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Aspect Term Extraction for Aspect Based Opinion Mining

M. Yesu Babu, P. Vijaya Pal Reddy, C. Shoba Bindu

Abstract: ***Opinion Mining (OM) is also called as Sentiment Analysis (SA). Aspect Based Opinion Mining (ABOM) is also called as Aspect Based Sentiment Analysis (ABSA). In this paper, three new features are proposed to extract the aspect term for Aspect Based Sentiment Analysis (ABSA). The influence of the proposed features is evaluated on five classifiers namely Decision Tree (DT), Naive Bayes (NB), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Conditional Random Fields (CRF). The proposed features are evaluated on the Two datasets on Restaurant and Laptop domains available in International Workshop on Semantic Evaluation 2014 i.e. SemEval 2014. The influence of proposed features is evaluated using Precision, Recall and F1 measures. The proposed features are highly influencing for aspect term extraction on classifiers. The performance of SVM and CRF classifiers with proposed features is more influencing for aspect term extraction compared with NB, DT and KNN classifiers.***

Keywords: ***ABSA, KNN, Naïve Bayes, CRF, SVM, Decision Tree (DT).***

I. INTRODUCTION

Nowadays the world is completely transforming into digital in all categories and domains. Part of this transformation of ratings of reviews, online reviewing and recommendation has become more popular and helpful these days. To visit a certain place or to buy a certain product people were heavily depending on these online reviews and ratings. We need an automatic system in order to categorize and evaluate the sentiment of these increasingly huge reviews into neutral, negative or positive.

With the growth of information on the Internet, opinion mining or sentiment analysis has become famous buzz words and gained a lot of importance. These fields of study have brought a lot of attention to the commercial sector. According to Liu [1], the Internet contains two kinds of information such as Facts and Opinions. Facts can be defined as the objective statements about events and entities in the world whereas Opinions are subjective statements that explain customers perceptions or sentiments about the events and entities. According to [1], processing of facts was given a lot of attention while processing of opinions very less importance was given. The Sentiment analysis was performed in three levels such as aspect level, document level and sentence level. Among these the ABSA is one popular research topic attracted by the several researchers which says extracting the sentiments present in the text about the aspects. Liu [2] identified that the research works for aspect extraction were categorized into four types such as frequent terms, infrequent terms, topic modeling and machine learning. In this work, a new machine learning approach is proposed for aspect identification and extraction. The sequential labeling algorithm is used in this approach to train the training dataset.

In recent times, Sentiment Analysis (SA) becomes a significant task in Natural Language Processing (NLP). As compared to various tasks of NLP the SA become a challenging one. The SA becomes very useful in several practical oriented applications. For example, understanding the popularity of a product by studying the users' opinions about any product becomes very easy. Most of the researchers were concentrated on analysis of individual sentences [5] and the general SA [3]. Sentence level or Document level SA is not capable to perform the complete investigation of an expressed opinion at the level of words by its design. Expressing sentiment at the level of words is named as the ABSA and this works on the important aspects level of the target entity [2]. Two main subtasks performed in the ABSA, one is the extraction of the aspect term and the other one is its polarity detection [4]. If we go in detail about each one of them, Aspect term extraction can be expressed as in a given set of review sentences, identification of the aspect terms present in each sentence. All aspect terms were identified including the aspect terms which are having no sentiment expression. The ontology is constructed with these aspect terms to identify frequently discussed aspects. Multi-word aspect terms should be treated as single terms. In this work, the task of identification of entities present in a given sentences, task of extraction of aspects and the task of finding the list of distinct aspect terms were addressed.

This paper is structured as 5 sections. The section 2 explains the existing work happened in extraction of aspect terms. The proposed system and the new set of features for extraction of aspect terms are described in section 3. The section 4 presents the datasets used for experimentation, the matrices used to evaluate the efficiency of the proposed system, the experimental results and the discussion on the obtained results. The conclusions drawn from the results and possible extensions to the proposed work are described in the section 5.

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***Correspondence Author(s)**
Mr. M. Yesu Babu, Research Scholar, Department of CSE, JNTU Anantapur, AndraPradesh, India.
Dr.P.Vijaya Pal Reddy, Professor & Head, Department of CSE, Matrusri Engineering College, Hyderabad, Telangana, India.
Dr. C. Shoba Bindu, Professor, Department of CSE, JNTUCE, Anantapur, Andhra Pradesh, India.

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II. LITERATURE REVIEW

Supervised machine learning was become a standard approach when experimented with bag-of-n-gram or bag-of-word feature sets to the classification of sentiment polarity since the seminal work done by Pang [3] on movie reviews dataset for polarity prediction. The heuristic methods considered a lexicon of sentiment words as good quality sentiment indicators in unsupervised induction [9]. The replacement of labels or scores of training or test words from sentiment lexicons was also used in [6], who supplement n-grams with generalized expressions like NEGATIVE location. The Linguistic features capture generalizations at the semantics level [8], syntax [7], and discourse [9] were also widely applied in different approaches. In [10], they derived binary features from the nodes of a decision tree for aspect based sentiment analysis and they used these features in different task of quality estimation for machine translation [10].

Hu and Liu worked [25, 26] on mining and summarizing customer reviews on products sold online. Their objective was to make it easier for potential customers to research a product by creating a search engine capable of taking a product feature as a search query and displaying a summarization of the sentiment of reviews it had appeared in. The used reviews mined from Amazon.com and Cnet.com which they then manually labeled for features before using the data to test various opinion feature mining techniques. They showed that their techniques perform quite well for both opinion feature mining and sentiment analysis.

The work of Dave, Lawrence and Pennock [27] used labeled training corpora available from websites, to train sentiment classifiers. They showed that using their classifiers on test reviews worked well, although the performance when classifying sentences obtained with a search engine with a product name as a search parameter was limited due to the shortness of the sentences. They did not mine features from their reviews.

Morinaga et al. [28] had the objective of extracting product reputations from the internet. They compare various products in the same category to find its reputation but they do however not mine product features nor summarize the results. Even though they don’t mine feature they do perform four types of text mining such as extraction of characteristic words, typical sentences for specific product categories, co-occurrence words and correspondence analysis among multiple product categories.

Bermingham and Smeaton [29] observed that the hypothesis easily classify the sentiment of short documents when compared with long documents. They also explore the difference in classification of microblogs vs microreviews. They trained and tested on both long- and short form documents, and had some success classifying microblogs but were unable to increase the efficiency by enhancing the representation of unigram features for these short form documents. Prediction accuracy for longer texts was worse than for the shorter text.

Most of the existing approaches to ABSA have focused on completely different aspects in a text [11] and sentence level composition produced [12] by approaches based on lexicon, which perform efficiently in a several domains, combined lexicon-based methods [13] and supervised learning. In [14], they used a dependency parser to produce a features set which depends on aspects for classification. The authors in [15] recognized the terms which express key concepts in a service review or product. They proposed a general approach to extract noun phrases and nouns as probable terms and certain filtering techniques were applied to ensure the experiment contains the most relevant terms only. These approaches comprise statistical association tests, and measures of association with certain predefined words classes like relation among whole and part indicators [11].

Some researchers divided their work into two research areas related to sentiment classification for aspect terms and research related to aspect and aspect term identification. Prior to these aspects has also been called as topics and features. Until more recently, the SA community lacked a dataset of correctly labeled data for ABSA which focuses on aspect terms. Earlier unsupervised or semi-supervised setting [16] was used for learning or identifying aspects. Previously aspect detection was done by using information extraction (IE) techniques by identifying frequently occurring noun phrases. Clustering [11] and topic models [17] are unsupervised techniques. The benchmark corpus for sentiment analysis concentrated more work on studying subjective phrases in a supervised setting. The behavior of the annotation data totally differs from the data used in this Semeval task which was focusing on articles of news and finding the source of the opinion, an entire opinion phrase. The recent SemEval tasks added the dataset which contain aspect annotations.

Several techniques used by various researchers to extract the aspect and the polarity associated with it inspired by their proposed approach which includes extraction-like approaches which uses sequence modeling [18] and semantic dependency or semantic parsing approaches [19] which sometimes uses sentiment lexicons [20] as background knowledge. If we spot the differences between Breck [18] that of our approach is the classifier used and some of the other features. We used Maximum entropy classifier while they used Conditional random Field and a wider range of dictionary-based and syntactic features. Secondly, Kim [19] has developed a corpus which includes more aspect information which also mainly didn’t focus on reviews but focused on new articles by expanding the types of aspects identified. The target of opinion for identification and FrameNet role labels of the holder and were used while the opinion is directed to the system. In Semeval task, more than 3000 restaurant reviews are used which are harvested by [21], and also for test data newly annotated sentences are used. The original corpus contains nearly 50000 structured reviews of restaurants which include star rating of reviews and restaurant information. Unsupervised [22] or semi-supervised [23] approaches are mostly used for exploring these types of corpuses. They observed that reviewing all the similar type of work is impossible when there is an explosion of research going on sentiment classification.

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If we look at the recent survey of [24], we observe that our proposed approach is using a standard machine learning approach with a proposed feature set. Finally, we have observed that various works has examined the combined task of identifying the targets and opinion phrases simultaneously with polarity.

III. PROPOSED APPROACH

The proposed approach to extract aspect terms follows various steps such as Text preprocessing, extraction of Features and Classification. The various steps followed for aspect term extraction is presented in Figure 3.1

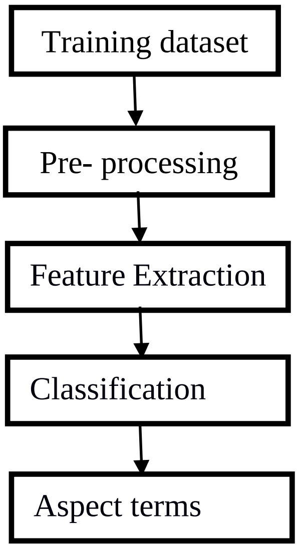

Figure 3.1: Aspect term extraction Approach

A. *Preprocessing*

Text preprocessing was used to remove noisy and unwanted data from the reviews dataset. Various preprocessing techniques such as tokenizer, lemmatizer and Part-of-Speech tagger were applied on reviews sentences of the dataset. The Stanford CoreNLP framework is used to perform these preprocessing techniques. The parsing information is used to extract various syntactic features. The noun phrases were extracted by using basic phrase chunking which is provided by the OpenNLPchunker. Natural Language Toolkit is used for stop words removal and lemmatization.

B. *Feature Extraction*

Many features were proposed in the existing works. In this paper, few features were used for term extraction and proposed a set of new features to increase the efficiency of the proposed approach. The features are presented below:

i) Local context (LC) : The word and it preceding and succeeding words.

ii) Parts of Speech (POS) tags: The POS tag of the present word and its previous and next words POS tagging.

iii) Named Entity Recognition (NE): Named Entities such as organization, person, location are extracted from thee sentences.

iv) Word n-gram (WN): All the word unigrams, word bigrams and word trigrams from the review text.

v) Chunk (CH): This feature is used to finding the boundaries of aspect terms. The POS taggers are used to extract the POS tag sequence of the sentences as the small phrases.

vi) Dependency tree (DT): Parse dependency tree is used to extract the adjectives and adverbs of the nouns in the tree.

C. *Proposed features*

i) Before be verb (BB): In most of cases, it is observed that the aspect terms were considered as nouns which occur before the be verbs.

ii) Inanimate words (IW): The inanimate nouns were considered as aspect terms. The WordNet database is used to identify the inanimate words.

iii) Number of Sentences (NS): It was observed that most of the reviews consist of at least one sentence. Because of this reason, the number of sentences is considered as a feature. In this work, Stanford Parser is used to count the number of sentences in a review.

D. *Classification*

In this paper, the proposed approach performance is evaluated using several machine learning algorithms like Naive Bayes (NB), Decision tree (DT), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). These algorithms were used to extract aspect terms using various combination of the existing features and proposed features.

Decision Tree algorithm i.e. C4.5 builds decision tree based on the entropy information. The algorithm chooses most appropriate feature to split the node based on information gain. This process repeated to identify the next best features to construct a tree like structure using information gain values. NB classifier is a linear classifier which works based on Bayes Rule. It assumes that the features are mutually independent. K-Nearest Neighbor classifier relies on computing the distance among the feature vector of unknown example and feature vectors of training examples. The decision is based on the k nearest neighbors of the unknown example.

SVM algorithm takes given known training data and generates an optimal hyperplane to predict the class label of unknown examples. CRF is used to predict the labels for words based on their conditional dependence. CRF assumes that the each label is depends on the label of the previous word.

IV. RESULTS AND DISCUSSION

A. *Datasets*

In this paper, the experiment performed on the sentences that were extracted from the consumer reviews of Laptops and Restaurants for ABSA. The reviews of laptop training data consists of 3045 sentences and aspect terms were annotated with polarity. The training data of Restaurant reviews consists of 3041 English sentences and the polarity of each aspect term is annotated. The test data consists of 800 sentences from both review sets. Additionally, two domain specific reviews datasets of restaurants and laptops were provided for training and these datasets consists of nearly 6000 sentences with aspect level annotations.

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Table 1: Dataset Description

Dataset	Training	Aspect terms	Testing	Categories
Restaurant	3041	3693	800	5
Laptop	3045	2358	800	-

B. *Performance Measures*

The aspect term extraction tasks were evaluated with Recall, Precision and F-measures. The formulas for precision, recall and F1 measure are as follows:

$$F1 = \frac{2.P.R}{P + R}$$

Where precision (P) and recall(R) are defined as

$$P = \frac{|S \cap G|}{|S|}, R = \frac{|S \cap G|}{|G|}$$

Here S is the set of aspect term that a system return for all the test sentences and G is the set of correct aspect term annotations.

C. *Analysis of Feature Engineering*

The proposed approach performance is evaluated on annotated dataset with 5-fold cross validation by splitting the reviews dataset into testing and training dataset. The training dataset was used to train the classifiers with the existing and proposed features. The recall, precision and F1 measure values are presented in the below tables for the five classifiers by eliminating each feature from all features. The proposed three features are treated as a set. The influence of each feature including the proposed feature set in measured and presented in the tables.

Table 2: (A) Aspect term extraction with feature ablation experiment for Restaurant Dataset using NB

Feature Set	Naive Bayes		
	P	R	F1
All features	0.816	0.763	0.788
- LC	0.805	0.752	0.777
- POS	0.790	0.737	0.762
- NE	0.812	0.757	0.783
- WN	0.786	0.735	0.759
-CH	0.802	0.745	0.772
-DT	0.812	0.757	0.783
- Set of Proposed Features	0.795	0.741	0.767

Table 2: (B) Aspect term extraction with feature ablation experiment for Restaurant Dataset using DT

Feature Set	Decision Tree		
	P	R	F1
All features	0.806	0.748	0.775
- LC	0.801	0.731	0.764
- POS	0.782	0.717	0.748
- NE	0.794	0.729	0.760
- WN	0.773	0.713	0.741
-CH	0.792	0.728	0.758
-DT	0.802	0.738	0.768
- Set of Proposed Features	0.785	0.721	0.751

Table 2: (C) Aspect term extraction with feature ablation experiment for Restaurant Dataset using SVM

Feature Set	Support Vector Machine		
	P	R	F1
All features	0.854	0.786	0.818
- LC	0.832	0.753	0.790
- POS	0.821	0.747	0.782
- NE	0.838	0.775	0.805
- WN	0.816	0.743	0.777
- CH	0.829	0.749	0.786
- DT	0.847	0.767	0.805
- Set of Proposed Features	0.824	0.750	0.785

Table.3: (A) Aspect term extraction with feature ablation experiment for Restaurant Dataset using K- Nearest Neighbor

Feature Set	K -Nearest Neighbor		
	P	R	F1
All features	0.803	0.742	0.771
- LC	0.792	0.727	0.758
- POS	0.768	0.711	0.738
- NE	0.793	0.728	0.759
- WN	0.765	0.705	0.733
- CH	0.782	0.724	0.751
- DT	0.795	0.722	0.756
- Set of Proposed Features	0.770	0.715	0.741

Table.3: (B) Aspect term extraction with feature ablation experiment for Restaurant Dataset using Conditional Random Fields

Feature Set	Conditional Random Fields		
	P	R	F1
All features	0.837	0.764	0.798
- LC	0.805	0.726	0.763
- POS	0.785	0.717	0.749
- NE	0.823	0.752	0.785
- WN	0.786	0.713	0.747
- CH	0.793	0.718	0.753
- DT	0.826	0.752	0.787
- Set of Proposed Features	0.787	0.715	0.749

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Table.4: (A) Aspect term extraction with feature ablation experiment for Laptop Dataset using NB

Feature Set	Naive Bayes		
	P	R	F1
All features	0.718	0.652	0.683
- LC	0.686	0.642	0.663
- POS	0.679	0.620	0.648
- NE	0.701	0.638	0.668
- WN	0.675	0.619	0.645
- CH	0.682	0.639	0.655
- DT	0.710	0.642	0.674
- Set of Proposed Features	0.673	0.618	0.644

Table.4: (B) Aspect term extraction with feature ablation experiment for Laptop Dataset using DT

Feature Set	Decision Tree		
	P	R	F1
All features	0.712	0.649	0.679
- LC	0.695	0.627	0.659
- POS	0.670	0.612	0.639
- NE	0.703	0.632	0.665
- WN	0.669	0.615	0.640
- CH	0.684	0.623	0.652
- DT	0.708	0.639	0.671
- Set of Proposed Features	0.672	0.609	0.638

Table.4: (C) Aspect term extraction with feature ablation experiment for Laptop Dataset using SVM

Feature Set	Support Vector Machine		
	P	R	F1
All features	0.743	0.687	0.713
- LC	0.732	0.671	0.701
- POS	0.711	0.648	0.678
- NE	0.738	0.669	0.701
- WN	0.706	0.643	0.673
- CH	0.728	0.675	0.699
- DT	0.735	0.678	0.705
- Set of Proposed Features	0.714	0.651	0.681

Table.5: (A) Aspect term extraction with feature ablation experiment for Laptop Dataset using K- NN

Feature Set	K – Nearest Neighbor		
	P	R	F1
All features	0.707	0.641	0.672
- LC	0.693	0.628	0.658
- POS	0.672	0.604	0.636
- NE	0.701	0.634	0.665
- WN	0.664	0.598	0.629
- CH	0.686	0.625	0.654
- DT	0.706	0.638	0.670
- Set of Proposed Features	0.676	0.612	0.642

Table.5: (B) Aspect term extraction with feature ablation experiment for Laptop Dataset using and CRF

Feature Set	Conditional Random Fields		
	P	R	F1
All features	0.738	0.672	0.703
- LC	0.715	0.653	0.682
- POS	0.697	0.645	0.669
- NE	0.727	0.661	0.692
- WN	0.694	0.636	0.663
- CH	0.697	0.657	0.676
- DT	0.732	0.668	0.698
- Set of Proposed Features	0.687	0.642	0.663

V. DISCUSSIONS

The importance of the each feature on restaurant and Laptop domains are evaluated using precision, recall and F1 measures with NB, SVM, KNN, DT and Conditional Random Fields. The influence of proposed feature set is also evaluated on the each dataset individually. From evaluations, it is observed that the performance of Linear SVM for all feature sets is high when compared with other classifiers. The CRF classifier is also performing well compared with the remaining three classifiers. The performance of NB, DT and KNN classifiers are almost equal in all the cases.

From the above tables, it is observed that the word n-gram feature is most influencing feature out of all seven features on both datasets. The POS tagging feature is the second most influencing feature. The impact of proposed set of features is also very good and comparable with the influence of POS tagging feature. The influence of chunking and local context is also acceptable. The impact of Named Entity and Dependency Tree features are not much influencing on aspect term extraction.

VI. CONCLUSIONS AND FUTURE SCOPE

The impact of features and classifiers for the task of aspect term extraction is evaluated on SemEval 2014 ABSA datasets. The experimentation is performed on Restaurant dataset and Laptop Dataset independently. A new set of three features are proposed for aspect term extraction and influence is also observed on five types of classifiers. From the obtained results, it is observed that SVM and CRF classifiers are performing well on these features. The word n-gram, POS tagging and proposed features are most influencing in aspect term extraction. The possible extensions of this work is more number features can be used to increase the efficiency of the proposed system.

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AUTHORS PROFILE

Mr. M. Yesu Babu is a Research Scholar at Department of Computer Science and Engineering, JNTU Anantapur. He has completed B.Tech from BEC, Bapatla, M.Tech from JNTU Hyderabad. He has more than 18 years of teaching Experience. His Research interests are Natural Language Processing and Text Mining.

Dr.P.Vijaya Pal Reddyis working as Professor & Head at Department of CSE, Matrusri Engineering Coolege, Hyderabad. He has completed B.Tech from BEC, Bapatla, M.Tech from AU, Vizag and Ph.D from JNTU, Hyderabad. He has more than 20 years of teaching Experience. He has published and presented 60 research papers at various national and International journals and conferences. Presently he is supervising for 8 Research Scholars. He published 5 Text books. His Research interests are Natural Language Processing, Text Mining, Data Mining, Optical Character Recognition.

Dr. C. Shoba Bindu is working as Professor at Department of CSE, JNTUCE , Anantapur. She has completed B.Tech from JNTUCE, Anantapur, M.Tech from JNTUCE, Anantapur and Ph.D from JNTU, Anantapur. She has more than 20 years of teaching Experience. She has published and presented 202 research papers at various national and International journals and conferences. Under her guidance 12 Ph.D’s are completed. Presently she is supervising for 8 Research Scholars. She published 7 Text books. Her Research interests are Networks and Network Security.

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