Proceedings of the 2nd International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/114/2024.18197

The Current State and Challenges of Aspect-Based Sentiment Analysis

Shaopu Yin

School of Software, Beijing University of Aeronautics and Astronautics, Beijing, 100191, China

22371277@buaa.edu.cn

Abstract. Aspect-Based Sentiment Analysis (ABSA) is an important branch of natural language processing that aims to identify the sentiment polarity of aspect terms in the target language. With the increasing amount of text data generated by social media, e-commerce review platforms, and online forums, traditional holistic sentiment analysis can hardly meet the demand for fine-grained sentiment understanding. In comparison to conventional holistic sentiment analysis, ABSA provides a more comprehensive insight into the sentiment expressed. In addition, it has been widely employed in the fields of online public opinion analysis and management, thereby attracting increasing attention from researchers. This paper presents a comprehensive review of the existing literature on this topic, aiming to identify the principal research methods and findings in order to inform future research. In addition, it explores key research issues, including summarizing the theoretical underpinnings of ABSA, outlining the current dominant approaches to ABSA research, and finally exploring potential future developments and challenges in ABSA research. The results indicate that while significant advancements have been made, challenges such as handling implicit sentiments and integrating multimodal data still persist.

Keywords: Aspect-Based Sentiment Analysis, Deep Learning, Aspect Term Extraction, Sentiment Classification

1. Introduction

In natural language processing, sentiment analysis plays a crucial role in recognizing and extracting subjective information from text. As the demand for the recognition of fine-grained sentiments has increased, traditional document-level and sentence-level sentiment analysis is no longer sufficient for complex sentence structures. In comparison to traditional document-level and sentence-level sentiment analysis, Aspect-Based Sentiment Analysis (ABSA) can provide more detailed sentiment analysis by shifting the focus from the entire document or sentence to specific entities or aspects of entities. According to QuestMobile, as of March 2024, the number of active mobile Internet users in China has reached 1.232 billion [1]. The Internet has accumulated a large amount of text data containing users' subjective emotions, and the research and utilization of these data are of significance. Government departments can use sentiment analysis tools to more scientifically and effectively monitor online public opinion, track social hot topics, and improve the precision and efficiency of governance and services. The product and marketing departments of enterprises can conduct sentiment analysis on user feedback to make targeted product adjustments and develop more precise marketing strategies. As ABSA continues to evolve, it is essential to refine existing methodologies and explore new approaches that can better understand complex sentiment expressions. This paper aims to bridge the gap in the literature by reviewing current ABSA methodologies, analyzing their effectiveness, and identifying areas for improvement. Through this in-depth analysis, the paper seeks to provide insights and guidelines for researchers and practitioners looking to advance the field of ABSA.

2. Overview of Aspect-Based Sentiment Analysis

2.1. Basic Theory of Aspect-Based Sentiment Analysis

The field of sentiment analysis often uses a quadruple structure, including Target, Sentiment, Holder and Time, where Target and Sentiment can be further refined into two ternaries: Target consists of Category, Entity and Aspect, while the Sentiment consists of Type, Orientation and Opinion term [2]. Thus, the sentiment can be viewed as a collection of eight elements. In practical research, for data constraints and research convenience, the octuple is usually simplified to a quadruple consisting of Aspect category, Aspect term, Opinion term and Sentiment polarity. For example, the sentence “The café is quite packed, yet the pastries are absolutely delightful” can be used to illustrate this structure. Aspect terms refer to the specific objects that users use to express sentiment in the text, and are divided into two categories: explicit and implicit. Explicit aspect terms appear directly in the text, such as “the café” and “the pastries”; implicit aspect terms are not explicitly mentioned, for example, in “This phone is very lightweight in hand”, the phone implicitly suggests the aspect of “weight.” Sentiment terms are subjective evaluations of entities in the text; in the above example, “packed” and “delightful” correspond to “café” and “pastries” respectively. Aspect categories are used to categorize the objects of evaluation, and usually presuppose concepts in different domains. “Café” and “pastries” belong to the environment and food categories, respectively. Sentiment polarity is the tendency of users to express sentiments towards aspect terms, which are usually categorized as positive, neutral and negative. In the given example, the aspect terms “cafe” and “pastries” are related to the sentiment terms “packed” and “delightful”, respectively, reflecting negative and positive sentiment polarities.

2.2. Fundamental Tasks and Evaluation Metrics of Aspect-Based Sentiment Analysis

ABSA consists of two main basic tasks, aspect term extraction and aspect-level sentiment classification. These tasks were initially proposed by Hu et al for mining and summarizing product reviews, aiming to uncover the objects described by users in the text and their emotional expressions [3]. Aspect Term Extraction involves extracting aspect terms from text, with the text serving as input, which is primarily divided into explicit aspect extraction and implicit aspect extraction. Implicit aspect term extraction poses greater challenges compared to explicit aspect term extraction the lack of explicit contextual cues. Aspect-Level Sentiment Classification takes text and given aspect words as input, aiming to determine the emotional polarity corresponding to the aspect word involved in the text, which is a subsequent task of aspect word extraction. Also, ABSA involves both opinion term and aspect category. Consequently, there are also independent tasks such as opinion term extraction, aspect sentiment extraction, category identification, and category sentiment classification, as well as combined tasks paired by independent tasks. These tasks expand the scope of ABSA and can be considered as extension tasks of ABSA. The aspect term extraction task is mainly evaluated by accuracy, recall and F1 score. The extraction is considered correct when it exactly matches the annotation. Its calculation formula is:

$$\text{Precision} = \frac{Correctly\ Extracted\ Aspect\ Words}{Total\ Number\ of\ Extracted\ Aspect\ Words} \tag{1}$$

$$\text{Recall} = \frac{Correctly\ Extracted\ Aspect\ Words}{Total\ Number\ of\ Annotated\ Aspect\ Words} \tag{2}$$

$$F1 - Score = \frac{2*Precision*Recall}{\text{Precision}+Recall} \tag{3}$$

For the aspect sentiment classification task, Accuracy and F1-Score are primarily employed as evaluation metrics. The formula for calculating accuracy is as follows:

$$\text{Accuracy} = \frac{Number\ of\ Correctly\ Predicted\ Samples}{Total\ Number\ of\ Samples} \tag{4}$$

To compute the F1-Score for classification task, the number of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) must be first determined from the classification results. Then, precision and recall are calculated based on these quantities.

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \tag{6}$$

The F1-Score is then calculated accordingly:

$$F1 - Score = \frac{2*Precision*Recall}{\text{Precision}+Recall} \tag{7}$$

2.3. Mainstream Aspect-Based Sentiment Analysis Datasets

ABSA datasets are essential for training and evaluating models that understand consumer opinions on specific aspects of products, services, or topics. They typically contain annotated data with aspect terms, sentiment polarity, and sometimes aspect categories, facilitating the development and testing of models across various domains. At present, some mainstream datasets commonly used in ABSA research are detailed in Table 1.

Table 1. Mainstream Datasets for Model Training in ABSA Research

Datasets	Language	Summary
Twitter 2014	English	Sampled from Twitter, covering data from various domains that contains products and businesses, annotated with aspect terms and sentiment polarity [4].
SemEval-2014	English	Contains reviews from the Restaurant and Laptop domains, annotated with aspect terms, sentiment polarity, and and aspect category [5].
SemEval-2015	English	Extension of SemEval-2014, including hotel domain data, used for cross-domain ABSA research [6].
SemEval-2016	Multilingual	Extension of SemEval-2015, covering seven domains, supporting eight languages, suitable for cross-domain and cross-linguistic research [7].
SemEval-2017	Multilingual	Sampled from Twitter, containing English and Arabic tweets, annotated with aspect term and sentiment polarity in the tweets [8].
MAMS	English	Restaurant domain reviews, each containing at least two aspect terms with distinct sentiment polarities [9].
ASAP	Chinese	Containing Chinese reviews across eight domains, annotated with sentiment polarity across 18 predefined aspect categories [10].
CASA	Chinese	Covering domains such as television dramas, films, and news, annotated with aspect term, opinion terms, and sentiment polarity [11].

3. Research Methods for Aspect-Based Sentiment Analysis

3.1. Aspect-Based Sentiment Analysis Based on Attention Mechanism

The attention mechanism is currently the most prevalent method for determining the sentiment polarity of aspect terms. Its core principle is to assign different weights to each word in the context of an aspect term based on the textual data, thereby enhancing the influence of words that are relevant to the aspect

DOI: 10.54254/2755-2721/114/2024.18197

term. Neural network models based on the attention mechanism can implicitly associate the aspect term with contextual information, which has consequently garnered widespread attention in the field of ABSA. Currently, various neural network architectures integrate the attention mechanism. Tang et al. proposed the MemNet model, which combines attention mechanisms with memory networks, enabling continuous updates to query memory units while performing stacked attention computations [12]. Wang et al. introduced the Attention-based LSTM with Aspect Embedding network model, combining attention mechanisms with recurrent neural networks to retain context features relevant to aspect terms [13]. Chen et al. proposed the Recurrent Attention Network on Memory model, which uses a multi-attention mechanism to capture the sentiment polarity of specific aspect terms in long-distance texts via memory storage units [14]. Ma et al. developed the Multi-grained Attention Network model, which enhances the interaction between aspect terms and contextual words [15]. Li et al. introduced the Transformation Network model by combining attention mechanisms with residual networks, achieving feature transformation for deep semantic analysis [16].

3.2. Aspect-Based Sentiment Analysis Based on Pre-Trained Language Models

The advent of pre-training and fine-tuning paradigms has led to the gradual mainstreaming of aspect-based sentiment classification using implicit semantic knowledge from large-scale pre-trained language models. In research on ABSA, pre-trained language models are initially used to process input text and then integrated into deeper neural network architectures. In 2017, Google introduced the Transformer model framework, which offers superior parallelization capabilities compared to RNNs. The Google team then developed the BERT model based on this framework, which led to the development of a series of pre-trained models based on Transformer. Xu et al. proposed the BERT PT model, which consists of post-training BERT on large-scale domain-specific corpora and fine-tuning the resulting model on datasets, leading to significant improvements over models based on word vectors [17]. Song et al. proposed an attention coding network combined with a BERT pre-trained language model using an attention mechanism encoder to model the context of aspect words [18]. Rietzeler et al. integrated self-supervised language model fine-tuning to propose the BERT ADA model [19]. Xu et al. explored the distribution of internal attention weights in the BERT PT model for aspect sentiment classification [20]. Instead of traditional dependency parsing, Dai et al. used a tree structure induced by a pre-trained language model to capture word relationships more efficiently [21]. Seoh et al. formalized aspect-based sentiment classification as a natural language inference task, incorporating the prompt-based technique that exploits the internal knowledge embedded in a pre-trained language model [22]. Yang et al. incorporating a local sentiment aggregation mechanism, proposed the Local Sentiment Aggregating model, using pattern-driven sentiment dependencies instead of traditional syntactic dependencies [23]. Zhang et al. proposed a Dynamic Re-weighting BERT model to better integrate dynamic semantics with the ABSA model through dynamic weighting allocation [24].

3.3. Aspect-Based Sentiment Analysis Based on Graph Neural Networks

Traditional neural networks usually utilize the translation invariance of Euclidean data to capture local feature information, typically handling data within Euclidean space. Due to this limitation, these models struggle to effectively interpret syntactic constraints and long-distance word dependencies, presenting challenges in extracting syntactic dependency information for aspect words. Zhang et al. integrated a dependency tree-based graph convolutional network to combine syntactic information and dependencies between target words with text dependency information, thus demonstrating the importance of syntactic information for long-distance text categorization [25]. Graph neural networks, which can operate on non-Euclidean graph data, possess the capability to process non-Euclidean space data, which makes them uniquely suited for ABSA, especially in capturing long-range dependencies. Li et al. proposed a Dual Graph Convolutional Networks model, which effectively enhances the parsing accuracy of models when dealing with complex texts that contains a large number of aspectual terms in the sentence [26]. To address the limitation that most of the current graph neural network-based sentiment classification methods use insufficient contextual sentiment knowledge of specific target words, Liang et al. proposed a Graph Convolutional Network model based on dependency trees and sentiment knowledge named Sentic GCN, strengthening the semantic correlation between aspectual words and context [27]. Besides, Chen et al. focused on the analysis of specific aspect terms, and introduced a discrete OpinionTree GCN model for aspectual words [28]. In addition, the integration of large-scale pre-trained language models with graph neural network models is a hot direction in current ABSA research. Graph neural network models are good at capturing relationships and structural information in textual data, while language models pre-trained on large-scale textual data can capture rich semantic information and linguistic structure. The combination of these two can further enhance the performance of ABSA tasks. Lin et al. proposed the BertGCN model by combining the transformer-based bidirectional encoder model with the GCN model [29]. Based on the BertGCN, Xue et al. proposed the BertGACN model to boost its text classification capabilities [30]. Li et al. presented a text classification model that integrates Bert with hypergraph convolution, achieving a more comprehensive and sufficient representation of text [31].

4. Challenges for Aspect-Based Sentiment Analysis

4.1. Implicit Sentiment Analysis

At present, ABSA research focuses on explicit opinion terms, while research on implicit sentiment analysis remains in its infancy. Implicit sentiment analysis targets texts that lack explicit opinion terms, requiring the integration of semantics, context, and domain knowledge or common sense to determine sentiment polarity. Implicit expressions of sentiment are widespread in daily life. For instance, the sentence “I absolutely love to be ignored!” seems to express favoritism, but actually conveys dissatisfaction. And the semantic extraction for implicit sentiment analysis primarily relies on context. Pan et al. have utilized gated recurrent neural networks and double-layer gated recurrent neural networks to extract useful information from the target sentence and its context, employing max-pooling for fusion [32]. Zhao et al. have replaced convolutional pooling layers with BiLSTM to extract contextual features at both word and sentence levels [33]. Yuan et al. enhanced temporal information of the target sentence by employing gated recurrent units alongside contextual information [34]. The success of pre-trained language models provides new ways for implicit sentiment analysis. For example, Huang et al. embedded external knowledge and entity information into word vectors via ERNIE 2.0 [35]. Zhang et al. utilized RoBERTa to capture word semantics within sentences and then used BiLSTM to extract deeper features from implicit sentiment texts [36]. Despite some progress in the implicit sentiment analysis, it still faces challenges, such as more implicit expressions and lack of explicit sentiment terms, when compared to traditional sentiment analysis.

4.2. Multimodal Sentiment Analysis

Individuals often use not only text but also images or videos when expressing emotions or opinions on social media. Therefore, designing new methods for extracting the semantics of visual features for unified analysis and sentiment classification of multimodal data has become an important research area. Ju et al. proposed a joint learning method with auxiliary cross-modal relation detection, utilizing auxiliary text-image control to apply visual information and achieve aspect-based sentiment classification based on jointly extracted aspect information [37]. Sun et al. employed parallel cross-attention and self-attention mechanisms to simulate the interaction relationships between modalities [38]. Georgiou argued that not all unimodal contributions are equal, proposing a lightweight masking layer to obscure the primary modality text during training, enhancing the contribution of weaker modalities and effectively improving model accuracy [39]. However, the field of multimodal sentiment analysis still faces challenges, such as inconsistent reliability of features across different modalities and the potential for high-dimensional disaster following modality integration, requiring further investigation by researchers.

5. Conclusion

ABSA is a critical component of natural language processing, gaining prominence in research due to its ability to provide more detailed insights than traditional overall sentiment analysis. Through an in-depth review of existing literature, this paper summarizes the key theories and current mainstream methodologies of ABSA, and analyzes future development trends and potential challenges. As research progresses, shallow sentiment classification tasks are encountering limitations. The focus of text sentiment analysis is increasingly shifting towards deeper areas such as sentiment understanding, sentiment generation, and sentiment interaction, with the scope of research expanding from unimodal to multimodal data. It is anticipated that, through continued research and innovation, ABSA will play a more significant role in areas such as public opinion monitoring, market analysis, and user experience enhancement, providing robust data support and decision-making references for societal and economic development.

References

[1] The Paper. (2024) China's Mobile Internet in Spring 2024: 1.232 Billion Users. https://www.thepaper.cn/newsDetail_forward_27284979
[2] Liu, B. (2020) Sentiment Analysis: Mining Opinions, Sentiments, and Emotion. Cambridge University Press, Chicago
[3] Hu, M. and Liu B. (2004) Mining and summarizing customer reviews. In:Proceedings of the 10th ACM SlGKDD International Conferenceon Knowledge Discovery and Data Mining. Seatle, USA:168-177
[4] Twitter. (2021) Twitter Sentiment Analysis (Entity-Level Twitter Sentiment Analysis Dataset). https://paperswithcode.com/dataset/twitter-sentiment-analysis
[5] SemEval-2014 Task 4. (2014) https://alt.qcri.org/semeval2014/task4/
[6] SemEval-2015 Task 12. (2015) https://alt.qcri.org/semeval2015/task12/
[7] SemEval-2016 Task 5. (2016) https://alt.qcri.org/semeval2016/task5/
[8] SemEval-2017 Task 4. (2017) https://alt.qcri.org/semeval2017/task4/
[9] MAMS (Multi Aspect Multi-Sentiment). https://paperswithcode.com/dataset/mams
[10] ASAP-AES (Automated Student Assessment Prize). https://paperswithcode.com/dataset/asap
[11] The project on Conversational Aspect Sentiment Analysis (CASA). https://github.com/freesunshine0316/lab-conv-asa
[12] Tang, D., Qin, B. and Liu, T. (2016) Aspect level sentiment classification with deep memory network. Conference on Empirical Methods in Natural Language Processing, 214-224.
[13] Wang, Y., et al. (2016) Attention based LSTM for aspect level sentiment classification. Conference on Empirical Methods in Natural Language Processing, 606-615.
[14] Chen, P., et al.(2017) Recurrent attention network on memory for aspect sentiment analysis. Conference on Empirical Methods in Natural Language Processing, 452-461.
[15] Ma, D., et al. (2017) Interactive attention networks for aspect-level sentiment classification. Proceedings of the 26th International Joint Conference on Artificial Intelligence, 4068-4074.
[16] Li, X., et al. (2018)Transformation networks for target-oriented sentiment classification. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, 946-956.
[17] Xu, H., et al. (2019) BERT post training for review reading comprehension and aspect-based sentiment analysis. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics:Human Language Technologies, 2324-2335.
[18] Song, Y., et al. (2019) Attentional encoder network for targeted sentiment classification. Artificial Neural Networks and Machine Learning- ICANN 2019: Text and Time Series: 28th International Conference on Artificial Neural Networks, 93-103.
[19] Rietzler, A., et al. (2020) Adapt or get left behind: Domain adaptation through BERT language mode finetuning for aspect target sentiment classification. Proceedings of the 12th Language Resources and Evaluation Conference, 4933-4941.

DOI: 10.54254/2755-2721/114/2024.18197

[20] Xu, H., et al. (2020) Understanding pre traine BERT for aspect based sentiment analysis.In: Proceeding of the 28th International Conference on Computational Linguistics, 244-250.
[21] Dai, J., et al. (2021) Does syntax matter?A strong baseline for Aspect-based Sentiment analysis with RoBERTa. Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics:Human Language Technologies. 1816-1829.
[22] Seoh, R., et al. (2021) Open aspect target sentiment classification with natural language prompts. Conference on Empirical Methods in Natural Language Processing, 6311-6322.
[23] Yang, H., et al. .(2021) Back to reality: Leveraging Pattern-driven Modeling to Enable Affordable Sentiment Dependency learning. In: arXiv.org 2021
[24] Zhang, K, et al. (2022) Incorporating dynamic semantics into pre-trained language model for aspect-based sentiment analysis. Findings of the Association for Computational Linguistics.
[25] Zhang, C., Li, Q. and Song, D. (2019) Aspect-based sentiment classification with aspect-specific graph convolutional networks. Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 4568-4578.
[26] Li, R., et al. (2021) Dual graph convolutional networks for aspeet-based sentiment analysis. The 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, 6319-6329.
[27] Liang, B., et al. (2022) Aspect-based sentiment analysis via affective knowledge enhanced graph convolutional networks. Knowledge-Based Systems, 235: 1-11.
[28] Chen, C., et al. (2022) Discrete opinion tree induction for aspect-based sentiment analysis. Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics, 2051-2064.
[29] Lin, Y., et al. (2021) BertGCN:Transductive Text Classification by Combining GNN and BERT. Findings of the Association for Computational Linguistics, 1456-1462.
[30] Xue, Y. (2023) BERTGACN:Text Classification by Combining BERT and GCN and GAT. 2023 3rd International Conference on Neural Networks, Information and Communication Engineering (NNICE), 422-426.
[31] LI Q X, PANG J, ZHU F R.(2023)Text Classification Method Based on Integration of Bert and Hypergraph Convolutional Network.In:Computer Engineering and Applications, 59(17):107-115.
[32] Pan, D., et al. (2020) A Chinese implicit sentiment classificationmodel combining contextual features. Computer Engineering & Science, 42(2): 341-350.
[33] Zhao, R., et al.(2020) lmplicit sentiment analysis for Chinese textsbased on a hybrid neural network. Journal of Sichuan University (Natural Scienee Edition), 57(2):264-270.
[34] Yuan, J., et al.(2021) Chinese implicit sentiment classification model based on sequence and contextual features. Journal of Computer Applications, 41(10): 2820-2828.
[35] Huang, S., et al.(2021) Implicit Sentiment Analysis Method Based on ERNIE2.0-BiSTM-Attention. Journal of Chinese Computer Systems, 42(12): 2485-2489.
[36] Zhang, J., et al.(2022) Implicit Sentiment Analysis Based on RoBERTa Fused with BiLSTM and Attention Mechanism.Computer Engineering and Applications, 58(23):142-150.
[37] Ju, X., et al.(2021) Joint multi-modal aspect-sentimentanalysis with auxiliary cross-modal relation detection. Conference on Empirical Methods in Natural Language Processing, 4395-4405.
[38] Sun, L., et al. (2021) Multimodal cross-and self-attention network for speech emotion recognition. lEEE International Conference on Acoustics, Speech and Signal Processing(ICASSP), 4275-4279.
[39] Georgiou, E., Paraskevopoulos, G. and Potamianos, A. (2021) M3: Multi-Modal Masking applied to sentiment analysis. Proc Interspeech, 2876-2880.