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Improved Technique of Sentiment Classification for Objective Word

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Abstract—

Currently sentiment analysis is dynamic era of research in which people's opinion is being extracted about particular product, service, and brand. The most practical application of sentiment analysis is the sentiment classification of product reviews. Basically the process of sentiment classification involves classification of user reviews either as positive or negative from textual information. But Along with positive and negative reviews, objective review play a crucial role in sentiment classification and important fact is that SentiWordNet is consist of 90% of objective expression which are considered as worthless while scoring polarity of word and sentence. This work proposes a new semi-supervised sentiment classification method by exploiting a large number of unlabeled instances to conduct sentiment classification for Web customer reviews. In the proposed method every customer review has been classified as positive, negative and objective words of reviews. Positive and negative customer reviews replicate the opinions expressed by opinion words, while the objective review is constructed by the remaining text features. In this method we use three sentiment classifiers that iteratively executed and present expected outcome. In the proposed method, the first sentiment classifier is build using the common unigram features coming from customer reviews. The second sentiment classifier is constructed for positive and negative word calculation extracted from consumer reviews. The remaining text features of these reviews are used for evaluating the objective word that can be trained for the third classifier. Experimental outcomes show the proposed method is effective, and classify reviews in positive, negative and objective words effectively.

***Keywords**— Sentiment Analysis, Sentiment Classification, Machine learning, SentiWordNet, Opinion mining, SVM, Naïve Bayes.*

I. INTRODUCTION

Large datasets are available on-line today, they can be numerical or text file and they can be structured, semi-structured or non-structured. Approaches and technique to apply and extract useful information from these data have been the major focuses of many researchers and practitioners lately. Many different information retrieval techniques and tools have been proposed according to different data types. In addition to data and text mining, there has seen a growing interest in non-topical text analysis in recent years. Sentiment analysis is one of them.

In the last decade, sentiment analysis (SA), also known as opinion mining, has attracted an increasing interest. It is a hard challenge for language technologies, and achieving good results is much more difficult than some people think. The task of automatically classifying a text written in a natural language into a positive or negative feeling, opinion or subjectivity [22], is sometimes so complicated that even different human annotators disagree on the classification to be assigned to a given text. Personal interpretation by an individual is different from others, and this is also affected by cultural factors and each person's experience. And the shorter the text, and the worse written, the more difficult the task becomes, as in the case of messages on social networks like Twitter or Facebook.

Wan emergence of online marketing number of blogs, forums and social networks in the Web drastically increased the amount of texts conveying not just facts but opinions. A large number of opinions are customers' reviews about products and services, as e-commerce became more popular. This trend motivated several research works and market applications aiming at the sentiment analysis of the available opinions. Understanding such opinion and sentiment information has become increasingly important for both service and product providers and users because it plays an important role in influencing consumer purchasing decisions [19]. Sentiment analysis is the study of the opinions, feelings or emotions expressed by text. In recent years there has been much emphasis on the study of the opinions of customers / users especially in social networks. Sentiment-classification is an practical approach of sentiment analysis that can help researchers in the study of such information on the Internet by identifying and analysing texts containing opinions and emotions. Basically the process of sentiment classification involves classification of user reviews either as positive or negative from textual information. But Along with positive and negative reviews, objective review play a crucial role in sentiment classification and important fact is that SentiWordNet is consist of 90% of objective expression which are considered as worthless while scoring polarity of word and sentence. In the proposed method we classify customer review into three class positive, negative and objective using semi-supervised sentiment classification method.

II. BACKGROUND

Users express their opinions about products or services they consume in blog posts, shopping sites, or review sites. Reviews on a wide variety of commodities are available on the Web such as, books (amazon.com), hotels (tripadvisor.com), movies (imdb.com), automobiles (caranddriver.com), and restaurants (yelp.com). It is useful for both the consumers as well as for the producers to know what general public think about a particular product or service. Sentiment classification has been applied in numerous tasks such as opinion mining [8], opinion summarization [9], contextual advertising [10], and market analysis [11]. For example, in an opinion summarization system it is useful to first classify all reviews into positive or negative sentiments and then create a summary for each sentiment type for a particular product. A contextual advert placement system might decide to display an advert for a particular product if a positive sentiment is expressed in a blog post.

The main task in sentiment classification is to determine the polarity of the comments as positive, negative or objective. It can be done at different levels such as word/phrase levels, sentence level and document level. Sentiment analysis is one of the most challenging areas in NLP because people express opinion in subtle and complex ways, involving the use of slang, ambiguity, sarcasm, irony and idiom. Most of the research in the field of sentiment classification focuses on polarity classification of review documents. This task can be done more easily by applying sentiment lexicons such as General Inquirer, SentiWordNet, WordNet Affect, and SenticNet. Once the sentiment words are identified, the score of the sentences can be calculated.

How sentiment analysis is performed?

Fig.1 Example of sentiment analysis performance

As shown in figure 1, the key to understanding the beneficial aspect of sentiment analysis is to know how it works, focusing on both the theoretical aspect of it, and also a practical level in professional capacity. First you have to know that the sentiment analysis uses the meaning of the text. The natural language processing and computational linguistics are observed, and extracts subjective information contained in the source materials. These are the elementary actual figures holding the "footstone" based on the analysis of feelings. Note that tend to work hand in hand, that is, so that feelings analysis can work, the three must be present. There are also other means of determining sentiment and achieve the same goal although not very accurate. These methods include the following:

- *The use of the rating system*

The classification system allows people to describe something using numbers or stars as a means of knowing whether the information is reliable or defective product. The problem with this technique is that the comments that are left on a particular web page may not have been actually generated by someone, to be accepted as correct, even though many people rely on this type of qualification.

- *The art of recommendation*

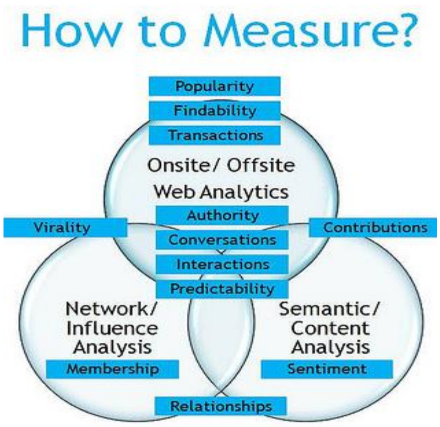

Fig.2 Example of how sentiments are measured in sentiment analysis.

Recommendations can give the whole idea of why there has been a certain opinion. The recommendations tend to be illustrative; therefore, they make others understand. The power of recommendation as shown in figure 2, can be seen in the large number of social sites that have emerged.

For example, if one wants to buy a particular product, it will read the recommendations or opinions that have been written by previous customers so that they can make the decision whether or not to buy that product. All this is done through sentiment analysis and thanks to that decision has been made easier during an online purchase.

Importance of sentiment analysis

Sentiment analysis is important because people want to know when they are doing their day to day business online and do not want to fall into several traps. For example, people do not want to end up buying a product online that is defective, therefore, they want a guide to help them in their purchases. The guide here is sentiment analysis, which tends to lead them and help them make their own decisions on what to buy and not buy.

III. SENTIMENT CLASSIFICATION TECHNIQUE

In the business world, it is increasingly important to know the feeling aroused by the brands and products that companies launched on the market. Sentiment analysis is the best way of knowing positive, negative or objective reviews of any brands or product of company. Sentiment analysis, also known as the meaning of the opinion, comes from the word feeling (a vision, feeling or emotion into something). The process to identify, organize and categorize the views expressed in a text through the polarity of context in order to know whether the attitude of writers towards the product, the subject, and among other things, was really positive, negative or neutral. This rapid technique is being adopted by many, especially those who own websites, and also those who want to do their own research to know if the analysis of a writer was genuine to qualify a product as positive, negative or objective sense.

Sentiment-classification techniques can help researchers study such information on the Internet by identifying and analyzing texts containing opinions and emotions (also referred to as direction-based text). They can help determine whether a text is objective or subjective and whether a subjective text contains positive or negative sentiments [20].

After extraction of information, such as Twitter, if the data set is small you could make an analysis of this type locally. But since the volume of data handled is currently too large, the best option is to use Big Data tools specifically designed for this task. An example is the use of Apache Hadoop with Hive, and finally combined with a software data analysis. In more complicated cases, where most classes are needed instead of making a simple count of words (positive and negative) can be used more complex methods such as Naive Bayes and Support Vector Machine.

The problem related to sentiment analysis has been tackled mainly from two different approaches [21]: Machine learning approach [23] and semantic or lexicon based approaches [24] as shown in figure 3.1.

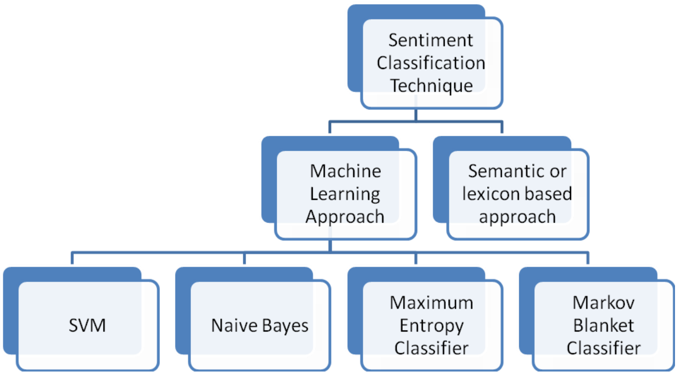

Fig.3 Sentiment Classification Techniques

A. *Machine Learning Approach*

Machine learning method consist on training a classifier using any supervised learning algorithm from a collection of annotated texts, where each text is usually represented by a vector of words (bag of words), n-grams or skip-grams, in combination with other types of semantic features that attempt to model the syntactic structure of sentences, intensification, negation, subjectivity or irony. Systems use different techniques, but the most popular are classifiers based on SVM (Support Vector Machines), Naive Bayes and KNN (K-Nearest Neighbor). More advanced techniques appear in the most recent investigations, such as LSA (Latent Semantic Analysis) and Deep Learning.

Pros and cons of Machine learning approach

The advantage of learning-based approaches is that it is quite easy and fast to build a sentiment/opinion analysis engine trained with the collection of tagged texts. It is therefore relatively easy to build classifiers adapted to a particular domain. In contrast, the effort to build a lexicon for a certain domain, starting from scratch, is very high, because it is based on a hard manual work, so these systems are generally less adaptable.

B. *Semantic Approach or Lexicon based Approach*

This approach is characterized by the use of dictionaries of words (lexicons) with semantic orientation of polarity or opinion. Systems typically preprocess the text and divide it into words, with proper removal of stop words and a linguistic normalization with stemming or lemmatization, and then check the presence or absence of each term of the lexicon, using the sum of the polarity values of the terms for assigning the global polarity value of the text. Typically, systems also include i) a more or less advanced treatment of modifier terms (such as very, too, little) that increase or decrease the polarity of the accompanying terms; and ii) inversion terms or negations (such as no, never), which reverse the polarity of the terms to which they affect.

Pros and cons of semantic or lexicon based approach

The main advantage of semantic approaches is that errors are relatively easy to correct, adding as many words as necessary, and theoretically, we could get a precision as high as we would like, simply investing more time in building the lexicon. In this regard, machine learning approaches are often a black box in which to correct errors or add new knowledge is more complicated, and it is often only possible by expanding the collection of texts and re-training the model.

IV. LITERATURE REVIEW

This section describes literature review or the studies which give an idea that for our research done in direction of sentiment classification.

In this approach of cross-domain sentiment classification[3] first sentiment sensitive distributional thesaurus is created using labeled data for the source domains and unlabeled data for both source and target domains. Sentiment sensitivity is achieved in the thesaurus by incorporating document level sentiment labels in the context vectors used as the basis for measuring the distributional similarity between words. Then thesaurus is created to expand feature vectors during train and test times in a binary classifier. The proposed method significantly outperforms numerous baselines and returns results that are comparable with previously proposed cross-domain sentiment classification methods on a benchmark data set containing Amazon user reviews for different types of products. This approach overcome feature mismatch problem arise in cross-domain sentiment classification, by using labeled data from multiple source domains and unlabeled data from source and target domains to compute the relatedness of features and construct a sentiment sensitive thesaurus. This method restricted to semi-supervised domain adaptation category. For fully supervised category, this method doesn't provide desirable result. This method can be extended for fully supervised category , in order to determine cross-domain sentiment classification. This method can also be extending to determine objective word along with the positive and negative approach.

This method [1] Mine sentiment of opinions from word-of-mouth (WOM) to improve the performance of word-of-mouth Sentiment classification by re-evaluates objective sentiment words in the SentiWordNet sentiment lexicon with the help of SVM classifier. Based on the average accuracy and standard deviation, the proposed, revised SentiWordNet model achieves a higher and more stable classification performance. This method, extracts the first sense of a word from assigned POS tag in SentiWordNet because this usage is generally the most common. But it can cause word sense disambiguation. The technique of word sense disambiguation could be applied before the extraction of SentiWordNet. Sentiment extraction from linguistic or semantic viewpoints is another possible direction. This work uses SVM techniques; a further research direction might focus on using various classification algorithms such as ensemble learning for sentiment classification.

This method improves the sentiment classification by modifying the sentiment values returned by SentiWordNet for intensifiers based on the context to the semantic of the words related to the intensifier and reassign some of the objective words to either positive or negative. Prediction accuracy of this method is much better than the traditional and existing methods. Though the existing method out performs the traditional method its accuracy is less compared to the presented method. This is because miss-classification is less in the proposed method related to the negative sentences as compared to the existing method. This improvement is due to the proper handling of intensifiers. This method can effectively handle intensifier but they doesn’t present effective approach for negation modifier. Word sense disambiguation and identification of the product feature about which the sentiment is expressed can be done as a future work.

In [17] the computational linguistics the extraction of actual sense of words from text has a long history in the field. Due to its importance in the field of sentiment analysis it is considered the most important one. During sentiment analysis more challenging problems are faced due to the ambiguous senses of words. In this work a new method is proposed regarding word sense disambiguation (WSD) using matrix map of the semantic scores extracted from SentiWordNet of WordNet glosses terms. The correct sense of the target word is extracted and determined for which the similarity between WordNet gloss and context matrix is greatest. This method improves the result of sentence level sentiment classification as evaluated on various domain datasets. This work introduce a method of matrix map for WSD, and sentence level semantic orientation taking into account all parts of speech and sentence contextual structure. They doesn’t specify matrix map method for WSD for document level semantic orientation. In future direction for further research lies in applying WSD using matrix map for semantic orientation at document level and feedback level and WSD matrix map will applied for the improvement of sentence clustering which may in turn be based on improved sentence similarity measures.

This approach [18] improves performance of sentiment classification with a proper handle of handling of word sense disambiguation and negation terms. The author used Lesk [16] algorithm for handling word sense disambiguation. For handling negation term, negation scope determination method has been introduced that specify four criteria of handling negation term i.e. ROS, FSW, NNL, and FWL. By handling negation we get more accuracy while performing sentiment classification. Presented method for handling negation are not subtle enough to deal with complex natural language. Interesting direction for future research would be to explore ways of incorporating a deeper understanding of the semantics in the negation handling process in order to to cope up with common phrases or context-dependent interpretations.

This method [2] present feature ensemble plus sample selection (SS-FE) approach to overcome domain adaptation problems arise often in sentiment Classification and provide better results by taking into account labeling adaptation and instance adaptation together. This approach will give effective result for both labeling adaption and instance adaption. Limitation of this approach is that training samples are selected in a "hard" way, which is sometimes too arbitrary. A "soft" manner, which assigns a sampling weight to each of the training samples, seems to be more promising. In the future, we plan to consider a "soft" manner in instance adaptation. Also we plan to integrate instance adaptation with some unsupervised labeling adaptation methods, such as structural correspondence learning (SCL) and spectral feature alignment (SFA), to test our model's effectiveness over a broad range

This method [5] present lexicon enhanced method for sentiment classification combines machine learning and semantic-orientation approaches into one framework that significantly improves sentiment classification performance. With introduction of sentiment features this approach provides better performance. This method requires further refinement in the direction of lexicon extraction process. For further study in this area is to refine the lexicon and extend the sentiment feature-extraction procedure. Further research can also explore other sentiment feature-generation methods, such as corpus-based techniques, and compare their performance.

This method [4] present simplistic a bag-of-word/lexicon-based ensemble method where lexicon-based BoW weak learners are used to provide input for a stronger decision tree based learner. Simplistic BoW methods with ensemble classifiers are much faster than a supervised approach to sentiment classification while yielding similar accuracy. BoW methods also are proved efficient and fast across all datasets. We thus conclude that such methods should be more widely used when available computational time is limited. Specified Lexicon-based Ensemble method provides better accuracy, with less time complexity as compared to other supervised learning approach. Accuracy obtained from such lexicons outperforms other lexicon based approaches. The presented methods do not satisfy expectations and more complex sentiment analysis aspects. In future novel approach can explore for handling complex sentiment analysis aspects in order to achieve higher accuracy.

V. PROBLEM STATEMENT

Design classification technique for an opinionated document d, which can be a product review comprise of consecutive sequence of sentences d = ⟨s1, s2, …, sm⟩ that express positive, negative or objective sentiment.

VI. OBJECTIVE

Objective of this work is

- To formulate algorithm that calculate objective word score along with positive and negative word.
- To develop a system based on the algorithm established above.
- To collect dataset and evaluate the accuracy of the algorithm of sentiment classification.

Our approach enhanced [3] algorithm and the main aim behind this enhancement calculate objective word are considered as useless while scoring polarity of word and sentence.

VII. PROPOSED METHODOLOGY

Mining sentiments of opinions enables consumers to develop buying, switching, and diffusing strategies. A term with a suitable sentiment tag is essential for sentiment classification. SentiWordNet is a public sentiment lexicon that's used to extract sentiments for sentiment classification. However, most existing sentiment mining models ignore objective words, which comprise more than 90 percent of the words in SentiWordNet. These objective words are often considered useless. Our research evaluates objective words along with positive and negative words from provided dataset.

- Document composed of Dataset comments and reviews is fed as input Data Preprocessing.
- Segment the documents into sentence.
- Apply Stanford post tagger on each sentence to extract sentiment feature word. We used noun, verb, adverb and adjective as sentiment feature word.
- After POS tagging, perform lemmatization to take the words into its base form.
- Remove the stop words from sentence.
- With the use of SentiWordNet, sentiment score of extracted sentiment feature i.e. noun, verb, adjective, and adverb has been determined. Since each word has multiple sense in SentiWordNet, we take the average of the three polarity scores (positive, objective and negative) for its noun, verb, adjective and adverb senses separately using the prior-polarity formula i.e.

$$\text{Senti\_Score}(\text{S\_F\_Word} = \text{POS})_i = \frac{\sum \text{SentiWordNet\_Score}(k_i)}{|\text{SynonymSets}(\text{S\_F\_Word} = \text{POS})|}$$

Where k ∈ SentiWordNet (S_F_Word =POS & polarity= *i*) and k denotes the synsets of a given word in a particular sense.

POS ∈ {Noun, verb, adjective, adverb)

i ∈ {positive, Objective, negative)

- For each word with given POS sense (noun, verb, adverb adjective), we get three scores in positive, negative, and objective direction. We employ feature computation strategy to determine the final score of word as a sentiment feature. This strategy use following rules for determining final sentiment feature word:
  If Senti_Score (S_F_Word =POS) $_{objective}$ > 0.5
  We consider the word to be objective.
  Else
  If Senti_Score (S_F_Word =POS) $_{positive}$ > Senti_Score (S_F_Word =POS) $_{negative}$
  We add (word = POS, | Senti_Score (S_F_Word =POS) positive|) to our sentiment feature set.
  If Senti_Score (S_F_Word =POS) $_{positive}$ < Senti_Score (S_F_Word =POS) $_{negative}$
  We add (word = POS, –| Senti_Score (S_F_Word =POS) negative|) to our sentiment feature set.
  If Senti_Score (S_F_Word =POS) $_{positive}$ = Senti_Score (S_F_Word =POS) $_{negative}$
  We eliminate it from our sentiment feature set.
- After performing feature computation strategy we get total number of positive, objective and negative word in whole document.

VIII. RESULT

We compare our result on Sentiment Labeled Sentences Dataset that we have collected from UCI Machine Learning Repository. The UCI Machine Learning Repository is a collection of databases, domain theories, and data generators that are used by the machine learning community for the empirical analysis of machine learning algorithms. The dataset contains sentences come from three different websites/fields:

- imdb.com
- amazon.com
- yelp.com

This dataset consists of text sentences, extracted from reviews of products (books, DVDs, kitchen appliances, electronics), movies, and restaurants.

Table I Dataset Specification

Dataset Characteristics:	Text	**Number of Instances:**	3000	**Area:**	N/A
Attribute Characteristics:	N/A	**Number of Attributes:**	N/A	**Date Donated**	2015-05-30
Associated Tasks:	Classification	**Missing Values?**	N/A	**Number of Web Hits:**	19944

Sentiment classification for both previous and proposed method for some UCI dataset are shown in table II. This table specifies classified positive and negative words for previous method and positive, negative and objective words for proposed method for given UCI dataset.

Table II Sentiment Classification For Both Previous And Proposed Method

Dataset Name	**No. of instances**	**Sentiment classification for previous method**		**Sentiment classification for proposed method**		
		Positive word	**Negative words**	**Positive word**	**Negative words**	**Objective words**
Amazon	1000	367	314	381	248	324
Yelp	1000	431	358	334	214	296
Imdb	1000	329	301	231	267	198

IX. CONCLUSION

In this research work we proposed a new method to improve the sentiment classification of product reviews by considering the objective words along with positive and negative word.

We evaluate sentiment sensitive thesaurus to group words that express similar sentiments for objectivity /subjectivity words. Here we use SentiWordNet, a lexical database with polarity scores. SentiWordNet assigns each synset (a set of synonymous words for a particular sense of a word) in WordNet3 with polarity scores ranges from 0 to 1. In our methodology, we take average of word sense value in its assigned part-of-speech tag as per Stanford POS tagger from SentiWordNet. After that we classify each based on its polarity score that we calculate.

If the degree of the positive polarity is greater than the degree of the negative polarity for a word, then it is classified as a positive word. If the degree of the negative polarity is greater than the positive polarity for a word, then it is classified as a negative word. If both the positive and negative polarity scores are equal and greater than 0.5, then it is classified as objective.

X. FUTURE WORK

In our method, we get average of word sense value in its assigned part-of-speech tag as per Stanford POS tagger from SentiWordNet. Thus, for possible future work, the technique of word sense disambiguation could be applied before the extraction of SentiWordNet. Sentiment extraction from linguistic or semantic viewpoints is another possible direction.

ACKNOWLEDGEMENT

Sentiment Labeled Sentences Dataset has been obtained from UCI database.

REFERENCES

[1] Chihli Hung; Hao-Kai Lin, "Using Objective Words in SentiWordNet to Improve Word-of-Mouth Sentiment Classification," Intelligent Systems, IEEE , vol.28, no.2, pp.47,54, March-April 2013 doi: 10.1109/MIS.2013.1

[2] Rui Xia; Chengqing Zong; Xuelei Hu; Cambria, E., "Feature Ensemble Plus Sample Selection: Domain Adaptation for Sentiment Classification," Intelligent Systems, IEEE , vol.28, no.3, pp.10,18, May-June 2013 doi: 10.1109/MIS.2013.27

[3] Bollegala, D.; Weir, D.; Carroll, J., "Cross-Domain Sentiment Classification Using a Sentiment Sensitive Thesaurus," Knowledge and Data Engineering, IEEE Transactions on , vol.25, no.8, pp.1719,1731, Aug. 2013 doi: 10.1109/TKDE.2012.103

[4] Augustyniak, L.; Kajdanowicz, T.; Szymanski, P.; Tuliglowicz, W.; Kazienko, P.; Alhajj, R.; Szymanski, B., "Simpler is better? Lexicon-based ensemble sentiment classification beats supervised methods," Advances in Social Networks Analysis and Mining (ASONAM), 2014 IEEE/ACM International Conference on , vol., no., pp.924,929, 17-20 Aug. 2014 doi: 10.1109/ASONAM.2014.6921696

[5] Yan Dang; Yulei Zhang; Hsinchun Chen, "A Lexicon-Enhanced Method for Sentiment Classification: An Experiment on Online Product Reviews,"Intelligent Systems, IEEE , vol.25, no.4, pp.46,53, July-Aug.2010 doi: 10.1109/MIS.2009.105

[6] R. Socher, A. Perelygin, J. Wu, J. Chuang, C. D. Manning, A. Y. Ng, and C. Potts, "Recursive deep models for semantic compositionality over a sentiment treebank," in Proceedings of the 2013 Conference on empirical Methods in Natural Language Processing. Stroudsburg, PA: Association for Computational Linguistics, 2013, pp. 1631–1642.

[7] Bhaskar, J.; Sruthi, K.; Nedungadi, P., "Enhanced sentiment analysis of informal textual communication in social media by considering objective words and intensifiers," *Recent Advances and Innovations in Engineering (ICRAIE), 2014* , vol., no., pp.1,6, 9-11 May 2014 doi: 10.1109/ICRAIE.2014.6909220.

[8] B. Pang and L. Lee, "Opinion Mining and Sentiment Analysis," Foundations and Trends in Information Retrieval, vol. 2, nos. 1/2, pp. 1-135, 2008.

[9] Y. Lu, C. Zhai, and N. Sundaresan, "Rated Aspect Summarization of Short Comments," Proc. 18th Int'l Conf. World Wide Web (WWW '09), pp. 131-140, 2009.

[10] T.-K. Fan and C.-H. Chang, "Sentiment-Oriented Contextual Advertising," Knowledge and Information Systems, vol. 23, no. 3, pp. 321-344, 2010.

[11] M. Hu and B. Liu, "Mining and Summarizing Customer Reviews," Proc. 10th ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining (KDD '04), pp. 168-177, 2004.

[12] Jun Fu Cai, Wee Sun Lee ,YeeWhye The (2007) Improving Word Sense Disambiguation Using Topic Features. In Proceedings of the 2007 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning

[13] Y. K. Lee and H. T. Ng. 2002. An Empirical Evaluation of Knowledge Sources and Learning ISSN 1013-5316; CODEN: SINTE 8 Sci.Int.(Lahore),25(4),937-943,2013 944 Algorithms for Word Sense Disambiguation. In Proc. of EMNLP.

[14] T. Joachims, "Text Categorization with Support Vector Machines: Learning with Many Relevant Features," Proc. 10th European Conf. Machine Learning (ECML '98), pp. 137-142, 1998.

[15] A. Esuli and F. Sebastiani, "SentiWordNet: A High-Coverage Lexical Resource for Opinion Mining" Proceedings of LREC, 2006, pp. 417-422.

[16] M. Lesk, "Automatic Sense Disambiguation Using Machine Readable Dictionaries: How to Tell a Pine Cone from an Ice Cream Cone," in 5th Annual International Conference on Systems Documentation (SIGDOC 1986). ACM, 1986, pp. 24–26.

[17] Muhammad Faheem Khan, Aurangzeb Khan and Khairullah Khan "Efficient Word Sense Disambiguation Technique For Sentence Level Sentiment Classification Of Online Reviews" Sci.Int.(Lahore),25(4),937-943,2013

[18] Hogenboom, A.; van Iterson, P.; Heerschop, B.; Frasincar, F.; Kaymak, U., "Determining negation scope and strength in sentiment analysis," Systems, Man, and Cybernetics (SMC), 2011 IEEE International Conference on , vol., no., pp.2589,2594, 9-12 Oct. 2011

[19] Rubicon Consulting, "Online Communities and Their Impact on Business: Ignore at Your Peril," 25 Mar. 2009; http://rubiconconsulting.com/ downloads/whitepapers/Rubicon-webcommunity. pdf.

[20] A. Abbasi et al., "Sentiment Analysis in Multiple Languages: Feature Selection for Opinion Classification in Web Forums," ACM Trans. Information Systems, vol. 26, no. 3, 2008, pp. 1–34.

[21] Liu, Bing. 2012. *Sentiment analysis and opinion mining*. Synthesis Lectures on Human Language Technologies, 5(1):1-167.

[22] Pang, Bo and Lillian Lee. 2008. *Opinion mining and sentiment analysis*. Foundations and Trends in Information Retrieval, 2(1-2):1-135.

[23] Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. 2002. *Thumbs up? Sentiment classification using machine learning techniques*. In Proceedings of the ACL-02 conference on Empirical methods in natural language processing – Volume 10, EMNLP'02, pp 79-86, Stroudsburg, PA, USA. Association for Computational Linguistics.

[24] Turney, Peter D. 2002. *Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews*. In Proceedings of the 40th Annual Meeting on Association for Computational Linguistics – ACL '02, 417, Philadelphia, Pennsylvania.

[25] Villena-Román Julio, Janine García-Morera, Miguel A. García Cumbreras, Eugenio Martínez Cámara, M.Teresa Martín Valdivia, and L. Alfonso Ureña López, eds. 2015. *Proceedings of TASS 2015: Workshop on Sentiment Analysis at SEPLN*. CEUR WS Vol 1397, http://ceur-ws.org/Vol-1397/.

[26] J. Blitzer, M. Dredze, and F. Pereira, "Biographies, Bollywood, Boom-Boxes and Blenders: Domain Adaptation for Sentiment Classification," Proc. 45th Ann. Meeting of the Assoc. Computational Linguistics (ACL '07), pp. 440-447, 2007.

[27] S.J. Pan, X. Ni, J.-T. Sun, Q. Yang, and Z. Chen, "Cross-Domain Sentiment Classification via Spectral Feature Alignment," Proc. 19th Int'l Conf. World Wide Web (WWW '10), 2010.

[28] H. Fang, "A Re-Examination of Query Expansion using Lexical Resources," Proc. Ann. Meeting of the Assoc. Computational Linguistics (ACL '08), pp. 139-147, 2008.

[29] G. Salton and C. Buckley, Introduction to Modern Information Retreival. McGraw-Hill Book Company, 1983.

[30] D. Shen, J. Wu, B. Cao, J.-T. Sun, Q. Yang, Z. Chen, and Y. Li, "Exploiting Term Relationship to Boost Text Classification," Proc. 18th ACM Conf. Information and Knowledge Management (CIKM '09), pp. 1637-1640, 2009.

