Ilkogretim Online - Elementary Education Online, 2021; Vol 20 (Issue 4): pp. 3796-3809
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.04.416

A Survey On The Aspect Based Sentiment Analysis Using Deep Learning Approaches

Vishan Kumar Gupta[1,*], Atika Bansal[2], Divya Kapil[3], Prof. (Dr) Ajay Kumar Saini[4]

[1]Graphic Era deemed to be University, Dehradun, Uttarakhand, India.
*Email: vishangupta@gmail.com

[2,3] School of Computing, Graphic Era Hill University, Dehradun, Uttarakhand, India.

[4]Professor, School of Management, Graphic Era Hill University, Dehradun.

Abstract

Sentiment analysis (SA) that is also referred to as opinion mining (OM) is the process in which the thoughts, feelings, emotions, and perspectives of individuals about a certain product, item or organization on web-based applications like Twitter, Facebook, Instagram, blogs etc. is gathered and analyzed. This article discusses a comprehensive examination of SA and its levels. The major focus of this manuscript is on aspect-based SA, as it aids manufacturing companies, to make better decisions by analyzing the perspectives and views of people about their products. The review discusses the various methodologies and techniques associated with the Aspect Based Sentiment Analysis (ABSA). In traditional methods, the features related to the aspects were drawn out manually, which makes it a time-consuming and error-prone process. Nevertheless, with the advancement of artificial intelligence, these limitations can be overpowered. Therefore, researchers nowadays, are employing artificial intelligence-based machine learning (ML) and deep learning (DL) techniques for enhancing the efficacy of ABSA. The automated general procedure for determining aspects from texts in the light of AI is also delineated in this manuscript. In addition to this, some of the recently published ABSA methods based on ML and DL are reviewed and compared and based on this review research gaps found in both techniques are also mentioned and highlighted.

Keywords: Sentiment analysis, Aspect based sentiment analysis, Machine learning, Deep learning algorithms in SA.

1. Introduction

With the continuous advancements in web technologies a number of new ways have been paved for connecting the content generated by the user like, blogs, social networks, forums and website reviews. The individuals and organizations working in the field of data mining have been highly inclined towards this flow because of the significant influx of data and difficulties in handling the unorganized texts in natural languages [1]. One of the most basic human desires is to understand the behavior, thoughts and convictions of individuals. As stated earlier that, as a result of latest innovations in web applications social networks, blogs, e-commerce websites and other new forms of communication have emerged which produces huge volume of data. As a result, the demand for an automated service to organize and evaluate this volume of information is also growing [2]. In this regard, sentiment analysis is considered as one of the most crucial tasks in the field of NLP (Natural Language Processing) that has received a lot of attention from experts [3]. Sentiment analysis (SA) also called as the opinion mining can be defined as the field in which the emotion, thoughts, beliefs, attitudes regarding certain entities like service, events, situations, companies are analyzed and studied. This means that sentiment analysis can be used to monitor public sentiment about a certain subject and generate actionable insights. It's used in a variety of industries, including banking, commerce, educational, advertising, medicine, and journalism. This kind of information can also be utilized to comprehend, interpret, and forecast social phenomena [4]. SA is critical in the business sphere since it allows companies to develop strategies and acquire knowledge of client's opinion for their products. Acknowledging the client is becoming extremely important in today's modern consumer-based company culture for increasing their business [5].

Over the last few years, a number of methods have been proposed by various researchers that were based on NLP techniques and ML models were also utilized for extracting the sentiments from textual data. the basic and fundamental task of a SA technique is to identify and classify the polarities of statements or any file as positive, negative and neutral. Meanwhile, sophisticated sentiment categories including happy, sad, and angry can be extended from previous categories. This type of SA finds its application in analyzing the social networking text processing and hate speech identification on different platforms [6]. To understand this in a better way, let's consider an example, "I like this software, it really is better than windows movie maker,". In the given sentence, the phrase "software" evokes the positive feeling while as the phrase "windows movie maker" evoke negative emotions respectively. Also, the words like Love and superior can be described as the opinion concepts in the given example. From the given example it is concluded that the expressive polarization of the aspect phrases can be derived from their associated opinion phrases [7]. Generally, in terms of theory SA can be divided into three levels (see Figure 1), one is called as the Document level, second one is called the sentence level and the third and final level is called as the aspect or feature level. In document level, the sentiments of the whole file or document are sensed and identified. While as, in case of the sentence level, the file or record is broken down into small sentences and then the polarity of each sentence is determined [8-9]. Similarly, in the third level of SA i.e., feature/ target level, the sentiments about a certain feature id analyzed to determine the people's feelings. Example of aspect levels is, "the processor has a high speed, yet the device is costly".

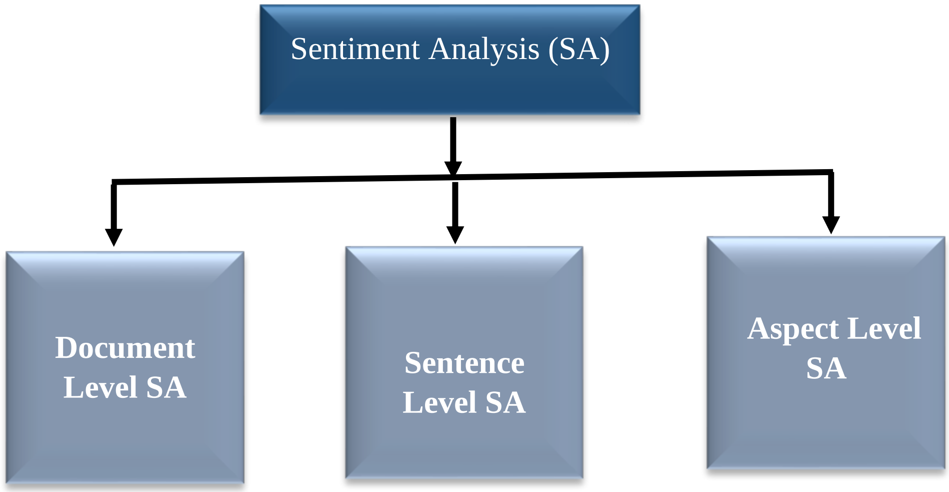

Figure 1. Level of Sentiment Analysis

Nonetheless, the sentiment analysis performed at the document level and sentence level identifies and detects the polarity of the overall sentence and doesn't consider the target entities and the features associated with them. On the other hand, when discussing the aspect-based sentiment analysis (ABSA), the sentiments are analyzed and detected for the target entity and then the polarity of every entity is determined [10]. The main aim of ABSA is to determine the polarities of a given viewpoint that is presented in the form of a reviewer's remark or rating. To determine the polarity in ABSA, several approaches were developed in the past few years. However, these approaches primarily focused on developing a final feature set called a bag of words and after that sentiment lexicon techniques were implemented for training the classifiers [11].

1.1 Review Motivation

The discipline of ABSA is not a straight path and has endured several modifications and entered different phases to consider. Scientists have already been trying hard to find solutions to multi-faceted problems which contain a variety of situations. To overcome these issues and to overcome them, they used several machine-learning approaches, particularly deep-learning approaches which demonstrated their essential ideas in the area. Utilizing various algorithms and neural-memory networks, researchers have given graphical representations and numerical modelling for addressing complicated concepts. As a result, the time has come for a thorough review to highlight the most recent progress of ABSA. In this perspective, a number of the newly enacted ABSA approaches for recognizing feelings/sentiments are reviewed in this study.

1.2 Organization of the survey

The poll begins with a short overview of ABSA and its critical importance. After this, different types of aspects and the process of detecting aspects (ATE, ATC and ATSC) are defined. Moreover, as the main focus of our review paper relies on ATE, therefore we studied the techniques used in determining ATE. Moreover, a brief introduction about the commonly used databases is provided, along with a comparison table. After that, the role of AI-based ML and DL methods is also highlighted in aspect-based sentiment analysis. Finally, a review is done for both ML and DL models along with the findings observed in them.

2. Aspect Based Sentiment Analysis (ABSA)

ABSA can be defined as the type of SA in which attention is given to the specific aspect of a given task. Considering an example, "The course is obsolete but the teacher is excellent". In the given sentence polarity for the course and teacher is negative and positive respectively. The authors in [12] analyzed that to understand the polarity of the phrase it is important to understand its content as well as its aspect. Hence, it is crucial to comprehend the context by recognizing the aspect before assigning polarity to a given phrase. In order to determine the polarity of a sentence, ABSA techniques undergo through three stages of Aspect Extraction (AE), Aspect Sentiment Analysis (ASA), and Sentiment Evolution (SE) to generate the final results. Figure 2 depicts the organization of the ABSA smaller tasks as a tree. In the aspect Term Extraction phase, the polarity of the aspects is extracted which can either be implicit or explicit [13-14]. Moreover, aspect words [15], objects [16] and even the Opinion Target Expression (OTE) based aspects can also be extracted in ATE. While as, in the second phase of Aspect Term Categorization (ATC), emotion polarity is classified as a predefined attribute, object, or entity [17]. In addition to this, ATC is also responsible for extracting the connections, linkages and context-specific linkages across diverse data items such as target, object, aspect and sentiment words so that the accuracy of sentiment classification is enhanced [18]. In the last stage of ABSA i.e., Aspect Terms sentiment classification, the dynamic nature of individuals' attitudes regarding various events is determined. The principal reasons for SE are thought to be social factors and self-experience [19-20]. Here, our key emphasis will be on the Aspect Term Extraction phase, wherein focus will be given to different implicit and explicit aspects.

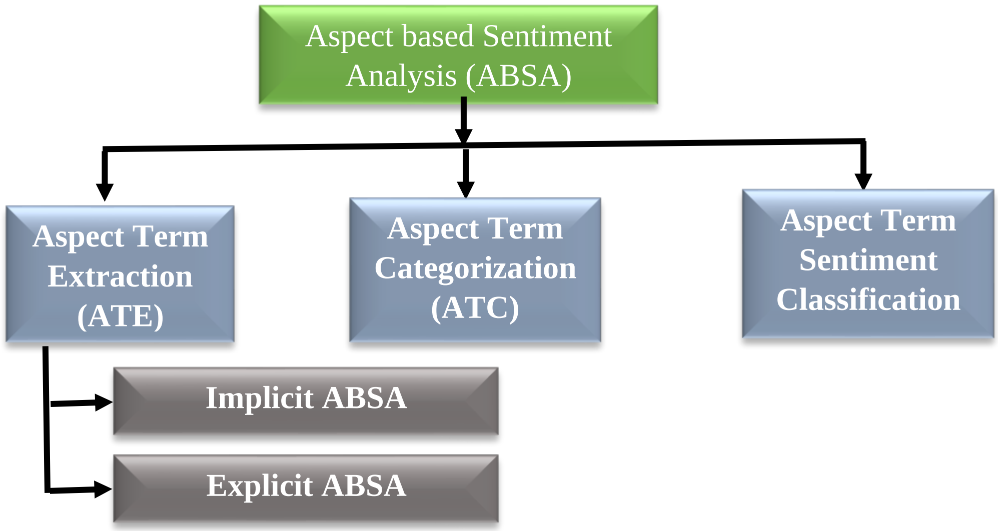

Figure 2. Sub Tasks in Aspect Based Sentiment Analysis (ABSA)

2.1 Aspect Term Extraction (ATE)

Aspect-based analysis which is sometimes also referred to as feature-based analysis is considered one of the finely grained methods for SA. It entails determining a user's feelings about a specific feature of an item or institution. Therefore, to effectively perform the sentiment classification task on aspects based, it is necessary to pull out the objects along with their related aspects. It entails determining a user's feelings about a specific feature of an item or institution. The consolidated opinion and its related visualization findings can be obtained as the final phase of ABSA. As mentioned earlier, usually two types of aspects are extracted from the sentences, one is implicit and the second one is explicit. The explicit aspects can be defined as the notions in the articulated statement which expressly define targets. For understanding the concept of explicit extraction, let's take an example of the statement, "I love my device's touchpad, but the battery capacity is too short". After analyzing the given sentences, it is observed that the terms like "touchpad" and "battery capacity" are included explicitly in the system which means that they are explicitly aspects. On the other hand, in the case of implicit SA, the aspects are mentioned indirectly [21]. Let's consider an example of another sentence demonstrating implicit SA. "This camera is elegant and quite economical," which implicitly expresses a positive judgement of the object camera's aspects "design" and "cost." Digging a bit too deep into the above-given examples to have a clear idea about the implicit and explicit aspects. The first example comprises two components, which are the touchpad and battery capacity. Because the two ideas given by the customer are completely opposite which means employing a sentence-level polarity identification algorithm, in this case, would produce incorrect polarization results that will be close to neutrality. As a result, aspects must first break down the phrase into product features before assigning a different polarity to all these characteristics. While talking about the second example for implicit SA, "The touchscreen of my cellphone is pretty great and its resolution is amazing," which has positive polarity, indicating that the reviewer enjoys the device. The positive feedback, though, is focused on the touchscreen and resolution. Be a result, these conceptions are referred to as opinion targets or components of this viewpoint. In order to extract the aspects from such opinionated texts, aspect extraction techniques have been used [22].

- **Aspect Extraction Techniques:** In this paper, the techniques that can be utilized for extracting the implicit and explicit SA are divided into three types, those are; Supervised, semi-supervised, and unsupervised techniques.
    a. **Supervised Aspect Extraction Techniques:** In this type of aspect extraction, supervised algorithms are used for determining the polarity from reviews. These types of techniques utilize the labelled data for extracting the implicit and explicit aspects from data. To put it another way, supervised approaches rely on methods which must be trained. Commonly utilized supervised techniques for extracting explicit, implicit and both implicit and explicit aspects are conditional Random Field (CRF) [31], hierarchy [32] and LSTM-based approaches [33], respectively.
    b. **Semi-supervised Aspect Extraction Techniques:** Methods that are able to identify aspects from reviews by using semi-supervised methodologies are referred to as Semi-supervised aspect extraction techniques. These techniques are helpful in determining and identifying the aspects of a given phrase in both labelled and unlabelled datasets. Semi-supervised strategies make use of strategies which need to be trained in a specific context. Some of the commonly employed semi-supervised techniques that are used for identifying aspects in implicit, explicit and both (implicit and explicit) are semantic-based, RNN [27-28] and lexicon-based [29-30], respectively.
    c. **Unsupervised Aspect Extraction Techniques:** Unsupervised procedures are methods which make use of the unsupervised methodology idea and are commonly used by scholars to retrieve distinctive aspects from review. Whenever a strategy extracts implicit or explicit aspects from unlabelled information, it is said to be unsupervised. To put it another way, it doesn't necessitate any training. Those approaches are applied to a variety of data fields, including language realms. Some of the commonly employed unsupervised techniques that are used for extracting explicit and implicit aspects are statistical [23] and topic modelling [24-25] respectively. Moreover, dependency parsing [26] is another unsupervised aspect extraction method that is widely used for detecting both implicit and explicit aspects.

All of these strategies, unfortunately, only produce the anticipated outcomes when adequate and appropriate databases are accessible. Hence, before we go into the specifics of the methodologies employed in aspect analysis, it is important to analyze some of the most widely utilized datasets, discussed in the coming up sections of this paper.

2.2 Aspect Term Categorization (ATC)

The second phase in the process of ABSA is aspect term categorization (ATC) in which the phrases with synonymous aspects are grouped to form categories. Every category illustrates a particular aspect that is also referred to as the aspect category [34]. For understanding the concept of ATC, an example is considered, “I have to mention that they have one of the fastest delivery times in the city”. in the given sentence, the term “Delivery time” represents the aspect term. Therefore, a number of similar group phrases with similar content can be put together into groups each having an aspect term. For example, concerning the delivery time, waiter and staff can also be included in the same aspect category of service. Although the two categories i.e., aspect category classification (ACC) and aspect term extraction (ATE) are closely related to each other, they are considered separately sometimes. Intrinsically, the learned knowledge from one learning assignment must influence another. In order to tackle both issues, the authors in [35], proposed a multi-task learning approach that was based on neural networks. As ACC was defined as the supervised classification job wherein the phrases are classified by using a portion of predetermined aspect tags, ATE was described as the sequence labelling job in which the phrase tokens, associated with the provided features were labelled by using a predetermined tagging strategy named as, Inside, Outside, Beginning or IOB. Moreover, they used the Bi-LSTM and CNN approaches together for ATE and ACC respectively to form a multi-task framework.

2.3 Aspect Term Sentiment Classification

In the last final step of ABSA comes the aspect term sentiment classification in which the polarity of the sentence or phrase is determined once aspect terms are extracted and classified from them. The authors in [36], proposed an LSTM-based two targeted approaches in which necessary information about the target is considered automatically. The authors validated the performance of their model on the Twitter dataset. Also, the simulated results attained by the authors demonstrated that the classification rate is significantly improved when target information is directly fed to the LSTM model. furthermore, it was observed that without employing any syntactic parser or external sentiment lexicons, the proposed model was able to achieve results similar to that of traditional approaches.

3. Datasets Available

In order to detect the aspects from the reviews, sentences or phrases a number of datasets including the Twitter dataset, Sem Eval datasets, Amazon product dataset, and IMDB movie review datasets are available on the internet. other than this, there are some other databases as well, a brief description of the most popular databases is given below.

3.1 Twitter Dataset

This dataset is one of the most prominent and frequently used datasets that have been used by a number of researchers in their studies. This database can generate remarkable results because the training data was generated automatically rather than humans manually annotating tweets. They demonstrated the concept of positive tweets by using the ":)" symbol while the negative tweets were represented by the ": (" symbol. The Twitter database represents the sentiments for 140 datasets in which a total of 1,600,000 tweets are present that are extracted via the Twitter API. In order to detect the sentiments in the given dataset tweets are represented as 0 for negative, 2 for neutral and 4 for positive. The six fields of the Twitter dataset are target, ids, and date. Flag user and text [37].

3.2 Sem Eval 2014 Dataset

In the year 2014, Pontiki and Pavlopoulos suggested a Sem Eval dataset for identifying and extracting aspects from the customer reviews. Sem Eval dataset can be defined as the collection of global NLP research events in which the primary objective is to enhance the traditional SA as well as assist in creating a unique dataset in rising to a variety of issues faced in language semantics. It is a domain-specific database in which information about laptops and restaurant reviews are mentioned. More than 6000 keywords for both domains are available with rich aspects present in the dataset [38]. The detailed information about the dataset is represented in table 1. This database has received a lot of attention from scholars while trying to extract the aspects from the sentences.

Table 1: Total reviews in the dataset

Domain	Train	Test	Total
Restaurants	3041	800	3841
Laptops	3045	800	3845
Total	6086	1600	7686

3.3 Amazon Product Data

Another database that is used widely by researchers in their work for extracting the aspects from users is the Amazon product database. This dataset is a sub-category of the huge 142.8 million amazon review database which was made publicly accessible by T. Julian McAuley a professor at Stanford. In this database, the reviews of the customers received on different products from MAY 1996 to July 2014 are included. Ratings, content, useful comments, description of the product, category information, cost, manufacturer, and image attributes are all included in the database evaluations. In the year 2018, a new version of the database was also made publicly accessible for ABSA. The new version of the database contains information about the product reviews from May 1996 to October 2018 and comprises a total of 233.1 million reviews.

3.4 IMDB Movie Reviews Dataset

IMDB is one of the huge movie datasets which includes around 50,000 reviews about the movies. This database contains only those reviews which are highly polarized. Moreover, the total number of positive and negative comments are equally added in the current dataset but still, the negative review received a rating of 4 out of 10 while the positive reviews received a ratio of 7 out of 10.

Table 2: Different Datasets used in the sentiment analysis

Authors	Dataset used	Performance metrics
L. Wang et al. [39]	Used Sem Eval implicit database	Accuracy, and F1-score
S. Kalim et al. [40]	Used Sem Eval-2016 Task 5 database	Precision, recall, and F1-score
M S Neethu et.al. [41]	Twitter dataset	Precision, Recall, and Accuracy
R. Xia et al. [42]	Multi-domain dataset	Accuracy
R. S. Ramanujam et al. [43]	Twitter dataset	Hourly sentiment analysis
M. Bouazizi et al. [44]	Twitter dataset	Precision, Recall, and Accuracy
G. Gautam et.al [45]	Twitter dataset that was based customer review	Accuracy
S.A. Bahrainian et al. [46]	Twitter dataset that was based on Smartphones reviews	Accuracy
A Agarwal et al. [47]	10,000 manually Annotated Tweets	Accuracy
D. Gurkhe et al. [48]	Twitter Dataset	Accuracy

From the above table, it is concluded that the majority of the works have been done by utilizing the Twitter dataset and Sem Eval datasets because of their diverse nature.

4. Conclusion

The subject of sentiment analysis (SA) has gained a lot of attention from researchers over the last few decades due to the continuous rise of social media users over the internet.

Millions and billions of individuals around the world are using social networking sites like Twitter, Facebook, Instagram etc. for expressing and sharing their thoughts, beliefs, emotions and opinions about different products, companies and items. This manuscript explores and categorizes frequently used classification algorithms for determining aspects in sentences or phrases. As the main focus of this paper is on ABSA, therefore, we reviewed some of the recently published articles related to it. After conducting the review, it is observed that traditionally features were extracted manually from texts for determining their polarity. However, with the exponential growth of data in the last few decades, manual feature extraction from texts turns out to be formidable. Therefore, researchers paved their way toward Artificial Intelligence (AI). To understand the concept of ABSA in the light of AI, we reviewed current ABSA approaches under two categories of ML-based ABSA and DL-based ABSA. From the review, it is concluded that ML-based binary classifier (SVM), tree algorithms like DT, RF, and NB were mostly used by researchers in their work for analyzing aspects in sentences, phrases or comments, as these techniques are simple and easy to implement. However, one of the prime drawbacks of SVM is that it doesn't perform well when multiple aspects are present in the text while as, the tree-based algorithms can cause instability because of minor changes in data. Additionally, ML algorithms were not able to handle the large and intricate datasets and they also tend to lose ample of information during pre-processing and feature extraction phases. To overcome these issues, researchers moved towards the DL based approaches. Substantial number of experts used CNN, RNN based LSTM, Bi-LSTM in their work because of their ability to detect features from text automatically. Despite the fact that DL methods can handle large datasets effectively but the need for huge training data and high error susceptibility affected the accuracy of detecting aspects from texts. At last, it can be concluded that the accuracy of detecting sentiments can be improved by using the hybrid DL approaches on standard datasets. The issues described subsequently show that sentiment analysis is still a growing subject of investigation.

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