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Semantic Aspect Based Sentiment Classification using Normalized Yahoo Distance based Particle Swarm Optimization

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Abstract

People's opinions and experience are important sources of information in our everyday life. In the modern digital age, text is the main method of communicating information on the Internet. Sentiment Classification is the process of judging the sentiments and emotions from reviews. The paper investigates new approaches to the automated extraction of opinions and aspects and sentiment classification from customer reviews. It focuses on aspect-based sentiment classification from customer reviews. Evaluations algorithms and lexicon approaches with normalized yahoo distance are utilized based on semantic relations of customer reviews. The contributions are significant, given both the rapid explosion of today's accessibility to the Internet and people's desire to make informed decisions.

Keywords: *Aspects, Sentiments, Sentiment Classification, Part of Speech Tagging, Particle Swarm Optimization.*

1. Introduction

These days, tremendous measures of information are created each day. It is an extremely difficult assignment to get usable data from information. One of the fundamental outlets of information is micro blogging sites and review sites [1]. Millions of tweets, comments and posts are posted on every day. In addition to opinion sites such as Epinions.com, rottentomatoes.com, and cnet.com which focuses on collecting both professional and amateur reviews for numerous products and services. Before the rise of internet to answer the question of "What do people think about any product or anything else", Surveys and polls are distributed in the form of paper in peoples. With the expeditious development of the internet and the popularity of Micro-blogging sites like Facebook, Twitter, etc. enables an alternative option for getting opinions from large populations. Now a day's Web becomes the necessity for people to share their ideas, experiences and opinions as well as seeking others experiences and opinions [2]. Millions of ideas and experiences are shared every day, It is impossible for peoples to read all ideas and experiences. About 2.7 million Google searches were made. A query "Artificial Intelligence" returns 98,400,000 results. This whole scenario demands fast, effective and accurate technique to track sentiments, opinions and ideas that are flowing on the internet. Sentiment classification is the key component of such techniques. Sentiment identification is an extremely complex issue, and hence much exertion has been put into investigating and attempting to comprehend its diverse perspectives[3]. Sentiment Classification or opinion mining has been studied at three different levels of classification [4] these include document level, sentence level and at aspect level. Classification of the whole document in a positive or negative is called document level

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classification. Sentence-level sentiment classification techniques read document sentence by sentence and decide whether each sentence gives a positive, negative or neutral opinion for a service, product, etc. Aspect level or entity level sentiment classification is the most modern technique which classifies the reviews or comments on the basis of aspects or entities.

When analyzing larger pieces of the text using sentence level and document level, sometimes doesn't give true reflection sentiments. This is where Aspect-Based Sentiment classification (ABSC) comes in. With ABSC, you can dive deeper and analyze the sentiment on a piece of text toward specific aspects. The whole paper is revolving around Aspect-Based Sentiment analysis.

2. Background Study

In the last two decades, a lot of research work has been carried out in sentiment analysis. Techniques of aspect based sentiment classification have been performed for a variety of applications over a wide range of classification algorithms.

Machine learning techniques are very much in sentiment analysis. Paper [5] uses Support Vector Machine, Navie Bayes and Maximum entropy with different feature extracting techniques on movie reviews. Experimental results show the SVM has better performance with unigram text representation. It has been noted that without POS tagging information accuracy of naive bases and maximum entropy increases, but it decreases the performance of SVM. Support Vector Machine (SVM) a more efficient classifier than Naive Bayes in many cases. The authors adopted SVM classifier with Gini Index feature selection method for sentiment classification for large movie review data set [4]. Experimental results show that Gini Index feature selection method is better in terms of accuracy and performance. Paper achieves the accuracy 78% using SVM classifier on a large dataset of movie reviews.

Another paper implements the three sentiment analysis algorithms for identifying the sentiments (positive or negative) from reviews [6]. Experiential results are then compared with the numerical ratings of hotels. Dataset of One million reviews with numerical rating is collected from Tripadvisor. Results show that the predicted rating from sentiment analysis algorithms are very close to actual ratings of hostel.Dependency relation (DR) can be used to generalize the changing relationship of opinion words and aspects.) Paper [7] enlisted the DR to get paired aspect-opinion by using movie reviews. By using the dependency relationship parser, the parsed words in a sentence are joined by definite dependency relationship. By using dependency sequence, encouraging results in various research fields by employing distinct approaches to point product features and their kindred point of view from various language reviewsThe Paper proposed new method using ConceptNet ontology based dependency relations to extract features from text [8]. They also used a method called " mRMR" which is basically a feature selection scheme to remove redundant information. Another paper proposed a technique that retrieves product aspects and opinions by taking signifies and linguistics information based on dependency relationship[9].

Paper [20] implement the three sentiment analysis algorithms for identifying the sentiments (positive or negative) from reviews. Experiential results are then compared with the numerical ratings of hotels. Dataset of One million reviews with numerical rating is collected from Tripadvisor. Results shows that predicted rating from sentiment analysis algorithms are very close to actual ratings of the hostel. Sentiment analysis techniques for web based patient reviews are proposed in [21]. The paper also describes how sentiment analysis is useful for patients, doctors as well as a healthcare manager. Author also explores some limitations which are proper dataset of patient reviews are not present and it is very hard to collect this type of dataset and second it is very hard to judge patient volume of disease using its comments.

3. System Architecture

System architecture includes the components which are used in system setup. System setup contains four steps. They are Dataset, Preprocessing, Aspect Extraction, Aspect Optimization,

Sentiment detection (positive and negative). Graphical representation of System Setup is shown in Figure 1

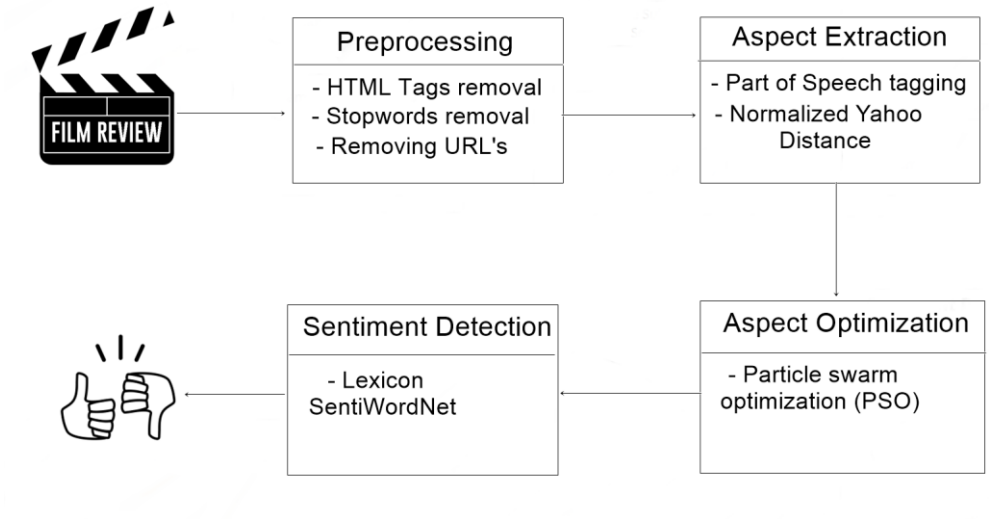

Figure 1: System Setup

3.1. Dataset

Selection of the dataset is very important in any research area, especially in sentiment classification. We are using movie reviews dataset for experiments [19]. The main reason behind choosing a movie review dataset is that it is slightly different from the other reviews dataset.This is because the reviews on movies are sometimes regarded the storyline or the content of the movie, which is occasionally different from the general opinion reading how the reviewers watch the movie. The movie review dataset contains fifty thousand movie reviews for testing and training.

3.2. Preprocessing

Reviews and comments that are overflowing on the internet contain syntactic features which are generally not useful in aspect based sentiment classification. Also, there are lots of stop words, slang words, URLs, etc are present in reviews are comments. Actually peoples don't pay much attention in writing reviews such as product reviews, movie reviews, etc. These stop words, slang words, HTML tags etc. slows down the sentiment classification process. Also, these these HTML tags and special words are the biggest hurdle in the extraction of aspects of product reviews. In order to clean the unprocessed data, this preprocessing step is needed [10].

3.2. Aspect Extraction

Preprocessed reviews are provided to part of speech tagger in order to find the aspects from reviews. Part of speech tagger is such a technique that assigns all words from reviews to part of speech classes. These classes are nouns, verb, adjective, etc. I am using a Sanford Part of Speech tagger [11] for assigning words to part of speech classes. We are using part of speech tagger for finding the aspects from reviews. Usually nouns are taking as aspects [12][13].

Semantic relations between aspects are calculated using Normalized Yahoo distance. Normalized Yahoo Distance (NYD) is based on Yahoo search engine is used to measure the semantic similarity of aspects. NYD search the words in number of pages indexed in Yahoo and aspects which have same meaning shows closer and aspects which are different meaning looks further apart. Semantic similarity between two aspects a1 and a2 are calculated by NYD:

$$\mathrm{NYD}(\mathrm{word1}, \mathrm{word2}) = \frac{MAX\{logf(word1), log(word2)\} - logf(word1, word2))}{log(N) - MIN\{log(f(word1), log(f(word2)\})}$$

Here a1 and a2 are the aspects, f(a1) and f(a2) are the number of hits for aspects a1 and a2. N is the total number of pages indexed in Yahoo. If NYD(aspect1, aspect2) = 0 and NYD(aspect1,aspect2)<1 then both aspects are closely related to each other and on the other hand, if NYD(aspect1, aspect2) > 1 then both aspects are very much different from each other.

3.2. Aspect Optimization

Particle Swarm Optimization [14] is used for the optimization of aspects. Population based stochastic optimization technique, named as Particle swarm optimization (PSO) was presented in 1995. PSO follow the social behavior of fish schooling or bird flocking. Like other evolutionary algorithms, PSO also takes input in the form of random solutions and solutions improves iterations to iterations. It searches global optima by updating generations. Position and velocity are the two main components of PSO. First one, position component represents the certain solution of particles. The second and most important component velocity represents the direction of particle movement in solution space. Same like Genetic Algorithm fitness function is used to calculate the fitness value of each particle.PSO searches the global optima by updating generations. Two best values (pbest and gbest) are updated on each iteration. Pbest is the 'particle best value in term of best solution achieve so far and gbest is the 'global best' is the best value from all particles best solution achieved so far [15]. Using pbest and gbest algorithm calculates the values of position and velocity.

3.2. Sentiment Detection

All optimal aspects are used as the input in this subsection and sentiment is detected using SentiWordNet [16]. SentiWordNet is a is publicly available lexical resource for sentiment classification and opinion mining. SentiWordNet assigns to three sentiment scores: positivity, negativity, objectivity. There are two versions of SentiWordNet which are publicy available for research. SentiWordNet 1.0 and SentiWordNet 3.0. Both versions of SentiWordNet are based on WordNet. SentiWordNet 3.0 [17] is the latest and more enhanced version of SentiWordNet. SentiWordNet provides the positive and negative scores as well as objective scores of any term. Sentiment scores of all optimal aspects are taken from SentiWordNet. Positive or negative sentiment will be detected by sum all scores of reviews divided by the total aspects of reviews.

4. Results and Experiments

K-Fold cross validation method with accuracy, is used in order to evaluate the results. K-fold is one of the well know type of cross valuation used in many papers. Basic idea of K-Fold validation is dividing the data set into K bins of equal size [18]. Take one bin for testing and other K-1 bins for training, Run this process K time and then calculate the average from K times results. In this way all datasets are used as a training as well as testing. The technique was run separately on the two selected datasets (product reviews and movie reviews) and as expected, different results were obtained from each other.

The Stanford Movie dataset has 50,000 movie reviews. For applying a K-fold cross validation we need create a bin of equal size so we create 5 bins having ten thousand (10,000) reviews in eachs bin. Accuracy table of all five bins with number of reviews is shown in table 1. Graphically representation is shown in figure 2.

Table 1: Accuracies of all bins.

#	Testing Bin	Training Bin	Testing Reviews	Training Reviews	Accuracy(%)
1	A	B,C,D,E	10,000	40,000	86.20
2	B	A,C,D,E	10,000	40,000	84.60
3	C	A.B.D,E	10,000	40,000	86.40
4	D	A,B,C,E	10,000	40,000	85.50
5	E	A,B,C,D	10,000	40,000	87.40

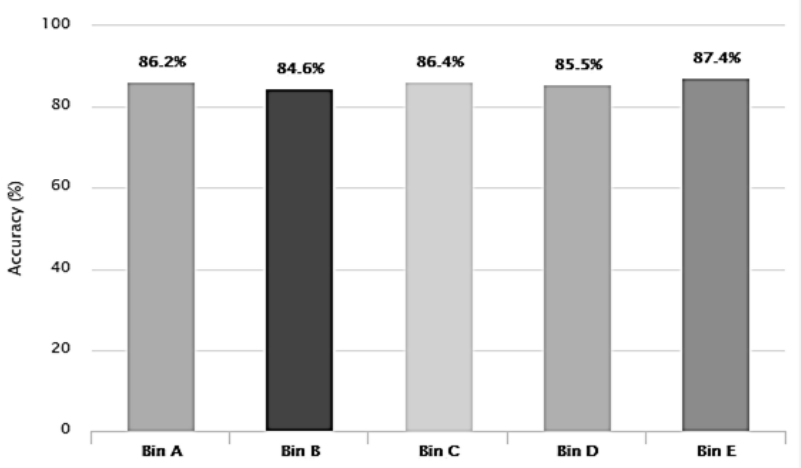

Figure 1: Accuracy Graph

We get the final accuracy by averaging all the accuracies that come from K-fold cross validations. Accuracy of our technique on Movie reviews dataset is 86.02%. As expected our proposed technique of aspect based sentiment classification using Normalized Yahoo distance and Particle Swarm Optimization provides best accuracy on the movie review dataset. The addition of SentiWordNet with NYD and PSO provides consistent performance in identifying the valid and correct aspects.

CONCLUSION

Sentiment Classification comes forth as a challenging field with lots of fences as it involves natural language processing and hidden emotions. It has a wide variety of applications that could benefit from its results, such as movie reviews, product reviews, news, analytics, and marketing, question answering, knowledge bases and so on. There are various areas in sentiment classification field where lots of improvement is needed with existing techniques Hence, efficient computing techniques are necessary for mining and summarizing reviews from Web documents, reviews and corpuses.

In this paper, we addressed the problem of determining sentiment class using aspect based sentiment classification. Aspect extracting and opinion extraction is an overlapping process, however, knowing the entities make the process of limited use. We model the aspect based sentiment classification in two parts. First one is extracting aspects from reviews and the second one is applying PSO using semantic relations of aspects. We successfully implement our model on movie reviews Binary classification is done in two classes: positive and negative. An experimental result showed improvement over the current state-of-the-art techniques.

References

[1] H. Keshavarz, M. S. Abadeh, and M. Almasi. "A new lexicon learning algorithm for sentiment analysis of big data."Intelligent Systems and Informatics (SISY), pp. 000249-000254, 2017.

[2] A. Zubiaga, I. S. Vicente, P. Gamallo, J. R. P. Campos, I. A. Loinaz, N. Aranberri, A. Ezeiza, and V. F. Fernández. "Overview of TweetLID: Tweet Language Identification", TweetLID@ SEPLN, pp. 1-11. 2014.

[3] O. Ahlgren. "Research on Sentiment Analysis: The First Decade," Data Mining Workshops (ICDMW), IEEE, pp. 890-899, 2016.

[4] A. S. Manek, P. D. Shenoy, M. C. Mohan, and K. R. Venugopal. "Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier." World wide web 20, no. 2, pp. 135-154, 2017

[5] B. Pang, L. Lee, and S. Vaithyanathan. "Thumbs up?: sentiment classification using machine learning techniques," ACL-02 conference on Empirical methods in natural language processing, vol. 10, pp. 79-86, 2002.

[6] B. López, R. Rodolfo, S. S. Alonso, and M. A. S. Urban. "Evaluating hotels rating prediction based on sentiment analysis services," Aslib Journal of Information Management, vol. 4, pp. 392-407, 2015.

[7] L. Zhuang, F. Jing, and X.Y. Zhu. "Movie review mining and summarization," In Proceedings of the 15th ACM international conference on Information and knowledge management, pp. 43-50, 2006

[8] A. Agarwal, A. Mulgund, A. Hamada, and M. R. Chyatte. "A unique view on male infertility around the globe," Reproductive Biology and Endocrinology, 2015.

[9] G. Somprasertsri, and P. Lalitrojwong. "Mining Feature-Opinion in Online Customer Reviews for Opinion Summarization." J. UCS, vol. 6, pp. 938-955, 2010.

[10] A. Saleem, K. H. Asif, A. Ali, S. M. Awan, and M. A. Alghamdi. "Pre-processing methods of data mining." In Utility and Cloud Computing (UCC) IEEE/ACM 7th International Conference, pp. 451-456, 2014.

[11] G. Wang, Z. Zhang, J. Sun, S. Yang, and C. A. Larson. "POS-RS: A Random Subspace method for sentiment classification based on part-of-speech analysis," Information Processing & Management, pp.458-479, 2015.

[12] J. Yu, Z. Zha, M. Wang, and T. Chua. "Aspect ranking: identifying important product aspects from online consumer reviews," In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, vol 1, pp. 1496-1505, 2011.

[13] Z. Zha, J. Yu, J. Tang, M. Wang, and T. Chua. "Product aspect ranking and its applications." IEEE Transactions on knowledge and data engineering, pp.1211-1224, 2014.

[14] D. K. Gupta, K. S. Reddy, and A. Ekbal. "Pso-asent: Feature selection using particle swarm optimization for aspect based sentiment analysis," In *International conference on applications of natural language to information systems*, pp. 220-233, 2015.

[15] A. P. Engelbrecht, "Particle swarm optimization: Global best or local best?." In *Computational Intelligence and 11th Brazilian Congress on Computational Intelligence (BRICS-CCI & CBIC),* pp. 124-135, 2013.

[16] A. Esuli, and F. Sebastiani. "SentiWordNet: a high-coverage lexical resource for opinion mining." Evaluation, pp. 1-26, 2007.

[17] S. Baccianella, A. Esuli, and F. Sebastiani. "Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining." In LREC, vol. 10, pp. 2200-2204, 2010.

[18] T. T. Wong, "Performance evaluation of classification algorithms by k-fold and leave-one-out cross validation." Pattern Recognition, pp. 2839-2846, 2015.

[19] A. L. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts. "Learning word vectors for sentiment analysis." In Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies, vol 1, pp. 142-150, 2011.

[20] W. He, X. Tian, R. Tao, W. Zhang, G. Yan, V. Akula, "Application of social media analytics: a case of analyzing online hotel reviews", Online Information Review, pp: 921-935, 2017.

[21] A.M. Abirami, A. Askarunisa, "Sentiment analysis model to emphasize the impact of online reviews in healthcare industry", Online Information Review,pp: 471-486, 2017.