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A Deep Analysis on Aspect based Sentiment Text Classification Approaches

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ABSTRACT

Now-a-days, people often express their opinions as reviews, comments, feedback in various social networking sites, business organizations. Feedbacks that are given by the end users have a great impact for the evolution of new version of product or service. For business invested in customers, analyzing each piece of feedback by hand can be overwhelming and similarly for an organization to rate an employee regarding his/her performance based on usual quantitative feedback system is a challenging task. Sentiment analysis, developed within this context can be helpful to solve such issues at early stage and provide guidance in improving their sales and productivity. Moreover, reviews written in natural language are mostly unstructured and needs huge time for processing. As the data is available in large size, it's impossible to process and analyze the information manually. In order to solve this issue, many machine Learning techniques and Deep Learning models are being proposed for automatic learning, extraction and analysis. As the technology advances businesses, organizations, social media and e-commerce sites can benefit from these in-depth insights and customer satisfaction can be analyzed. Sentiment analysis is an excellent source to perform fine-grained analysis like feature-based sentiment analysis and it can be used to identify different aspects expressed at either document or sentence level. This paper highlights the insights of extracting the most important aspects from the opinions expressed in the input text using various machine learning techniques.

Key words: Aspects, Deep Learning, machine learning, reviews, Sentiment.

1. INTRODUCTION

1.1 Sentiment Analysis

The field of sentiment analysis includes the intersection of information retrieval, natural language processing, and artificial intelligence. People often share their knowledge, experience and thoughts with the surrounding world by means of Social Media in the form of blogs, forums, wikis, review sites, tweets and so on. This changed the way of communication between people and had a great impact in influencing social, political and economic behavior. By making the use of user generated opinions, there is a need for the companies, politicians, service providers, social psychologists, researchers and other actors for analyzing and implementing better decision choices. It allows every individual to have a promising voice to build human collaboration capabilities on worldwide scale, enabling everyone to share their opinions through world-wide web.

The demand for sentiment analysis is increasing because of the need to analyze and structure the hidden information. Companies across the world have implemented machine learning techniques to do this automatically. Sentiment Analysis identifies what the people like and dislike and helps in building things like recommendation systems and more targeted marketing campaigns.

1.2 Techniques for Analyzing Sentiments

Emotions are hard to express and difficult to let alone get understandable, but that's where AI can help us. AI can understand us better than we do in analyzing our emotional data to make optimal decisions for achieving the goal that we specify. But how would it do this? There are generally two main approaches for analyzing the sentiments or emotions.

A. Lexicon based approach

In Lexicon based-approach the words in a sentence are searched in a Dictionary or a corpus. The lexicon dictionary or corpus dataset contains the words with polarity label or a number reflecting as either +1, -1,0 which expresses each word polarity/emotion. The polarity label can be assigned to the sentence based on the majority score obtained from the trained set. This approach can be implemented in two ways.

- Dictionary-based
- Corpus-based

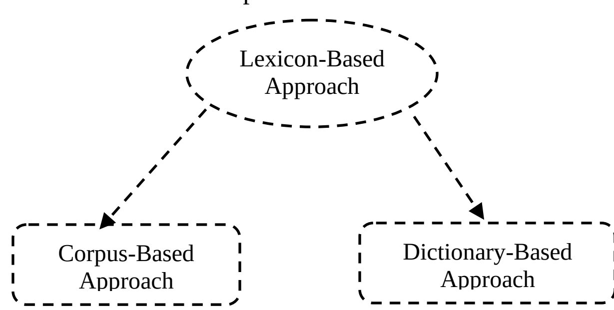

Figure 1: Lexicon-Based Approaches for sentiment classification

Algorithm
Step 1: Tokenization- Split the given input text into smaller tokens, which can be a word, phrases or whole sentence.
Step 2: Bag of Words- Count each word in the document by number and the resulting value is called the bag of words.
Step 3: Subjectivity- Look at the polarity of each word from the existing lexicon, available in the database consisting the emotional values for words which are prerecorded by the analysts.
Step 4: Finally, if we have those values, then we can compute the sentiment of the input text.

This approach is not more accurate and leads to misclassification because of the dependency on the lexicon. If for the words to which the polarity needs to be analyzed are not found in the lexicon then the sentence will remain unlabeled. There are strategies that lexicon-based approach is bad, like sarcasm. Sarcasm seems to be one thing, but really mean another.

B. Machine Learning approach

Machine learning approach is more efficient to detect polarity/emotion when compared to lexicon-based approach. This approach makes use of machine learning techniques which uses the following three different types of class learning styles.

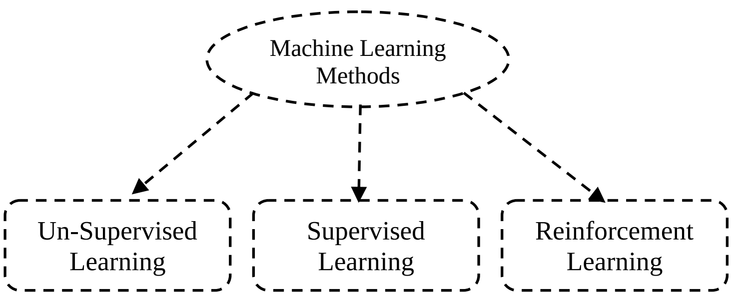

Figure 2: Opinion classification techniques using Machine Learning

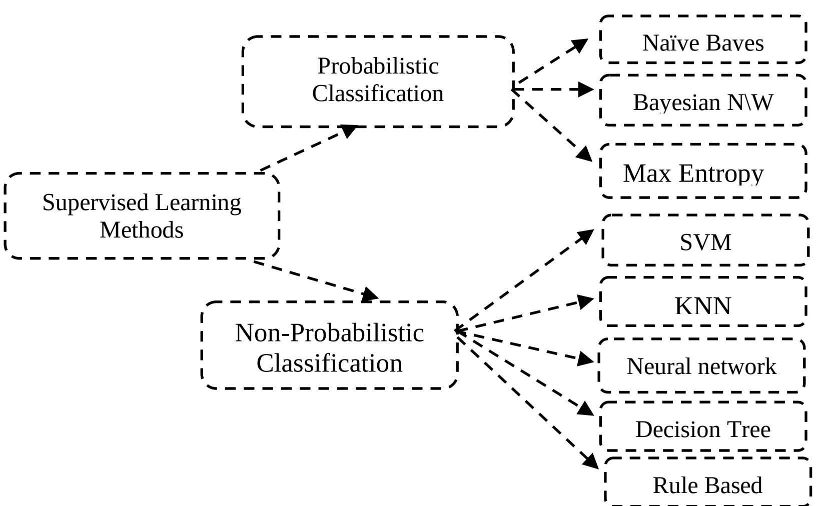

Figure 3: Opinion classification using supervised learning

- **Supervised Learning:** It's where we train a model using a labeled dataset. It needs to learn the mapping in between the labels in the training data to solve the given task. It's all a straight forward task and gives incredible results.

- **Un-Supervised Learning:** This type of model is used when we have a model and dataset without class labels. It must learn by itself about what is the structure of the data given to solve the given task. It is tough to do but more convenient.

- **Reinforcement Learning:** This type of model is linked to the idea of interacting with an environment through a trial and error mechanism.

If the corpus of say, tweets are labeled as either positive or negative then there is a possibility in training the classifier on it. It's also possible to give a new tweet as test data to classify the polarity of the test tweet as either a positive or negative using any of the different machine learning algorithms, generally treated as classifiers for the model. The results from this approach are more accurate when compared to the lexical-based approach.

The following are the different types of classifiers in machine learning.

- Bayesian Networks Classifier
- Naive Bayes Classification
- Maximum Entropy Classifier
- Neural Networks
- Support Vector Machine Classifier

Algorithm
Step 1: Generate a dataset containing tweets.
Step 2: Drop uncertain variables from the tweets.
Step3: Create a corpus by removing punctuation stop words whitespace and stemming.
Step 4: Create a document term matrix tf - idf.
Step 5: Construct the model as a classifier and run the model.
Step 6: Upon using this model, the text data has been applied for the prediction of its sentiment polarity.

The rest of the article is organized as follows: Section II is 'Related work' which presents the overview of the Aspect based sentiment analysis, Section III is 'Literature review' which gives details of how aspect-based sentiment classification is carried out earlier, Section IV is 'Experimental results and Discussion' which shows the experimental results drawn from various reviews by using aspect-based sentiment analysis. And finally, the findings of the review work are concluded in Section V 'Conclusion'.

2. RELATED WORK

Understanding the exact opinion of a sentence in the document with respect to the aspect is treated as a difficult task in the area of sentiment analysis. Collomb et al. (2014) had classified sentiment analysis into three levels like document level, sentence level and word/feature level which can be termed as aspect level.

In the document Level sentiment analysis, the document for classification is considered as a whole for analysis and the polarity can be classified as either positive or negative. But one of the drawbacks with this type of approach is that it's not possible to know which topic of the document is related to either positive or negative.

In the sentence and aspect level type of sentiment analysis, the opinion is retrieved at finite level, so that it's possible to analyze which topic or aspect of the review is been liked or disliked by the customer.

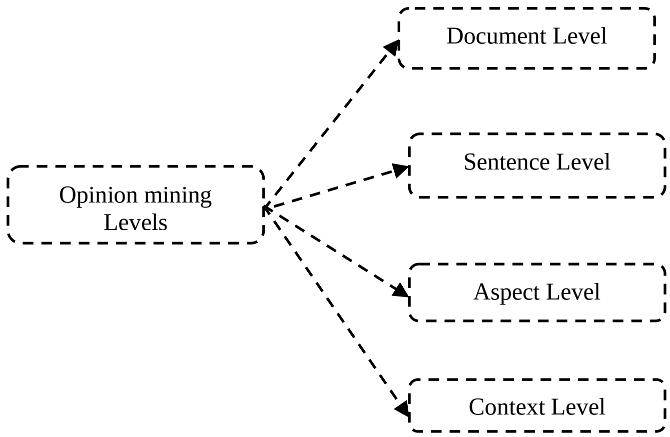

Figure 4: Opinion mining Levels

2.1 Tasks in Aspect based sentiment analysis

In Aspect-based sentiment analysis classification can be done by performing two tasks:

(A) Aspects identification.

(B) Sentiment classification of identified aspects into positive or negative.

A. Aspects identification

Aspect identification is the primary task in opinion mining.
Issues in Aspects identification: In aspect identification task, there are three main issues.

a) It's difficult to identify the implicit aspects. Implicit aspects extraction has not been targeted by any of the existing approaches. For example, consider an opinion about a restaurant 'Last night my family visited Good Wife restaurant, the taste was delicious'. In this review text, the person implicitly gives a sentiment as positive about an important aspect 'food' which was not mentioned explicitly in the review text.

b) It's difficult to identify co-referential aspects. Co-referential aspects are the aspects which are mentioned in the reviews using synonyms. The co-referential aspects are less emphasized in the literature. Review sentences have different synonym words and expressions to depict an aspect. For example, ecosystem and biosphere are co-referential aspects because both refer to the environment.

c) It's difficult to identify the infrequent aspects, i.e. the aspects which are not frequently used in the review but have a great importance in the domain. Aspect identification methods are not effective in removing the irrelevant and completely neglected aspects. For example, swimming pool and Wi-Fi are less frequent aspects, but both carry a lot of importance in hotel and restaurant domain.

B. Sentiment classification of identified aspects into positive or negative

The second task of aspect-based sentiment analysis is sentiment classification of identified aspects; here there is a major problem in handling multi-aspect reviews. Classification of the multi-aspect reviews is a complex task because multiple aspects discussed in a review need to be considered and each aspect should be identified as either a positive or a negative sentiment. For example, take a review posted about a college 'The students in the college are extremely rude, but the faculty are very polite. The management is taking utmost care to provide all benefits. Good library and laboratory 'facilities. In this review, it gives sentiments about multiple aspects namely 'students', 'faculty', 'management' and 'facilities. It can be seen that the review has aspects with different sentiments, that is, for 'students', there is negative sentiment while for 'faculty', 'management' and 'facilities' there is a positive sentiment.

3. REVIEW ON ASPECT BASED SENTIMENT ANALYSIS

This section presents the literature survey on aspect-based sentiment classification. The objective of this section is to critically evaluate and identify the gaps and limitations in the existing approaches of aspect identification and aspect classification

3.1. Aspect Identification

The work carried out in this area of aspect identification has been broadly categorized into three methods namely rule-based, seed-based and topic model-based aspect identification [1].

A. *Rule-based method*

Rule-based methods identify aspects by employing certain rules based on the importance of score and frequency in the occurrence.

Jime ́nez-Zafra et al. [2] has proposed an approach which uses bag of words for extracting aspect terms based on frequency using Freebase. Freebase is a collaborative knowledge base that contains information about more than 70 different domains.
Muangon et al. [3] extracted high-rated aspects by using a rank-based approach. In this approach, features are obtained using LexToPus lexicon and ranked according to their frequency of occurrence in reviews. This type of approach is helpful in extracting the aspects having high ranks.

Wang et al. [4] proposed a different approach by using part-of-speech (POS) tagger. A novel porter stemming algorithm was used to select only the potential, common morphological aspects and remove in flexional endings. This algorithm helps in tagging similar aspects to enhance the classification process. Words that are having identical spellings are easily and automatically identified using this porter algorithm.

Marrese-Taylor et al. [5,6] also proposed a similar POS–based approach. In their work, the author transformed reviews into sentences and later applied POS tagger on sentences to extract nouns. A frequency threshold of 10 was set to extract similar aspects.

Afzaal et al. [7] proposed a fuzzy-based learning method as advancement to the existing rule-based approaches. This paper uses a ML-based algorithm called fuzzy unordered rule induction algorithm (FURIA). By this algorithm, frequent nouns and noun phrases from the reviews are extracted, and rules were generated.

Limitation in Rule-based approach

Although rule-based methods are easy to adopt and very effective in the identification process, still there are a number of problems which can't be tackled by this method. For instances, rule-based methods tend to produce very limited number of rules. Moreover, the generated rules are unable to identify infrequent aspects, as several irrelevant aspects are extracted by using this limited generated rule.

B. *Seed-based approach*

In seed-based approach, the aspects are identified using the grammatical connection between seed sets and review words. Colhon et al. [8] has choosen five most-discussed aspects from reviews and formed a seed set for each aspect. In order to build seed sets, grammatical connections between the terms in the sentence and every aspect in seed sets are checked. Then these terms were assembled accordingly. It helps to identify the important aspects of a review by using co-occurrence of different words.

Mukherjee et al. [9] in the search of finding interconnection of review words, proposed a method for finding semantic relationship between review words. Words which have semantic relationships are grouped in the form of a seeds set. This approach helps to identify not only the co-occurrence of aspect terms but also the semantic relationships between them.

Kayaalp et al. [10] proposed a slightly different seed-based approach which makes use of an index-based method for aspects extraction. The index-based aspect extraction method consists of three main steps. First, most-discussed aspects in the reviews are selected. Second, review words are indexed and stored in different files with proper tagging. And finally, indexed words are categorized under the selected aspects based on the similarity between aspects and indexed words.

Unlike the rule-based methods, the seed-based approach uses the relationship among different review words and offer a number of advantages in terms of identification of co-referential aspects.

Limitation in Seed-based approach

Seed-based methods need extensive domain knowledge for the selection of aspects and seed key words. In addition, the words that are extracted with limited number of aspects are not sufficient to cover the complete domain. For instance, students, faculty, management and facilities cannot cover the complete domain of a college or university as this domain has many other important aspects like location and fee structure.

C. *Topic model–based techniques*

The last category of aspect identification is topic model–based technique, which depend on the assumptions that every sentiment is a blend of different topics and each topic under discussion is basically a probability distribution of various words.

Wu et al. [11] proposed and bought together a probabilistic model on client's inclinations about different aspects. In this model, it is expected that every sentiment is associated with an aspect. Aspect importance can be described by the sentiment which relies upon three components: global importance, user importance and how much probability that an aspect holds. Beyond these assumptions, they also used an added substance-generative technique to identify the aspects.

Shams et al. [12] proposed an enriched latent Dirichlet allocation (LDA) model to discover more precise aspects from reviews by incorporating co-occurrence relations as prior domain knowledge into the LDA topic model. In the proposed method, first, the preliminary aspects are generated based on LDA. Then the prior knowledge is extracted automatically from co-occurrence relations and similar aspects of relevant topics in an iterative manner.

Finally, the extracted knowledge is incorporated into the LDA model. The iterations improved the quality of the extracted aspects as compared to the simple LDA model.

3.2 Aspect-based sentiment classification

In this section, we present a review of the work conducted under aspect-based sentiment classification. It is important to highlight here that we had only reviewed the ML-based approaches in this study.

A. *Classification using Machine Learning Algorithms*

Mubarok et al. [13] proposed a naïve Bayes-based model to classify the restaurant reviews. In this model, three simple steps were performed to achieve the classification task. First, reviews were pre-processed to remove irrelevant information and converted into POS tags. Second, feature selection was applied on POS tags by using chi square to select highly relevant words from each review. Finally, naïve Bayes classifier was employed on selected features to classify the reviews into polarity classes for each aspect. Results showed that the proposed model achieved 77% accuracy of aspect-based classification.

Xueke et al. [14] used SVM on tourist reviews to predict sentiments about different aspects discussed in the reviews. In this method, natural language processing (NLP) toolkit was applied for sentence segmentation and to improve the classification performance. Sentences annotated with either 'positive' or 'negative' sentiments were used for achieving better accuracy results. Experimental results on real world data sets showed 83.9% accuracy using seven-fold cross-validation. Authors proved that for sentiment classification, SVM produces better results than naïve Bayes algorithm.

Catal et al. [15] used the fore-mentioned algorithms to develop a newly vote ensemble classifier. This classifier used each machine learning algorithm on individual basis to predict the sentiment class in tourist reviews. First, bagging algorithm was used as base classifier for ensemble classifier. Second, naïve Bayes was employed because of its features-handling power. Third, SVM was applied to find maximum margin and provide maximum separation between sentiment classes. Finally, voting mechanism was adopted to predict the sentiment class based on majority voting.

Pontiki et al. [16, 17] to achieve better accuracy employed a ME to classify the aspect related opinions into positive or negative. In this system, unigram features from the given sentence are extracted and then integer-valued functions were used to identify the aspect category. ME classifier was trained on extracted features, and prediction was tested using golden data set labeled by experts of that domain. The results of the system indicated that the robustness and stable performance of the model is better with 78.69% accuracy on restaurant reviews.

Instead of adopting the traditional ML algorithms Afzaal et al. [7] used fuzzy-based algorithms for aspect-based sentiment classification. In this proposal, a three-stage fuzzy method was developed for classification. In the first stage, opinion-less sentences were reviewed from the reviews. In the second stage, features were built from filtered opinion sentences like n-grams and POS tags. In the last stage, fuzzy logic algorithms were applied on the built features to classify the sentiments into positive and negative.

Several approaches have been proposed recently, which worked on features selection before classifying the reviews in order to improve the classification results. Akhtar et al. [18] used the particle swarm optimization (PSO) for features selection to improve the classification of tourist reviews. In this approach, authors extracted different feature sets from reviews using lexical and semantic information and then selected the most suitable feature set based on PSO. After that ML algorithms such SVM, ME and conditional random field were employed on selected features to classify the reviews.

Ali et al. [19] worked on feature selection to remove irrelevant reviews and enhance the performance of classification. In this technique, raw reviews were converted into words to generate tokens using semantic information. Fuzzy domain ontology was developed to select the relevant features from generated tokens. In feature selection process, the authors made sure that each review should contain a noun and a verb. On selected features set, SVM [22] was applied to classify the reviews into different polarity classes.

Limitation in ML based Approach

Although ML-based methods are easy to adopt and very effective in the classification process, there are also some challenges to be handled. First, existing methods are unable to classify the multi-aspect opinions into positive [23] or negative in the review data containing sentences that discuss multiple aspects in a single sentence. Another related issue is about handling noisy data. When reviews are crawled from third-party websites, some irrelevant and opinion-less sentences like self-introductions and previous stories are present in the review text and affects the opinion classification accuracy of aspects in a negative way.

4. COMPARATIVE ANALYSIS OF RESULTS OBTAINED IN LITERATURE REVIEW

In this section, we present the comparison and analysis of aspect identification and aspect classification approaches seen in the literature review.

The approaches used for aspect-based sentiment analysis is carried out on different datasets, which belongs to diverse kind of domains and languages. Most of the work focused on English language datasets, but many researchers also have conducted the experiments on domains belonging to Chinese language. The results of one domain cannot be compared with the results of other domains. Therefore, this is necessary to identify the domains and languages of all the approaches to conduct a comprehensive and justifiable comparison. Figure 5 illustrates the domains followed in the studies. Experiments were conducted on 13 different domains but more than 50% of research has focused on product reviews only [20]. In the chart, there are some solo product items like camera, cellphone, mobile, headphone and MP3 but when we are talking about product domain, it contains more than one product and hence cannot be compared with a single item.

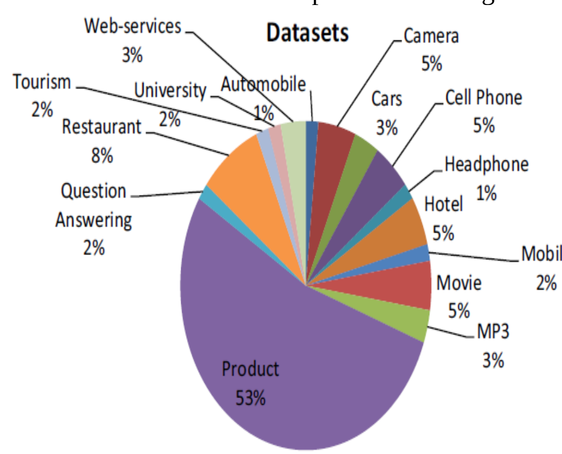

Figure 5: Dataset domains used for aspect extraction

Table 1: Comparison with different aspect identification methods

References	Year	Technique used	Accuracy	Dataset
Jimenez.Zafra et al.[2]	2016	Rule based	71.2%	SemEval 2014
Kayaalp etal. [10]	2017	Seed based	66%	Customer reviews
Shams et al. [7]	2016	Topic based	75%	Tourist reviews
Afzsal et al. [7]	2016	FURIA based	79%	Tourist reviews

Table 2: Comparison with different aspect classification methods

References	Year	Technique used	Accuracy	Dataset
Mubarok et al.[13]	2017	Naïve Bayes	77%	Product reviews
Xu etal. [14]	2013	Support vector machine	83.9%	Online customer reviews
Akhtar et al. [6]	2014	Conditional random field	77.3%	Tourist reviews
Pontiki et al. [17]	2015	Maximum entropy	78.69%	Restaurant reviews
Afzaal et al. [7]	2016	Fuzzy logical reasoning	86.02%	Tourist reviews

Due to the large number of papers, diverse nature of datasets and divergent varieties of approaches, this would be almost impractical to plot a precise comparison among all the approaches. Therefore, to better understand the effectiveness of each approach, we have analyzed and summarized different approaches for each of the category separately [21], as mentioned in Figure 6. Although, it would be unjustifiable to compare the results from the different domains but this can help to understand the contribution of each approach. As highlighted in Figure 5, most of the research has focused on product domain, therefore, the domain is mentioned explicitly only with those approaches which used other than product domain for the experiments. If the domain is not mentioned then the results will be representing the product domain.

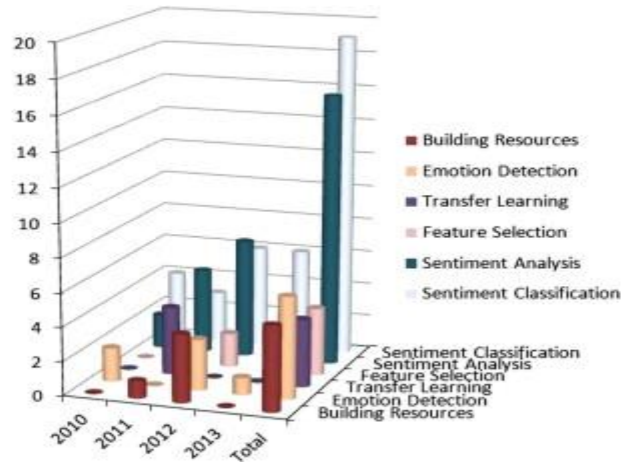

Figure 6: Analysis of Sentiment Classification

5. CONCLUSION

In this article, an aspect-based sentiment classification framework has been reviewed for classifying sentiments with respect to various aspects. In this paper various aspect identification methods which automatically identify the explicit, implicit and co-referential aspects have been presented. An ML algorithm–based opinion classification approach is presented to classify the opinion of the extracted aspects into positive or negative. A detailed comparative analysis highlights the supremacy of aspect-based sentiment analysis framework over the existing similar approaches reported in the past.

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