Considering Two Sides of One Review Using Stanford NLP Framework

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Abstract— Sentiment analysis is a type of natural language processing for tracking the mood of the public about a particular product or a topic and is useful in several ways. Polarity shift is the most classical task which aims at classifying the reviews either positive or negative. But in many cases, in addition to the positive and negative reviews, there still many neutral reviews exist. However, the performance sometimes limited due to the fundamental deficiencies in handling the polarity shift problem. We propose an Improvised Dual Sentiment Analysis (IDSA) model to address this problem for sentiment classification. We first propose a novel data expansion technique by creating sentiment-reversed review for each training and test review. We develop a corpus based method to construct a pseudo-antonym dictionary. It removes DSA's dependency on an external antonym dictionary for review reversion. We conduct a range of experiments and the results demonstrates the effectiveness of DSA in addressing the polarity shift in sentiment classification. .

Keywords- *machine learning, sentiment analysis, natural language processing, opinion mining*

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I.   INTRODUCTION

Sentiment Analysis is an area of focus over last decade. Increase in user-generated content provide an important aspect for the researchers, industries and government to mine this information and is truly differentiating and valuable to today's corporations. The user-generated content is an important source for various organizations to know/learn/identify the general expression/sentiment of different users on the product. The Social Web has changed the ways people communicate, collaborate, and express their opinions. The potential for the sharing of opinions today is unmatched in history. So many knowledgeable people been connected by such a time and cost efficient and effective network. Due to the vast growth and emergence of the consumer generated media (CGM) on internet such as blogs, forums ,websites and news articles, ecosystem of corporations has changed significantly[1]. Customers, retailers are tremendously interested in and about reviews and insight of companies, their products and services, brands offered on the web. The reviews of customers are really important to attract huge number of customers. In particular, an important form of insights can be derived from sentiment analysis from the web contents[2].

Recently, sentiment analysis of online customer reviews has emerged as a very important research topic. In text mining, Sentiment Analysis and Opinion Mining consists study of sentiments, attitudes, reactions, emotions of a person and evaluation of the content of the text.   Sentiment Analysis is also known as Opinion Mining. Sentiment Analysis (SA) or Opinion Mining (OM) is nothing but the computational study of people's opinions, attitudes and emotions towards an entity such as services, products, organizations, individuals , events, topics, issues and their attributes.. The entity can represent events ,topics or individuals. These topics are likely to be covered by reviews. The two expressions SA or OM are actually interchangeable and they express a mutual meaning.

Some researchers also said that OM and SA have slight different notions.

Opinion Mining analyzes and extracts people's opinion about an entity while Sentiment Analysis identifies sentiment expressed in a piece of text then analyzes it. Therefore, the aim of SA is to find opinions, identify the sentiments they express and then classify their polarity. Basically sentiment analysis have two types of polarity: i) Positive polarity and ii) Negative Polarity [3]. An object which holds the positive opinion comes under the positive polarity. (e.g., awesome, happy, nice, joy, fun, excellent).An object which holds the negative opinion comes under the negative polarity. (e.g., bad, worst, rubbish, terrible).

Although the BOW (Bag-of-words) model is simple and quite efficient in topic-based text classification, but it is not very suitable for sentiment classification because it breaks the syntactic structures. It also disrupts the word order and discards some semantic information.   Thereupon, large number of researches in sentiment analysis marked to enhance BOW by incorporating linguistic knowledge. Despite, the fundamental deficiencies in BOW, most of these efforts showed light effects in improving the classification accuracy. One of the most well known difficulties is the polarity shift problem.

Polarity shift is a kind of linguistic phenomenon which can reverse the sentiment polarity of the text. The most important type of polarity shift is negation. For example, by adding a negation word "don't" to a positive text "I like this picture" in front of the word "like", the sentiment of the text will be reversed from positive to negative. However, the two sentiment-opposite texts are contemplated to be very similar by the BOW representation. Because of this standard machine learning algorithms often fail under the circumstance of polarity shift.

In this paper, we propose a simple yet efficient model, called improvised dual sentiment analysis (IDSA), to address the polarity shift problem in sentiment classification. By considering the property that sentiment classification has two opposite class labels (i.e., positive and negative), we first propose a data expansion technique by creating sentiment-reversed reviews. The original and reversed reviews are constructed in a one-to-one correspondence.

Thereafter, we propose a dual training (DT) algorithm and a dual prediction (DP) algorithm respectively which are the two main stages of DSA, to make use of the original and reversed samples in pairs for training a statistical classifier and make predictions. In DT, the classifier is learnt by maximizing a combination of likelihoods of the original and reversed training data set. In DP, predictions are made by considering two sides of one review. That is, we measure not only how positive/negative the original review is, but also how negative/positive the reversed review is. Further we extend our DSA framework from polarity (positive-negative) classification to 3-class (positive negative- neutral) sentiment classification, by taking the neutral reviews into consideration in both dual training and dual prediction.

To have least DSA's dependency on an external antonym dictionary, we finally implemented a corpus-based method for constructing a pseudo-antonym dictionary. The pseudo antonym dictionary is language-independent and domain adaptive. It makes the DSA model possible to be applied into a wide range of applications.

II.   RELATED WORK

Existing studies found in the literature of sentiment analysis has symbolic highlights on sentiment classification, which is aimed to differentiate user opinions and classify opinion comments into positive, negative and neutral categories. Following are some papers describe different kinds of researches in the era of sentiment analysis.

A] Effects of Adjective Orientation and Gradability on Sentence Subjectivity

To compute the subjectivity of a sentence, Hatzivassiloglou and Wiebe [7] presented supervised classification technique to forecast sentence subjectivity. Hatzivassiloglou and Wiebe enlightened the overall effects of semantically oriented adjectives, dynamic adjectives and also gradable adjectives on predicting subjectivity of the text document holding reviews. The sentences in a document are either subjective or objective to be visible to this Pang and Lee [8] proposed a sentence-level subjectivity detector. This explained technique retains subjective sentences and discards the objective sentences. After that they applied sentiment classifier. Major task of sentiment classifier is to contemplate resulted subjectivity with enhanced results.

B] Thumbs up: Sentiment Classification Using Machine Learning Techniques

Pang et al. [9] introduced machine learning model as maximum entropy, naive Bayes, and support vector machines to sort entire movie reviews into negative or positive

sentiments,. They concluded results generated by standard machine learning methods are rover to result by human-generated baselines. Yet machine learning method performs well on only traditional topic based categorization and lack in functionality on sentiment classification.

C] Hidden Sentiment Association in Chinese Web Opinion Mining

To categorize review documents into positive or negative in which as thumbs up represented positivity of document and thumbs down represents negativity of document an unsupervised learning method was stated [10]. Average sentiment orientations of phrases and words are counted for each review document to compute sentiment of review document. Domain-dependent contextual information is serviced to anticipate sentiments of phrases in review document, but this technique has limitation as it relies on external search engine.

D] Sentiment Analysis of Chinese Documents: From Sentence to Document Level

Zhang et al. [11] presented a rule-based semantic analysis technique to distribute sentiments for text reviews. Word dependence structures are supplied to classify the sentiment of a sentence. The author has predicted document-level sentiments by aggregating sentiments of sentence. This technique has some limitation as rule-based methods experience poor exposure also they do not hold comprehensiveness in their rules.

E] Thumbs Up or Thumbs Down: Semantic Orientation Applied to Unsupervised Classification of Reviews

To avoid the above limitation, Maas et al. [12] introduced method for both document-level and sentence-level sentiment classification. The proposed method provides integration of unsupervised and supervised approaches to learn vectors and for learning process, they take semantic term-document information as well as rich sentiment content.

F] Effective Sentiment Analysis of Social Media Datasets using Naive Bayesian Classification

Dhiraj Gurkhe et al. (2014) [13] uses combination of different labeled dataset. Various Approaches like Machine Learning Unigram, Bigram, Unigram are used. It gives best results with Unigram detection without neutral labels. But the drawback is that it leads to less accuracy as the size of training data is less also the sarcasm cannot be detected.

G] Twitter Sentiment Analysis using Machine Learning and Knowledge-based Approach

Riya Suchdev et al. (2014) [14] introduced the use of hybrid approach gives 100% of accuracy. Techniques used are machine Learning & knowledge-based approach using feature vector. The dataset used is Sanders Analytics dataset.

H] Sentiment Analysis and Text Mining for Social Media Microblogs using Open Source Tools: An Empirical Study

There has been a recent encourage of interest in sentiment analysis, Eman M.G. Younis et al. (2015) [15] proposed that Sentiment Analysis can be carried out by unsupervised technique without using pre classified training dataset. System gives a way to improve business competitive and customer relationship management in real-time. It has drawback that it leads to false sentiment classification as sarcasm cannot be detected.

I] TwiSent: A Multistage System for Analyzing Sentiment in Twitter

Subha-brata Mukher-jee et al. [17] expressed a hybrid approach that is machine learning approach & Rule based approach with extended module for each phase in architecture. TwiSent achieves higher negative precision improvement than positive precision improvement, it can capture negative sentiment strongly. But System cannot capture sarcasm or implicit sentiment.

III. DATA EXPANSION TECHNIQUE

The data expansion technique has been seen in the field of handwritten recognition [3], ,where the performance of the handwriting recognition systems was symbolically improved by adding some synthetic training data. In this paper, we perform the data expansion by constructing the original and reversed reviews in one-to-one correspondence. Another point of this work is that we expand the data set not only in the training stage, but also in the test stage also the original and reversed test review is used in pairs for sentiment prediction.

3.1 Data Expansion By Creating Reversed Reviews

In this section, we summarize the data expansion technique of creating sentiment-reversed reviews. Based on an antonym dictionary, for each original review, the reversed review is created according to the following rules:

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

b) Label reversion. For each of the training review, the class label is also reversed to its opposite (i.e., positive to negative, or vice versa), as the class label of the reversed review.

Table1

An example of creating reversed training reviews

	Review Text	Class
Original Review	I don't like this book. It is boring.	Negative
Reversed Review	I like this book. It is interesting.	Positive

Table 1 gives two simple examples of creating the reversed training reviews. Given an original training review,

such as "I don't like this book. It is boring. (class: Negative)", the reversed review is obtained by three steps:

1) the sentiment word "boring" is reversed to its antonym "interesting".

2) the negation word "don't" is removed. Since "like" is in the scope of negation, it is not reversed.

3) the class label is reversed from Negative to Positive. Note that in data expansion for the test data set, only Text Reversion is conducted. A joint prediction is made based on observation of both the original and reversed test reviews.

IV. IMPROVISED DUAL SENTIMENT ANALYSIS

Figure below illustrates the process of dual sentiment analysis (DSA). The Black rectangle denotes the original data, and the White filled rectangle denotes the reversed data. DSA contains two main stages: 1) dual training and 2) dual prediction[5].
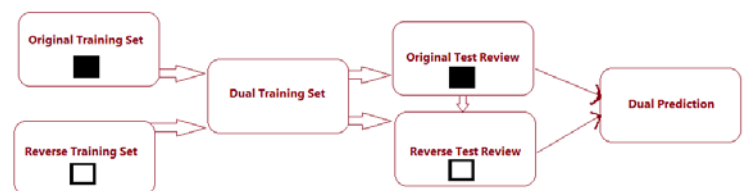

Figure1: Dual sentiment analysis

1. Dual Training

In the training stage, all of the original training samples are reversed to their opposite ones and we refer to them as "original training set" and "reversed training set" respectively. In the data expansion technique, there is a one-to-one correspondence in between the original and reversed reviews. The classifier is trained by maximizing a combination of the feasibilities of the original and reversed training samples. This process is known as dual training.

In this paper, we derive the DT algorithm by using the logistic regression model as an example. Our method can be easily adapted to the other classifiers such as naive Bayes and Stanford NLP . In the experiments, the three classification algorithm examined.

Now let us take the example from Table 1 to explain the effectiveness of dual training in addressing the polarity shift problem. We suppose "I don't like this book. It is boring. (class

label: negative)" is the original training review. Therefore, "I like this book. It is interesting. (class label: positive)" is reversed training review. Due to negation, the word "like" is (incorrectly) associated with the negative label in the original training sample. So, its weight will be added by a negative score in maximum likelihood estimation. Hence, the weight of "like" will be falsely updated. While in DT, due to the removal of negation in the reversed review, "like" is (correctly) associated with the positive label, and its weight will be added by a positive score. Hence, the learning errors caused by

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negation can be partly compensated in the dual training process.

2. Dual Prediction

In the prediction stage, for every test sample x, we create a reversed test sample $\tilde{x}$. Note that the target is not to predict the class o $\tilde{x}$. But rather, we use $\tilde{x}$ to assist the prediction of x. This process is entitled as dual prediction. A simple yet efficient model, known as dual sentiment analysis (DSA) addresses the polarity shift problem in sentiment classification.

Let us take the example in Table 1 again to explain why dual prediction works in addressing the polarity shift problem. We suppose "I don't like this book. It is boring" is traditional BOW, "like" will contribute a high positive score in predicting overall orientation of the test sample, despite of the negation structure "don't like". Therefore, it is very likely that the original test review will be mis-classified as Positive. While in DP, due to the removal of negation in the reversed review, "like" this time the plays a positive role. Hence, the probability that the reversed review being classified into Positive must be high. In DP, a weighted combination of two component predictions is used as the dual prediction output. In this way, the prediction error of the original test sample can also be compensated by the prediction of the reversed test sample. Apparently, this can reduce some prediction errors caused by polarity shift. .
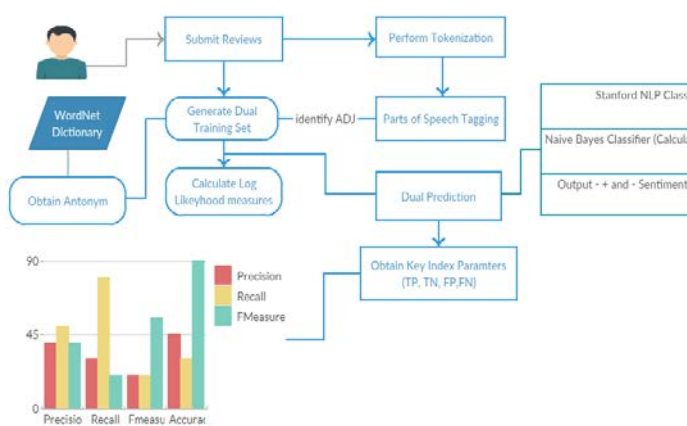
V.PROPOSED SYSTEM

Figure 1: Proposed Architecture.

The above figure shows our proposed architecture. The following section explains framework, dictionary, classifiers and the dataset we have used.

1. Framework Used

We have used Stanford NLP framework. Semantic word spaces have been very useful but cannot express the meaning of longer phrases in a principled way. Further progress towards understanding compositionality in tasks such as

sentiment detection requires richer supervised training and evaluation resources and more powerful models of composition. To remedy this, we introduce a Sentiment Treebank. It includes fine grained sentiment labels for 215,154 phrases in the parse trees of 11,855 sentences and presents new challenges for sentiment compositionality. To address them, we introduce the Recursive Neural Tensor Network. When trained on the new treebank, this model outperforms all previous methods on several metrics. It pushes the state of the art in single sentence positive/negative classification from 80% up to 85.4%. The accuracy of predicting fine-grained sentiment labels for all phrases reaches 80.7%, an improvement of 9.7% over bag of features baselines. Lastly, it is the only model that can accurately capture the effects of negation and its scope at various tree levels for both positive and negative phrases

2. Model Analysis:

High Level Negation is done. We investigate two types of negation. For each type, we use a separate dataset for evaluation.

Set 1:

Negating Positive Sentences. The first set contains positive sentences and their negation. In this set, the negation changes the overall sentiment of a sentence from positive to negative. Hence, we compute accuracy in terms of correct sentiment reversal from positive to negative.

Set 2:

Negating Negative Sentences. The second set contains negative sentences and their negation. When negative sentences are negated, the sentiment treebank shows that overall sentiment should become less negative, but not necessarily positive. For instance, 'The movie was terrible' is negative but the 'The movie was not terrible' says only that it was less bad than a terrible one, not that it was good.

Hence, we evaluate accuracy in terms of how often each model was able to increase non-negative activation in the sentiment of the sentence.

3. Classifiers:

We have used two types of classifiers. The naïve bayes classifier helps us classifying the review in positive, negative class while the Stanford NLP classifier helps us in classifying the review in positive, negative, neutral class.

4. Dataset:

We have used two datasets. Multi-domain dataset having four domains Book, DVD, Kitchen, Electronics. Each domain has thousand positively labeled and thousand negative labeled data. And the another dataset having three domains Cannon, Nokia, Nikon having original product reviews.

5. Experimental Study:

In this section, we have included the performance evaluation on the basis of two tasks which includes dataset and

experimental study, also on experiments on polarity classification across 7 sentiment datasets, 2 classifiers and a wordnet dictionary.

5.1 Datasets and Experimental Settings

We use multi-domain dataset and another dataset. Multi-domain dataset contain product reviews taken from Amazon.com including four different domains: Book, DVD, Kitchen, and Electronics. Each domain contains 1000 positive and 1000 Negative reviews. The another dataset contains three domains namely Nokia, Nikon, Cannon. These domains contain original product reviews.

For Positive-negative-neutral sentiment classification, we have created a manual dataset having twenty reviews, which have taken from Amazon product review dataset. Table 3.7.4.1 and table 3.7.4.2 gives the detailed information of these two datasets, used for sentiment classification.

5.2 Experiments on Polarity Classification

For the Polarity Classification task the experimental results are reported in this section. For this task, we evaluate the following five systems that are proposed in the literature with the aim at addressing the polarity shift.

1. Baseline: Baseline. The standard machine learning methods based on the BOW representation;
2. DS. The method proposed by [6], where "NOT" is attached to the words in the scope of negation, e.g., "The book is not interesting" is converted to "The book is interesting-NOT";
3. LSS. The method proposed by [21], where each text is split up into two parts: polarity-shifted and polarity- un shifted, based on which two component classifiers are trained and combined for sentiment classification. To our knowledge, this is the state-of the- art approach of considering polarity shift without using external resources;
4. DSA-WN. The DSA model with selective data expansion and the WordNet antonym dictionary;
5. DSA-MI. The DSA model with selective data expansion and the MI-based pseudo-antonym dictionary.

6. Results on Multi-Domain Dataset

The table 4.4 shown below gives the detailed view of classification accuracy of multi-domain dataset using Naïve Bayes Classifier. In the table below, we can see that as compared to baseline system, the improvements of DS approach are very limited that is only 1.1 %. The performance of LSS is effective but still limited.

Our proposed approach IDSA that is improvised dual sentiment analysis approach shows the best performance. In comparison with the baseline system it shows the improvement of 4.3% and comparing with the LSS system it gives the improvement up to 3.2%. Also comparing with the DSA-WN and DSA-MI system our IDSA approach provides 1.7% improvement in both.

The graph shown in the figure 1 illustrates the comparative study on multi-domain dataset having four domains Book, DVD, Kitchen, and Electronics. It shows the classification accuracy on multi-domain dataset using naïve bayes classifier.

7. Results on Another Dataset

This section illustrates the results on Another dataset having three domains namely Nokia, Nikon, Cannon and also its comparison with the other techniques. The table 3 shows the experimental results of our model in terms of Fscore in comparison with ARM, SPE, UADSA and our proposed IDSA technique.

The UADSA that is the unsupervised aspect detection for sentiment analysis technique used the multi-word aspects and heuristic rules, iterative bootstrapping with A-score and aspect pruning. ARM is the association rule mining and SPE is the semantic based product aspect detection technique. The table below shows comparative study of another dataset.

Table 2: Classification Accuracy using Naive Bayes Classifier.

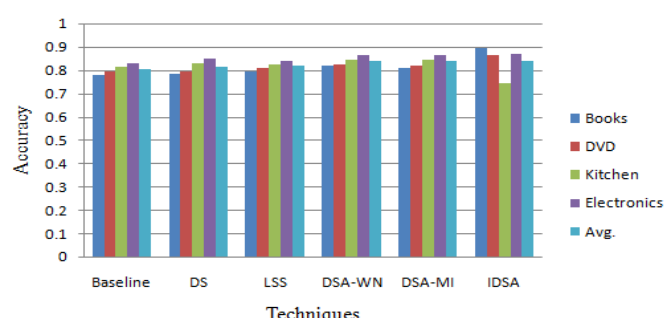| Dataset	Baseline	DS	LSS	DSA-WN	DSA-MI	IDSA
Books	0.779	0.783	0.792	0.818	0.808	**0.892**
DVD	0.795	0.793	0.810	0.824	0.821	**0.862**
Kitchen	0.815	0.828	0.824	0.844	0.843	**0.742**
Electronics	0.830	0.847	0.840	0.864	0.864	**0.867**
Avg.	0.804	0.813	0.817	0.838	0.838	**0.841**

Figure 1: Graph showing comparative study of Multi-domain dataset

The graph shown in the figure above illustrates the comparative study on multi-domain dataset having four domains Book, DVD, Kitchen, and Electronics. It shows the classification accuracy on multi-domain dataset using naïve bayes classifier.

Table 3: F measures of ARM, SPE, UADSA, and IDSA

Dataset	ARM	SPE	UAD	IDSA
Cannon	56.42	59.05	76.82	86.8
Nikon	58.13	58.29	76.9	86.48
Nokia	53.32	63.5	74.8	80.38
Avg.	55.95	60.28	76.17	84.55

The table above shows F-scores of ARM, SPE, UADSA and our proposed model IDSA for another dataset having three domains Cannon, Nokia, Nikon.
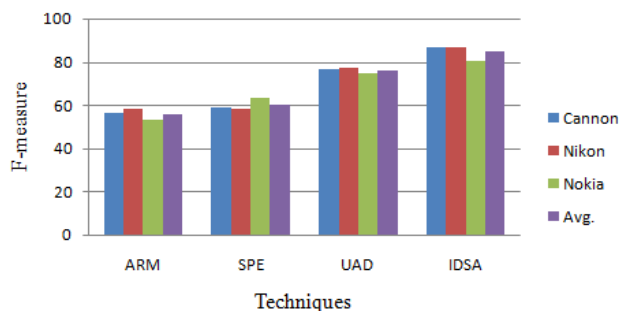

Figure 3: Graph showing F-scores of ARM, SPE, UADSA and IDSA.

Above figure 3 shows the graphical representation of F-score values of different approaches that is ARM, SPE, UADSA, and IDSA using three product datasets. In all three Nokia, Nikon, and Cannon datasets, our model IDSA achieves the highest F-scores. This indicates that our semi-supervised model is effective and is superior to the existing techniques.

VI.CONCLUSION AND FUTURE SCOPE

In this work, we propose a method, called improvised dual sentiment analysis, to address the polarity shift problem in sentiment classification. The basic idea of IDSA is to create reversed reviews that are sentiment-opposite to the original reviews, and make use of the original and reversed reviews in pairs to train a sentiment classifier and make predictions. IDSA is highlighted by the technique of one-to-one correspondence data expansion and the manner of using a pair of samples in training (dual training) and prediction (dual prediction). Improvised IDSA can deal with 3 class (positive-negative-neutral) sentiment classification. The neutral reviews are also taken into consideration.

In this paper, we focus on creating reversed reviews to assist semi-supervised sentiment classification. We propose an improved dual sentiment analysis approach to identify polarity shift problem by applying heuristic rules to obtain corpus from the given reviews and make predictions based upon dual training on two English dataset. In future we can generalize this method to remove external dependency on pseudo antonym dictionary and create a decision based machine learning technique, which can analyze the antonym by calculating the weighted score. We can generalize the IDSA algorithm to a wider range of sentiment analysis tasks. We

also plan to consider more complex polarity shift patterns such as transitional, subjunctive and sentiment-inconsistent sentences in creating reversed reviews.

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