Dual Sentiment Analysis: Considering Two Sides of One Review

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1 Introduction

Nowadays sentiment analysis, also known as opinion mining, has become one of the most important parts in the field of natural language processing and text mining. Generally traditional topic-based classification is used to classify sentiments with Bag-of-words (BOW) model. As BOW model is very simple, it often fails to handle polarity shift problem which leads to wrong sentiment classification. To handle this problem, a new framework named Dual Sentiment Analysis is introduced which works with the both positive and negative sides of a review.[2]

1.1 Sentiment Analysis

Sentiment Analysis is the process to identify and categorize opinions expressed as text computationally in order to determine whether the writer's attitude is positive, negative, or neutral towards a particular topic.[1]

1.2 Polarity Shift

Polarity shift is a kind of linguistic phenomenon which can reverse the sentiment polarity of the text. Negation is one of the most important types of polarity shift.[3]

1.3 Dual Sentiment Analysis

Dual sentiment analysis is a framework to address the polarity shift problem in sentiment classification. It contains two main stages:

1. Dual training
2. Dual prediction

1.3.1 Dual Training

The classifier is trained by maximizing a combination of the likelihoods of the original and reversed training samples. This process is called dual training.

1.3.2 Dual Prediction

For each test sample x, we create a reversed test sample $\tilde{x}$ using antonym corpus dictionary. Our aim is not to predict the class of $\tilde{x}$. Instead of this, we will use $\tilde{x}$ to assist the prediction of x. This process of prediction is called dual prediction.

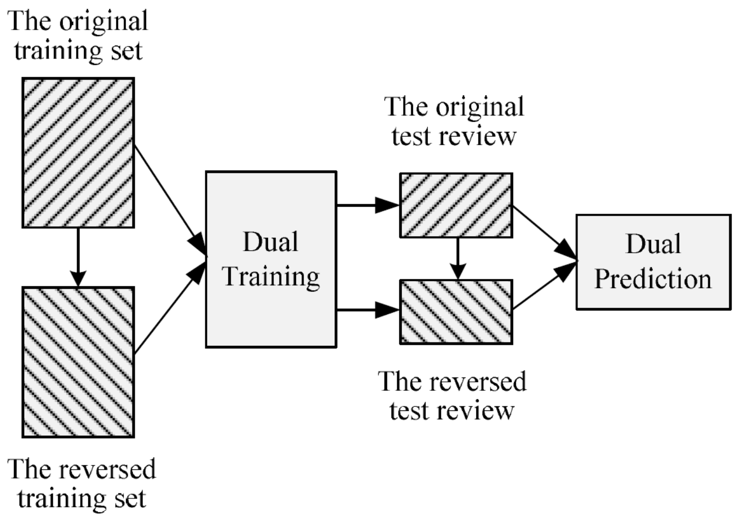

Figure 1: The process of dual sentiment analysis

2 Methodology

The following methods are taken into action for this Dual Sentiment Analysis experiment :

2.1 Data Expansion by Creating Reversed Reviews

Based on an antonym dictionary, for each original review, the reversed review is created according to the following rules:

2.1.1 Text Reversion

If there is a negation, we first detect the scope of negation. All sentiment words out of the negation scope are reversed to their antonyms. In the negation scope, negation words like "no", "not", "don't", etc. are removed, but the sentiment words are not reversed.

2.1.2 Label Reversion

For each of the training review, the class label is also reversed to its opposite like, positive to negative, or negative to positive, as the class label of the reversed review.

In Table 1, we have got an example of creating the reversed training reviews. An original training review given, such as "I don't like this food. It is tasteless. and Class is Negative", the reversed review is obtained by following three steps:

Table 1: Reversed Training Reviews

	Review Test	Class
Original Review	I **don't like** this food. It is **tasteless**.	Negative
Reversed Review	I **like** this food. It is **tasty**.	Positive

1) Sentiment word "tasteless" is replaced by its antonym "tasty";
2) Negation word "don't" is removed.
3) The class label is changed from Negative to Positive.

2.2 Dual Training

In the data expansion technique, there is a one-to-one correspondence between the original and reversed reviews. The classifier is trained by maximizing a combination of the likelihoods of the original and reversed training samples. This process is called dual training.

- If x_i is a positive training sample, the standard likelihood score with respect to x_i is log h(x_i). While in DT, the likelihood score becomes log$[h(x_i)(1 - h(\tilde{x}_i))]$. That is, the feature weights in DT are learnt by considering not only how likely is x_i to be positive, but also how likely is $\tilde{x}_i$ to be negative.

- If x_i is a negative training sample, the standard likelihood score with respect to x_i is log(1 - h(x_i)). While in DT, the likelihood becomes log$[(1 - h(x_i))h(\tilde{x}_i))]$. That is, the feature weights in DT are learnt by considering not only how likely is x_i to be negative, but also how likely is $\tilde{x}_i$ to be positive.

2.3 Dual Prediction

In the prediction stage, for each test sample x, we create a reversed test sample x̃. Our aim is not to predict the class of x̃. Instead of this, we use x̃ to assist the prediction of x. This process is called dual prediction.

- When we want to measure how positive a test review x is, we will consider how positive the original test review is (i.e., p$(+ \mid x)$, as well as consider how negative the reversed test review is (i.e., p$(- \mid \tilde{x})$);

- Conversely, when we measure how negative a test review x is, will consider how negative the original test review is (i.e., p$(- \mid x)$), as well as consider how positive the reversed test review is p$(+ \mid \tilde{x})$.

2.4 Prediction Score Calculation

p$(+ \mid x, \tilde{x}) = (1 - \alpha)\ .\ p_d$ p$(+ \mid \tilde{x}) + \alpha\ .\ p_d$ p$(- \mid \tilde{x})$
p$(- \mid x, \tilde{x}) = (1 - \alpha)\ .\ p_d$ p$(- \mid \tilde{x}) + \alpha\ .\ p_d$ p$(+ \mid \tilde{x})$
p$(* \mid x, \tilde{x}) = (1 - \alpha)\ .\ p_d$ p$(* \mid \tilde{x}) + \alpha\ .\ p_d$ p$(* \mid \tilde{x})$

where $\{+, -, *\}$ denote the class labels of positive, negative and neutral, respectively and α is a trade-off parameter ($0 \leq \alpha \leq 1$).
And we can guarantee that $p(+ \mid x, \tilde{x}) + p(- \mid x, \tilde{x}) + p(* \mid x, \tilde{x}) = 1$.

2.5 Positive-Negative-Neutral Classification

In dual prediction, when we measure how positive/negative a test review is, we not only consider how positive/negative the original review is, but also how negative/positive the reversed review is[2]. In addition to that, in 3-class sentiment classification, when we measure how neutral a test review is, we not only consider how neutral the original review is, but also how neutral the reversed review is.

2.6 Datasets and Experimental Settings

For polarity classification, four English datasets and two Chinese datasets are used. The Multi-Domain Sentiment Datasets are used as English datasets. These contain product reviews from Amazon.com including four different domain of products: DVD, Book, Kitchen and Electronics. Each of the reviews is rated by the customers from 1-Star to 5-Star. The reviews with 1-Star and 2-Star are labeled as Negative, and those with 4-Star and 5-Star are labeled as Positive.The reviews with 3-Star is labeled neutral. Each of the four English datasets contains 1,000 positive and 1,000 negative reviews. The Chinese datasets contain two domains extracted from the ChnSentiCorp corpus: Hotel and Notebook. Each of them contains 2,000 positive and 2,000 negative reviews.[2]

3 Result

For Polarity Classification, Linear SVM, Naive Bayes and Logistic Regression classifiers are used here. If we compare the average classifier accuracies,

Table 2: Average Acuuracies for Different Classifiers

Classifier	**Unigrams**		**Unigrams and Bigrams**	
	English	**Chinese**	**English**	**Chinese**
SVM	82.8%	89.8%	84.1%	90.7%
Naive Bayes	83.8%	89.4%	85.9%	90.5%
Logistic Regression	83.9%	90.1%	85.0%	90.8%

In case of Linear SVM classifier, for unigram features only, the accuracy measured for English and Chinese datasets are 82.8% and 89.8% respectively. But when we consider features of both unigrams and bigrams, accuracy measures increase to 84.1% and 90.7% for English and Chinese datasets respectively. That is, an improved measure of 1.3% and 0.9% respectively.

In case of Naive Bayes classifier, for unigram features only, the accuracy measured for English and Chinese datasets are 83.8% and 89.4% respectively. But when we consider features of both unigrams and bigrams, accuracy measures increase to 85.9% and 90.5%

for English and Chinese datasets respectively. That is, an improved measure of 2.1% and 1.1% respectively.

In case of Logistic Regression classifier, for unigram features only, the accuracy measured for English and Chinese datasets are 83.9% and 90.1% respectively. But when we consider features of both unigrams and bigrams, accuracy measures increase to 85.0% and 90.8% for English and Chinese datasets respectively. That is, an improved measure of 1.1% and 0.7% respectively.

4 Conclusion

In this article, a novel data expansion framework called Dual Sentiment Analysis is proposed to handle polarity shift problem in sentiment analysis. Again 3-class Dual Sentiment Analysis model is also introduced which can classify neutral sentiments along with negative and positive ones. And elimination of polarity shift problem helps to improve the machine learning classifiers' performances.[4] In this paper, mainly creating reversed reviews are focused to assist supervised classification. In case of unsupervised and semi-supervised classification term counting methods can be taken into consideration.[2]

References

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