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Review Article

A Technical Review of the State-of-the-Art Methods in Aspect-Based Sentiment Analysis

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Abstract: With the advent and rapid advancement of text mining technology, a computer-based approach used to capture sentiment standpoints from data in textual form is increasingly becoming a promising field. Detailed information about sentiment can be provided using aspect-based sentiment analysis, which can be used in better decision-making. This study aims to study, observe, and classify previous methods used in aspect-based sentiment analysis. A systematic review is adopted as the method used to collect and review papers to achieve this research's aim. Papers focused on sentiment analysis, aspect extraction, and aspect aggregation from different academic databases such as Scopus, ScienceDirect, IEEE Explore, and Web of Science were gathered based on the inclusion and exclusion criteria of the study. The gathered papers were further reviewed to answer the stated research questions. The findings from the research show the most used methods for aspect extraction, sentiment analysis, and aspect aggregation in aspect-based sentiment analysis. This research offers a robust synthesis of evidence to guide further academic exploration in sentiment analysis.

Keywords: Aspect-based sentiment analysis; Big data; Sentiment analysis; Systematic review; Text mining.

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1. Introduction

Due to the fast technological development in this digital age, there is a large amount of information. This information positively and negatively impacts people and the environment, especially in politics, business, academics, entertainment, etc. Sentiment Analysis is a technique that categorizes text collection into different emotions[1]. Sentiment analysis can be used to give recommendations based on the opinions of individuals. Front-line technologies like machine learning, deep learning, and natural language processing are employed for sentiment analysis. The application of sentiment analysis is used in multiple areas, such as movie reviews, product reviews, student feedback, customer feedback, political cement, and entertainment. If the recommendation is based on the user's desired criteria, it is called aspect-based sentiment[2]. Aspect-based sentiment analysis is a technique used in commenting on sentiments, which works by dividing texts and defining their sentiments according to their aspects[3]. Aspect-based sentiment analysis is the best tool to provide a positive experience throughout a customer journey. Aspect-based sentiment analysis can analyze interactions of customers at all levels and detect what makes a customer satisfied or otherwise. As opposed to examining the entire text as a single unit, aspect-based sentiment analysis (ABSA) focuses on recognizing and assessing sentiment expressed towards particular parts or characteristics inside a piece of text. ABSA offers a more detailed knowledge of sentiment by going deeper into the complex beliefs and feelings connected to certain elements or entities stated in the text.

On the other hand, conventional sentiment analysis usually classifies a document's, sentences, or phrase's general sentiment without considering particular elements or entities into account. ABSA makes analysis more focused and accurate, especially in product evaluations, social media conversations, or customer feedback, where it's important to grasp how people feel about particular features or traits. In general, aspect-based sentiment analysis can majorly be divided into three sub-processes, which are (i) aspect detection, (ii) sentiment analysis, and (iii)aspect aggregation[4]. The process in which an opinion is detected in a sentence is known as aspect detection. Additionally, a comment that contains an aspect without opinion is known as an objective aspect. An example of an objective aspect is the sentence, "If you credit my bank account, I will my boss a gift." This sentence contains no opinion but a suggestion; thus, the aspect is objective. On the other hand, the process of discovering sentiments attached to an opinion aspect in a particular domain is known as sentiment analysis. For instance, "life span of a laptop battery is very long" has a positive opinion in the word "long" which belongs to the computing device domain. However, the statement, "the program took a very long time to complete the tax." Has a negative opinion in the word "long" which belongs to the application domain. Therefore, it is very vital to be attentive to content and domain when determining the sentiment of an aspect. Additionally, the process of grouping aspects and presenting them in summary to provide recommendations for end users is known as aspect aggregation[5]. For instance, the sentence "The picture that was taken with this phone is good " and " the image quality of iPhone's camera is better than Nokia's camera" has aspects of pictures and images, so the two aspects can be combined as one because they have the same meaning.

In this paper, we carried out a systematic review to study and analyze papers on aspect-based sentiment analysis from different reputable academic databases. This research has been divided into different sections. Section 2 describes the method used to achieve the aim of this study. Section 3 shows the result/discussion based on the methodology that was proposed in Section 2, while Section 4 shows the conclusion of the study

2. Methodology

This work uses a methodical literature research approach to explore aspect-based sentiment analysis (ABSA). To start, research questions were developed to direct the investigation. Afterward, pertinent publications were methodically collected using predetermined inclusion and exclusion criteria from various databases. The databases searched were Scopus, ScienceDirect, IEEE Explore, and Web of Science. After collecting the articles, a comprehensive evaluation and analysis were conducted to extract relevant data related to the study issues. Reviewing each study's methodology, conclusions, and ramifications was part of the process. Ultimately, the research questions and conclusions about the status of ABSA research were addressed using the combined data. This systematic methodology guarantees thoroughness and accuracy while locating and combining pertinent ABSA literature.

2.1. Search and Selection Process

2.1.1. Data sources

Choosing from a wide and standard database is more practical as research becomes more multidisciplinary and interactive. The following are the databases consulted to get related and relevant papers used in this research.

- Scopus: This database was launched in 2004 and contains many academic journal articles, citations, and abstracts. Scopus contains technical, scientific, medical, and even social research and over thirty-six thousand four hundred papers[6].
- ScienceDirect: is Elsevier's highest information resource for students. Science Direct offers subscribers and open-access services. The database contains over nineteen million articles & chapters [7].
- IEEE Xplore: a database containing journal articles, conference proceedings, and documents related to electronics, electrical engineering, and computer science. The database contains over three thousand peer-reviewed journals, over one thousand nine hundred international conferences, over eleven thousand technical standards, and over five thousand e-books[8].
- Web Science: The Web of Science, previously known as the Web of Knowledge, offers paid subscriptions, providing students access to many databases with citation information from academic papers in various academic subjects [9].

2.1.2. Search String

Related papers used to answer research questions were obtained using our created search string to conduct searches on the four database indexes stated earlier. The search string is "opinion mining", "sentiment analysis", "aspect-based sentiment analysis", "aspect detection", "aspect aggregation", "feedback assessment", "sentiment analysis algorithms", "sentiment classification', "sentiment analysis framework" or/and "sentiment analysis tools".

2.1.3. Selection Process

- Step 1: Using the search strings, related papers in terms of titles and abstracts were extracted from the earlier stated databases. A total of 700 papers were selected from the databases.
- Step 2: A selection was made manually to separate the relevant papers from the irrelevant papers. This selection was done based on the inclusion and exclusion criteria according to the guidelines from[10]. After the selection, we obtained a total number of 59 selected papers.
- Step 3: A full-text assessment was conducted to narrow the selection further. We carefully evaluated each paper against our inclusion/exclusion criteria, resulting in a final set of 42 papers eligible for review. This search process was carried out in October 2023.

Table1. Summary of paper collection and selection

S/N	Database	Result from search strings	Papers selected based on criteria	Final papers selected full-text assessment
1	Scopus	145	10	8
2	Science Direct	147	12	10
3	IEEE Xplore	257	19	14
4	Web Science	151	18	10
Total number of papers collected		700	59	42

2.2 Inclusion Criteria and Exclusion Criteria

- Inclusion criteria: The inclusion criteria for this paper are as follows: The paper must be written in English, focus on aspect-based sentiment analysis, and fall within the publication years between 2013 and 2023.
- Exclusion criteria: The exclusion criteria for this paper are as follows: Paper that is not written in English, duplicated papers, papers that do not relate to aspect-based sentiment analysis, papers published before 2013, and papers that do not explicitly state their result are all excluded from this review.

2.3 Snowballing

This study utilized a snowballing technique known as the backward snowballing technique. This technique involves considering related references contained in the papers that were retrieved from the database that was presented earlier. The references were then filtered based on the inclusion and exclusion criteria.

3. Research Questions

Generally, aspect-based sentiment analysis is divided into three sub-processes: aspect extraction, sentiment analysis, and aspect aggregation [10]. Over the past decade, many researchers have employed different techniques on these sub-processes. Thus, the research questions in this study are focused on the methods employed over the past ten years in these sub-processes. Three research questions are answered in this paper based on valid arguments. The research questions are:

- RQ1. What technical methods are used for aspect extraction in aspect-based sentiment analysis?
- RQ2. What technical methods are used for sentiment analysis in aspect-based sentiment analysis?

- RQ3. What technical methods are used for aspect aggregation in aspect-based sentiment analysis?

4. Answering Research Questions

4.1 Answer to RQ1: What technical methods are used for aspect extraction in aspect-based sentiment analysis?

Research to obtain aspects from tourism reviews was carried out by [11]. The researchers employed the frequency-based method. The dataset used contained aspects from candidates, and these aspects were collected using part-of-speech (POS) tagging for all noun and noun phrases. Aspects that are used the most by reviewers were collected with the use of frequent item-set mining.

To predict the sentiment polarity of text, [12] extracted aspects from feedback using a frequency-based approach. The researchers focused on aspect extraction. The result shows that the approach was better than the existing ones.

Study [13] proposed the linguistic rule method to detect aspects during the process of developing a domain-independent model that can do without label data. The researchers used a part-of-speech combination to extract aspects from candidates. Modification scores from PointWise-Mutual-Information (PMI) and heuristic rules were used to filter the aspect candidates.

Another research [14] proposed an aspect-based sentiment analysis technique used for textual reviews. The techniques use an almost unsupervised approach. The research used linguistic rule with Latent Dirichlet allocation for aspect extraction, and the ranking of aspects was based on their Probability-Distribution-Value. The result of the experiment, when tested with labeled data, is superior to other existing methods.

A sentiment analysis aspect extraction based on supervised learning was conducted by [15]. Three different aspect extraction techniques were used, including the linguistic, the lemma, and a hybrid of both linguistic and lemma. The dataset used by the researchers was from the Kaggle dataset, Yep, and reviews from SemEval restaurant. The hybrid feature set achieved an accuracy of 94.78% and an f1-score of 85.2ed in the aspect class prediction task.

Research that proposed an aspect extraction novel framework that integrates linguistic and contextual attributes based on the artificial bee colony features selection approach was conducted by [16]. The real word dataset was further used to conduct an extensive experiment after the aspect extraction. The framework achieved a higher F1 score than other existing methods. Four different datasets were used, and the model achieved f1 scores of 72.20%, 74.80%, 80.70%, and 84.70%.

An aspect-level sentiment analysis was carried out on movie reviews by[17]. The researchers adopted a linguistic rule-based method that extracts opinions from aspects. Aspects such as directing, acting, cinematography, and choreography were considered. The experiment was performed on the dataset from two movies. The result from the experiment showed that good accuracy was achieved.

A comparative analysis between the seven-layer deep learning CNN, CNN, and the linguistic rule-based approach for sentiment extraction was conducted by [18]. The researchers try to improve the linguistic-based rule by categorizing aspects using clustering. The seven-layer deep learning CNN approach performed better than the compared approaches with an accuracy of 87%, which is 7-12% higher than the compared method.

A two-fold rule-based mode was used to extract aspects [19]. The model uses rules based on sequence patterns that were mined from customer reviews. Aspects were extracted from opinions that were domain-independent in the first fold, while aspects were extracted from those that were domain-independent in the second fold. Also, the researcher applied similarity and frequency-based approaches to improve the proposed model's performance aspect extraction process. The evaluation performed on the experiment show that the model achieves better results than the previous approaches.

A supervised method of aspect extraction was conducted by [20]. The paper focuses on aspect extraction of aspect-level sentiment. The researchers claim that classifier algorithms that can handle imbalanced data with minimal robust features have achieved results that can be compared to the state-of-the-art aspect extraction approaches. Based on their assessment, the random forest classifier was reported as the algorithm with the best result.

Research [21] used an unsupervised aspect extraction method with monitoring tools that support visualizing analyzed data to monitor real-time reviews. The aspect extraction method was based on an open information extraction strategy. The method's effectiveness was tested on benchmarks from the SemEva campaign, and the result showed a good performance.

An unsupervised aspect extraction method based on multi-criteria decision-making MCDM and game theory was used on restaurant reviews by [22]. The purpose of the research is to improve the restaurant customer satisfaction. The research experiment was performed on a dataset containing reviews from two restaurants. Statistical analysis was used to validate the significance of the result. The model ensured a consistent and rational result.

Study [23] performed an aspect extraction using an unsupervised approach. The unsupervised approach combines a lexical rule based on reference resolution. Two benchmark datasets were used for the experiment evaluation, and the proposed approach outperformed the baseline approaches.

A joint model of multiple convolutional neural networks for aspect extraction was proposed by [24]. The research focused on three types of representation: word embedding from Word2Vec, word embedding from GloVe, and one-hot character vectors. The result shows that the proposed model can perform well, like the state-of-the-art approaches, in terms of aspect extraction and sentiment classification.

Table 2. Summary of technical methods used for aspect extraction in aspect-based sentiment analysis

S/N	Technical methods	Source of application
1	Frequency-based	[11], [12]
2	Linguistic rules	[13]–[19]
3	Supervised learning	[20]
4	Unsupervised learning	[18], [21]–[24]
5	Hybrid	[15], [16]

Based on the reviewed papers, we observed that the methods used for aspect extraction in aspect-based sentiment analysis are frequency-based, linguistic rule, supervised learning, unsupervised learning, and hybrid methods. Researchers have also mostly used the linguistic rule method in recent years. Fewer papers were based on unsupervised learning, frequency-based, and hybrid methods, while only one paper used the supervised learning method, which appears to be the least used method.

- Frequency-based: Frequency-based aspect extraction uses algorithms based on association rules. It identifies aspects frequently appearing in reviews with a minimum support threshold. This method is easy to implement but has a drawback: if an aspect lacks frequency, it will be discarded, resulting in low recall.
- Linguistic rules: This method tags input data to identify sentiments based on predefined rules. One advantage is its high precision, which relies on grammar rather than a specific domain. However, if a sentence is grammatically incorrect, it can lead to errors in aspect collection.
- Supervised learning: This method utilizes labeled datasets to train the model. It exhibits the best performance on training data. However, its effectiveness is highly dependent on the domain used; for instance, data from the health domain may perform differently than data from the agricultural domain.
- Unsupervised learning: This method does not require a training process, and thus, dataset labeling is unnecessary. However, its accuracy heavily depends on the initial seed as a guideline. It determines aspects using the seed word via topic or distance modeling methods. While it doesn't require labeled data, it may struggle with accuracy without proper initial seeds.
- Hybrid: This approach combines two or more existing approaches, often merging linguistic rules with other methods. It can be implemented in various phases, such as aspect representation, training model, and aspect identification. The hybrid approach can leverage the strengths of each method but may also inherit its weaknesses, requiring careful consideration of integration points and trade-offs.

4.2 Answer to RQ2: What technical methods are used for sentiment analysis in aspect-based sentiment analysis?

Research that performed a sentiment analysis on the EndSARS protest in Nigeria was carried out by [25]. The researchers adopted the lexicon-based method for the sentiment analysis. A collection of 12,357 tweets with EndSARS and other related hashtags was extracted from TwitterNG and used as the dataset for the analysis. The result from the method shows eight emotions expressed during the EndSARS protest.

Research using the lexicon-based method for sentiment analysis was carried out by [26]. The research uses a lexicon-based method to analyze sentiments about COVID-19 in six different countries (India, USA, UK, Spain, Italy, and France). The dataset used consisted of tweets about COVID-19 from 15th March 2020 to 15th April 2020 that were extracted from Twitter. The lexicon-based method was used to identify sentiment as negative, positive, or neutral.

A lexicon-based method with a Naïve Bayes algorithm was used to analyze sentiment about COVID-19 #newnormal hashtag on Twitter. The research was conducted by [27]. The result shows that 33.19% of the tweets about #newnormal are negative, while 66.36% are positive. Meanwhile, the Naïve Bayes algorithm was able to achieve 79.72% accuracy.

Student feedback sentiment analysis was carried out by[28]. The lexicon-based approach was utilized for the analysis. The dataset that was used was collected through open-ended electronic questionnaires. The lexicon-based method was able to achieve an accuracy of 98%. The researchers further applied machine learning algorithms such as NB, SVM, and KNN, which achieved 97%, 97%, and 96%, respectively.

A sentiment analysis of web chats using SentiWordNet lexicons was carried out by [29]. The sentiment analysis that was performed was lexicon-based. The method works by extracting and modifying lexicons prior polarity scores based on context. The research used three group discussion datasets, and the result shows that the proposed method could be used for other web discussion sentiment analyses.

A study [30] performed a sentiment analysis on a Twitter dataset. The researchers used the lexicon-based and machine learning approaches (Random Forest, multinomial Naïve Bayes (MNB), and SVM). The researchers further compare the result of the lexicon-based approach to that of the machine learning approaches. The dataset consists of sentiments about COVID-19 in England on Twitter. All the methods used perform well, but the SVM performs best with an accuracy score of 71% due to insufficient training dataset.

A sentiment analysis experiment was carried out by [31]. The researchers used two different approaches, which include the DL and the supervised ML approaches. The first method utilized deep learning methodologies with word2vec but was not as accurate as the machine learning methods. The machine learning classifier algorithms used were the MNB, KNN, Logistic regression (LR), and RF. The LR performed better than all other compared algorithms. The researcher further built another LR model with advanced ML methodologies (Synthetic Minority Over-sampling for data balancing issue and shuffle split cross-ventilation). The final LR model achieved an accuracy of 87%, which is 3% higher than the initial performance.

Another research [32] utilized the supervised machine learning method for sentiment analysis. The researchers used two different machine learning algorithms, the LR and the NB. The researchers further perform a comparative analysis between these supervised learning algorithms. The LR was able to perform better than the NB. The LR has an accuracy score of 93.59% on train data and 89.76% on test data, while the NB achieved an accuracy score of 90.6% on train data and 86.14% on test data.

A paper that presented a supervised learning approach for sentiment analysis was proposed by [33]. The researchers made use of different regression models and a pre-trained BERT. The experiment was performed on financial data collected from the Financial-Opinion-Mining and Question-Answering-Open-Challenge held in Lyon, France. From the experiment result, it was observed that the Linear SVR outperformed all other algorithms used.

A semi-supervised learning method was proposed for sentiment classification using a small number of labeled data. The research was performed by [34]. The research trains a semi-supervised Deep Neural Network (DNN) and a supervised DNN with the same amount of labeled data. Then, it performs a comparative analysis between the two methods. The result shows that the model performance will be degraded if the unlabeled is not handled with care.

A study was carried out to analyze south Africans tweets on Twitter during a South African local government election to understand her politics was carried out by [35]. A semi-supervised sentiment analysis method was used for the implementation. The tweets were successfully classified as positive and negative sentiments using the semi-supervised learning method.

A study [36] conducted a sentiment analysis on the Philippines presidential election 2020. The approach for the sentiment analysis was based on the semi-supervised approach. Sentiments about the election on Twitter were extracted and used for the analysis, and the tweets were processed and trained to classify Tagalog and English tweets into neutral, positive, and negative sentiments. The dataset with 30% unlabeled data was trained using self-training with Multinomial Naïve Bayes. The result was 84.83% accurate.

An unsupervised learning approach was used for sentiment analysis of social media short text classification in Roman Urdu. The research was conducted by [37]. The model first normalized the text to overcome variations in the spelling of different words. After normalizing the text, the English and Roman Urdu opinion lexicons were used to identify users' opinions correctly.

Research [38] proposed a novel unsupervised learning method based on hierarchical clustering and content-based to analyze sentiments on Twitter data. Hierarchical clustering algorithms such as average, complete, and single linkage were ensemble. The researchers compared the result with the naïve Bayes classifier and neural network results. The performance method shows that the proposed unsupervised method is comparable to supervised learning techniques.

Another study [39] researched sentiment analysis. The research uses a semantic similarity method based on the perspective of lexicons. The researcher also performed an extensive experiment to determine the model's effectiveness. The experiment result shows that the adopted method can improve the performance of sentiment analysis over a strong baseline.

Research that considered the statistics and the semantic methods for sentiment analysis is performed by [40]. The authors combined a machine learning approach that is based on statistical properties of the linguistics and word rules. The method considered for the sentiment analysis is based on the probabilistic model of the word occurrence in documents. The dataset used by the researchers was collected from the organizers of ROMIP, and these datasets are in three categories, which include book reviews from imhonet.ru, camera reviews from the Yandeks market, and movie reviews.

Table 3. Summary of technical methods used for aspect-based sentiment analysis

S/N	Technical methods	Source of application
1	Lexicon Based	[25]–[30]
2	Supervised Learning	[30]–[33]
3	Semi-Supervised Learning	[34]–[36]
4	Unsupervised learning	[37], [38]
5	Semantic-Based	[39], [40]

From our reviews, we found the methods used for sentiment analysis in aspect-based sentiment analysis to be lexicon-based, supervised learning, semi-supervised learning, unsupervised learning, and semantic-based methods. Lexicon-based methods appear to be the most used method among researchers. In contrast, fewer papers were based on supervised and semi-supervised learning, and the least used methods are the unsupervised and the semantic-based methods.

- Lexicon-based: This method assumes that sentiments relate to specific phrases or words in a document, a processed structural representation of raw text[26]. An advantage of this approach is its ease of implementation. However, a disadvantage lies in the polarity value ambiguity of static words. For instance, a word like "long" may carry a positive connotation when referring to the duration of battery discharge but a negative connotation when describing the time for a battery to charge.
- Supervised Learning: This method involves using labeled datasets to train the model [41]. The sentiment analysis supervised learning method relies on manually labeled linguistic data. The strength of this approach lies in its reliance on labeled data, which

can significantly enhance model accuracy. However, the data quality strongly influences the accuracy of the model, thus posing a challenge.

- Semi-Supervised Learning: Combining aspects of supervised and unsupervised learning, this method utilizes a large amount of unlabeled data and a small amount of labeled data [36]. By doing so, it harnesses the benefits of supervised and unsupervised learning, thus overcoming challenges associated with obtaining a large number of labeled data. However, the effectiveness of this method may depend on the quality and representativeness of the small labeled dataset.
- Unsupervised Learning: This method leverages natural language processing to automatically identify and analyze sentiment within specific aspects of text, eliminating the need for predefined training data [36]. Its strength lies in its ability to work without labeled data, which can be advantageous when labeled data is scarce or unavailable. However, the accuracy of the analysis may vary depending on the complexity and nuances of the text being analyzed.
- Semantic-Based: In this method, sentences are grouped based on context, and the sentiment of words within the same context is assumed to have the same sentiment value [42]. This approach allows for a more nuanced understanding of sentiment within specific contexts. However, its effectiveness may be limited by the granularity of context analysis and the variability of sentiment within similar contexts.

4.3 Answer to RQ3: What methods are used for aspect aggregation in aspect-based sentiment analysis?

Research conducted by [43] used the hub set and word relations to determine the aspect similarity of two aspects. The hub set consists of 2 hub words, and hub words are words highly related to aspects. The length of the document and aspects determine the strength of the relation, making it a distance-based approach.

Another research [44] presented a conference paper that uses aspect-based opinion mining to estimate public opinion on social media. The researchers employed the distance-based method for aspect aggregation, determining the similarity of aspects using Synset of WordNet.

Another conference paper that utilized the distanced-based method for aspect aggregation was presented by [45]. The researchers used the word similarity to categorize aspects into groups. Word similarity calculates similarity values between aspects and keywords obtained from Wikipedia.

Research conducted by [46] on restaurant review sentiment analysis also adopted the distance-based approach of combining aspects. The hybrid of Embeddings from Language Models (ELMo) and the cosine similarity method were used, and the aspect keywords that were used were obtained from Wikipedia using Term-Frequency Inverse-Document-Frequency (TF-IDF).

Study [47] used a knowledge-based approach for sentiment aggregation. In this method, a tagged word from tagged reviews was matched with extracted keywords to identify aspects and opinions associated with it. Then, if the tagged data doesn't match any keyword, it uses semantic relations to find implicit aspects from their similarity-based lexical database WordNet.

Another study [48] researched using latent Dirichlet allocation (LDA) for hotel review sentiment analysis. The knowledge-based method was used for combining aspects. The Wu-palmer WordNet similarity method was used to classify aspects with the seed word. The seed words are the categories of words that are manually selected and used. The TF-IDF was used to expand the term list when calculating similarity measurement.

Similar to [48], another research on sentiment analysis of hotel aspects was conducted by [49]. The researchers also applied the knowledge-based method of aspect aggregation. The research uses Probability-Latent sentiment analysis, long short-term memory (LSTM), and Word Embedding to achieve its objectives.

Table 4. Summary of methods used for aspect aggregation in aspect-based sentiment analysis

S/N	Technical methods	Source of application
1	Distance-based	[43]–[46]
2	Knowledge-based	[47]–[49]

It is observed that two major methods are used for aspect aggregation in aspect-based sentiment analysis, which are distance-based and knowledge-based methods, but the distanced-based method is used more than the knowledge-based method.

- Distance-based Method: This aspect aggregation method aims to measure the distance between two words where the word is derived from the initial seed word, a keyword, with the aspect word in a sentence. The strengths of this method lie in its ability to provide a quantitative measure of similarity, allowing for straightforward comparisons. Additionally, it can effectively capture semantic relationships between words, especially in contexts where the distance metric is well-defined. However, its weakness lies in its reliance on the availability of comprehensive datasets or corpora for accurate distance calculation. Moreover, it might not adequately handle nuances in meaning or context, leading to potential inaccuracies in certain cases.
- Knowledge-based Method: This method tries to look for similarities among words using external sources like dictionaries, with one of the common ones being WordNet. WordNet similarity is based on the distance between two nodes in a tree structure. Its strength lies in its ability to leverage structured knowledge representations to infer semantic similarity, which can be particularly effective in scenarios where explicit semantic relationships are well-defined. Additionally, it can offer insights into the hierarchical structure of language. However, its weakness lies in its dependency on the quality and coverage of the external knowledge base being utilized. Incomplete or outdated information in these sources can lead to inaccuracies. Additionally, it may struggle with capturing nuances or evolving meanings not explicitly represented in the knowledge base.

To create an integrated framework for Aspect-Based Sentiment Analysis (ABSA), we propose a comprehensive approach incorporating state-of-the-art techniques. First, for aspect extraction, we leverage a multi-faceted approach that combines frequency-based methods, linguistic rules, supervised and unsupervised learning, as well as hybrid techniques to ensure robustness in identifying aspects. Next, for sentiment analysis within ABSA, we employ diverse methods, including lexicon-based approaches, supervised learning models, semi-supervised techniques, unsupervised methods, and semantic-based strategies, accommodating the varying complexities of sentiment detection. Lastly, for aspect aggregation, we favor distance-based methodologies while incorporating knowledge-based approaches when appropriate, ensuring a balanced aggregation process.

5. Discussion

The systematic literature review on aspect extraction, sentiment analysis, and aspect aggregation methods in aspect-based sentiment analysis (ABSA) revealed various techniques employed by researchers across different domains. The analysis provides valuable insights into the strengths and weaknesses of various approaches, shedding light on the trends in methodology selection and areas for further improvement.

Aspect Extraction Methods: The review identified several prevalent methods for aspect extraction, including frequency-based, linguistic rule-based, supervised learning, unsupervised learning, and hybrid approaches. Each method offers unique advantages and challenges. Frequency-based methods, for instance, excel in simplicity and ease of implementation, yet they may suffer from low recall when aspects with lower frequencies are disregarded. On the other hand, linguistic rule-based methods demonstrate high precision but are sensitive to grammatical errors, potentially leading to inaccuracies in aspect collection. Supervised learning methods leverage labeled datasets for training, achieving high performance on specific domains but requiring extensive domain-specific data. While not relying on labeled data, unsupervised learning methods heavily depend on initial seed words and may lack accuracy without careful selection. Hybrid approaches, combining multiple techniques, aim to capitalize on the strengths of individual methods while mitigating their weaknesses.

Sentiment Analysis Methods: Similarly, sentiment analysis in ABSA employs various techniques, including lexicon-based, supervised learning, semi-supervised learning, unsupervised learning, and semantic-based methods. Lexicon-based methods, being straightforward to implement, dominate the literature, although they face challenges with static polarity values for words. Supervised learning methods offer high accuracy but require extensive labeled data and are sensitive to domain shifts. Semi-supervised learning techniques, by leveraging labeled and unlabeled data, aim to address the scarcity of labeled data but need careful handling of unlabeled data to prevent performance degradation. Unsupervised learning methods, not relying on labeled data, offer flexibility but require robust initializations and suffer from potential inaccuracies. Semantic-based methods, focusing on context and word relationships, offer promising results but may require complex computational resources.

Aspect Aggregation Methods: The review identified distance-based and knowledge-based methods as the primary approaches in aspect aggregation. Distance-based methods measure the similarity between aspects based on word distances, while knowledge-based methods leverage external sources like WordNet for similarity calculations. Distance-based methods offer straightforward comparisons and effective semantic relationship capture but may lack accuracy without comprehensive datasets. While leveraging structured knowledge representations, knowledge-based methods are sensitive to the quality and coverage of external sources.

Integrated Framework for ABSA: To achieve a comprehensive ABSA, an integrated framework combining aspect extraction, sentiment analysis, and aspect aggregation is essential. By leveraging a multi-faceted approach to aspect extraction and sentiment analysis, researchers can ensure robustness in accurately identifying aspects and detecting sentiments. Aspect aggregation can benefit from a balanced combination of distance-based and knowledge-based methods, leveraging the strengths of both approaches to achieve accurate and nuanced aspect aggregation. Combining these aspects contributes to the overall effectiveness of ABSA systems, ensuring comprehensive and insightful analysis of text data.

The systematic review underscores the importance of methodological diversity in ABSA research, highlighting the need for tailored approaches to address specific challenges in aspect extraction, sentiment analysis, and aspect aggregation. By understanding the strengths and weaknesses of different methods and their combinations, researchers can develop more robust and accurate ABSA systems capable of capturing nuanced opinions and sentiments from text data across various domains.

6. Conclusion

Based on our reviewed papers, we concluded that the methods used for aspect extraction are the frequency-based, linguistic rule, supervised learning, unsupervised learning, and hybrid methods, where the linguistic rule is the most used method. Secondly, the methods used for sentiment analysis are lexicon-based, supervised learning, semi-supervised learning, unsupervised learning, and semantic-based methods, where the most used method is lexicon-based. Finally, the methods used for aspect aggregation are the distanced-based and the knowledge-based methods, where the distanced-based method is mostly used.

The findings from this systematic literature review hold significant relevance in the current landscape of sentiment analysis and its future applications. As the work underscores the diverse range of technical methods in Aspect-Based Sentiment Analysis (ABSA), it establishes a solid foundation for researchers and practitioners. In the immediate context, these insights can inform the development of more accurate and adaptable sentiment analysis systems, especially in domains where nuanced understanding is crucial, such as customer feedback analysis and product reviews. Looking ahead, the methodologies uncovered here pave the way for innovation, allowing for the integration of emerging techniques and technologies. Future work in ABSA can build upon this knowledge, exploring novel combinations of methods, deepening our understanding of context, and extending applications to new domains, thereby advancing the field and its practical utility.

Future aspect-based sentiment analysis (ABSA) research may concentrate on various directions to develop the subject. First off, developing new hybrid techniques that build on the advantages of current methods may result in ABSA systems that are more reliable and accurate. Furthermore, exploring how to include ontologies or domain-specific knowledge graphs into ABSA frameworks may improve sentiment contextual comprehension. Additionally, investigating methods for addressing cross-cultural and multilingual sentiment analysis problems might benefit applications in various linguistic situations. Ultimately, studies into deep learning architectures like attention-based or hierarchical models tailored especially for ABSA tasks may enhance the accuracy and scalability of sentiment analysis across a range of languages and topics.

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