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Review of Aspect-Based Sentiment Analysis Based on Data Augmentation and Pre-Trained Models

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ABSTRACT

This paper systematically reviews the aspect-based sentiment analysis techniques that integrate data augmentation and pre-trained language models. Aspect-based sentiment analysis aims to identify the sentiment tendency of specific aspects in texts. Traditional methods face challenges such as data sparsity and insufficient model generalization. Data augmentation and pre-trained language models bring opportunities to solve these problems. Data augmentation can alleviate data sparsity, and pre-trained language models have powerful feature extraction and transfer learning capabilities. This paper elaborates on the task definition of aspect-based sentiment analysis, focusing on specific methods based on data augmentation and pre-trained language models, including data augmentation strategies and methods, as well as methods based on pre-trained language models such as BERT, RoBERTa, BART, and XLNet, and explores how to combine data augmentation and pre-trained models to improve the performance of aspect-level sentiment analysis. Finally, it is pointed out that there are still some challenges and opportunities in this field, such as the diversity of data augmentation techniques, optimization of pre-trained models, multimodal sentiment analysis, interpretability, and credibility, which need to be further explored.

KEYWORDS

Aspect-based sentiment analysis; Data augmentation; Pre-trained language model; BERT; RoBERTa

1. INTRODUCTION

Sentiment analysis is an important task in the field of natural language processing, which aims to automatically identify and extract the emotional tendencies contained in text. With the rapid development of the Internet and the widespread application of social media, sentiment analysis has been widely used in product evaluation, public opinion analysis, recommendation systems, and other fields (Liu & Zhao, 2023; Shanthini & Subalakshmi, 2023; Wang et al., 2024). However, traditional sentiment analysis methods mainly focus on the sentiment polarity of sentences or documents as a whole, ignoring the phenomenon that different aspects of an object (i.e., attributes or features) may present different sentiment tendencies.

To obtain more fine-grained sentiment analysis results, aspect-based sentiment analysis (ABSA) came into being. ABSA focuses on the user's emotional expression of specific aspects of the commented entity (Liu, 2022). By identifying the object aspects mentioned in the text and judging the emotional polarity expressed by the aspect, it can more accurately and comprehensively characterize the emotional distribution of the object (Zhang et al., 2022).

Since its proposal, aspect-based sentiment analysis has attracted widespread attention from academia and industry, and researchers have proposed many classic methods. Early studies mainly adopted dictionary-based or rule-based methods to judge aspect sentiment polarity by constructing sentiment dictionaries and designing rules(Yadav & Vishwakarma, 2020). With the rise of deep learning, a series of neural network-based methods have been applied to ABSA tasks to improve performance, such as attention mechanisms (Wang et al., 2021), memory networks (Ismet et al., 2022), and graph neural networks (Lu et al., 2022).

However, existing methods still face some challenges: First, aspect-level sentiment analysis is a fine-grained classification task that requires high quality and quantity of training data, while the cost of manually annotating data is high, resulting in serious data sparsity problems; second, most existing deep learning models are trained from scratch on specific task data, lack prior knowledge, and have insufficient generalization capabilities (Kumar & Sharan, 2020). Therefore, it is urgent to explore new ways to alleviate the data sparsity problem and improve the generalization of the model.

In recent years, the rapid development of data augmentation and pre-trained language models has brought new opportunities to aspect-level sentiment analysis tasks. Data augmentation generates more samples by transforming the original data, which can effectively alleviate the data sparse problem and improve the robustness of the model (Rebuffi et al., 2021). In addition, the pre-trained language model has acquired rich semantic knowledge through self-supervised pre-training on a large-scale unlabeled corpus and has powerful feature extraction and transfer learning capabilities (Wang et al., 2021). More and more research work has begun to try to apply data enhancement and pre-training models to ABSA tasks and has achieved significant performance improvements (Mukherjee et al., 2023; Tareq et al., 2023). However, there is still a lack of a systematic summary of the advantages, disadvantages, and applicable scenarios of these methods.

Therefore, the purpose of this paper is to comprehensively sort out and summarize the aspect-based sentiment analysis methods based on data augmentation and pre-trained language models in recent years, systematically summarize the representative works, and analyze their innovations, advantages, and disadvantages, as well as their implications for future work. By writing this review, we hope to provide reference and guidance for the subsequent research on ABSA and even sentiment analysis, fine-grained text classification, and other tasks, and promote the further development of related fields.

2. ASPECT-BASED SENTIMENT ANALYSIS TASK DEFINITION

Aspect-based sentiment analysis is one of the important branches of fine-grained sentiment analysis, which is dedicated to identifying specific aspects mentioned in the text and determining the speaker's emotional inclination towards each aspect (Varia et al., 2022). Compared with sentence-level and document-level sentiment analysis, aspect-level sentiment analysis can provide more detailed and specific sentiment information and has broad application prospects in e-commerce, catering, tourism, education, and medical fields (Avasthi et al., 2023; Ismet et al., 2022; Li et al., 2023; Melba Rosalind & Suguna, 2022; Serrano-Guerrero et al., 2024).

The task of ABSA can be formally defined as follows: given a text sequence consisting of words, the goal of ABSA is to identify all mentioned aspects and determine the sentiment polarity corresponding to each aspect. Sentiment polarity is usually divided into three categories: positive, negative, and neutral.

Specifically, the ABSA task requires the extraction of four key elements (Varia et al., 2022): Aspect Term (AT), Aspect Category (AC), Opinion Term (OT), and Sentiment Polarity (SP).

Taking the review text in Figure 1 as an example, "Prices" as an aspect term shows a positive sentiment polarity; while another aspect term "delivery time" shows a negative sentiment polarity. This example intuitively demonstrates the basic task of aspect-level sentiment analysis, which is to identify the aspects mentioned in the text and judge the sentiment tendency expressed by each aspect.

ABSA involves the following four key concepts:

(1) Aspect Term (AT): refers to the specific entity or entity attribute that users explicitly mention when expressing emotions in text. For example, "Service (a1)" and "Pizza (a4)" in Figure 1 are both aspect terms.

(2) Aspect Category (AC): is the semantic classification of the evaluation object, which usually belongs to a predefined limited set of concepts related to the field. For example, "Price" and "food" in Figure 1 are aspect categories.

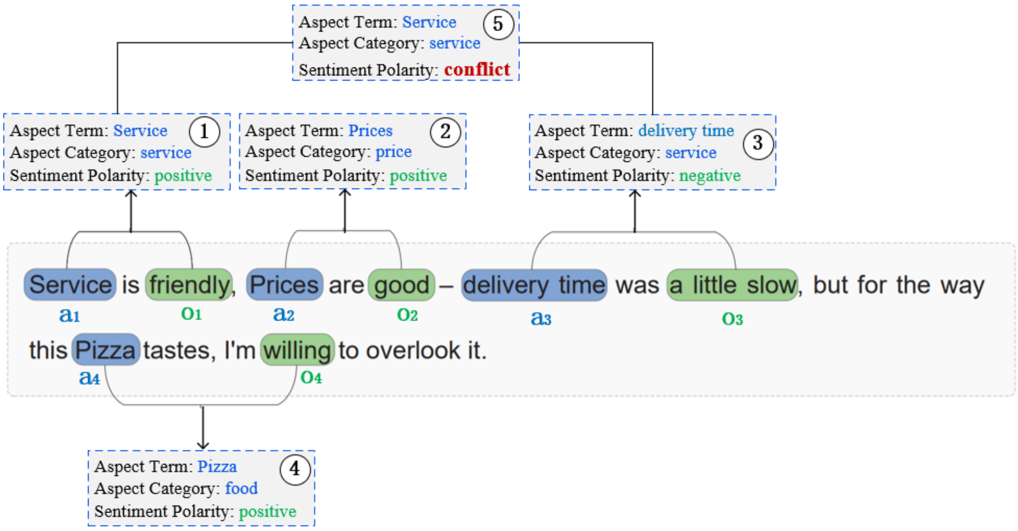

Figure 1. Example of comment text

(3) Opinion Term (OT): a word or phrase that expresses emotional tendency, often appearing in pairs with aspect terms. For example, "friendly (o1)" and "good (o2)" in Figure 1 are both opinion terms.

(4) Sentiment Polarity (SP): refers to the emotional tendency expressed by people toward a specific aspect, which can be divided into three categories: positive, negative, and neutral. Taking "Service is friendly" in Figure 1 as an example, it expresses that the user has a positive emotion towards the aspect term "service".

The basic tasks of ABSA can be summarized into three categories: aspect term extraction (ATE), aspect sentiment classification (ASC), and aspect-sentiment pair extraction (ASPE) (Chen et al., 2023).

In addition, since ABSA also involves two types of elements, opinion terms, and aspect categories, multiple extended subtasks can be derived, such as opinion term extraction (OTE), aspect-opinion pair extraction (AOPE), aspect category detection (ACD), aspect-category-sentiment detection (ACSD), aspect sentiment triplet extraction (ASTE), aspect-based sentiment quadruple prediction (ASQP), implicit aspect identification (IAI), etc.

(1) Aspect Term Extraction (ATE): It aims to accurately extract words that represent different attributes or aspects of the evaluation object from the text, usually nouns or noun phrases. This is an extraction task and is the basis of ABSA. For example, "price" and "delivery time" in Figure 1 are two aspect terms.

(2) Aspect Sentiment Classification (ASC): After identifying the aspects of the text evaluation, further determine the sentiment tendency expressed by the aspect, that is, positive, negative, or neutral. This is a classification task that is crucial to understanding the overall evaluation. As shown in Figure 1, the sentiment tendency of "price" is positive and the sentiment tendency of "delivery time" is negative.

(3) Aspect-Sentiment Pair Extraction (ASPE): At the sentence level, simultaneously identify each aspect term and its corresponding sentiment tendency category to obtain a structured analysis result in the form of ("aspect", "sentiment"). This is a task that combines extraction and classification, which is equivalent to organically integrating the first two tasks. The result in Figure 1 is [("price", "positive"), ("delivery time", "negative")].

(4) Opinion Term Extraction (OTE): Identify words with subjective sentiment in the text. For example, "The screen of this phone is very clear, but the battery life is too poor." The words "clear" and "poor" are opinion terms, expressing positive and negative sentiments respectively.

(5) Aspect-Opinion Pair Extraction (AOPE): Extract aspect terms and opinion terms, and identify the corresponding relationship between them. For the above example, the result of AOPE should be [("screen", "clear"), ("battery life", "poor")].

(6) Aspect Category Detection (ACD): Based on the preset category system, determine which aspect category the text expresses the evaluation of. For example, in a restaurant review, you can define the aspect categories of "food", "service", and "environment". "The sushi here is delicious, the environment is also good, but the service is a bit slow." This sentence involves the above three categories.

(7) Aspect Category Sentiment Classification (ACSA): Based on the determination of the aspect category involved in the text, further determine the sentiment tendency expressed under the category. For the above example, the result of ACSA should be [("food", positive), ("environment", positive), ("service", negative)].

(8) Aspect Sentiment Triplet Extraction (ASTE): Extract (aspect term, opinion term, sentiment tendency) triples from the text. For example, the triple result of a review about a mobile phone is [("screen", "clear", positive), ("battery life", "poor", negative)].

(9) Aspect Category Opinion Sentiment Quadruple Extraction (ACOS): Extract (aspect category, opinion term, sentiment tendency, sentiment intensity) quadruple from the text. Compared with ASTE, it has an additional dimension of sentiment intensity. The above example can be expressed as [("screen", "clear", positive, very strong), ("battery life", "poor", negative, very strong)].

(10) Implicit Aspect Identification (IAI): Identify evaluation aspects that are implicitly mentioned but not explicitly stated in the text. For example, "I have washed this dress three times and the color has not faded at all." implies a positive evaluation of "quality" and "washability", although it is not directly mentioned in the sentence.

The input, output, element composition, and mutual correlation of each task of aspect-level sentiment analysis are shown in Figure 2.

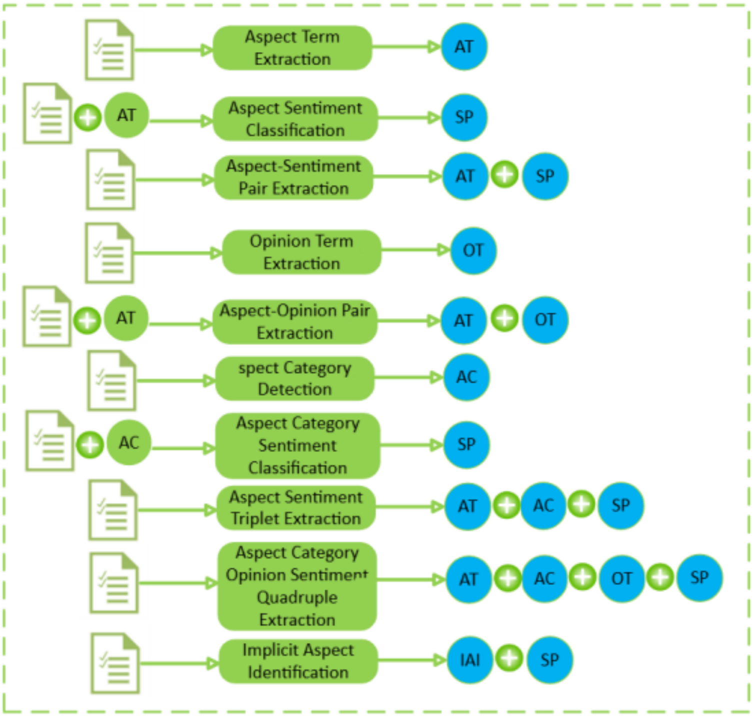

Figure 2. Aspect sentiment analysis subtasks

3. ASPECT-BASED SENTIMENT ANALYSIS METHOD BASED ON DATA ENHANCEMENT

Data augmentation is a technique that generates synthetic data by making subtle adjustments to existing data and is often used when data is insufficient (Sun et al., 2020). Correct application can significantly improve the diversity of training samples and increase the size and quality of training data sets, thereby helping to build more accurate deep-learning models.

3.1. Data Augmentation Strategy for Aspect-based Sentiment Analysis

Data augmentation is an effective means to solve the data scarcity problem in ABSA tasks. Through data augmentation, the amount and diversity of training data can be increased, thereby improving the generalization ability and performance of the model. Data augmentation strategies mainly include the following:

(1) Researchers have proposed a variety of data augmentation strategies based on pre-trained language models (PLMs). One method is to use the language knowledge learned by PLMs such as BERT and RoBERTa on large-scale corpora to fine-tune the original data or generate new data. Chen et al. (2022) adopted an unsupervised data augmentation (UDA) method based on BERT to generate augmented data by simply replacing unlabeled data with tokens, and combined with consistency training, achieved performance competitive with the current state-of-the-art methods when using only 75% of the training data.

(2) Contrastive learning is another effective data augmentation strategy. Zhang et al. (2023) designed a contrastive learning framework (CLF-TrLSTM) that combines tree-structured LSTM (Tree-LSTM) and self-attention mechanism. This framework generates high-quality positive and negative samples in the domain through mask generation operations and contrastive learning, enabling the model to better capture emotional targets and enhance noise resistance. By generating positive and negative samples, the model is encouraged to learn the differences between different samples, thereby improving the model's ability to distinguish.

(3) In response to the problem of insufficient data in specific domains in ABSA tasks, researchers have also explored cross-domain data enhancement strategies. Xue et al. (2023) proposed a cross-domain generative data enhancement framework (CDGDA), which aims to learn from similar, coarse-grained out-of-domain datasets to generate in-domain, fine-grained sentences to alleviate the problem of sparse data in the target domain. This method of using datasets from other related fields for data enhancement provides a new idea for solving the problem of insufficient data in specific domains.

3.2. Data Augmentation Methods for Aspect-based Sentiment Analysis

Data augmentation methods play a key role in aspect-level sentiment analysis, and mainly include the following strategies:

(1) Synonym replacement is a commonly used data augmentation method that generates new sentences by finding synonyms and replacing them. Feng et al. (2022) designed the Tailored Text Argumentation (TTA) algorithm. When performing synonym replacement, the sampling probability is assigned according to the discriminative power of the word and its relevance to sentiment. For sentiment-related words such as "great" and "bad", the TTA algorithm gives a higher probability of being replaced with synonyms, thereby introducing more high-quality sentiment discriminative words into the synthetic training samples.

(2) Back translation is another effective data augmentation method. Its basic idea is to translate the original text into another language and then translate it back to the original language to generate a new text (Liesting et al., 2021). However, back translation may lead to problems such as sequence length changes and index mismatch, which requires special attention when dealing with span-level classification tasks such as ABSA.

(3) Random insertion, deletion, and swapping are a set of simple but effective data augmentation operations that increase data diversity by randomly inserting, deleting, or swapping words in the text. The EDA method Wei and Zou (2019) includes these three operations as well as synonym replacement.

(4) Masked language model (MLM) is also used for data augmentation. The principle is to use MLM to predict masked words to achieve single-token or multi-token replacement. For example, Zhang et al. (2023) used MLM for masking operations to generate positive samples for contrastive learning.

(5) Generative methods use generative models to generate new text data, providing another idea for data augmentation. Xue et al. (2023) used generative models to learn patterns of out-of-domain data and generate fine-grained sentences in the domain; Wang et al. (2023) used generative data augmentation methods to predict aspect-sentiment quadruplets.

4. ASPECT-BASED SENTIMENT ANALYSIS METHOD BASED ON PRE-TRAINED LANGUAGE MODELS

In recent years, pre-trained language models have achieved remarkable success in the field of natural language processing. These models learn universal representations of language by pre-training on a large-scale unsupervised corpus and can be applied to downstream tasks through fine-tuning or prompt learning.

Commonly used pre-trained language models include BERT (Bidirectional Encoder Representations from Transformers), RoBERTa (A Robustly Optimized BERT Pretraining Approach), BART (Bidirectional and Auto-Regressive Transformers), and XLNet, etc. These models have achieved remarkable results in the field of aspect-based sentiment analysis.

4.1. BERT-based Methods

BERT is a pre-trained language model based on a bidirectional Transformer encoder structure proposed by Google (Devlin et al., 2018). It learns rich language knowledge and semantic representations by performing unsupervised learning on large-scale text. BERT uses a bidirectional encoding method that can simultaneously consider the context information of words to better understand the meaning of the text.

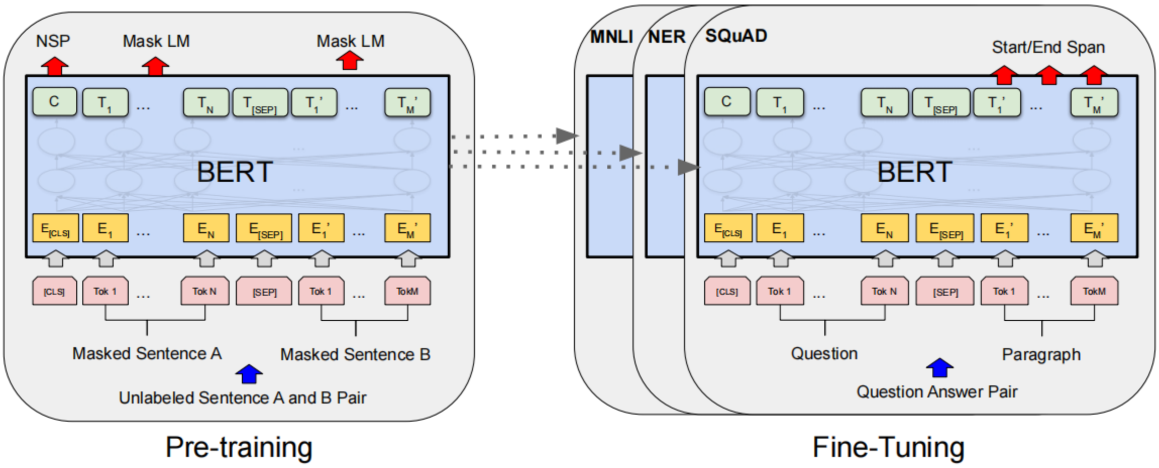

Figure 3. Overall pre-training and fine-tuning procedures for BERT (Devlin et al., 2018)

Figure 3 shows the two-step framework of BERT, namely pre-training and fine-tuning. In the pre-training stage, the model uses a large amount of unlabeled data to train on a variety of different pre-training tasks to learn the general representation of language. In the fine-tuning stage, the BERT model is first initialized with the parameters obtained from pre-training, and then all parameters of the model are fine-tuned according to the labeled data of the downstream task to adapt it to the specific task. It is worth noting that although the fine-tuning models of different downstream tasks are initialized with the same pre-training parameters, each task has its independent fine-tuning model to better adapt to the characteristics of the task.

In the task of aspect extraction from multi-sentence reviews, Chauhan et al. (2022) method combines unsupervised rules and a BERT-based hierarchical attention network, outperforming existing supervised deep learning methods. By adding a sentence core reference parsing step before performing ABSA, this method effectively removes insufficient information and captures the referential relationship between aspects. In addition, domain-irrelevant aspects are pruned using BERT-based dynamic embedding, further improving the model's precision and recall.

For the aspect-level sentiment analysis task, researchers have proposed a variety of innovative model architectures. The MAPA BiLSTM-BERT model (Wankhade et al., 2023) introduces an explicit multi-aspect position-aware attention mechanism, which cleverly combines the context modeling capability of BERT and the processing capability of BiLSTM for sequence information. By better capturing the relationship between aspect words and context words in the text, the model effectively improves the accuracy of sentiment classification.

In the field of Arabic aspect-level sentiment analysis, Bensoltane et al. (2024) designed an end-to-end model based on sequence annotation. The model adopts a unified annotation scheme to simultaneously identify aspect terms and related sentiment polarity. The model architecture consists of a BERT layer, a BiGRU layer, an attention layer, and a CRF layer, which can effectively handle syntactic constraints in sentences and dependencies between labels, and realize the joint identification of aspect terms and sentiment polarity.

To meet the challenges of the target-aspect-sentiment joint detection (TASD) task, Li et al. (2024) proposed an innovative model called Twin Towers End to End (TTEE). TTEE cleverly transforms the complex TASD task into a simple end-to-end multi-task framework to perform target and aspect-sentiment detection simultaneously. The model builds a dual-tower system based on BERT or its updated version, which significantly improves computational efficiency by decoupling context and given aspects. In addition, the TTEE model can effectively identify implicit target entities in the context and their related aspect-sentiment, showing excellent performance.

4.2. Based on RoBERTa Method

As an extension of BERT, RoBERTa has shown excellent performance in sequence-to-sequence modeling by optimizing the training process and increasing the amount of training data (Liu et al., 2019). Based on RoBERTa, researchers have proposed a variety of methods for aspect-level sentiment analysis.

ABSA-based Roberta-LSTM model Sirisha et al. (2022) cleverly combines the advantages of ROBERTa in processing text sequences and extracting semantic information, and the ability of LSTM to capture long-distance contextual semantics, effectively improving the performance of aspect-level sentiment analysis. Kumar et al. (2024) found in a sentiment analysis study of product reviews that the accuracy of the RoBERTa model exceeded that of the VADER model, reaching about 91%, highlighting the key role of sentiment analysis in business and consumer decision-making.

Park and Kim (2022) designed a step-by-step multi-task learning model that improved the performance of the holder extraction task in aspect-level sentiment analysis and reduced the sensitivity to domains by using step-by-step features from previous tasks and a BIO labeling scheme. However, the model is sensitive to noise in the dataset, and its performance is somewhat dependent on the errors of the previous tasks.

Knowledge Graph Enhanced Network Zhong et al. (2023) capture sentiment feature representations from multiple perspectives and fuse them through a hierarchical fusion module, demonstrating effectiveness and robustness on multiple benchmark datasets. KGAN is complementary to pre-trained language models such as RoBERTa, achieving new state-of-the-art performance.

The hybrid BERT (HybBERT) model Goud et al. (2023) showed effectiveness in the ABSA task, whereas the DISTILBERT model showed high accuracy when used alone or combined with other models. The ASK-RoBERTa model proposed by You et al. (2022) integrates aspect emotion knowledge into the pre-training model through aspect emotion masking and two emotion pre-training targets and proposes rules based on part-of-speech and sentence dependency grammar to mine accurate aspect terms and optimize Masking rules,better capture the dependencies between aspects and sentiment,words.

In applications in the financial field, Lengkeek et al. (2023) explored the method of using hierarchical language models for aspect-level sentiment analysis. Through the two-step model, they significantly improved the F1 score of financial classification and improved the test F1 score of the original challenge task. These studies show that RoBERTa-based methods have broad application prospects and excellent performance in aspect-level sentiment analysis tasks.

The models, advantages and disadvantages, experimental datasets, F1 values, and accuracy of various RoBERTa methods for aspect-level sentiment analysis are shown in Table 1.

Table 1. Models and advantages and disadvantages of the RoBERTa method

Model	Datasets	F1-Score	Accuracy	Advantage	Disadvantage
KGAN-RoBERTa (Zhong et al., 2023)	Laptop14 Restaurant 14 Twitter Restaurant 15 Restaurant 16	Laptop14: 81.07% Restaurant14: 84.05% Twitter: 79.63% Restaurant15: 74.36% Restaurant16: 83.23%	Laptop14: 83.91% Restaurant14: 88.45% Twitter: 80.55% Restaurant15: 88.60% Restaurant16: 94.38%	Leveraging context, syntax, and knowledge graphs enhances Aspect-Based Sentiment Analysis efficiency.	The model requires robustness against prior errors and enhanced comprehension of complex sentence structures.
HybBERT(Goud et al., 2023)	Hugging Face dataset (SemEval2014Task4 Raw)	97.19%	97.24%	The HybBERT model integrates the advantages of multiple models to significantly improve the accuracy of sentiment analysis.	The ROBERTa model is not accurate enough when used independently and needs to be optimized.
RoBERTa + VADER(Kumar et al., 2024)	Amazon Product Review Dataset	-	-	Combining RoBERTa and VADER, the accuracy rate reaches 91%, and the research method is advanced.	The data source is not clear, and the generalization ability of the model needs to be verified.
RoBERTa+ Bi-LSTM(Park & Kim, 2022)	Laptop14 Laptop15 Laptop16 Restaurant 14Restaurant15 Restaurant 16	- - - - - -	Laptop14: 85.62% Laptop15: 82.67% Laptop16:83.23% Restaurant14: 82.27% Restaurant15: 82.13% Restaurant16: 82.25%	Combining RoBERTa and Bi-LSTM to enhance holder extraction under multi-task learning.	The model is sensitive to specific datasets and may have domain adaptability limitations.
RoBERTa+ LSTM(Sirisha et al., 2022)	Twitter dataset related to the Ukrainian-Russian war	Negative: 97% Neutral: 93% Positive: 94%	94.7%	A hybrid model based on RoBERTa and LSTM is proposed, which has high accuracy and is suitable for sentiment analysis.	The model has limited adaptability and is sensitive to specific data sets.
ASK–RoBERTa(You et al., 2022)	Laptop14 Restaurant 14 Restaurant 15 Restaurant 16	Laptop14: 77.91% Restaurant14: 82.19% Restaurant15: 71.04% Restaurant16: 79.21%	Laptop14: 81.19% Restaurant14: 87.50% Restaurant15: 84.32% Restaurant16: 91.99%	The ASK-RoBERTa model enhances pre-training by mining sentiment knowledge and improves ABSC performance.	The performance of the model is limited in specific fields and needs further optimization.
L1AC L2AC PC(Lengkeek et al., 2023)	FiQA (Maia et al., 2018)	BERT-TRC2: 68% RoBERTa-base: 70% RoBERTa-twostep: 72%	-	Using hierarchical model innovation combined with BERT to improve the performance of ABSA in the financial field.	The dataset is small, which may affect the generalization ability of the model.

4.3. BART-based Methods

BART is an innovative natural language processing model that combines the advantages of BERT's bidirectional encoder and GPT's autoregressive decoder (Lewis et al., 2019). By performing a series of noise operations on the input text, such as randomly deleting words, disrupting the order of sentences, inserting additional content, and then training the model to recover the original text from these noises, BART enhances its ability to understand and generate language.

In the Aspect-Category-Opinion-Sentiment (ACOS) extraction task, Cao et al. (2022) proposed a method based on a generative transformer model. By modifying the outer layer of the data and the model, using the BART-Aspect-Based-Sentiment-Analysis (BARTABSA) model, and introducing the concept of categories and appropriate modifications to the BARTABSA model, this method has achieved remarkable results in processing implicit information and improving performance.

Rezapour (2024) applied a sentiment analysis method based on a question-answering framework and used the BART model to extract sentences with specific sentiment polarity from the text. By creating natural language questions to guide BART to focus on relevant sentiment clues in the text and predict the start and end positions of the answer in the text, the purpose of sentiment analysis was achieved.

For the ACOS quadruple extraction task, Xiong et al. (2023) proposed a BART-based contrastive and retrospective network (BART-CRN). The model processes ACOS extraction through sequence generation tasks and learns the associations between different types of quadruple through supervised contrastive and retrospective learning modules based on machine reading comprehension (MRC), which improves the performance of the model.

These studies show that BART-based methods have broad application prospects in aspect-level sentiment analysis and association tasks. Through innovations in model structure and training methods, researchers have continuously improved BART's ability to process implicit information, extract specific sentiment polarity sentences, and learn the associations between different types of elements, promoting the development of aspect-level sentiment analysis technology.

4.4. XLNet-based Methods

XLNet is a pre-trained language model based on an autoregressive language model. It addresses some limitations of the masked language model in BERT by introducing the concept of a permutation language model (Yang et al., 2019).

In the field of sentence-level aspect-level sentiment analysis, Sweidan et al. (2021) proposed a hybrid ontology-XLNet transfer learning method for classifying adverse drug reactions (ADRs). This method combines lexicalized ontology and the XLNet model to improve the performance of feature extraction and sentiment classification.

To solve the polysemy problem of words in traditional word embedding models and capture the syntactic dependencies between context words and sentence aspects, Xu et al. (2023) proposed an aspect-level sentiment analysis model based on XLNet-GCN. Effectively Solving these problems and improving the effect of ABSA.

In the task of aspect-level sentiment classification of comment text, Wu et al. (2024) introduced a dual-channel method combining XLNet-CNN-GRU. This method uses Glove word vectors and dynamic word vectors generated by XLNet, supplemented by the LDA topic model and attention mechanism, to enhance the ability to capture the characteristics of comment text, thereby improving the accuracy of sentiment classification.

To further overcome the challenge of polysemy and improve the accuracy of existing attention mechanisms in identifying sentiment-related words, Xu et al. (2023) proposed an aspect-level text sentiment analysis model based on XLNet-GCN. The model uses dynamic word vectors generated by XLNet, extracts text features through BiLSTM, applies multi-layer graph convolution on the output of BiLSTM to extract aspect-specific features, and finally calculates sentiment polarity as the output of the model.

From the above research, it can be seen that the XLNet-based method shows great potential in aspect-level sentiment analysis tasks. By combining with other technologies such as ontology, graph convolutional neural network, convolutional neural network (CNN), gated recurrent unit (GRU), etc., researchers have continuously improved the performance of XLNet in feature extraction, word sense disambiguation, syntactic dependency capture, etc., further promoting the advancement of sentiment analysis technology.

4.5. Fine-tuning-based Methods

Fine-tuning a pre-trained model on specific task data is a common application method, and many studies have applied it to aspect-level sentiment analysis tasks. Sun et al. (2019) transformed the aspect-level sentiment analysis task into a sentence pair classification problem by constructing auxiliary sentences and then used BERT for fine-tuning. This method can effectively improve the performance of aspect-level sentiment analysis and make full use of BERT's contextual understanding ability to capture the relationship between aspects and sentiment.

To further improve the performance of the model in aspect-level sentiment classification tasks, Xiao et al. (2021) proposed an innovative method combining BERT and graph convolutional network (GCN). This method uses the intermediate layer output of BERT to provide GCN with initialized node features, and then fine-tunes specific task data, achieving satisfactory results.

For the problem of facet-level sentiment analysis with few samples, Wang et al. (2023) designed a simple and effective framework FS-ABSA. Through Domain Adaptive Pre-training (DAPT) and Text-Filling Fine-tuning (TIFT), this framework narrows the domain gap and target gap between pre-training and fine-tuning and promotes knowledge transfer. Experimental results demonstrate that the FS-ABSA framework significantly improves the performance of aspect-level sentiment analysis tasks in a few-sample setting and reaches new optimal performance in a fully supervised setting. In addition, the application of this framework in low-resource languages also demonstrates its effectiveness and versatility.

In the aspect extraction task in ABSA, Akram, and Sabir (2023) built a framework based on BERT and conducted experiments on the multi-domain SEMEVAL dataset. By fine-tuning BERT, the model showed high accuracy, recall, and F1 score in the aspect extraction task, demonstrating its effectiveness in feature extraction of text data.

Lee et al. (2024) explored a fine-tuning method to improve the performance of the generation-based ABSA model and achieve efficient learning by introducing low-rank adaptation (LoRA) to the generative language model. By introducing LoRA and fine-tuning the GPT2 model, GloABSA (GPT2+LoRA Aspect-Based Sentiment Analysis) can predict aspects and polarity using enhanced contextual information and reduce the number of parameters for efficient learning.

These research works demonstrate the wide application and excellent performance of Fine-tuning pre-trained models in aspect-level sentiment analysis tasks. By constructing auxiliary sentences, combining graph convolutional networks, domain adaptive pre-training, text-filling fine-tuning, and introducing low-rank adaptation, researchers have continuously improved the performance of models in aspect-level sentiment analysis tasks and promoted the development of this field.

4.6. Prompt Learning-based Methods

As an emerging few-shot learning method, prompt learning reduces the reliance on labeled data by converting the task into a Cloze-fill-in-the-blank task and using natural language prompts (prompts) to guide the model to make predictions. In the field of aspect-level sentiment analysis, Seoh et al. (2021) designed a suitable prompt template, converted the aspect-level sentiment analysis task into a sentiment word prediction task, and used few-shot learning to improve the generalization of the model, demonstrating the application potential of prompt learning in this task.

The research work of Yin et al. (2023) combines prompt learning and aspect-attention mechanisms and achieves significant performance improvements on fine-grained sentiment analysis (ABSA) tasks. It is worth noting that the model has demonstrated stable performance in a low-resource environment, verified its effectiveness and interpretability, and provided new ideas for solving the problem of data scarcity.

To further enhance the perception ability of the model in the ABSA task, Yin et al. (2024) proposed the SynPrompt method. This method constructs prompts by mining syntactic information and constructs the Auto Prompt and Soft Prompt frameworks, which show excellent performance in both low-resource and full-data scenarios, providing a more powerful alternative to traditional prompt adjustment.

5. ASPECT-BASED SENTIMENT ANALYSIS BY INTEGRATING DATA AUGMENTATION AND PRE-TRAINED MODELS

Pre-trained language models (such as BERT) have achieved great success in various NLP tasks, but their performance on fine-grained tasks such as aspect-level sentiment analysis still needs to be improved. This is mainly attributed to the lack of sufficient annotated data to fully train these complex models. To address this problem, researchers began to explore combining data augmentation techniques with pre-trained models to improve the performance of aspect-level sentiment analysis (Zhang, 2023).

In each subtask of aspect-level sentiment analysis, methods that integrate data augmentation and pre-trained models are applied. In response to the multi-faceted challenges in the ABSA task, Wang et al. (2022) proposed a new training framework C3DA. This framework uses in-domain generators and contrastive learning to enhance the robustness of the model, generates samples through dual channels of aspect enhancement and sentiment polarity enhancement, and uses entropy minimization filters to improve the quality of generated samples.

To handle three fine-grained sentiment analysis tasks, Lu et al. (2021) developed a unified model called PEA. PEA cleverly combines data augmentation and pre-trained language models, and specially designs entity replacement and double noise injection methods to address the problems of low resources and sentiment polarity bias.

Li et al. (2022) proposed a generative cross-domain data augmentation framework (GCDDA) to address the problem of imbalanced training data in the task of co-extraction of aspects and opinions. Through automatic induction of prompt templates and multi-prompt learning, GCDDA can generate finely annotated target domain data, thereby balancing training data of different polarities.

Zhu et al. (2023) proposed a BERT prompt model combined with semantic refinement (Prompt-CSR) for aspect-level sentiment analysis. This model solves the problems of data imbalance and insufficient understanding of ambiguous sentiments through a reasonable prompt template structure, multi-prompt learning, and an improved BERT semantic refinement method.

Pahari et al. (2024) explored the effects of multi-task learning (MTL) and data augmentation using BERT, splitting the BERT layers into top, middle, and bottom layers, and conducting experiments with different configurations.

In summary, the method of integrating data augmentation and pre-trained models has shown great potential in aspect-level sentiment analysis tasks. By designing new training frameworks, unified models, cross-domain data augmentation, semantic refinement prompt models, and multi-task learning techniques, researchers have continuously improved the performance of models in aspect-level sentiment analysis tasks, especially in low-resource and data-imbalanced situations.

6. SUMMARY AND OUTLOOK

This paper provides a comprehensive review of aspect-level sentiment analysis techniques based on data augmentation and pre-trained language models. First, the basic concepts and tasks of aspect-level sentiment analysis are introduced, and then the application of data augmentation technology, pre-trained language models, and various methods of integrating the two in aspect-level sentiment analysis are systematically discussed. These methods include designing innovative training frameworks, building unified models, performing cross-domain data enhancement, introducing semantic refinement prompt models, and adopting strategies such as multi-task learning. Through these advanced methods, researchers have made significant progress in solving the problems faced by aspect-level sentiment analysis tasks such as data scarcity, category imbalance, and insufficient understanding of fuzzy emotions.

Although methods based on data augmentation and pre-trained models have shown great potential in aspect-level sentiment analysis tasks, there are still many challenges and opportunities worthy of further exploration. The following research directions can be considered in the future:

Exploring more diversified and innovative data enhancement technologies, such as adversarial generation, multilingual data enhancement, etc., is expected to further improve the robustness and generalization capabilities of the model.

The pre-training model is adaptively optimized for aspect-level sentiment analysis tasks, such as designing pre-training goals in a targeted manner, introducing emotional knowledge, etc., to better capture the complex relationship between aspects and emotions.

With the increasing abundance of multi-modal data, extending data enhancement and pre-training models to multi-modal aspect-level sentiment analysis tasks is expected to further improve model performance and achieve more comprehensive emotional understanding.

While integrating data enhancement and pre-training models, it is necessary to focus on the interpretability and credibility of the model to enhance users' understanding and trust of the model's decision-making process and improve the practicality of the model.

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