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Aspect-based Sentiment Analysis based on Graph Convolutional Network

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ABSTRACT

Aspect-based sentiment analysis (ABSA), a critical task in the field of natural language processing, aims to identify and analyze the sentiment orientation towards specific aspects within texts. In recent years, Graph Convolutional Networks (GCN), as a potent type of graph neural network, have demonstrated unique advantages in handling graph-structured data, offering new perspectives and methods for ABSA. In this paper, we provide an overview of the research progress in graph convolution-based ABSA methods. Initially, it introduces three pivotal methods in the ABSA domain, encompassing representative work based on dictionaries, machine learning, and deep learning, while analyzing their strengths and limitations. Subsequently, it elaborates on graph convolution-based ABSA methods, highlighting existing problems and challenges in current research. Finally, we further explore future research directions for ABSA, particularly in achieving more accurate analyses of nuanced emotional expressions within textual content.

KEYWORDS

Aspect-Based Sentiment Analysis; Sentiment Dictionary; Machine Learning; Deep Learning; Graph Convolutional Networks

1. INTRODUCTION

With the rapid advancement of internet technology and the widespread adoption of social media, user-generated content has experienced exponential growth. This content is rich in user sentiments and opinions, and Aspect-Based Sentiment Analysis (ABSA) provides refined support for business decision-making and public opinion monitoring by analyzing the sentiment tendencies towards specific targets within text. As an important branch of fine-grained sentiment analysis, ABSA aims to identify and analyze sentiment tendencies towards specific aspects in text. For instance, Fig 1 shows a review in restaurant, customers may express opinions on multiple aspects of the restaurant. The goal of ABSA is to identify these aspects and determine whether the customer's sentiment towards each aspect is positive, negative, or neutral. Traditional sentiment analysis tasks often focus on overall sentiment polarity, whereas ABSA must address the semantic associations between aspect terms and their context, as well as resolve sentiment ambiguities in complex contexts.

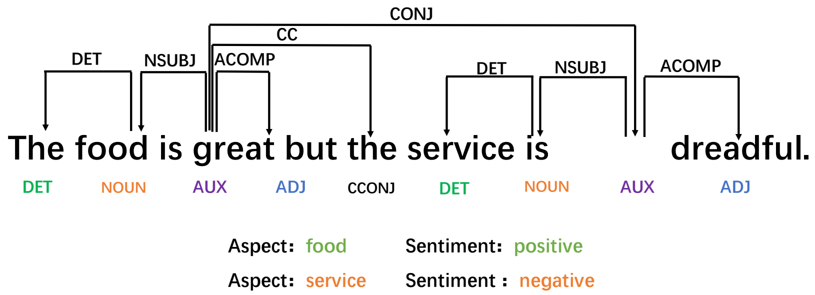

Figure 1. An example of aspect-based sentiment analysis sentence

2. DEVELOPMENT OF ASPECT-BASED SENTIMENT ANALYSIS

The research on Aspect-Based Sentiment Analysis (ABSA) can be traced back to the early stages of sentiment analysis tasks. Initially, researchers focused primarily on document-level or sentence-level sentiment analysis, which involves determining the sentiment polarity of an entire document or sentence. However, this coarse-grained approach failed to meet the demands of practical applications, as users often require more detailed analysis of sentiments towards specific aspects. Consequently, ABSA emerged as a response to this need and has gradually become a research hotspot in the field of natural language processing.

2.1. Dictionary-Based Aspect-Level Sentiment Analysis Methods

In the early stages of Aspect-Based Sentiment Analysis (ABSA) research, methods primarily relied on rule-based and template matching techniques. For instance, some researchers attempted to construct sentiment dictionaries and used the sentiment words within these dictionaries to determine the sentiment polarity of text. Dictionary-based ABSA methods mainly focus on identifying and judging sentiment information in text by constructing sentiment dictionaries that include sentiment words and aspect terms. The core of these methods lies in creating a dictionary that contains sentiment words and aspect terms, and using this information to determine the sentiment polarity of text.

Jia and Li et al. [1] combined a sentiment dictionary with semantic rules to improve the method for calculating the sentiment intensity of sentiment words with different sentiment categories, enhancing the effectiveness of sentiment classification. Hu and Liu et al. [2] first constructed a dictionary containing positive and negative sentiment words and then used these words to identify subjective sentences in reviews. They subsequently employed heuristic rules to recognize aspect terms within sentences and determined the sentiment polarity of each aspect based on the association between aspect terms and sentiment words.

However, these methods often struggle with complex linguistic phenomena and are challenging to extend to new domains. Additionally, constructing dictionaries requires substantial human effort and is difficult to cover all sentiment words and aspect terms.

2.2. Machine Learning-Based Aspect-Level Sentiment Analysis Methods

Machine learning-based ABSA methods involve constructing models through learning from a large amount of labeled data, thereby enabling the automatic identification and judgment of sentiment information in text. These methods typically consist of steps such as feature engineering, model selection, and model training.

Pioneering work by Pang et al. [3] applied machine learning to the field of sentiment analysis by using machine learning methods to classify the sentiments of movie reviews. Jo and Oh et al. [4] proposed a joint model for simultaneously identifying aspects and sentiments. They first used a Conditional Random Field (CRF) model to recognize aspect terms in text and then employed a

Support Vector Machine (SVM) to identify the sentiment polarity of each aspect. However, this method requires manual feature design and has a complex training process. Liu et al. [5] proposed a semi-supervised learning method for ABSA tasks. They initially trained an initial model using a small amount of labeled data and then used this model to predict a large amount of unlabeled data, treating the predictions as pseudo-labels to train a new model. Wang et al. [6] presented a novel aspect-based sentiment analysis method based on the incremental machine learning paradigm to achieve accurate machine annotation.

Machine learning-based methods can automatically learn representations of text and handle more complex linguistic phenomena. However, they also face challenges such as the difficulty of feature engineering and poor model interpretability.

2.3. Deep Learning-Based Aspect-Level Sentiment Analysis Methods

Traditional sentiment analysis methods have been unable to meet the demands of the big data era in terms of labor cost and time efficiency for efficient and high-quality sentiment classification tasks. Deep learning-based ABSA methods utilize deep neural networks to learn representations of text and automatically identify and judge sentiment information within the text, thereby overcoming the issue of traditional machine learning relying on manually extracted text features.

With the advent of deep learning, ABSA research saw a significant shift. Models like Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs) were applied to ABSA tasks. These models could capture complex patterns in text and improved the performance of ABSA systems. The emergence of attention mechanisms [7] has provided additional methods for Aspect-Based Sentiment Analysis (ABSA), offering new avenues for enhancing the accuracy and effectiveness of sentiment analysis tasks. Ma et al. [8] introduced a method that constructs two separate attention mechanisms to model aspect terms and their context, allowing them to interact and capture sentiment information related to aspect terms more accurately.

While Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) can capture some contextual information, they struggle with modeling syntactic structures and resolving semantic ambiguities, especially in complex sentences. In this context, using pre-trained models to enhance semantic representations and deepen the model's understanding of textual syntactic dependencies is a promising approach. Peng et al. [9] proposed a collaborative gating network based on a single BERT encoder, which effectively integrates contextual information and aspect term features through a collaborative gating mechanism, achieving precise judgment of aspect term sentiments. Kumar et al. [10] introduced a BERT-based semi-supervised hybrid method that combines the strengths of supervised and unsupervised learning, leveraging BERT's powerful semantic understanding to improve classification performance in scenarios with limited labeled data.

Pre-trained models have addressed the semantic bottlenecks of traditional models, but their adaptability to syntactic structures and domain differences still needs optimization. Some researchers have introduced Graph Convolutional Networks (GCN) into ABSA, using dependency trees to model the semantic associations between aspect terms and their context, compensating for the shortcomings of pre-trained models in syntactic modeling. The incorporation of GCN further unleashes the potential of models by structuring the syntax.

3. GRAPH CONVOLUTIONAL NETWORK-BASED ASPECT-LEVEL SENTIMENT ANALYSIS METHODS

Graph Convolutional Networks (GCN) are an efficient variant of Convolutional Neural Networks (CNN) that operate directly on graphs, with their core being graph-based representation learning. For data that can be structured as a graph, it is typically represented by a set of nodes $N \in \mathrm{R}^{\mathrm{n} \times \mathrm{n}}$ and a set of edges E, where the node set stores feature information of n nodes with m dimensions, and the edge set stores information about all edges. GCN can encode information by performing convolutions on connected nodes, with nodes aggregating more global information through learning.

Previous work [11-14] has extended GCN models by constructing adjacency matrices from sentences on syntactic dependency trees. This type of graph convolutional network requires an external dependency parser to construct an adjacency matrix $A^{dep} \in \mathrm{R}^{\mathrm{n} \times \mathrm{n}}$ for each sentence as input to the GCN to encode syntactic information. The matrix A records the dependency relationships between any two nodes, with the element $A_{\{i,j\}}$ indicating whether node i is connected to node j. The adjacency matrix is composed of 0 and 1. The adjacency matrix A^{dep} is defined as Eq1.

$$A_{i,j}^{dep} = \begin{cases} 1 & , i = j \; or \; w_i \infty w_j \\ 0 & , \text{others} \end{cases} \tag{1}$$

Where i, j represent words and their positions in the sentence, $w_i = w_j$ represents a dependency relationship between w_i and w_j and the adjacency matrix is assigned a value of 1.

GCN performs convolution operations on the graph, aggregating information from the node and its directly connected neighboring nodes to learn local information. To enhance the model's expressive power, it is common to stack multiple layers of graph convolutional layers, allowing information on the graph to propagate further through the connections between nodes, thereby capturing global information. GCN takes the adjacency matrix and text embedding vectors as input to capture the dependency relationships between sentences. The update formula for the hidden layer state of the i-th node in the L-th layer is as Eq2.

$$\mathrm{h}_{\mathrm{i}}^{\mathrm{l}} = \sigma\left(\sum_{\mathrm{j}=1}^{\mathrm{n}} A_{ij} W^l h_j^{l-1} + b^l\right) \tag{2}$$

Where W^l represents the weight matrix, b^l represents the bias, and σ is the activation function, such as $ReLU$.

The relationships between words in a sentence are not only influenced by their linear positions in the text but also by syntactic structure and grammatical relations. Traditional neural network models struggle to capture these complex relationships and structures. Therefore, models that perform convolution operations on graph-structured data can more accurately learn and simulate the nonlinear connections within sentences, thereby enhancing the accuracy of text analysis and understanding.

Zhang et al. [15] constructed a GCN model based on a dependency parser, innovatively using GCN to leverage the syntactic dependency structure within sentences and addressing the challenge of long-distance multi-word dependencies. Wang et al. [16] reshaped and pruned the basic syntactic dependency tree to obtain an aspect-based dependency tree and constructed a Relation Graph Attention Network (R-GAT) to encode the connections between aspects and potential opinion words. Chen et al. [17] proposed an aspect-specific and language-independent discrete latent opinion tree model as an alternative to explicit dependency trees.

However, these models only considered the syntactic dependency relations between specific aspects and their context, neglecting contextual dependencies and aspect-specific words. Zhang et al. [18] introduced two separate GCNs to model the syntactic dependencies and word co-occurrence information of context features. Sun et al. [19] incorporated external features into GCN to improve classification performance. Phan et al. [20] created a heterogeneous graph SSC by integrating syntactic, semantic, and context-based graphs. The nodes of the heterogeneous graph were transformed into phrase vectors using a two-layer Graph Convolutional Network (GCN). Finally, a Convolutional Neural Network (CANN) focusing on position embeddings was used for aspect-level sentiment evaluation of the SSC-GCN model's output. Liang et al. [21] constructed a graph neural network by combining sentiment information from SenticNet without considering contextual information.

The constituent tree provides hierarchical aggregation of syntax at different levels. PhraseRNN [22] and others have used dependency trees and constituent trees as input to reconstruct the target-dependent binary phrase dependency tree through rule-based methods. Then, the reconstructed tree is applied to extend the phrase recursive neural network to obtain syntax-enhanced aspect term representations. Wu et al. [23] developed a knowledge-aware dependency graph network by utilizing a dependency graph that integrates domain knowledge, dependency labels, and syntactic paths.

Kipf and Welling [24] applied semi-supervised learning to graph convolutional neural networks based on graph structures. To further improve GCN, Veličković et al. [25] proposed the Graph Attention Network (GAT), which uses a masked self-attention layer to assign different weights to different nodes in the neighborhood, allowing the correlation between vertex features to be better integrated into the model. Many studies [26-28] have utilized and extended the graph attention network for ABSA tasks, achieving good performance. Liang et al. [29] fully utilize the grammatical information of the sentence constituent tree to model the sentiment-aware context of each aspect and the cross-aspect sentiment relationships, improving the accurate modeling of aspect terms and the alignment of their corresponding sentiments.

4. CONCLUSION

Aspect-Based Sentiment Analysis (ABSA) is a significant research direction in the field of natural language processing, receiving extensive attention from both academia and industry. In recent years, ABSA has made remarkable progress in methods and techniques, including dictionary-based approaches, machine learning-based approaches, and deep learning-based approaches. Each method has its own strengths and limitations. Dictionary-based methods are simple and efficient but struggle with complex linguistic phenomena; machine learning-based methods can automatically learn text representations but face challenges in feature engineering; deep learning-based methods can capture more complex semantic information but require large amounts of training data and can be time-consuming in training and inference.

In the future, ABSA research can expand in several directions. Firstly, most existing ABSA models rely heavily on large-scale labeled data during training. However, obtaining a substantial amount of labeled data in practical applications is often challenging. Therefore, future research can explore the application of few-shot learning techniques to train ABSA models, thereby reducing the dependence on labeled data. Secondly, deep learning models typically lack interpretability, making it difficult to understand the decision-making process. Hence, future research can focus on enhancing the interpretability of ABSA models to increase users' trust in them. Lastly, current ABSA models are usually trained and tested within specific languages or domains. Future research can investigate the construction of cross-lingual and cross-domain ABSA models to improve their generalization capabilities.

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