Sentiment Classification Approaches – A Review

N. Anitha
Assistant professor
Department of IT
Kongu Engineering College
Erode
B. Anitha
Assistant professor
Department of IT
Kongu Engineering College
Erode
S. Pradeepa
Final Year ME (CCE)
Department of IT
Kongu Engineering College
Erode

Abstract - With the outbreak of web 2.0, several types of social media such as blogs, discussion forums, review websites and community websites that can be useful for determine the public; sentiment and opinion, towards products and services. Recent surveys impart that online reviews have greater economic impact compared to claric media. The major task of opinion mining or sentiment analysis is used to find the subjective information from the user defined opinions. The expressed opinions may be positive, negative or neutral. Machine learning techniques are widely used for sentiment classification. In this paper, we look insight into the various machine learning techniques for sentiment classification and research challenges exist in this field.

Keywords – Opinion Mining, Sentiment Machine Learning, Semantic, POS Tagger

I. INTRODUCTION

Sentiment analysis is also called as opinion mining used to extract the public's opinion information from unstructured text data. It is a finger-grain analysis compared to subjective analysis and it uses natural language processing and data processing techniques to automate the classification or extraction of sentiment information. Researchers look insight into this emerging area and new approaches are come to light up the growth of both service/product providers and users. There are various levels in sentiment analysis. For example, in movie review, the opinion like "The movie was good "and "The movie was horrible", in that "good and "horrible" are the word level sentiment analysis." His film was great" is the sentence level sentiment analysis and "His film was great and interesting. He is one of the legends" is the document level analysis.

Several challenges in sentiment analysis are sentiment classification, feature based sentiment classification and finally opinion summarization. These are the research predominate areas in sentiment analysis [1]. Among various issues in sentiment analysis, sentiment classification aims to analyze direction-based text, i.e. text contain opinions and emotions, to determine whether a text is objective or subjective, or weather a subjective text contains positive ,negative or neutral sentiments. It is harder than traditional text classification, due to the effects of syntax on sentiments, domain dependence and use of neutral words in sentiment expression. Sentiment classification techniques can be used to examine the sentiment and opinion information from social media websites. Much work has been done in this issue and commonly used machine learning approaches and semantic orientation approach. Most of the existing approaches rely on supervised learning models in that labeled corpus are used in the document to identify positive or negative text. But this approach was failed for domain independence and reported poor accuracies on the movie review data [2].This results into the arrival of new schema of using weakly or unsupervised models for domain independent sentiment detection from online reviews.

Machine learning approaches clarify the sentiments based on training and test sets [3] and it is called as "**Supervised Learning**". But semantic orientation approach to opinion mining is "**Unsupervised Learning"** because it does not require prior training data sets. Both the approaches have limits and delimits. Even though supervised machine learning approaches predominantly gives more accurate results than unsupervised learning. In this paper we provide summarization of machine learning techniques such as Naive bayes, Maximum entropy, SVM, Bayesian, Neural networks and Decision tree and Semantic Orientation approaches.

II. SENTIMENT CLASSIFICATION

Research interests in the area of opinion mining and sentiment analysis has been raised quite a while. Early projects found in the area [4, 5]. Later in year 2001, research problems and opportunities in opinion mining and sentiment analysis have been wide spread among researches, academicians and industry peoples [6, 7, and 8]. More research done in sentiment analysis of user opinion data, which major determines the polarities of user reviews. There are two approaches namely machine learning and semantic orientation approaches are mostly used for semantic classification. We have summarized the literature review on the approaches of sentiment classification [9, 10] as follows:

A. Machine Learning Approaches--

Machine learning approaches are used to predict the polarity of sentiments based on trained and test data sets. The following are machine learning approaches widely used for classify the sentiments.

A.1. Naive Bayes Classification--

The Naive Bayes Classifier technique is based on the so-called Bayesian theorem and is particularly suited when the dimensionality of the inputs is high. Despite its simplicity, Naive Bayes can often outperform more sophisticated classification methods. Maximum Likelihood estimates the parameters for Naïve Bayes models. It requires minimal number of training to estimate the parameters. So it can be work efficiently in supervised learning. Thus Bayes'forumula is [1]:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \qquad \text{----- (1)}$$

This theorem helps us to find the conditional probability of contrary and independent events. Thus we can estimate the probability of an opinion may contain positive, negative or neutral. Many survey papers said that Naive-Bayes classification performs well [12, 13, 14], indeed [15] proves that Naïve Bayes is optimal for certain problem classes with high dependent feature. It will produce good results [16].Some author used Naïve Bayes algorithm and proved that efficiency has improved and yield a value of 0.816.So we conclude that Naive Bayes performs well in high dependant features and outperforms often compared to Neural Networks, Decision Trees etc.,. However standard maximum likelihood parameter learning for Naïve Bayes classifier tends to be suboptimal.

A.2. Maximum Entropy--

The principle behind Maximum Entropy is to find the best probability distribution among prior test data. It yields maximal entropy information which gives proper distribution. Maximum entropy classifiers are generally used as alternatives to naive Bayes classifiers because they do not assume statistical independence of the random variables (commonly known as features) that serve as predictors. However, learning in such a model is slower than for a naive Bayes classifier, and thus may not be appropriate given a very large number of classes to learn. In particular, learning in a Naive Bayes classifier is a simple matter of counting up the number of co-occurrences of features and classes, while in a maximum entropy classifier the weights, which are typically maximized using maximum a posterior (MAP) estimation, must be learned using an iterative procedure.

Kamal Nigam et.al. Proposed [17, 18] that Maximum Entropy suits best for text classification and compared with Naïve Bayes. Another author said that Maximum Entropy classification has proven effective in a number of natural language processing applications [19].Its estimate P (C| D) as: [9]

$P_{ME}(c \mid d) = \frac{1}{Z(d)} \exp\left(\sum_i \lambda_{i,c} F_{i,c}(d,c)\right)$ ------ (2)

$F_{i,c}(d,c') = \begin{cases} 1 & n_i(d) > 0 \text{ and } c' = c \\ 0 & \text{otherwise} \end{cases}$ -------- (3)

We summarized that Maximum Entropy makes no assumptions about the relationship between features and so might potentially perform better when conditional independence assumptions are not met.

A.3. Support Vector Machine--

SVMs were originally proposed by Boser, Guyon and Vapnik in 1992 and gained increasing popularity in late 1990s. SVM is a supervised learning model which analyzes data and patterns that can be used for classification and regression analysis. The basic idea behind this is to find a maximum margin hyper plane represented by vector. It finds an optimal solutions.SVM classified into linear classification, soft margin classification and non-linear classification. Non-linear classification is achieved through "kernel trick" function.

A.3.1. Linear SVM mathematically--

- Assume that all data is at least distance 1 from the hyper plane, then the following two constraints follow for a training set $\{(\mathbf{x_i}, y_i)\}$

  $\mathbf{w}^{\mathbf{T}}\mathbf{x_i} + b \geq 1 \quad \text{if } y_i = 1$ --------- (4)

  $\mathbf{w}^{\mathbf{T}}\mathbf{x_i} + b \leq -1 \quad \text{if } y_i = -1$

- For support vectors, the inequality becomes an equality

- The margin is:

  $\rho = \frac{2}{\|\mathbf{w}\|}$ ------------ (5)

Then we can formulate the quadratic optimization problem:

$r = y \frac{\mathbf{w}^T \mathbf{x} + b}{\|\mathbf{w}\|}$ ------------- (6)

Find w and b such that is maximized; and for all

$\{(x_i, y_i)\}$ refer equation (4)

A better formulation (min $\|\mathbf{w}\|$ = max $1/\|\mathbf{w}\|$):

Find w and b such that $\phi(w) = ½ w^T w$ is minimized; and for all $\{(x_i, y_i)\}$: $y_i (w^T x_{i} + b) >= 1$

A.3.2. Soft Margin mathematically--

If the training data is not linearly separable, *slack variables* ξ_i can be added to allow misclassification of difficult or noisy examples.

The new formulation incorporating slack variables:

Find w and b such that $\phi(w) = ½ w^T w + C\sum €_I$ is minimized and for all $\{(x_i, y_i)\}$ $y_i (w^T x_i + b) >= 1-€_I$ and $€_I >= 0$ for all i.

A.3.3. Non-linear SVM Mathematically--

The general idea behind in non-linear classification is the original feature space can always be mapped to some higher-dimensional feature space where the training set is separable. A *kernel function* is some function that corresponds to an inner product in some expanded feature space.

The solution is:

$$f(x) = \sum \alpha_i y_i K(x_i, x_j) + b \text{ ---- } (7)$$

SVMs are currently among the best performers for a number of classification tasks ranging from text to genomic data. It is effective, accurate and work well in small amount of training data [**21**].So we conclude that SVM outperforms Naïve Bayes and Maximum Entropy for standard text classification.

A.4. Bayesian Network --

A Bayesian network is a probabilistic model and it is a directed acyclic graph in which nodes are variables (discrete or continuous) and arcs indicate dependence between variables. There are three main inference tasks in Bayesian networks. They are inferring unobserved variables, parameter learning and structure learning. The most common approximate inference algorithms are importance sampling, stochastic MCMC simulation, mini-bucket elimination, loopy belief propagation, generalized belief propagation, and variation methods [22]. Valarmathi author proposed that classify the sentiments along with decision tree induction and classification and regression tree methods (CART) provide pretty good results particularly in movie domain. A Bayesian network models relationships between features in a very general way. If you know what these relationships are, or have enough data to derive them, then it may be appropriate to use a Bayesian network. A Naive Bayes classifier is a simple model that describes particular class of Bayesian network - where all of the features are class-conditionally independent. Because of this, there are certain problems that Naive Bayes cannot solve. However, its simplicity also makes it easier to apply, and it requires less data to get a good result in many cases [23].

A.5. Neural Networks--

I. A Neural Network is a collection of natural or artificial neurons that uses for mathematical and computational model analysis. Popular algorithms in neural networks are Back-Propagated Delta Rule Networks (BP) (sometimes known and multi-layer perceptions (MLPs)) and Radial Basis Function Networks (RBF) are both well-known developments of the Delta rule for single layer networks (itself a development of the Perception Learning Rule). Both can learn arbitrary mappings or classifications. Further, the inputs (and outputs) can have real values. Kohonen clustering Algorithm is used for unsupervised neural networks. Long-Sheng Chena, proposed new methodology for sentiment classification The author combined two efficient methodologies such as BPN and SO approaches [24]. This study proposed an NN based approach to classify sentiment in blogospheres by combining the advantages of the BPN and SO indexes. Compared with traditional techniques such as BPN and SO indexes, the proposed approach shows its superiority not only in classification accuracy, but also in training time. Long-Sheng Chen* and Hui-Ju Chiu proposed that [25] study proposed a Neural Network (NN) based index which combines the advantages of machine learning techniques and information retrieval (semantic orientation indexes) to help companies detecting harmfully negative bloggers' comments quickly and effectively. Experimental results indicated that our proposed NN based index outperforms traditional approaches, including Back-Propagation neural network (BPN) and several semantic orientation indexes.

This [26] paper proposes a sentiment classification model using back-propagation artificial neural network (BPANN). Information Gain and three popular sentiment lexicons are used to extract sentiment representing features that are then used to train and test the BPANN. This novel approach combines the strength of BPANN in classification accuracy with intrinsic subjectivity knowledge available in the sentiment lexicons. The results obtained from experiments on the movie and hotel review corpora have shown that the proposed approach has been able to reduce dimensionality, while producing accurate results for sentiment based classification of text.

We summarized that the above few recent survey papers explained the use of neural networks in the sentiment classification. Neural Networks performed well and produce accurate results.

B. Semantic Orientation Approaches--

It is nothing but **"unsupervised learning"** because it does not need any prior training in order to mine the data. Kamps et al (2004) focused on the use of lexical relations in sentiment classification. Chunxu Wu (2009) proposed an approach which resort to other reviews discussing the same topic to mine useful contextual information, and then use semantic similarity measures to judge the orientation of opinion.

B.1. Dictionary based approach--

Dictionary based approach is a method in which it translates a word by word as a dictionary but not correlate the meaning of words between them. Starting from a set of primary emotion adjectives, **Alm et al**, retrieve similar words from WordNet utilizing all senses of all words in the synsets that contain the emotion adjectives. **Whitelaw et al,** use a semi-automatic method to create a dictionary of words that express appraisal.

B.2. Corpus based approach--

Corpus based approach have been widely used to explore both written and spoken texts. **Mihalcea and Liu** have used this method to assign a happiness factor of words that depends on frequency of their occurrences in happy labeled blog posts. Corpus contains blog posts label such as "happy" and "sad" mood annotations.

An unsupervised learning algorithm use three approaches namely: TF-IDF, K-means clustering algorithm and POS- tagger. TF-IDF (term frequency – inverse document frequency), weighting factor in information retrieval and text mining. K-means clustering algorithm is a method of cluster analysis and hence it partition n observations into k-clusters and each observation belongs to the cluster with nearest mean. Among these three approaches, the Part Of Speech (POS) - tagger is an efficient algorithm because it is a piece of software that reads text in some language and assign parts of speech to each word and other token, such as noun, verb, adjective, etc. Computational applications use more fine grained POS tags like 'non plural'.

C. Novel Machine Learning Approaches in Sentiment Classification--

Wei Jein [27] adduced novel approach for web opinion mining and extraction. They developed new framework of lexicalized HMMs called Opinion Miner. This approach integrates important linguistic features into automatic learning. Valarmathi [22] suggested new methodology using word score based on Singular Value Decomposition. They used Bayes Net and Decision Tree Induction algorithms to classify the opinions. This method shows pretty good results. This method shows pretty good results. Silvio Moreira proposed new novel method for sentiment classification called REACTION [28] .They employed Random Forest Algorithm with main features such as word vectors and lexicon word counts for to classify the tweets. Pu Jang [29] introduced novel weakly supervised approach for Chinese sentiment classification.

D. Ensemble Approaches In Sentiment Classification--

Ensemble machine learning techniques increase classification accuracy by combining arrays of specialized learners. Bootstrap aggregating also called Bagging was one of the first ensemble machine learning techniques. Saraswathi [30] proposed Inverse Document Frequency and classify the opinions by using bagging algorithms. They concluded that results acquired better classification accuracy. Random subspace method is another ensemble technique and Shousan Li author [31] used this technique for imbalanced sentiment classification and proved great effectiveness. Rui Xia [32] employed a comprehensive approach, named feature ensemble plus sample selection (SS-FE), which takes both types of adaptation into account. A feature ensemble (FE) model is first proposed to learn a new labeling function in a feature re-weighting manner. Furthermore, a PCA-based sample selection (PCA-SS) method is proposed as an aid to FE. Experimental results show that the proposed SS-FE approach could gain significant improvements, compared to FE and PCA-SS, due to its comprehensive consideration of both labeling adaptation and instance adaptation. Ying su [33] introduced the ensemble learning framework, stacking generalization is introduced based on different algorithms with different settings, and compared with the majority voting. According to the characteristic of reviews, the opinion summary of review is proposed in this paper, which is composed of the first two and last two sentences of review. Results show that stacking has been proven to be consistently effective over all domains, working better than majority voting, and that using the opinion summary can improve the performance further. Zhongqing Wang [34] propose a multi-strategy ensemble learning approach to this problem. Our ensemble approach integrates sample-ensemble, feature-ensemble, and classifier-ensemble by ex-ploiting multiple classification algorithms. Evaluation across four domains shows that our ensemble approach outer-forms many other popular approaches that handling imbalanced classification problems, such as re-sampling and cost-sensitive approaches, and is proven effective for imbalanced sentiment classification. Finally Boosting is the popular ensemble technique and employed by many authors for to improve the accuracy. We have concluded that ensemble models in machine learning techniques yield very good classification accuracy results.

III. SUMMARIZATION RESULT AND DISCUSSION

The importance and familiarity of sentiment classification with machine learning approaches has led to recent research papers, a few of them are listed in table 1,

Table 1: Recent papers on the related tasks of Opinion Mining

Technique Name	Year	Title of Paper
Naïve Bayes	2012	Some methods to address the problem of unbalanced Sentiment Classification in an Arabic context.
	2012	An empirical study to address the problem of unbalanced data sets in Sentiment Classification.
Maximum Entropy	2012	Sentiment Classification for Indonesian message in social media.
SVM	2013	Sentiment Analysis and Classification based on textual reviews.
	2012	Investigation of pre – processing of multi lingual online reviews for automatic classification.
		Utilizing support vector machines in mining online customer reviews.
	2012	A non – parametric LDA – Based induction method for Sentiment Analysis.

	2012	
POS-Tagger	2013 2012	Developing Corpora for Sentiment Analysis: The case of Irony and Senti – TUT. Error analysis and Gyro – Bias calibration of analytic coarse alignment for airborne POS.
Neural Network	2012 2012	Sentiment compositionality through recursive matrix vector spaces. Sentiment multi dimensional scaling for open domain Sentiment Analysis.
Decision Tree	2013 2013 2013	Decision tree for mining data strees based on the Mc Diarmid's Bound. Predicting school failure and dropout by using data mining technique. Online dynamic security assessment with missing PMU measurements: A data mining approach.
Bayesian Network	2012	Classifying Sentiment in Arabic Social Network: Naïve Search versus Naïve Bayes.

K - Means Algorithm	2013 2013 2012	Document Clustering for Forensic Analysis: An approach for improving computer inspection. Dictionary Training for Sparse Representation as Generation of K – Means Algorithm. Optimized Data Fusion for Kernel K – Means Clustering.

IV. COMPARISONS BETWEEN SUPERVISED AND UNSUPERVISED CLASSIFICATION APPROACHES

The extent literature [35, 36, and 37] proves that two types of techniques have been utilized in sentiment classification: Machine learning and Semantic orientation .Former is a supervised model and later is a unsupervised model. Both of the two approaches have its pros and cons. Supervised approach yield better classification accuracy compare to unsupervised model. But supervised model takes more time for to train the data sets. Pimwadee Chavalit [38] compared the above two approaches in the challenged movie domain. Empirical results proved that supervised model achieved 84.49% accuracy while unsupervised yielded 66.27% only. But supervised takes more time to train the data and unsupervised is very efficient to use in real-time applications.

V. EVALUATION OF SENTIMENT CLASSIFICATION

Sentiment classification is evaluated by using following equations,

- $\text{Accuracy} = \dfrac{TN + TP}{TN + TP + FP + FN}$
- $\text{Precision} = \dfrac{TP}{TP + FP}$
- $\text{Recall} = \dfrac{TP}{TP + FN}$
- $\text{F1} = \dfrac{2 \times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call}$

VII. CONCLUSIONS AND FUTURE WORKS

This review paper discussed some of the machine learning approaches and semantic orientation approaches. Both of them are widely used in Sentiment Classification. Finally the paper explained the importance and usage of several techniques. Opinion Mining is the emerging field in data mining for the past decade years. New researches use these techniques and overcome the challenges in this field.

REFERENCES

[1] G.vinodhini,R.M.Chandrasekaran,"Sentiment analysis and Opinion Mining: A Survey", International Journal of Advanced Research in Computer Science and Engineering,vol.2,Issue 6,pp.282-292,2012.
[2] A.Aue and M.Gamon,"Customizing Sentiment Classifiers to New Domains: A case Study",Proc.Recent Advances in Natural Language Pro cessing(RANLP),2005.
[3] Chenghua Lin, Yulan He, Richard Everson,"A Comparative Study of Bayesian Models for unsupervised Sentiment Detection", Proceedings of the Fourteenth Conference on Computational Natural Language Learning, pages 144–152, 2010.
[4] J.Carbonell,"Subjective Understanding :Computer Models of Belief Systems".PhD Thesis,Yale,1979.
[5] Agarwal and P.Bhattacharyya,"Sentiment analysis:A new approach for effective use of linguistic knowledge and exploring similarities in a set of documents to be classified," in Proceedings of the International Conference on Natural Language Processing (ICON), 2005.
[6] Cardie,J.Wiebe,T.Wilson,and D.Litman,"Combining low-level and summary representations of opinions for multi-perspective question answering," in Proceedings of the AAAI Spring Symposium on New Directions in Question Answaering, pp.20-27, 2003.
[7] S.Das and M.Chen,"Yahoo! For Amazon:Extracting market sentiment from stock message boards," in Proceedings of the Asia Pacific Finance Assocaition Annual Conference (APFA), 2001.
[8] K.Dave,S.Lawrence,and D.M.Pennock,"Mining the peanut gallery:Opinion extraction and semantic classification of product reviews," in Proceedings of WWW,pp.519-528,2003.
[9] S. ChandraKala and C. Sindhu ," OPINION MINING AND SENTIMENT CLASSIFICATION: A SURVEY," in ICTACT JOURNAL ON SOFT COMPUTING, OCTOBER 2012, VOLUME: 03, ISSUE: 01 ISSN: 2229-6956(ONLINE).
[10] A Survey"S Padmaja and Prof. S Sameen Fatima," Opinion Mining and Sentiment Analysis –An Assessment of Peoples Belief," in International Journal of Ad hoc, Sensor & Ubiquitous Computing (IJASUC) Vol.4, No.1, February 2013.
[11] Wikipedia. [Online]. http://en.wikipedia.org (2012, Mar.)
[12] G.Vinodhini, RM.Chandrasekaran ,"Sentiment Analysis and Opinion Mining: A Survey," in International Journal of Advanced Research in Computer Science and Software Engineering , Volume 2, Issue 6, June 2012 ISSN: 2277 128X.
[13] Nilesh M. Shelke, Shriniwas Deshpande, Vilas Thakre, "Survey of Techniques for Opinion Mining**,"** in International Journal of Computer Applications (0975 – 8887) Volume 57– No.13, November 2012
[14] Sindhu C, Dr. S. ChandraKala,"A SURVEY ON OPINION MINING AND SENTIMENT POLARITY CLASSIFICATION," in International Journal of Emerging Technology and Advanced Engineering, ISSN 2250-2459 (Online).
[15] Pedro Domingos and Michael J. Pazzani. 1997, "On the Optimality of the Simple Bayesian Classifier Under Zero-One Loss. Machine Learning", 29(2-3):103–130.
[16] Ion SMEUREANU, Cristian BUCUR," Applying Supervised Opinion Mining Techniques on Online User Reviews," in Informatica Economică vol. 16, no. 2/2012.
[17] McCallum and Kamal Nigam. 1998. "A Comparison of Event Models for Naive Bayes Text Classification". In Proc. of the AAAI-98 Workshop on Learning for Text Categorization, pages 41–48.
[18] Stanley Chen and Ronald Rosenfeld. 2000. "A Survey of Smoothing Techniques for ME Models". IEEE Trans. Speech and Audio Processing, 8(1):37–50.
[19] Adam L. Berger, Stephen A. Della Pietra, and Vincent J. Della Pietra. 1996. "A Maximum Entropy Approach to Natural Language Processing". Computational Linguistics, 22(1):39–71.
[20] Tam P. Ngo," Clustering High Dimensional Data Using SVM," December 2006.
[21] B Valarmathi, Dr.V Palanisamy," Opinion Mining Classification Using Key Word Summarization Based on Singular Value Decomposition**",**International Journal on Computer Science and Engineering (IJCSE).
[22] Yushi Jing," Efficient discriminative learning of Bayesian network classifier via boosted augmented naïve Bayes," in Proceedings of ICML '05 international conference on Machine Learning, Pages 369 – 376.
[23] Long-Sheng Chen," A neural network based approach for sentiment classification in the blogosphere," in Journal of Informetrics Volume 5, Issue 2,April 2011,Pages 313-322.
[24] Long-Sheng Chen* and Hui-Ju Chiu ," Developing a Neural Network based Index for Sentiment Classification", in Proceedings of the International MultiConference of Engineers and Computer Scientists 2009, Vol I IMECS 2009, March 18 - 20, 2009, Hong Kong.
[25] Anuj Sharma,Shubhamoy Dey," Document level sentiment analysis approach using artificial network and sentiment lexicons," in ACM SIGAPP Applied Computing Review, Volume 12 Issue 4, December 2012, Pages 67-75.
[26] Wei Jin, Hung Hay Ho, Rohini K. Srihari," OpinionMiner: A Novel Machine Learning System for WebOpinion Mining and Extraction," in Proceddings of KDD'09, June 28–July 1, 2009, Paris, France.
[27] Silvio Moreira," REACTION: A naive machine learning approach for sentiment Classification," in Proceedings of the 7th International Workshop on Semantic Evaluation (SemEval 2013), in conjunction with the Second Joint Conference on Lexical and Computational Semantics .
[28] Pu Zhang,Zhonghi He," A weakly supervised approach to Chinese sentiment classification using partitioned self-training, " in Journal of Information Science April 9 2013.
[29] Saraswathi.K ,Tamilarasi.A,"A Modified Metaheuristic Algorithm for Opinion mining," in International Journal of Computer Applications (0975-0887),Volume 58,November 2012.
[30] Shoushan Li, Zhongqing Wang, Guodong Zhou and Sophia Yat Mei Lee, "Semi-Supervised Learningfor Imbalanced Sentiment Classification", in Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence.
[31] Rui Xia, Chengqing Zong, Xuelei Hu, Erik Cambria, "Feature Ensemble Plus Sample Selection: Domain Adaptation for Sentiment Classification", is Published by the IEEE Computer Society in IEEE INTELLIGENT SYSTEMS, May-June 2013 (vol. 28 no. 3).
[32] Ying Su, Yong Zhang, Donghong Ji, Yibing Wang, Hongmiao Wu, "Ensemble Learning for Sentiment Classification**",** in Volume 7717, 2013, pp 84-9, Springer Berlin Heidelberg 2013.

[33] Zhongqing Wang ; Suzhou, China ; Shoushan Li ; Guodong Zhou ; Peifeng Li, "Imbalanced Sentiment Classification with Multi-strategy Ensemble Learning", Asian Language Processing (IALP), 2011 International Conference on 15-17 Nov. 2011 .
[34] Kushal Dave, Steve Lawrence, and David M. Pennock, "Mining the Peanut Gallery: Opinion Extraction and Semantic Classification of Product Reviews," presented at the 12th international conference on World Wide Web, Budapest, Hungary, 2003.
[35] Peter D. Turney and Michael L. Littman, "Measuring Praise and Criticism: Inference of Semantic Orientation from Association," ACM Transactions on Information Systems, vol. 21, pp. 315-346, 2003.
[36] Peter D. Turney, "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews," presented at the Association for Computational Linguistics 40th Anniversary Meeting, New Brunswick, N.J., 2002.
[37] Pimwadee Chaovalit, Lina Zhou, "Movie Review Mining: a Comparison between Supervised and Unsupervised Classification Approaches", in Proceedings of the 38th Hawaii International Conference on System Sciences – 2005.