Improving Sentiment Classification Using Feature Highlighting and Feature Bagging

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***Abstract*—Sentiment classification is an important data mining task. Previous researches tried various machine learning techniques while didn't make fully use of the difference among features. This paper proposes a novel method for improving sentiment classification by fully exploring the different contribution of features. The method consists of two parts. First, we highlight sentimental features by increasing their weight. Second, we use bagging to construct multiple classifiers on different feature spaces and combine them into an aggregating classifier. Extensive experiments show that the method can evidently improve the performance of sentiment classification.**

***Keywords*-Sentiment analysis; Feature highlighting; Feature bagging.**

I. Introduction

With the rapid development of internet, more and more kinds of online information are available. In these information resources, there are abundant of subjective comments and views, for example, comments for electronic products, cars, movies, or reviews for some events or policies. It is valuable to decide whether the comments are positive or negative, if the reviews are supportive or oppositive, and if a product is recommendable or not? These requirement elicited the research topic of *sentiment analysis*. In some literatures, sentiment analysis is also referred as opinion mining. Its primary objective is to predict the sentimental polarity of given context by identifying sentimental constituents like sentimental words, subjective sentences, etc. Sentiment analysis examines a wide variety of texts, from sentences to documents, such as forum comments, web pages, blog articles, product reviews, and movie reviews, etc. Pang et al [2] made a comprehensive review of sentiment analysis and opinion mining.

Nowadays, sentiment analysis is deployed very extensively in internet settings, because it can, to some extend, help to manage large scale of information and to locate interesting information. Particularly, sentiment analysis is very helpful to analyze consumers' feedbacks and consuming tendency. One example is in recommending systems, sentiment analysis helps to automatically classify online feedbacks of products or services, and select recommendable ones for consumers. Pang et al [1] introduced review mining to re-rank search engine results. Their method substantially improves the initial results produced by the Yahoo! search engine.

Previous researches applied various machine learning algorithms on sentiment classification while didn't make fully use of the different contribution of features. But for sentiment classification, it is intuitive that feature selection and weighting scheme plays a critical role. Based on this premise, in this paper, we are to try to improve sentiment classification by: 1, *feature highlighting*, i.e., highlight labeled sentimental features by elevating their weight. 2, *feature bagging*. i.e., train sub-classifiers on randomly selected feature spaces and then combine them into a final classifier by voting. Experimental results indicate the effectiveness of feature highlighting and feature bagging.

The rest of this paper is organized as follows. Section 2 introduces related works. Section 3 elaborates on our method. Section 4 is about experiments and discussion before concluding this paper at the last section.

II. Related Work

The task of sentiment classification is classifying the polarity of the expressed opinion [3], which can be positive or negative, supportive or not, and etc. Various machine learning methods have been introduced into this task. For example, Turney [4] utilized web search engine to compute semantic tendency. Hu et al [5] tried to classify word into opinion and non-opinion terms. [18] explored word relations for sentiment classification.

Pang et al [6] applied three different methods, i.e., Support Vector Machines (SVMs), Naïve Bayes and Maximum Entropy, to conduct a comparison experiment, in which SVMs yielded the best result. Besides, for feature weighting, they found that in sentiment classification, Binary (presence/absence of words) is better than Term Frequency (TF). They collected 1400 film comments as experiment data set, on which the highest accuracy reached 82.9%. Later, Pang et al [7] achieved even better result by applying artificial filtration to get rid of objective sentences and select subjective sentences for learning, which addressed the importance of subjective features and sentences for sentiment classification. Recently, researches were trying novel techniques to cope

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with this task. For example, Prem et al [8] combined lexical knowledge with text classification to implement sentiment classification. Tao et al [9] introduced transfer learning technique into sentiment classification. Rui [10] studied two kinds of features and three kinds of classifiers. Ainur et al [11] studied the contribution of different sentences to form document-level sentiment classifier.

Schapire [12] proposed the first boosting algorithm. Later, Freund [13] proposed *AdaBoost* algorithm which is more efficient than *boosting*. Breiman [14] proposed bagging algorithm which utilizes the instability of classifiers. To apply integrating learning algorithms to sentiment classification, Li et al [15] generated different classifiers on feature sets with different POS, then combine them into a final classifier. It was found that the final classifier exhibited improved accuracy, with an improvement of 2.56% over the best individual classifier. Similarly, Tsutsumi et al[16] integrated three kinds of classifiers and got some improvement. [19] used POS-based ensemble model for cross-domain sentiment classification.

III. Algorithm

We are trying to improve the performance of sentiment classifiers by exploring the different contribution of features. To do this, two strategies are proposed, i.e., *feature highlighting* and *feature bagging*, as follows.

A. Strategy 1: Feature Highlighting

With vector space model (VSM), a document d is considered as a set of features and corresponding weights, i.e., a vector $\vec{d} = (w_1, w_2, ..., w_n)$, where w_i is the weight of feature f_i. $\vec{d}$ is called the representation vector of document d.

There are several means to compute feature's weight, such as Binary (presence/absence of words), TF, TF-IDF and so on. In traditional topic-oriented text classification, TF-IDF has been proven better than Binary and TF. But for sentiment classification, Binary turns out to be more effective than TF and TF-IDF[6]. This is partially because the sentimental polarity does not merely depend on topic keywords, but also depend on specific sentimental words, often adjective, such as ”good”, ”perfect”, ”wasteful”, etc. Usually, these sentimental words rarely appear repeatedly due to language custom and wide range of selection. So TF and TF-IDF can't work well to distinguish sentimental attributes because they can introduce “irrelative” features. With binary representation, a document is represented as:

$$\vec{d} = (I(f_1), I(f_2), ..., I(f_m)) \tag{1}$$

where $I(\cdot)$ is a indicator function. If f_i appears in d, $I(f_i)$ = 1, otherwise $I(f_i)$ = 0.

However, in binary representation, the features are equally treated. It does not highlight the critical effect of sentimental constituents (such as sentimental words). For example, given sentence “The cumulative effect of the movie is repulsive and depressing”. We confirm this sentence expressing negative sentiment according to the sentimental words *repulsive* and *depressing*. If binary representation is deployed, obviously, all the features are equally important. In other words, it doesn't reflect the dominant effect of the sentimental words. It is acknowledged that the greater the weight of a feature is, the more indicative it is for the article's class. Therefore, to highlight the impact of sentimental words, we elevate the weight of sentimental words, which may be labeled ahead of time. After highlighting, a feature vector is:

$$\vec{d} = (w(f_1), w(f_2), ..., w(f_m)) \tag{2}$$

where $w(f_i)$ is the weight of feature f_i. If f_i appears in d and sentimental word list, $w(f_i)$ = k. If f_i appears in d and not in sentimental word list, $w(f_i)$ = 1. Otherwise $w(f_i)$ = 0. Here, $k > 1$ is the highlighting factor which aims to elevate the weight of sentimental words. As the above example is concerned, if the words *repulsive* and *depressing* are in sentimental word list, their weight will be lifted, so that their contribution to sentiment classification is amplified. In practice, $\vec{d}$ should be $L2$ normalized.

B. Strategy 2: Feature Bagging

Breiman [14] proposed the *bagging* algorithm. Given a learning set of L consists of data $\{(x_n, y_n), n = 1, ..., N\}$ where y's are class labels. Take repeated bootstrap samples $\{L^B\}$ from L, each consisting of N cases, drawn at random and with replacement, from L. Each $(\mathbf{x}_n, y_n)$ may appear repeated times or not at all in any single L^B. Bagging trains a sequence of sub-classifiers $\{\varphi(\mathbf{x}, L^B)\}$ from $\{L^B\}$. The aggregated classifier can be formed by voting. If $\varphi(\mathbf{x}, L^B)$ predicts a class $j \in \{1, ..., J\}$, let $N_j = \#\{k|\varphi(\mathbf{x}, L^B) = j\}$, then $\varphi_A(\mathbf{x}) = \arg\max_j N_j$. Here the subscript A in φ_A denotes aggregation.

A critical factor in whether bagging will improve accuracy is the stability of the procedure for constructing φ. Improvement will occur for unstable procedures where a small change in L can result in large changes in φ. Instability was studied in Breiman [14], where it was pointed out that neural nets, classification trees were instable, while kNN were stable.

But using the instable classifiers are not the only way to reach improvement. We argue that any factor that causes classifier to be instable can used to improve original classifier. Besides instable classifiers, stable ones also can be used as the base predictors in bagging. What we need to do is to perturb the procedure of constructing classifiers to make them instable.

It is well known that the selection of features is a critical factor that will “change” classifier's performance. That is to say, classifiers will be *instable* if they are learned on elaborately generated feature spaces. This instability is right the requirement of improvement for bagging. We call bagging on feature sets as *feature bagging*. The basic idea of feature bagging strategy is to implement bagging through varying feature space: learn a sequence of classifiers on different feature spaces, then form aggregated classifiers by voting.

Formally, given learning set L and a feature space F. Take repeated sub-feature spaces $\{F^B\}$ from F with a proportion, drawn at random and **without replacement**. Then train a sequence of sub-classifiers $\{\varphi(\mathbf{x}, L, F^B)\}$ on $\{F^B\}$. The aggregated classifier is $\varphi_A(\mathbf{x}) = \arg\max_j N_j$, $N_j = \#\{k|\varphi(\mathbf{x}, L, F^B) = j\}$.

C. Why do the strategies work?

As Strategy 1 is concerned, artificially increasing the weight of sentimental features is equal to form artificial learning samples in which the reoccurring possibility of sentimental words increases. These sentimental words are informative to sentiment classification and appropriately increasing their TF will not change document's sentiment attribute. So the result of highlighting sentimental features is highlighting documents's sentiment attribute and thus improve classifiers' performance.

The explanation for Strategy 2 is more complicated.

Axiom 1. Invariability of Category Attribute. For text classification including sentiment classification, given a document, any part from it with an enough large proportion remains its category attribute.

For example, if we randomly choose one third or one half from a document to make new documents, the category attribute of the new documents should be as same as the original document. However, when the extraction proportion is too small, such as just one or few words, it is possible that the extracted document can not represent the original document's category because of the lost of useful features.

Definition 1. *Partition set*. Given a document set, for each document in it, extract words from it with a proportion to form new documents, thus form a new document set. We call this new document set a *partition set* of the original set.

Based on Axiom1, we can get partition sets from a learning document set. For classification task, obviously, partition sets are similar because the category attribute of each document in them does not vary.

Presumption 1. Given a labeled document set, if it is partitioned with a proper proportion, classifiers learned from its partition sets is comparable with the classifier learned from itself.

We examine this presumption experimentally. As a validation experiment, a task of binary text categorization is examined. We got web pages of category Automobile and Education, with size of 700 respectively. 100 documents of each category are selected at random as learning set and the remains as testing set. Partition sets are formed by extracting different words with certain proportion from each document, without repetition. SVMs are trained on partition sets (libsvm [17] is used). For each proportion, experiments are performed 10 times and the average accuracy is recorded, as shown in Figure 1.

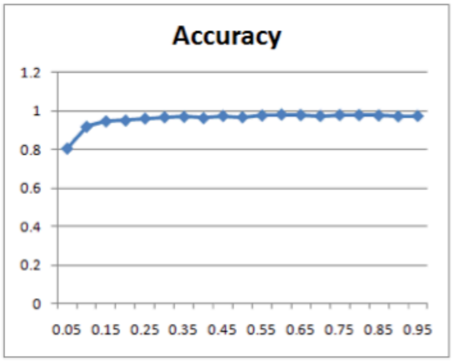


Figure 1. Results of binary classification on partition sets of Automobile and Education classes. The X-axle is the proportion of partition sets.

From Figure 1 we can see that when the proportion falls in [0.5, 1.0), the accuracy of SVMs are very similar without falling. And the performance falls evidently till the proportion is less than 0.25. While when the proportion falls in [0.25, 0.5] the performance fluctuates. The results prove this presumption.

Axiom 2. For learning classifier, if binary representation (presence/absence of words) is adopted, randomly sampling on feature space with fixed learning set is equal to randomly forming partition set with fixed feature set.

In other words, for a given document, the effect of using a randomly generated sub-feature space to represent it, is equal to using randomly words from it to represent it with original feature space. And vice versa. Because for any parts of a given document, we can always find a sub feature space in which the representation of the original document is identical to the representation of the extracted parts in original feature space.

Theorem 1. Feature bagging with proper proportion can yield improved performance.

Proof: According to Axiom 1 and Axiom 2, we know that feature bagging is equal to bagging on partitioned sets. From presumption 1, we know that classifiers' performance on partitioned sets may be similar to original learning set, or may fluctuate on different feature space. It is known that bagging on learning set can improve performance, which is proved in literature [14]. So, if classifiers' performance varies on different partitioned sets, which reflects the different contribution of features, without loosing too much accuracy, classifier's performance can be improved.

Apparently, there are two key factors in whether feature bagging can improve accuracy. One is classifier's instability on different partition sets and the other is whether the performance of classifier deteriorates too much. There is a cross-over point at which $\varphi_A(x, F^B, L)$ stop improving $\varphi(x, L)$ and does worse.

IV. Evaluation

A. Set-up

Pang et al compared three classification algorithms in literature [6]. When unigrams and Binary were used to represent documents, SVMs is better than Naïve Bayes and Maximum Entropy by 2%∼3%. Based on their results, in our experiments, SVMs are used as the basic classifier.

We use the movie review dataset as literature [2] did. This dataset contains total of 1400 film comments, i.e., 700 positive comments and 700 negative comments. The dataset is firstly pre-processed, including feature flittering and negative words processing, as follows. (1) Filter features according to their frequency. We exclude the words which appear less than 4 times in this dataset. (2) Add the prefix "$NOT\_$" to every word after a negation word ("not", "no", "isn't", etc.). They will be seemed as sentimental words in the training and classifying stage. In pre-procession, no stemming is performed nor stoplist is applied, since they have little impact to the final performance.

After pre-precession steps we got original feature space of size more than 15000. We use unigrams and VSM to represent comments. L2-normalization is performed on feature vectors except Binary.

Three-fold cross-validation is used to get average performance of algorithms. The whole dataset is randomly and equally divided into three portions. In each iteration, two portions are used as training data and the remaining one as testing data. The average accuracy of the three iterations is recorded as performance of algorithms. The accuracy is calculated as:

$$accuracy = \frac{N(d^{'})}{N(d)} \tag{3}$$

where $N(d)$ is the total number of test comments and $N(d')$ is the number of comments which are classified properly.

In order to label sentimental words, OpinionFinder's subjectivity lexicon [**?**] is introduced. It consists of over 8000 subjectivity clues which are compiled from several sources. Words in this lexicon are labeled by four types of sentiment: *positive*, *negative*, *both*, and *neutral*. And according to sentimental strength, words in this lexicon are classified into two types: *weaksubj* and *strongsubj*. We choose positive and negative words as sentimental features. The total number of the sentimental features is 7630 and the quantitative distribution is shown in table I.

As the sentimental strength of *strongsubj* words is different from that of *weaksubj* words, we give them different highlighting factor, k_s and k_w, respectively, which are to be determined by experiments.

	#strongsubj	*#weaksubj*
Positive	1589	1129
Negative	3737	1175

Table I
Statistic features of sentimental word list.

B. Experimental results

1) Single SVMs (Baseline): First, we use single Support Vector Machines to train and predict the movie comments. Libsvm library [17] is used to implement SVMs. For all SVMs we use linear kernel and with parameter c=2.0 and γ = 2.0. The TF and Binary weighting scheme are evaluated. The experimental results are listed in Table II.

Weighting	Accuracy
TF	76.68%
Binary	81.26%

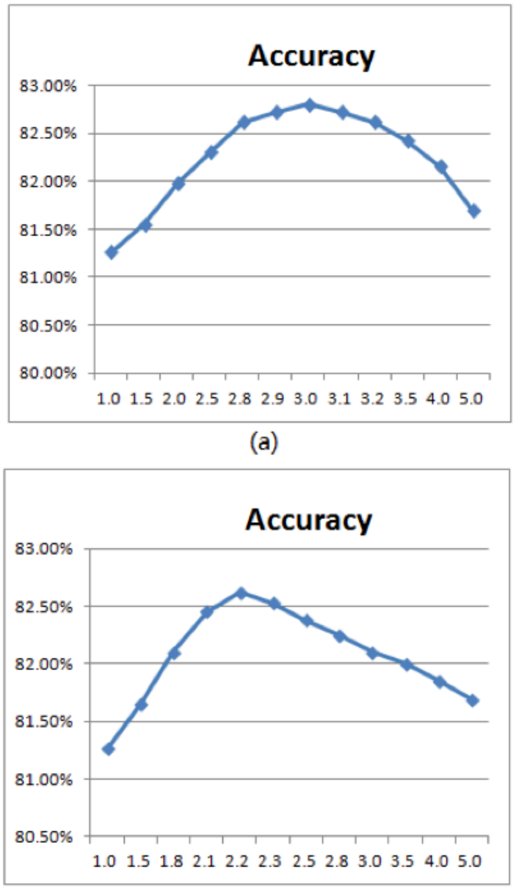
Table II
Result of single SVMs with TF and Binary. The performance of Binary will be used as the baseline in following evaluations.

From Table II we can see that the accuracy of Binary is obviously higher than that of TF, which verifies the difference between sentiment classification and traditional text classification. In the following experiments, the performance of the Binary is used as baseline.

2) Sentimental Feature Highlighting: In this experiment, we experimentally check the effect of sentimental feature highlighting and the optimal parameter k_s and k_w. The graph of accuracy against k_s and k_w is show in Figure 2 (a) and (b), respectively.

From Figure 2 we can see that with appropriate weight promotion of sentimental words, classifier's accuracy will be increased to some extent. But the performance of classifier will deteriorate if sentimental words are highlighted too much. The optimal value for k_s and k_w is 3 and 2.2 respectively. The higher value of k_s verified the higher indicative effect of *strongsubj* words than *weaksubj* words. In the following experiments, the optimal values will be used.

3) Feature bagging: This experiment implements feature bagging in which sub-classifiers are trained on different feature spaces. The objective is to verify the importance of feature selection for sentiment classification and the performance lifting benefits from boosting learning on randomly feature sampling. Through experiments we found that when T is greater than 50, the performance of final classifiers become stable. So we set T=50 in this experiment. We train T sub-SVMs on different sub-feature spaces which are randomly extracted from original feature space with proportion λ. Then, the sub-SVMs are integrated by voting mechanism.



(a)

(b)

Figure 2. Results of feature highlighting. (a) is the effect of highlighting *strongsubj* words and (b) is the effect of highlighting *weaksubj* words.

The performance of final classifiers with different λ are show in Figure 3.

When λ is 1, the algorithm is equal to original SVMs. With the decrease of λ the accuracy increase correspondingly. The accuracy reaches its highest value when λ is 0.3. After that, when λ is further decreased, the accuracy deceases correspondingly. After integrating, the final classifier outperforms the baseline by 2.2%. This reflects the advantage of bagging idea.

Table III gives out the accuracy of several random selected sub-classifiers when λ is 0.3. It is worth noticing that for each sub-classifier on sub-feature space, its accuracy is worse than the baseline. This is because of that in sub-feature space, an abound of informative features are skipped which make original classifiers become weak classifiers. This satisfies the requirement for weak classifiers of bagging boosting algorithm.

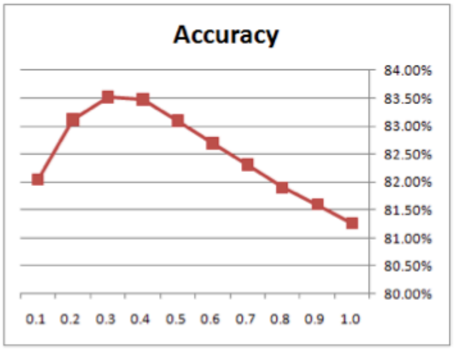


Figure 3. Performance of integrating classifiers of feature bagging with different λ.

No.	Accuracy
1	72.10%
2	73.82%
3	69.53%
4	75.38%
5	70.36%
6	73.68%
7	76.24%

Table III
PERFORMANCE OF RANDOM SUB-CLASSIFIERS WHEN λ IS 0.3. EACH SUB-CLASSIFIER'S PERFORMANCE IS WORSE THAN THE BASELINE.

Another important observation from table III is that even with λ = 0.3, the accuracy of sub-classifier on different sub-feature space varies obviously, with variance of 6.19. This observation proves our basis premise: sentiment classification greatly depends on feature selection, and, feature sampling with relatively smaller ratio can satisfies the instability requirement of sub-classifiers of bagging boosting.

4) Combination of feature bagging and feature highlighting: In this experiment, the above two strategies are combined to further improve the classifier. On the basis of sentimental feature weight lifting, again, boosting learning on feature bagging is deployed. With the optimal parameters got from previous experiments, we got the final accuracy of 84.63%. For comparison convenience, Table IV lists the accuracy of the four methods.

Method	Accuracy
Single SVMs	81.26%
Feature Highlighting	83.27%
Feature Bagging	83.52%
Combination	84.63%

Table IV
RESULT OF FOUR METHODS: SINGLE SVMS, FEATURE HIGHLIGHTING, FEATURE BAGGING AND COMBINATION.

From Table IV we can see that, compared with baseline, sentimental feature highlighting technique outperforms the single SVMs by 2.01%. And feature bagging technique improves the accuracy by 2.36%. The combination of the two techniques yields accuracy of 3.37% higher than the baseline. This result shows the overall performance of the proposed method.

V. Conclusions and Future Work

In this paper, the impact of features to sentiment classification was studied. The objective is to minimize the interference from unrelated features while highlighting the contribution of sentimental words. First, sentimental words are highlighted by weight lifting. Second, multiple classifiers are learned from randomly generated sub-feature spaces. Then the final classifier is set up from these sub-classifiers by voting. We named the two strategies as *feature highlighting* and *feature bagging*. Based on experimental outcomes, we can conclude that:

- Sentimental words play a critical role in determining the sentiment polarity of a document. To increase accuracy of classification, it is important to increase the weight of sentiment words although they are not the only determinant.
- Aggregating learning method based on randomly feature sampling can increase the accuracy of classifiers, behaving like traditional bagging.
- The improvement of the above two techniques is stable, the combination of them could substantially increase the accuracy.

Although it is found that highlighting sentimental words was proved to be very useful in sentiment classification, it is arbitrary to give them the same highlighting factor. We are planning to generate fine weight scheme by machine learning techniques to further improving classifiers.

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References

[1] Pang, Bo and Lillian Lee. *Using very simple statistics for review search: An exploration*. In Proceedings of the 22nd International Conference on Computational Linguistics, Manchester, U.K., 18-22 August, 2008, pp.75-78.

[2] Pang, Bo and Lillian Lee. *Opinion Mining and Sentiment Analysis*. Foundations and Trends in Information Retrieval series. Now publishers, 2008.

[3] Soo-Min Kim and E. Hovy. *Determining the sentiment of opinions*. In Proceedings of COLING-04, 20th International Conference on Computational Linguistics, Geneva, CH, 2004, pp. 1367–1373.

[4] Turney Peter. *Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews*. In: Proceedings of the 40th Annual meeting of the Association for Computational Linguistics, 2002.

[5] M. Hu and B. Liu. *Mining Opinion Features in Customer Reviews* [A]. In: Proceedings of Nineteenth National Conference on Artificial Intelligence (AAAI 2004) [C]. San Jose, USA, 2004.

[6] Pang, Bo, L. Lee, and S. Vaithyanathan. *Thumbs up? Sentiment Classification Using Machine Learning Techniques*. In Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP), 2002, pp. 79-86.

[7] B. Pang, and L. Lee. *A sentimental education: Sentiment analysis using subjectivity summarization based on minimum cuts*. In: Proceedings of ACL-04, 42nd Meeting of the Association for Computational Linguistics, Barcelona, ES: Association for Computational Linguistics, 2004, pp. 271-278.

[8] Prem Melville, Wojciech Gryc and Richard D. Lawrence. *Sentiment analysis of blogs by combining lexical knowledge with text classification*. In Proceedings of KDD'2009. pp. 1275-1284.

[9] Tao Li, Vikas Sindhwani, Chris H. Q. Ding and Yi Zhang. *Knowledge transformation for cross-domain sentiment classification*. In Proceedings of SIGIR'2009. pp.716-717

[10] Rui Xia, Chengqing Zong, Shoushan Li. *Ensemble of feature sets and classification algorithms for sentiment classification*. Information Sciences, Vol.181(6), 2011, pp. 1138 - 1152.

[11] Ainur Yessenalina, Yisong Yue and Claire Cardie. *Multi-level Structured Models for Document-level Sentiment Classification*. In Proceedings of the 2010 Conference on Empirical Methods in Natural Language Processing, MIT, Massachusetts, USA, 9-11 October 2010, pp. 1046C1056.

[12] Schapire R. E., *The strength of weak learnability*, Machine Learning, 1990, 5(2), pp. 197-227.

[13] Freund Y. *Boosting a weak learning algorithm by majority*. Information and Computation, 1995, 121(2), pp. 256-285.

[14] Breiman L. *Bagging Predictors*. Machine learning, 1996, 24(2), pp. 123-40.

[15] S. Li, C. Zong and X. Wang. *Sentiment Classification through Combining Classifiers with Multiple Feature Sets*. Processing and Knowledge Engineering, 2007.

[16] Tsutsumi, K., Shimada, K. and Endo, T. (2007). *Movie Review Classification Based on a Multiple Classifier*. In Proceedings of the 21st Pacific Asia Conference on Language, Information and Computation (PACLIC21), pp. 481-488.

[17] C.C. Chang, C.J. Lin. 2001. *LIBSVM: a library for support vector machines*. http://www.csie.ntu.edu.tw/ cjlin/libsvm/

[18] R. Xia, C. Zong. 2010. *Exploring the use of word relation features for sentiment classification*. In Proceedings COLING-2010.

[19] R. Xia, C. Zong. 2011. *A POS-based ensemble model for cross-domain sentiment classification*. In Proceedings IJCNLP-2011.