as described above.

```
cc(had-2, but-1)
root(ROOT-0, had-2)
neg(delph-4, no-3)
dobj(had-2, delph-4)
dobj(had-2, cutlery-6)
conj_or(delph-4, cutlery-6)
```

Fig. 1. Collapsed Typed Dependencies of the phrase "but had no delph or cutlery"

However, not all such target words are negated by the *neg*, due to the presence of adverbial modifier (advmod) or adjectival modifier (amod). As an example the phrase "The room is not only good" bears a positive sentiment despite having a "neg" relationship between "not" and "good" as in Figure 2. The word "good" is not negated by the negation term, due to the presence of amod "only". Thus, if there exists a grammatical relationship $y \xrightarrow{rel} x$, in which *rel* is *amod* or *advmod* and y is a word such as "only" or "very", such target words x, are not considered to be negated by the corresponding negation term.

Once the target terms affected by the negation are identified, such words are prefixed with *neg* term followed by a "_".

Further, we considered the conjunct relations "and" (conj_and) and "or" (conj_or) to propagate the effect of negations, since such conjunctions expand the scope of the negations. As shown in Figure 1, we identify the effect of negation on "cutlery" through $delph\text{-}4 \xrightarrow{conj\_or} cutlery\text{-}6$.

```
nsubj(good-5, room-1)
cop(good-5, is-2)
neg(good-5, not-3)
advmod(good-5, only-4)
root(ROOT-0, good-5)
```

Fig. 2. Collapsed Typed Dependencies of the phrase "room is not only good"

The process outlined in Algorithm 3.1 was employed to incorporate scope of negation to the feature vector.

C. Contextual Polarity

Adjectives in a given phrase play a vital role in sentiment classification. However, polarity of an adjective highly depends on the domain as well as context. Also, a naïve method, like extracting the Nouns closest to the adjective, does not work so well when the sentence has multiple aspects and distributed emotions.

Algorithm 3.2: ASSIGN ADJECTIVE CONTEXT($phrase$)

$ContextUnits \leftarrow \{\}$
$R1 \leftarrow \{\text{"nsubj"}\}$
$R2 \leftarrow \{\text{"ccomp"},\text{"acomp"}\}$
$R3 \leftarrow \{\text{"conj\_or"},\text{"conj\_and"}\}$
$contexts \leftarrow \{\}$
$D \leftarrow$ all dependency rules of $phrase$
for each $adj \in phrase$

$$\textbf{do} \begin{cases} \textbf{for each } adj \xrightarrow{rel} x \in D \textbf{ and } rel \in R1 \\ \quad \textbf{do } ContextUnits \cup (adj\_ + x); contexts \cup x \\ \textbf{for each } x \xrightarrow{rel} adj \in D \textbf{ and } x \in R2 \\ \quad \textbf{do } ContextUnits \cup (adj\_ + x); contexts \cup x \\ \textbf{for each } c \in contexts \\ \quad \textbf{do} \begin{cases} \textbf{for each } (c \xrightarrow{rel} w2 \in D \textbf{ and } rel \in R3) \\ \quad \textbf{do } ContextUnits \cup (negWord\_ + w2) \end{cases} \end{cases}$$

return $(ContextUnits)$

In our model, insight of contextual polarity is added by considering adjectival complement (acomp), clausal complement (ccomp) and nominal subject (nsubj) grammatical relationships generated using Stanford Dependency Parser. Hence, after the information extraction step, for each adjective *adj* in a phrase, we search for grammatical relationships $adj \xrightarrow{rel} y$, such that *rel* ∈ {"nsubj","acomp", "ccomp"} in D. Afterwards, each target word *y* is prefixed with the *adj* followed by a "_". Further, as in negation scope detection, the conjunct relations are considered to expand the context of the adjectives.

The process outlined in Algorithm 3.2 was employed to incorporate contextual polarity to the feature vector.

IV. EXPERIMENTS

We used a data set that consists of 65 hotel reviews from TripAdvisor.com created by [14]. Data set contains 1541 elementary discourse units (EDUs), which were created by segmenting all sentences using SLESG software package[1]. Afterwards, all individual EDUs were manually annotated by 9 annotators with the sentiment negative, positive or neutral. Since all the sentences were segmented, our data set consists of phrases that can be used for evaluating our phrase-level sentiment analysis model. However, since we are not interested in analyzing the subjectivity of phrases, we have only considered negative and positive phrases. Thus, our data set contains 1125 phrases with 548 negative phrases and 577 positive phrases.

Initially, all the phrases were tokenized into words using Stanford Word Tokenizer and standard Naïve Bayes algorithm was applied considering each word as a feature. Also, Naïve Bayes algorithm was applied after removing stop words and considering each word as a feature. Further, in both the occasions above bi-gram approach has also been considered. Accuracy of these approaches is considered as the baseline for phrase-level sentiment analysis and accuracy of our model is compared against the baseline.

[1]http://www.sfu.ca/ mtaboada/research/SLSeg.html

TABLE I
CLASSIFICATION ACCURACY

Method	n-gram	Accuracy	Positive		Negative	
			Precision	Recall	Precision	Recall
Standard Naïve Bayes	uni-gram	0.65	0.73	0.72	0.5	0.5
	bi-gram	0.69	0.76	0.76	0.56	0.56
Naïve Bayes + Negation Scope	uni-gram	0.75	0.71	0.88	0.83	0.63
	bi-gram	0.74	0.70	0.85	0.80	0.62
Naïve Bayes + Negation Scope + Contextual Polarity	uni-gram	**0.78**	0.73	0.9	0.86	0.65
	bi-gram	**0.81**	0.74	0.9	0.88	0.68

In the proposed model, phrases are tokenized and POS tagged using Stanford Tokenizer and Stanford POS tagger. Then, the information extraction is performed based on POS tags. Next, we incorporated only the effect of negation to the feature set of bag-of-words model. Afterwards, Naïve Bayes algorithm was applied considering the modified feature set. Accuracy was evaluated considering both uni-gram and bi-gram approaches. Finally, we applied our full model incorporating effect of negation together with context of adjectives to the words extracted based on POS tags. Also, Naïve Bayes algorithm was applied on the enhanced feature set considering both uni-grams and bi-grams.

Even though, we have discussed only the Naïve Bayes algorithm in this paper, we have employed SVM algorithm as well. However, as pointed out in [6], accuracy of Naïve Bayes algorithm outperforms SVM in short snippet sentiment tasks. Moreover, we observed the same results with our phrase-level data set as well. Nevertheless, even SVM algorithm behaved similar to Naïve Bayes, showing an improved accuracy with our enhanced bag-of-words model, but in a lower accuracy range compared to Naïve Bayes.

Results of above experiments are summarised in Table I. Further, we have evaluated the performance of our model in terms of precision and recall in positive and negative classes separately.

V. Evaluation & Discussion

Results confirm that standard bag-of-words model does not capture the effect of negation and the contextual polarity efficiently. Incorporating effect of negation to the bag-of-words features, improved the classification accuracy by 10%. Further, incorporating context of adjectives together with effect of negation to the features of the bag-of-words model proved to be highly efficient with an increased classification accuracy of 78%. Bi-gram model has been shown to extremely effective, since it captures more contextual meaning by considering the neighbouring words of a given phrase, resulting a classification accuracy of 79%.

We have observed the precision and recall for each sentiment category separately, since the effect of our proposed method has a significantly different impact on the negative and positive class as shown in Table I. Although, the proposed method increases the precision and recall of both the classes, we could observe a significantly higher improvement of precision and recall in negative class. This is a clear indication of the effectiveness of incorporating effect of negation to the feature vector.

However, some of the phrases as do not directly contain enough information to decide the polarity, especially due to the absence of anaphora resolution, tend to produce inaccurate classifications as listed in Table II. Local information is not sufficiently informative to decide the polarity of the phrases. Accuracy of our model could be further improved by incorporating anaphora resolution.

TABLE II
PHRASES WITH INSUFFICIENT LOCAL INFORMATION

Phrase	Actual Class	Predicted Class
"but it is hot"	Neg	Pos
"and small in size"	Neg	Pos

VI. Conclusion and Future Work

The model described in this paper proposes a method to recognize sentiment at the phrase level. The system first performs morphological processing and then applies rules to incorporate contextual polarity and effect of negation to the features of the bag-of-words model in order to perform phrase-level sentiment classification. Incorporating only the effect of negations to the feature vector significantly improved the classification accuracy. Also, the importance of contextual information in sentiment analysis is clearly visible

Moreover, experimental results show that our method obtains a sentiment classification accuracy that significantly better than baseline performance. Further, the efficiency of the algorithm improves over standard Naïve Bayes algorithm, due to the dimensionality reduction of feature vector.

Future research will focus on enhancing the proposed method further by incorporating anaphora resolution to phrases in order to have sufficient local information to determine the polarity. Further, we believe that role of adverbial modifiers or adjectival modifiers should be studied thoroughly to identify their effect on sentiment classification tasks. Moreover, we focus on applying the presented method to more fine-grained sentiment classification tasks such as aspect/feature level sentiment classification.

References

[1] B. Pang and L. Lee, "A sentimental education: sentiment analysis using subjectivity summarization based on minimum cuts," in *Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics*, Barcelona, Spain, 2004.

[2] A. khan, B. Baharudin, and K. khan, "Sentence based sentiment classification from online customer reviews," in *Proceedings of the 8th International Conference on Frontiers of Information Technology*, ser. FIT '10. New York, NY, USA: ACM, 2010, pp. 25:1–25:6.

[3] T. Wilson, J. Wiebe, and P. Hoffmann, "Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis," *Comput. Linguist.*, vol. 35, no. 3, pp. 399–433, Sep. 2009.

[4] H. Zhang, Z. Yu, M. Xu, and Y. Shi, "Feature-level sentiment analysis for chinese product reviews," in *3rd International Conference on Computer Research and Development (ICCRD)*, vol. 2, Shanghai, China, March 2011, pp. 135–140.

[5] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs up ? sentiment classification using machine learning techniques," in *Proceedings of the ACL-02 conference on Empirical methods in natural language processing - Volume 10*, Philadelphia, PA, USA, 2002, pp. 79–86.

[6] S. Wang and C. D. Manning, "Baselines and bigrams: Simple, good sentiment and topic classification," in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers - Volume 2*, ser. ACL '12. Stroudsburg, PA, USA: Association for Computational Linguistics, 2012, pp. 90–94.

[7] B. Kasthuriarachchy, K. De Zoysa, and H. Premaratne, "A review of domain adaptation for opinion detection and sentiment classification," in *Proceedings of the International Conference on Advances in ICT for Emerging Regions (ICTer), 2012*, Dec 2012, pp. 209–213.

[8] A. M. Popescu and O. Etzioni, "Extracting product features and opinions from reviews," in *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing (HLT '05)*, Vancouver, 2005, pp. 339–346.

[9] L. Polanyi and A. Zaenen, *Computing Attitude and Affect in Text: Theory and Applications*, ser. The Information Retrieval Series. Springer Netherlands, 2006, vol. 20, pp. 1–10.

[10] P. D. Turney, "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews," in *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, Philadelphia, Pennsylvania, 2002, pp. 417–424.

[11] M. Hu and B. Liu, "Mining and summarizing customer reviews," in *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, Seattle, WA, USA, 2004, pp. 168–177.

[12] K. Toutanova, D. Klein, C. D. Manning, and Y. Singer, "Feature-rich part-of-speech tagging with a cyclic dependency network," in *Proceedings of the 2003 Conference of the North American Chapter of the Association for Computational Linguistics on Human Language Technology - Volume 1*, ser. NAACL '03. Stroudsburg, PA, USA: Association for Computational Linguistics, 2003, pp. 173–180.

[13] M.-C. de Marneffe, B. MacCartney, and C. D. Manning, "Generating Typed Dependency Parses from Phrase Structure Parses," in *Proceedings of the IEEE / ACL 2006 Workshop on Spoken Language Technology*. The Stanford Natural Language Processing Group, 2006.

[14] A. Lazaridou, I. Titov, and C. Sporleder, "A bayesian model for joint unsupervised induction of sentiment, aspect and discourse representations," in *Proceedings of the The 51st Annual Meeting of the Association for Computational Linguistics (ACL 2013)*, Sofia, Bulgaria, 2013, pp. 1630–1639.