Dual Sentiment Analysis: Considering Neural Sides of One Review

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Abstract- *In Sentiment Analysis Bag-of-words (BOW) is a popular way for modeling the text in the statistical machine learning approach .But the performance of BOW is limited due to some fundamental deficiencies in handling polarity shift problem. Here proposed model is introduced that is, Dual Sentiment Analysis (DSA) to solve this problem for sentiment classification. First By creating a sentiment reverse review for every test review and training review propose a novel data expansion technique. DSA model includes two algorithms, Dual training(DT)algorithm which uses the original and reversed review together in pair for learning sentiment classifier, and Dual prediction(DP) algorithm to classify the test reviews, by considering two sides of one review. Extending the DSA model from two classes (Positive-Negative) to three classes (Positive-Negative-Neutral) classification Considering the Neutral review for the classification. Finally construct pseudo antonym dictionary developing the corpus based method which helps to remove the dependency of DSA on external antonym dictionary for review reversion. It conduct the Multiple experiments including two tasks, two antonym dictionary ,nine data sets, three classification algorithms and two types of features. The result demonstrate the effectiveness of DSA in supervised sentiment classification.*

Keywords- Natural Language processing, Sentiment Analysis, Machine learning, Opinion mining .

I. INTRODUCTION

Now-a-days use of internet is increases. With the growing volume of online net, Sentiment analysis and opinion mining for determining the subjective attitude (i.e. sentiment) of given text is now becoming a hotspot in the data mining field. Natural language processing sentiment analysis is a basic task in sentiment analysis. Aim of sentiment analysis is to classify the sentiment (i.e. positive or negative) of given text. In a sentiment classification mostly the Bag-of-word (BOW) is used for the text classification. In bag-of-word model a review text is represented by vector of independent words. The statistical machine learning algorithms like nave Bayes, maximum entropy classifier and support vector machines are then employed to train a sentiment classifier. BOW is very simple and quite efficient model for topic base text classification. But the bag-of-words is not suitable for the sentiment classification because it changes the words order, breaks the structures of sentence also discards some semantic information. In sentiment analysis large number of researches is done which aims to improve the BOW by incorporating linguistic knowledge. However because of some fundamental deficiencies in BOW, most of the researches show normal effect in improving the classification accuracy. The polarity shift problem is the most well-known difficulties.

II. REVIEW OF LITERATURE

Selecting attributes for sentiment classification using feature relation networks:

A major concern when incorporating large sets of diverse n gram features for sentiment classification is the presence of noisy, irrelevant, and redundant attributes. These concerns can often make it difficult to harness the augmented discriminatory potential of extended feature sets. We propose a rule-based multivariate text feature selection method called Feature Relation Network (FRN) that considers semantic information and also leverages the syntactic relationships between n-gram features. FRN is intended to efficiently enable the inclusion of extended sets of heterogeneous n-gram features for enhanced sentiment classification. Experiments were conducted on three online review test beds in comparison with methods used in prior sentiment classification research. FRN outperformed the comparison univariate, multivariate, and hybrid feature selection methods; it was able to select attributes resulting in significantly better classification accuracy irrespective of the feature subset sizes. Furthermore, by incorporating syntactic information about n-gram relations, FRN is able to select features in a more computationally efficient manner than many multivariate and hybrid techniques.[1]

Exploring automatic word sense disambiguation with decision lists and the web

The most effective paradigm for word sense disambiguation, supervised learning, seems to be stuck because of the knowledge acquisition bottleneck. In this paper we take an in-depth study of the performance of decision lists on two publicly available corpora and an additional corpus automatically acquired from the Web, using the fine-grained highly polysemous senses in WordNet. Decision lists are shown a versatile state-of-the-art technique. The experiments reveal, among other facts, that SemCor can be an acceptable (0.7 precision for polysemous words) starting point for an all-words system. The results on the DSO corpus show that for some highly polysemous words 0.7 precision seems to be the current state-of-the-art limit. On the other hand, independently constructed hand-tagged corpora are not mutually useful, and a corpus automatically acquired from the Web is shown to fail.[2]

Training set expansion in handwritten character recognition

A process of expansion of the training set by synthetic generation of handwritten uppercase letters via deformations of natural images is tested in combination with an approximate k-Nearest Neighbor (k-NN) classifier. It has been previously shown that approximate nearest neighbors search in large databases can be successfully used in an OCR task, and that significant performance improvements can be consistently obtained by simply increasing the size of the training set. In this work, extensive experiments adding distorted characters to the training set are performed, and the results are compared to directly adding new natural samples to the set of prototypes.[3]

Learning with compositional semantics as structural inference for sub sentential sentiment analysis.

Determining the polarity of a sentiment-bearing expression requires more than a simple bag-of-words approach. In particular, words or constituents within the expression can interact with each other to yield a particular overall polarity. In this paper, we view such sub sentential interactions in light of compositional semantics, and present a novel learning-based approach that incorporates structural inference motivated by compositional semantics into the learning procedure. Our experiments show that (1) simple heuristics based on compositional semantics can perform better than learning-based methods that do not incorporate compositional semantics (accuracy of 89.7\% vs. 89.1\%), but (2) a method that integrates compositional semantics into learning performs better than all other alternatives (90.7\%). We also find that "content-word negators", not widely employed in previous work, play an important role in determining expression-level polarity. Finally, in contrast to conventional wisdom, we find that expression-level classification accuracy uniformly decreases as additional, potentially disambiguating, context is considered.[4]

What's great and what's not: Learning to classify the scope of negation for improved sentiment analysis

Automatic detection of linguistic negation in free text is a critical need for many text processing applications, including sentiment analysis. This paper presents a negation detection system based on a conditional random field modelled using features from an English dependency parser. The scope of negation detection is limited to explicit rather than implied negations within single sentences. A new negation corpus is presented that was constructed for the domain of English product reviews obtained from the open web, and the proposed negation extraction system is evaluated against the reviews corpus as well as the standard Bioscope negation corpus, achieving 80.0\% and 75.5\% F1 scores, respectively. The impact of accurate negation detection on a state-of-the-art sentiment analysis system is also reported.[5]

III. SYSTEM ARCHITECTURE

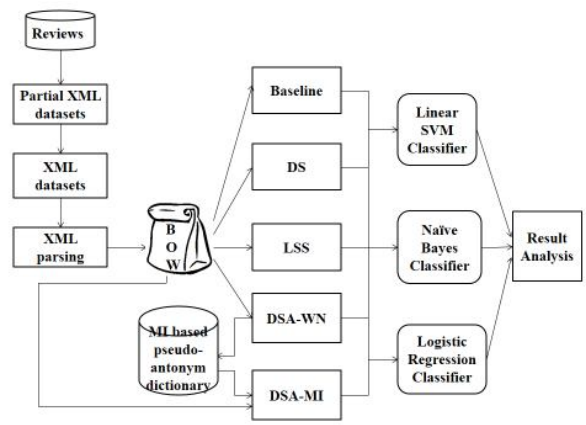


Figure 1. Architecture of system

First the dataset is in partial XML format then converted into XML format, then after XML parsing the reviews are extracted and saved in separate document.

The following five systems are proposed to address the polarity shift.

BOW: bag-of- words (BOW) model is typically used for text representation. In the BOW model, a review text is represented by a vector of independent words.

DS: In this, “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”.

LSS: In LSS, each text is split up into two parts: polarity-shifted and polarity- unshifted, based on which two component classifiers are trained and combined for sentiment classification.

DSA-WN: The DSA model with selective data expansion and the WordNet antonym dictionary.

DSA-MI: The DSA model with selective data expansion and the MI-based pseudo-antonym dictionary.

IV. SYSTEM ANALYSIS

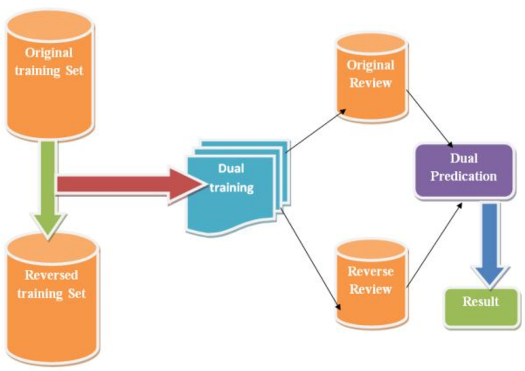


Figure 2. Dual Sentiment analysis Model

the above diagram shows the DSA model of sentiment analysis, the original data set includes the collection positive words and the reverse data set include the exact reverse data set of original data set. this set is totally depends on original data set. In dual training (DT) it uses pair of original and reverse review for learning sentiment classifier, If any query passed here it give reverse response of statement ,Always opposite response come as a output.

IV. MATHEMATICAL MODEL

Let U,P,N,R be a User, Neural and Non-Neural Analysis respectively.
U(Z) = u1,u2,u3.......un;
P(Z) = p1,p2,p3....pn;
N(Z) ={m1,m2,m3,...mn}
R(Z) = r1,r2,r3.........rn }
B(Z)={b1,b2,b3.......bn}
D(Z) = {d1,d2,d3....dn}

x - The original sample
x ~ - The reversed sample
y E {0,1} - The class label of the original sample
y ~ =1- y -The class label of the reversed sample

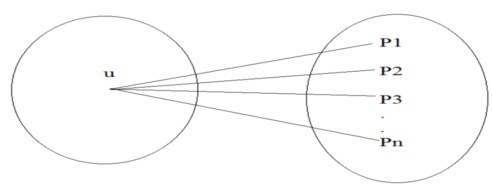
D ={xi; yi} i=1 -The original training set
D~ ={xi~; yi~} i=1 -The reversed training set
w - Weights of features in a linear model
J(w) Log-likelihood function
p(.|x) Prediction for the original sample
p(.|x~) Prediction for the reversed sample
p(.|x,x~) Dual prediction based on a pair of samples

U(Z) -> Number of user
P(Z) ->{x,y} Number of Positive word
N(Z) ->{x~,~y} Number of Negative word
B(Z) -> Book Dataset
D(Z) -> Dual Score

$$J(w) = \sum_{i=1}^{N} \log p(y_i|x_i)$$

Let D{xi; yi}i=1 and D{~ x ~i; y ~i}i=1 be the original and reversed training sets, respectively, where x and x ~ denote the feature vector of the original and reversed reviews respectively, y E{0; 1} denotes the original class label, y ~ = 1 y denotes the reversed class label, and N is the number of the original training samples. Let w denote the weight of features, and J(w) be the cost function.

U(Z) U P(Z):



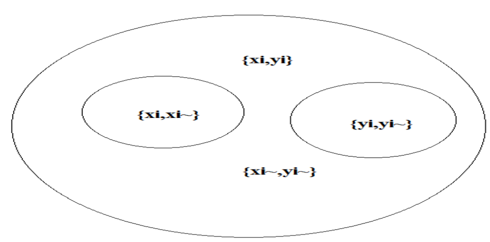


Figure 1.

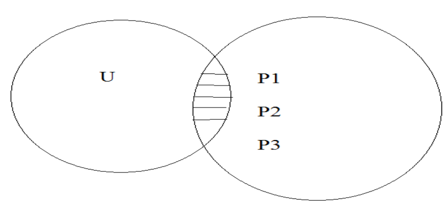


Figure 2.

- Any query gives reversed review.
- We can easily extract positive & negative review.

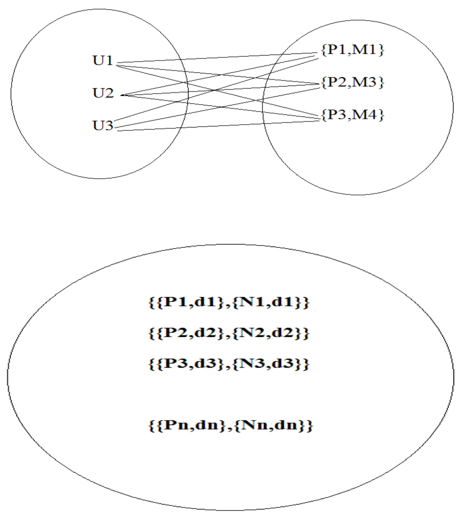


Figure 3.

- Above diagram shows how to analyzed word types and respective score.
- Every query having positive & negative word check {Good, Bad ,Moderate , Excellent}

VI. IMPLEMENTATION DETAILS

For polarity classification taking a dataset of book which includes collection of reviews having positive and negative reviews together .Dataset is in XML format then performing xml parsing on that dataset. then stopwords are removed from data. The data pre-processing phase incorporates steps to modify the data into a form that can be easily and effectively used by the data mining phase.

VII. RESULT AND DISCUSSION

In a proposed system DSA model is used for sentiment classification .It includes dual training and dual prediction algorithms for analysis. Supervised dataset of book is taken in XML format then after xml parsing reviews are extracted. Then Dual training and dual predictions are perform on available reviews.

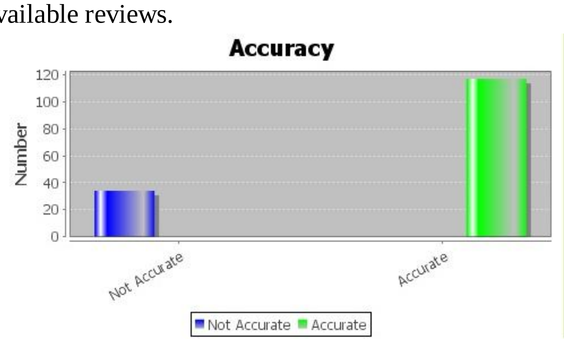


Figure 4. accuracy of all reviews of book. how many perfectly match(accurate) or not matched (not accurate)

VIII. CONCLUSION

To Propose a novel data expansion approach, called DSA, to address the polarity shift problem in sentiment classification. The basic idea of DSA 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. DSA 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). A wide range of experiments demonstrate that the DSA model is very effective for polarity classification and it significantly outperforms several alternative methods of considering polarity shift.

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