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ASPECT-BASED SENTIMENT ANALYSIS: AN OVERVIEW OF TECHNIQUES AND APPLICATIONS

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Abstract

With the rise of the modern web, micro-blogging sites, blogs and online communities have also upsurged. This user-generated content may be about products, movies, hotels, events, etc. These sentiments are very helpful for various businesses, organizations etc. Sentiment analysis is the process where we extract, gather and analyze the sentiment and opinions of people. The field of sentiment analysis also emerges in the presence of online communities. This survey focuses on one of the most modern types of sentiment analysis, known as Aspect-based Sentiment Analysis (ABSA). ABSA is a Sentiment Analysis (SA) subtask to interpret the text sentiment orientation concerning different aspects. ABSA yields fine-grained sentiment information that can be worthwhile for applications in numerous fields. This survey has made an effort to provide a comprehensive overview of various ABSA methodologies and approaches, along with the pros and cons. Further, the applications and importance of ABSA are also discussed.

Keywords

Aspect; Customers; Opinions; Sentiment analysis; Machine learning; Lexicons.

1. Introduction

Nowadays, many peoples utilize forums, blogs, and social networking platforms, such as Twitter, Instagram, and Facebook, to articulate their ideas to the global community. Social media has emerged as one of the most efficacious communication channels in contemporary times. As a result, a large quantity of data, known as big data, is produced (Rana *et al*., 2021). Sentiment analysis was developed to analyze vast amounts of data in a proficient and effective manner (Onan, 2021). The capability of a business or organization to comprehend the sentiments of their users has become indispensable. Sentiment analysis (SA) is the process of identifying and extracting subjective data from textual data (Nagamanjula & Pethalakshmi, 2020). This includes opinions, attitudes, emotions, and feelings expressed by individuals toward a specific topic, product, service, or entity (Rana *et al*., 2023). Since the objective of SA is to recognize polarity and define opinionated texts as either negative or positive. The class range of the dataset that is used for SA is not restricted to only positive or negative; rather, it may also be true or false, bad or good, etc. On a 5-point scale, it can alternatively be rated as strongly false, false, neutral, true, or highly true (Prabowo & Mike, 2009). According to the Liu (2012) an opinion consists of five different factors e_i, a_i, $sent_i$, h_i and t_i Here e_i is the name of an entity, a_i is an aspect of entity, $sent_i$ is the sentiment on aspect of entity, h_i is the holder of an opinion and t_i is the time, when opinion holder expressed an opinion. An example of Opinion is shown in Figure 1.

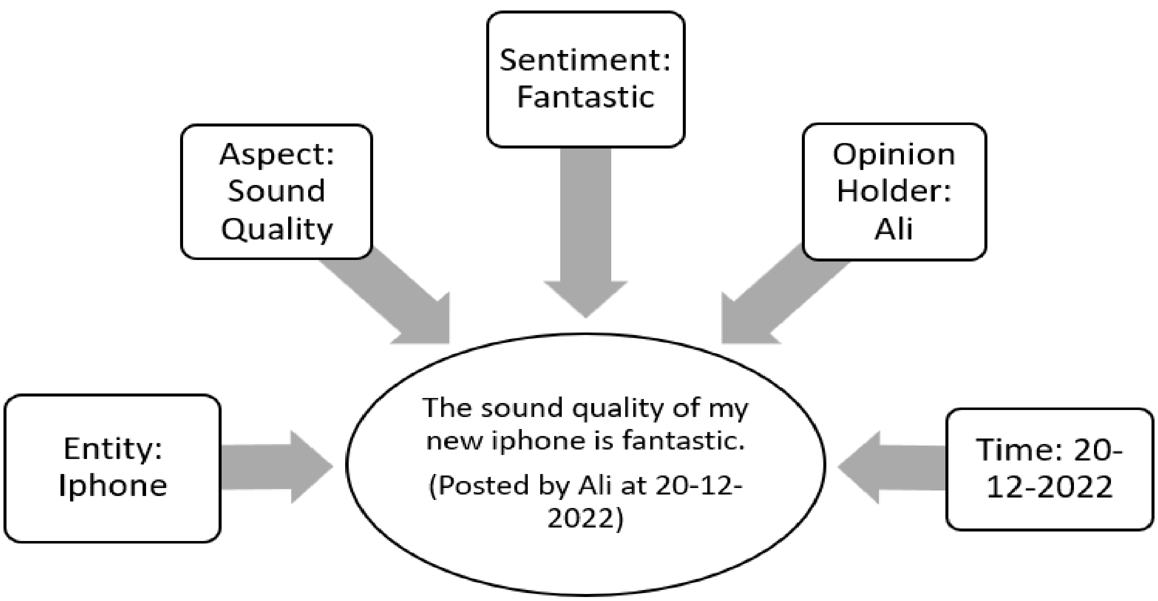

Figure 1: Factors of Opinion

Qiang, Zang, and Law (2009) conducted a study wherein they utilized sentiment analysis to evaluate vacation destinations in the United States and Europe. The ratings given to these destinations ranged from one to five. The researchers classified reviews with one or two stars as having a negative sentiment, while those with more than two stars were considered to have a positive sentiment. These indicators were acquired from customer evaluations in the tourist sector to categorize sentiment into 5-star ratings ranging from awful to excellent. Additionally, there are three degrees of sentiment analysis from the text. On the Yelp dataset, which includes ratings of services rated from 1 to 5, authors have applied machine learning algorithms to the dataset to get the expected results. There has been a wide range of research on the task of sentiment analysis. However, emotions and ideas are primarily observable at the document, sentence and aspect levels (shown in figure 1) (Rana, Iqbal and Nawaz, 2018). The first and second levels are fascinating and quite tricky. The third level, however, is more challenging since it conducts a fine-grained study (Nazir *et al*. 2020). Document-level SA analyzes the whole document as once in positive, negative, or neutral. Sentence level SA works at the level of sentences and checks whether the sentence is negative, positive, or neutral. Aspect-level SA or aspect-based SA (ABSA) is one of the modern techniques which works at the aspects and opinions level for ABSA.

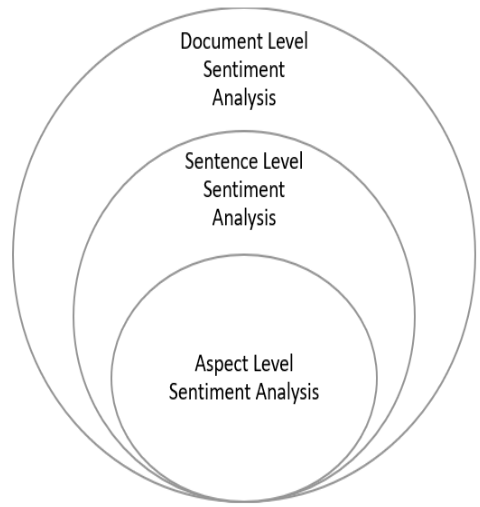

Figure 2: Sentiment Analysis Levels

ABSA systems use as input a collection of texts describing a certain item (such as product evaluations or social media comments) (e.g., the new cellphone size is very good) (Hai *et al*., 2019). The system first finds out the entity (i.e size), then the aspect (i.e size) and then opinion (i.e good). Ultimately, it calculates the average sentiment score in terms of negative, positive, etc. Many different ABAS systems have been proposed for mostly research prototypes. There isn't a defined task decomposition for ABSA, nor are there any defined assessment metrics for the subtasks ABSA systems. Using fine-grained analysis at this level reveals sentiments toward certain item attributes. Consider the statement, "The camera in the cellphone is fantastic," as an illustration. The comment is on the "camera," which is a component of the entity " cellphone" and it is positive. Thus, the study at this level contributes to establishing exactly what people want or detest (Chen & Qain, 2020, Chiha, Syed & Pereira, 2022). Three imperative advances can be utilized to perceive aspect-level sentiments. These are identification, classification and aggregation. By and large, every one of these means is not performed in each procedure, in a few methods, two steps will likewise be performed. As a rule, these steps rely upon the dataset and algorithm. 'Identification' is the first step where sentiment–target pairs will be identified. The subsequent stage is the taxonomy, where sentiment–target pairs are provided to the classifier to express sentiment. If there are two classes i.e. positive and negative, the binary classification would be used. Some additional concerns of aspect-level SA are vigor, flexibility and speed. Vigorousness is one of the most important concerns because sentiment analysis is usually applied to reviews such as product reviews, movie reviews, etc., so many grammar and spelling mistakes exist (Asif *et al*., 2020). People commit many errors in their writing styles without concerning emotions and sentiments (Zainuddin *et al*., 2018). According to research in the field of SA, ABSA is domain-oriented to deal with multiple domains, requiring a flexible system that works well on all domains (Wahyudi & Sibaroni, 2022). Finally, the need for high-speed performance and we can achieve these steps with a preprocessed dataset with no stop words, etc. This survey is organized into several stages. Primarily, we explored the various sentiment analysis methods used in previous studies. Later, a comparison was presented of Sentiment analysis algorithms along with their pros and cons. Section 3 discussed the applications of sentiment analysis. We ended the study with a knowledgeable perspective on the domain of ABSA, highlighting the most potential parameters for future research.

2. Literature Review

ABSA is used to discover the sentiment-target pairs in the reviews or comments in the form of sentences, whole documents, etc. In ABSA, sentiments revolve around entities and sentiments attached to aspects. Using entity and aspects, ABSA gives us a clearer picture of opinions in the text data. Consequently, this survey will focus on aspect-based sentiment analysis. Also, it discusses the most recent developments in ABSA. ABSA is further divided into two sub tasks, Aspects extraction and analysis of sentiments.

2.1. Aspect Extraction

In this part, all approaches including an aspect extraction method of interest are explored. Aspect extraction approaches are further divided into four different approaches as shown in Figure 3.

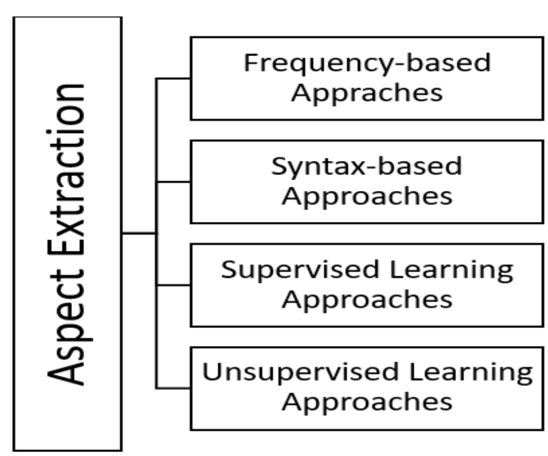

Figure 3: Aspect Extraction Approaches

2.1.1 Frequency-based Appraches

In reviews, a limited number of words are used far more often than the remainder of the lexicon. These common words are likely to be aspects (often, only singular and compound nouns are evaluated). This easy technique proves to be highly effective, as seen by the huge number of aspect detection methods that use it. Evident flaws include the fact that not all common nouns truly correspond to characteristics. Some words, such as 'dollar' or 'bucks', are used often in customer evaluations. On the other side, frequency-based techniques will overlook things that are not regularly stated, such as highly specific characteristics that few people address. The frequency-based strategy may be complemented by a set of rules to account for some of these shortcomings in order to counteract them. The approach of aspect identification described in (Hu & Liu, 2004) only considers singular and compound nouns as potential aspects. The nouns do not need to be adjacent; they should just be in the same phrase. Two criteria are used to reduce the amount of false positives by pruning the results. The first seeks to eliminate pairings where the nouns never exist in close proximity, while the second seeks to eliminate single-word aspects that never appear as part of a multi-word aspect. This procedure is improved in Chong, Zhang and Zhu (2010), where grammatical dependencies are used to identify rare characteristics rather than word distance. In this research, the objective is to identify the most extensive reviews for a certain element, so that SA may be conducted on text data.

2.1.2. Syntax-based Approaches

Rather than relying on frequency to identify characteristics, syntax-based approaches identify aspects based on the syntactic relations they occupy. The adjectival modifier connection between an emotion word and an aspect, as in "wonderful food," where "fantastic" modifies the aspect "food," is a fairly basic relation. A strength of syntax-based approaches is the ability to identify low-frequency characteristics. Nevertheless, numerous syntactical links must be articulated for adequate coverage (Zhao *et al*., 2010) proposes a generalization step for syntactic patterns using a tree kernel function to address the issue of poor recall. The syntactic patterns of all annotated characteristics are recovered from a labelled data collection. Then, using the unseen data, all sentences' syntax trees are obtained. The number of matching substructures may then be used to quantify the similarity between a pattern and a text.

2.1.3. Supervised Learning Approaches

There are a limited number of unsupervised machine learning approaches for aspect detection. In Jakob and Gurevych (2010), aspect identification is framed as a labelling issue, which is handled by applying a linear chain Conditional Random Field (CRF), a technique often used in natural language processing, to an entire series of words (e.g., a sentence). Kobayashi *et al*. (2007) conducted a study in which they utilized machine learning techniques to extract aspects from a collection of blog posts. Rana and Cheah (2019) presented a supervised method in which sequential patterns are employed to identify potential syntactic phrases that are acceptable for opinion and aspect words. Initially, the method necessitates opinion and aspect labels to eliminate extraneous patterns. Later, the newly created phrases are generalized into a set of rules that are used to retrieve unidentified characteristics.

2.1.4. Unsupervised Machine Learning

Yi *et al*. (2003) presented an unsupervised strategy for ABSA that includes aspect creation as a subtask. Based on their technique, aspects are identified utilizing patterns based on nouns. Commonly, nouns are considered aspect candidates, which is backed by Liu's (2012) assertion that sixty to seventy percent of aspects are nouns. Then, non-aspect nouns are eliminated using two distinct sorting techniques. While not quite an aspect-level sentiment analysis approach, Choi and Cardie (2008) is fascinating since it does sentiment analysis on very brief phrases that might be correlated with aspects (Zhu *et al*., 2009). Given that this technique focuses only on sentiment analysis, the expressions (i.e., brief words conveying a single emotion about a single feature or item) are provided. The suggested approach is an SVM-based binary sentiment classifier.

2.2. Sentiment Analysis

Sentiment Analysis are usually performed as supervised learning, unsupervised learning and lexicon-based methods. Pang and Lee (2008) first wrote an admirable introduction and survey on the field of sentiment analysis. They not only discussed the algorithms and techniques of sentiments but also discussed the practical applications of SA. The scope of their survey is on document level SA. Later Tang, Tan and Cheng (2009) also discussed the study, which is on the document level. Another survey was published in 2012 and focused on document-level sentiment analysis; the novelty is that it also discussed some techniques of sentiment extraction (Tsytsarau & Palpanas, 2012). (Mowlaei *et al*., 2020) proposed a technique for ABSA using aspect-based lexicons and a Genetic Algorithm. For improving aspect-based sentiment analysis, the authors created two ways for building dynamic lexicons, one utilizing a statistical method and the other a genetic algorithm. To get a higher performance, two or more levels can be joined to do sentiment analysis rather than just one level. Long and Le (2021) suggested a combined strategy of sentiment analysis at the aspect and phrase levels for product comments on YouTube. The authors believed that a joint approach could effectively address the issues at both levels. The author's emotional response was extracted from the pre-processed comments using a BERT-based model (Jacob *et al*., 2018), both at the sentence and entity levels. Chen *et al*. (2017) improved sentence-level SA by employing a sentence-type approach. First, they divided words into three groups depending on the number of targets they included using a neural network-based sequence model. Although phrase and document-level sentiment analysis are significant and beneficial, they fall short in providing a comprehensive understanding of people's opinions on all aspects of an entity. This limitation arises from their inability to precisely identify the specific aspects that people like or dislike (Medhat *et al*., 2014). Zhao, Rao and Feng (2017) proposed a Domain-Independent Framework SA with weighting recommendations based on the rhetorical structure theory. They converted articles into structure trees and used weighting factors to combine sentence scores and determine the sentiment polarity of the document. Lijuan *et al*., (2022) perform a SA on Weibo posts concerning passengers' commercial air travel experiences. Various travel-related situations, such as a flight delay, may harm the disposition of passengers. They built a unique multi-modal event-aware network for assessing sentiment from text and image-based Weibos posts. Then, they used a multi-task framework concurrently to evaluate the event and emotion by modeling the cross-modal links to produce more discriminatory representations. They first extracted characteristics from each modality. Numerous tests demonstrate that the proposed method outperforms the most current cutting-edge techniques. This technique has an accuracy of 95%. Huang *et al*., (2020) suggested a novel classification approach for sentiment analysis. It was used to extract distinguishing elements from photos and text. Using a unique approach for SA that exploits the association between the modalities of pictures, texts, and extracts, it was proposed to gain attended visual aspects for each word by using a visual-semantic attention paradigm. A semantic self-attention model focuses on the differentiating characteristics for automatically categorizing emotions. Numerous research has focused on both manually annotated and poorly machine-labeled datasets. AMGN provides an accuracy of 88% for Flickr photos and 79% for Twitter data. Xu *et al*., (2020) suggested a methodology that effectively incorporates substantial social information to improve the efficacy of multi-modal sentiment analysis. They developed a gradual dual attention module intended to capture visual and textual interactions. AHRM assigns Flickr and Getty images an accuracy rating of 87%. Liao *et al*., (2022) suggested a neural network for the sentiment analysis of visual textual interaction graphs. Text features were extracted using a text-level graph neural network, whilst picture features were extracted using a convolutional neural network that had been pre-trained. A network of image-text interactions was then constructed. The text and image characteristics were utilized to initialize the graph network's node features, and the graph attention approach was used to update the node features. Lastly, an image-text aggregation layer and an emotion classification layer are coupled. In testing, the Twitter image-text sentiment analysis dataset was used. Another research proposed the ensemble model is a mix of three hybrid models of deep learning models (Tan *et al*., 2022). The predictions made by the proposed model are coupled with those of the averaging ensemble, which improves the sentiment analysis's overall performance. In addition, the problems caused by the imbalanced dataset have been addressed by augmenting the data with pre-trained GloVe word embedding, which has been employed. Table 1 illustrates the summary of three ABSA approaches: Supervised learning, Unsupervised learning and lexicon-based approaches in terms of their pros and cons.

Table 1: Summary of ABSA Approaches

ABSA Approaches	Pros	Cons
Supervised Learning	Reliable and Accurate Outcomes. More frequent usage	it performs poorly when input data is known but labels are not. Knowledge acquisition prerequisites.
Un supervised learning	Effective with unknown data. No previous knowledge is required. Effective when the number of classes is unknown.	Modest, Precise and Consistent Results. Slow.
Lexicons based methods	Reliable and fast Accurate	Requires extensive language resources, which are not always accessible. There are no dictionaries for many languages.

3. Applications

Sentiment analysis becomes a colossal hope for governments and multi-national organizations because these organizations continuously battle to judge people's opinions. For example, a market store needs to check the general population’s opinion about its products. They can enhance their store by including more products that individuals like and expel the products which people detest. It is just conceivable because of the advanced web that people share their ideas and remarks on the web; oodles of comments are airmailed these days. The network allows people to write fast and sensible feedback about any product, movie etc. It is tough to collect this type of data in the future. These product reviews significantly influence people, as before buying any product, people usually read the comments or reviews of other people (Shaha *et al.*, 2018). Also, people’s reviews about any product are considered trustworthy as compared to the information provided by a market vendor. From the market’s perspective, everybody is a discretionary customer and knows the pros and cons of a product that can be good for developing new products (Gang and Liao, 2021), and evacuating or modifying old products (Luo *et al.*, 2021). Moreover, these comments or reviews are also important for companies that develop these products. In a cutting-edge world, enormous companies dependably investigate client surveys to enhance their products. In that way, sentiment analysis is very much important in an economic and financial market. SA has turned into an essential component for undertakings to comprehend clients' feelings about their items. Sentiment analysis sources, for example, internet-based life, give tremendous client-created information, which is a commendable wellspring of sentiments and are loved for some applications that include comprehension of the general sentiment about occasions, items, people, and so forth. For instance, a venture that may catch customers' conclusions about their items may apply some assessment investigation to propel the nature of their items. Be that as it may, more examination is obligatory to see more aspects that can cooperate with conclusion variables to understand the popular sentiment better. For instance, item "A" has numerous positive estimations over the three months. However, does it imply that the ventures which created item "A" need to keep up the nature of this item, as regardless, it has a positive notion by the clients, and does the undertaking need to build the generation of this item to meet the prevalence of the item? Opinion investigation alone may not be sufficient to answer these inquiries. In this manner, factors like contenders' data, the nation's monetary development, customer certainty list, and different components may impact indisputable choices. In any case, future examinations need to coordinate assessment investigation strategies with different variables to make viable techniques for a wholly computerized basic leadership framework in light of a few elements. Besides, future research needs to explore whether enormous information-based strategies can supplant customary techniques (poll-based techniques) in settling on choices or whether both can work best when incorporated into a framework (Ilavendhan, 2021). A client (A) with an expansive amount of admirers posts an undesirable remark about item X, and a client (B) with a couple of admirers posts a positive remark regarding a similar item. Factually, we have an equal amount of positive and negative remarks on item X, however as a general rule, the negative post ought to have more effect since client A has a few supporters who can be affected by his/her assessment contrasted with client B, who has a couple of followers; thusly, his conclusion impacts fewer clients contrasted with client A. In addition, by and large, the immediate amount of supporters may not demonstrate a high impact. Thusly, upcoming research must additionally explore the impact of sentiment polarity inside the associated systems of clients (Nawaz *et al*., 2022). Integrated ABSA also impacts estimation and can give an exact feeling estimation that considers both the post's polarity and impact to catch consumers' perspectives on a more significant and profound scale.

4. Conclusıon and Future Work

This paper provides an overview of contemporary techniques for ABSA and a detailed comparison of techniques for aspect-level sentiment analysis. Nevertheless, it is evident from the current stateof-the-art approaches that ABSA remains in its infancy. ABSA utilizes several machine learning methods, such as supervised and unsupervised learning. For ABSA, researchers also used semi-supervised algorithms. In the last ten years, lexicon-based methods have also gained prominence. Developing new lexicons such as SentiWordNet, etc., used benchmark projects such as WordNet. The primary disadvantage of lexicon-based techniques is that lexicons include a limited number of terms, and in several important languages, lexicons are still under development. Combining novel lexicon techniques with machine learning capability will provide algorithms with a new degree of language and idea reasoning. It will give improved aspect-based sentiment analysis on complicated linguistic structures. In addition, it accelerates the process of aspect-based sentiment analysis. In the future, some work will be done on the detailed systematic literature review of ABSA, focusing on aspect extraction and optimization techniques.

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