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Polarity Shift Handling Techniques: A Survey

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ABSTRACT

This paper presents a survey on sentiment analysis with respect to the polarity shifting problem. Sentiment Analysis is one of the most widely researched applications of Natural Language Processing. The opinions mostly expressed in social networking sites can be harnessed through automated methods using sentiment analysis. Polarity classification is the most classical sentiment analysis task which aims at classifying reviews into either positive, negative or neutral. Polarity shifting is a challenge to sentiment classification and is considered as one of the main reasons why the standard machine learning algorithms make inaccurate predictions. In this paper various techniques to handle the polarity shift problem are explained. A comparitive study is done on these techniques and the classification performance of each technique is explained.

Keywords

Logistic Regression, Naive Bayes, Polarity Shift, Sentiment Classification, SVM

1. INTRODUCTION

Sentiment analysis or opinion mining refers to the application of natural language processing, computational linguistics and text analytics to identify and extract subjective information in source materials(Source:Wikipedia). Sentiment analysis can be performed at various levels [1]. They are

(1) Document level: As the name suggests document level sentiment analysis tags individual documents with their sentiments. The approach here is to find the sentiment polarities of individual sentences or words and combine them together to find the polarity of the document.
(2) Sentence or phrase level: Individual sentences are tagged with their respective sentiment polarities. The general approach is to find the sentiment polarity of each word and combine them to find the sentiment of the whole sentence.
(3) Aspect level: Aspect level sentiment analysis aims to classify sentiment with respect to the specific aspects of entities. The first step is to identify entities and their aspects. The opinion holder can give different opinion for different aspects of the same entity [2].

Sentiment analysis classification techniques are broadly divided into 3 categories. They are a) Machine learning b) Lexicon based approach and c) Hybrid approach. Machine learning explores the study and construction of algorithms that can learn from and make predictions on data(Source:Wikipedia). The lexicon based approach is based on the assumption that the contextual sentiment orientation is the sum of the sentiment orientation of each word or phrase. The hybrid approach is the combination of both the machine learning and the lexicon based approaches. It has the potential to improve the sentiment classification performance [3]. Many of these techniques use Bag-of-words(BOW) model for text representation.

Polarity shift is a linguistic phenomenon which can reverse the sentiment polarity of a given text. For eg by adding a word ”don't” to the sentence ”I like this movie” in front of the word ”like”, the sentiment polarity of the word completely changes from positive to negative. But these sentiment oppposite texts are considered to be pretty similar in the BOW model. This leads to many failures in standard machine learning algorithms.

Negation is the most important cause of polarity shift of a given sentence. Negation words include ”don't”, ”not”, ”never” etc. For eg consider the sentence ”This movie is not good”. The presence of negation words shifts the polarity of ”good” in the sentence. Negations can be implicit also using words like ”avoid”, ”hardly” etc.

Contrast transitions are another important factor. Words like ”but”, ”however”, ”unfortunately” etc when used in sentences like ”I liked the movie but terrible acting” polarity shifting is introduced. The contrast indicator shifts the polarity of the phrase preceeding it. While the above polarity shifts are easy to detetct there are some that are not so explicit.

Sentiment inconsistency in sentences like ”I don't like this movie. Great actor, awful scenario” where the first phrase ”I don't like this movie” expresses a negative sentiment toward the whole film, the second phrase ”great actor” shows a positive sentiment toward acting, and the third phrase ”awful scenario” expresses the negative sentiment toward the aspect of scenario [4].

Other less common yet productive polarity shifting types include Exception and Until. Exception structure is usually expressed by the trigger phrase ”the only” to indicate the one and only advantage of the product, e.g., in the sentence ”The only thing that I like about it is that bamboo is a renewable resource”. Until structure is often expressed by the trigger word ”until” to show the reversed polarity, e.g. in the sentence ”This unit was a great addition until the probe went bad after only a few months” [5].

Several approaches have been proposed to address the polarity shift problem but most of them require complex linguistic knowledge or extra human annotations. They have high dependance on lexical resources and makes the system difficult to be used in other domains and languages [6]. This paper describes various methods to handle polarity shift problem in sentiment analysis.

2. POLARITY SHIFT HANDLING TECHNIQUES

2.1 CP Approach

In this approach they create a corpus with prior and contextual polarity. They begin with a lexicon of words with established prior polarities and identify the "contextual polarity" of phrases based on some refined annotations [7].

2.2 Word-level Polarity Shifting Model

The presence of polarity shifters like negators cause the polarity of a word to be different from the polarity of the sentence. This model is a binary classification model which determines whether the polarity is shifted by its context. This method assigns a score to the sentiment word x in a sentence S. Capturing these polarity shifts will improve the classification performance of the majority voting classifier as well as of more sophisticated classifiers [8].

2.3 NC Approach

This approach uses negation and contrast transitions to help in sentence segmentation. Sentences are segmented using punctuations and manually collected keywords. These segmented sentences are then divided into sentiment reversed and sentiment non-reversed parts. Based on whether the sentence has a negation or contrast transition, the sentiment reversed sentences are identified using appropriate rules [9].

2.4 Plug-In Approach

This approach to dealing with specialised domains is based on the idea of "plug-in" lexical resources which can be applied on demand. The plug-in approach works by overriding the default polarity of lexical items with those assigned to the lexical items when they are used in specialized domains. Here candidate terms are extracted from specialised corpora to be matched against existing general language polarity database to obtain sentiment bearing words whose polarity is domain specific [10].

2.5 PSDEE

This approach uses polarity shift detection, elimination and ensemble method. In this technique polarity shift is first detetcted using hybrid method. Rule based polarity detection is used for negation and explicit contrasts and Statistical polarity shift detection for implicit contrasts. In the second phase, negations are eliminated eg. "I don't like this book" is converted to "I dislike this book". The idea is to use antonym words to replace the negated words. A corpus based antonym dictionary is used in the process.

In the third phase each document is split three component parts 1) the eliminated negation part 2) the contrast part 3) the sentiment inconsistency part. An ensemble model is used to train three component classifiers for sentiment classification based on the above mentioned parts of text [4].

2.6 PSDetector Approach

In this approach the documents are first fed to the Polarity shift detector to segregate the sentences as polarity-shifted and polarity-unshifted part. A feature selection method is adpoted to build a large scale training corpus of polarity shifting sentences. Given the polarity shifting training data SVM algorithm is used to train the polarity shift detector with word unigram features. After detection each document is divided into polarity shifted and unshited part [5].

2.7 Dual Sentiment Analysis

For each original review a sentiment reversed review is created. Text reversion and label reversion rules are followed to create the sentiment reversed review. The review thus created may not be grammatically accurate but the sentiment strength of the reversed review is maintained as much as the original review. This is done with the help of an antonym dictionary. The original training review and reversed training review are used in pairs to train the classifier and is called dual training. There is a one to one correspondance between the original and reversed review. Dual Prediction is done by considering two sides of the review before making a prediction [6, 11].

3. LITERATURE SURVEY

Wilson et al [7] studied the effects of complex polarity shift. They proposed a new approach to phrase-level sentiment analysis that first determines whether an expression is neutral or polar and then disambiguates the polarity of the polar expressions. They use the CP Approach to automatically identify the contextual polarity for a large subset of sentiment expressions, achieving results that are significantly better than baseline.

They use a two-step process that employs machine learning and a variety of features. The first step classifies each phrase containing a clue as neutral or polar. The second step takes all phrases marked in step one as polar and disambiguates their contextual polarity. This system assigns contextual polarity to individual expressions in a sentence and can be used to automatically identify the contextual polarity for a large subset of sentiment expressions.

Ikeda et al [8] propose a machine learning based method that models the polarity-shifters. The inconsistency of word-level polarity and sentence-level polarity often causes errors in classification by simple majority voting method. The Word-level Polarity Shifting model is used . This model can be trained in two different ways: word-wise and sentence-wise.

This model improves the accuracy of sentence classification compared with simpler methods and the improvement is more significant with limited amount of training data. This method can be easily combined with existing methods to show better performance. The feature generation method used in this paper does not generate optimal feature sets, which is planned to be improved by exploring dependency relations between words.

Li et al [9] proposed an approach to incorporate their classification information into sentiment classification system. Negation and contrast transition are two kinds of linguistic phenomena which are commonly used to reverse the sentiment polarity of some words and sentences. The sentiment reversed and sentiment non-reversed parts which are obtained using the NC approach are classified using two bag-of-words modeling. The three general strategies to do classification with two-bag-of-words modeling are:

(1) Remove sentiment reversed part.
(2) Tune parameters of sentiment reversed part according to the ones learnt from sentiment non reversed part.
(3) Simultaneously learn sentiment reversed and non reversed parts.

The sentiment-reversed sentences obtained by this approach sometimes may not be really sentiment reversed. This is due to some mistakes in sentence segmentation and reversed-sentiment detection. Meanwhile, some real sentiment-reversed sentences may not be recognized.

Moreno et al [10] propose a method to integrate domain specific sentiment analysis in a lexicon based system. The need to have seperate domain-specific lexicons in the plug-in approach is apparent from words like ”growth” which in medicine usually refers to a tumor and in general language is highly context-dependant. The procedure to identify relevant terms is:

(1) Check semantic orientation of each candidate term.
(2) Discard neutral terms.
(3) Match list of polarised terms against existing list.
(4) Discard terms whose polarity matches.
(5) Approve remaining terms.

Although this method is simple to implement and effective, it falls short as specialisation level increases since sentiment is lexicalized differently to some extent.

Xia et al [4] propose a three-stage cascade model to address the polarity shift problem in the context of document-level sentiment classification. In the PSDEE approach the base classifiers are trained using subsets divided by different types of polarity shifts, and use a weighted combination of the component classifiers for sentiment classification. Ensemble techniques, that combine the outputs of several base classification models to form an integrated output, increase classification accuracy with the trade-off of increasing computation time.

Li et al [5] propose a feature selection method to automatically generate the training data for a binary classifier on polarity shifting detection of sentences. Using the PSDetector approach, each document in the original polarity classification data is split into two partitions polarity-shifted and polarity-unshifted which are used to train two base classifiers.

Since this approach is language-independent, it is readily applicable to sentiment classification tasks in other languages. This approach improves the overall performance across different domains and training data sizes, although the automatically generated polarity shifting training data is prone to noise.

Xia et al [11] proposed the Dual sentiment analysis approach to solve the polarity shift problem. It follows the Dual Training, Dual Prediction stages as mentioned in this technique. This approach makes use of the well-defined lexicon such as Wordnet. The Wordnet dictionary is simple and direct. However in many languages other than english, such an antonym dictionary may not be readily available.

Xia et al [6] studied the polarity shift problem and proposed DSA to address the same. This approach is very effective for polarity classification and it significantly outperforms several alternative methods of considering polarity shift. Apart from dual training and dual prediction, selective data expansion used in this approach where only those reviews that have a sentiment degree metric that is above a threshold value are selected for data expansion. Thus only the most sentiment-distinct training reviews are selected for data expansion and hence yields better performance.

In this approach a pseudo antonym dictionary is used to create sentiment reversed reviews. This dictionary is language-independent and domain adaptive. The corpus-based pseudo-antonym dictionary is learnt using the labeled training data only. The basic idea is to first use mutual information (MI) to identify the most positive-relevant and the most negative-relevant features, rank them in two separate groups, and pair the features that have the same level of sentiment strength as pair of antonym words. This method however does not consider more complex polarity shift patterns such as transitional, subjunctive and sentiment-inconsistent sentences in creating reversed reviews.

Kennedy et al [12] proposed a method that examines three types of context valence shifters: negations, intensifiers and diminshers. While negations reverse the sentiment polarity of a particular term intensifiers and diminishers increase and decrease, respectively, the degree to which a term is positive or negative. As in the Word-level Polarity Shifting Model approach, in this approach , they compute corpus-based semantic orientation values of terms, using their association scores with a small group of positive and negative terms. They show that extending the term-counting method with contextual valence shifters improves the accuracy of the classification. The second method uses a machine learning algorithm like SVM. They combine these 2 methods to use a hybrid classification technique which achieves better results than either method alone.

4. COMPARISON OF POLARITY SHIFT HANDLING TECHNIQUES

In Section 2, we have described various shift handling techniques. Various approaches have different accuracy rates under different domains which are summarized in Table 1. The performance of sentiment classification can be evaluated using the following equations:

Accuracy = (TP+TN)/(TP+TN+FP+FN)
Precision = TP/(TP+FP)
Recall = TP/(TP+FN)
F1 = (2 $\times$ Precision $\times$ Recall)/(Precision+Recall)

where TP, FN, FP and TN refer respectively to the number of true positive instances, the number of false negative instances, the number of false positive instances and the number of true negative instances.

Dual Sentiment Analysis technique provides the highest accuracy of 89.8%. This technique uses a machine learning based approach which provides significantly higher classification accuracy than lexicon based approach like Word-level Polarity Shifting model which provides an accuracy of 84.0%. Though lexicon based approaches may not yield high classification performance, they are simpler to implement and cost effective. SVM is seen to be used more commonly than other classifiers, due to its good performance on text categorization and with the ability to generalize high dimensional feature space; SVM eliminates need of feature selection [13]. The hybrid approach of combining machine learning method with lexicon based method in order to improve the accuracy of sentiment classification is seen to improve classification performance.

Table 1. Comparative study of Polarity shift Handling Techniques.

Technique	Level	Domain	Methodology	Accuracy
Dual Sentiment Analysis [6]	Sentence level	Product reviews taken from Amazon.com	Evaluated against Baseline, DS, LSS and DSA-WN systems using SVM, Naive Bayes and Logistic Regression Classifier	89.8% using SVM
PSDEE [4]	Document level	Product reviews taken from Amazon.com	Evaluated against Baseline, DAS, REV and LSS using SVM, Naive Bayes and Logistic Regression Classifier	83.2% using Logistic Regression
Plug-in [10]	Sentence level	Financial domain	Context dependant polarity identified for specialised corpora	84.21%
NC Approach [9]	Sentence level	Movie and product reviews	SGD linear classifier	85.9%
CP Approach [7]	Phrase level	15,991 subjective expressions from 425 documents annotated with contextual polarity	28-feature classifier	75.9%
Word-level Polarity Shifting Mode [8]l	Sentence level	Customer and movie reviews	Evaluated against Baseline, BOW, Simple-Voting, Negation Voting, Word-wise, Sentence-wise	84.0%
PSDetector Approach [5]	Document level	Product reviews	All classifiers trained by SVM using SVM light tool with Logistic Regression method for probability measuring	84.9%
Hybrid Approach [12]	Sentence level	Product reviews	Combination of SVM and lexicon based method	86.2%

No technique or method alone can give complete efficiency since the performance depends on a number of factors.

5. CONCLUSION

In this paper the polarity shift problem in sentiment classification is analysed and the causes of polarity shift and the various techniques to solve them are studied. The techniques are used at all levels of sentiment analysis including document, sentence and phrase level. A comparative study of the techniques is explained with the evaluation metrics. Research results show that machine learning methods using classifiers such as SVM provide highest accuracy and can be regarded as the baseline learning methods, while lexicon based methods can be effective in cases which require less effort in human-labeled document. Future scope in this area includes efficient techniques to handle more complex polarity shift patterns such as transitional, subjunctive and sentiment-inconsistent sentences.

6. REFERENCES

[1] Vidisha M. Pradhan, Jay Vala, Prem Balani, A Survey on Sentiment Analysis Algorithms for Opinion Mining, *International Journal of Computer Applications* , 133,(2016).

[2] Sebastian Ruder, Parsa Ghaffari, John G. Breslin. Deep Learning for Multilingual Aspect-based Sentiment Analysis, *Proceedings of SemEval-2016*, (2016)330-336.

[3] Alessia DAndrea, Fernando Ferri, Patrizia Grifoni, Tiziana Guzzo, Approaches, Tools and Applications for Sentiment Analysis Implementation, *International Journal of Computer Applications* , 125,(2015).

[4] Rui Xia , Feng Xu , Jianfei Yu , Yong Qi and Erik Cambria, Polarity shift detection, elimination and ensemble: A three-stage model for document-level sentiment analysis, *Information Processing and Management*, 52,(2016)36-45.

[5] Shoushan Li, Sophia Yat Mei Lee, Ying Chen, Chu-Ren Huang, and Guodong Zhou. Sentiment Classification and Polar-

ity Shifting, *23rd International Conference on Computational Linguistics*, (2010)635-643.

[6] Rui Xia, Feng Xu, Chengqing Zong, Qianmu Li, Yong Qi, and Tao Li. Dual sentiment analysis: Considering two sides of one review, *IEEE Transactions on Knowledge and Data Engineering*, 27,(2015)2120-2133.

[7] T. Wilson, J. Wiebe, and P. Hoffmann, Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis, *Comput. Linguistics*, 35,(2009)399-433.

[8] Daisuke Ikeda, Hiroya Takamura,Lev-Arie Ratinov and Manabu Okumura, Learning to Shift the Polarity of Words for Sentiment Classification, *Transactions of the Japanese Society for Artificial Intelligence*, 25,(2010)50-57.

[9] S. Li and C. Huang, Sentiment classification considering negation and contrast transition, *in Proc. Pacific Asia Conf. Lang., Inf. Comput.*, (2009)307-316.

[10] Antonio Moreno-Ortiz and Javier Fernndez-Cruz, Identifying polarity in financial texts for sentiment analysis: a corpus-based approach, *7th International Conference on Corpus Linguistics*,198,(2015)330-338.

[11] Rui Xia, Tao Wang, Xuelei Hu, Shoushan Li and Chengqing Zong. Dual Training and Dual Prediction for Polarity Classification, *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics*, (2013)521-525.

[12] Alistair Kennedy and Diana Inkpen. Sentiment Classification of Movie Reviews Using Contextual Valence Shifters, *Computational Intelligence*, 22,(2006)110-125.

[13] Aamera Z. H. Khan, Dr. Mohammad Atique, Dr. V. M. Thakare. Sentiment Analysis Using Support Vector Machine, *International Journal of Advanced Research in Computer Science and Software Engineering*, 5,(2015).