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BSAN: bilateral synergistic aggregation network for aspect-based sentiment analysis

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Abstract

Aspect-Based Sentiment Analysis (ABSA) focuses on understanding fine-grained sentiment information by analyzing the sentiment polarity corresponding to particular aspects in sentences. At present, graph neural networks are widely utilized to model the explicit relationships between aspects and opinions derived from the syntactic structures of dependency trees. However, these methods struggle to handle sentences with complex structures and multiple aspect–sentiment pairs. To solve this problem, we propose a Bilateral Synergistic Aggregation Network (BSAN) that integrates semantic and syntactic information to capture sentiment features that are specific to particular aspects. Specifically, within the Syntactic Distillation Module (SDM), we employ a Syntax View Graph Convolution (SynVGC) layer to encode the dependency-tree graph and extract syntactic features, while a Transformer layer is incorporated to capture sequential dependencies and refine the representations of aspect terms. Furthermore, the Semantic Optimization Module (SOM) utilizes Abstract Meaning Representation (AMR) as structured input and integrates attention mechanisms with graph convolutional networks to effectively model the semantic relations represented in the AMR. In addition, the Graph Cognitive Fusion Module (GCFM) is designed to facilitate the integration and interaction of syntactic and semantic representations. Finally, extensive experiments on four publicly available benchmark datasets demonstrate that our proposed BSAN model achieves competitive performance.

Keywords Aspect-based sentiment analysis · Graph cognitive fusion · Abstract meaning representation · Syntactic distillation · Semantic optimization

1 Introduction

As a prominent research area in natural language processing (NLP) [1–3], Aspect-Based Sentiment Analysis (ABSA) aims to model sentiment tendencies associated with each aspect in a multidimensional space and to represent them using continuous numerical scales along affective dimensions such as valence and arousal. In recent years, several studies have explored approaches to modeling relational sentiment in a multidimensional manner, typically based on multi-label or multi-task learning frameworks. These methods focus on simultaneously modeling multiple affective dimensions, thereby enabling a better representation of both the intensity and type of sentiments expressed toward different aspects. ABSA primarily consists of four subtasks: aspect-based sentiment classification (ASC), aspect-based sentiment triplet extraction [4, 5] (ASTE), aspect-based sentiment quadruple extraction (ASQP), and dimension-based aspect sentiment analysis (dimABSA). Unlike most ABSA methods that represent sentiment using classification models (e.g., positive, negative, and neutral), dimABSA adopts a dimensional model to represent sentiment scores across multiple dimensions.

By identifying the emotional polarity of specific aspects of a text, such as negative, neutral, and positive polarities [6], ABSA can gain a more comprehensive and accurate understanding of the emotional content of a text. For example, as shown in Fig. 1, in the sentence “The book, though filled with complex language, is truly captivating”,

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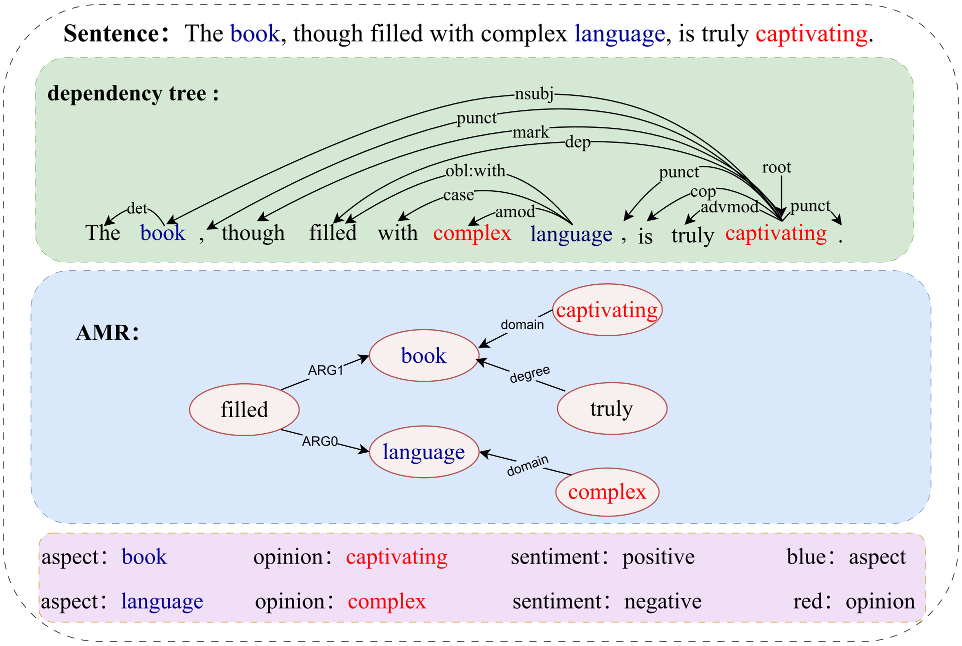


Fig. 1 An example sentence, along with its dependency tree and abstract semantic representation, contains two aspects with contrasting sentiment polarities

the sentiment polarities of the aspects are positive for book and negative for language. ABSA can accurately determine the sentiment orientation of individual aspects, instead of assigning an overall sentiment label to each sentence or document. Currently, effectively modeling the dependency between specific aspects and their associated opinions is a major challenge in ABSA.

Initially, ABSA research relied heavily on features extracted manually for classification, which depended on their quality and failed to establish syntactic relationships. For example, classic methods include sentiment lexicons [7], support vector machines [8], and the bag-of-words model. In contrast, neural networks can automatically learn sentiment features from the context, reducing the time and effort involved in manual extraction of features. Methods based on Deep Neural Networks (DNNs) [9], Recurrent Neural Networks (RNNs) [10], and Convolutional Neural Networks (CNNs) have been widely applied in the ABSA domain. They learn contextual information to generate low-dimensional tensor representations that capture the sentiment associated with specific aspects. Although they have led to significant improvements in ABSA performance, most of them overlook the syntactic dependency between the context and specific aspects.

Recently, ABSA has combined attention mechanism [11–13] with RNN to implicitly generate contextual representations of specific aspects. Although these methods have proven effective, they face challenges when sentence structures become more complex and contain multiple aspect-sentiment pairs. For example, in Fig. 1, for the aspect “book”, the opinion word “bad” gains more focus than “captivating" because “bad" is closer to the aspect word “book". However, “bad" actually refers to another aspect in the sentence, “language".

Nowadays, many researchers have explicitly employed syntactic dependency trees [14–16] to establish complex connections between aspects and opinions. Syntactic dependency trees are employed to obtain comprehensive syntactic information, and then RNNs are utilized to model the syntactic structure. In this method, aspect-related syntactic structures are integrated with their sentiment information, thereby improving the capacity to model multi-aspect sentiment information in sentences. Currently, Graph Convolutional Networks (GCNs) [17–20] and Graph Attention Networks have been widely adopted for learning representations of syntactic dependency trees. When a sentence lacks a clear syntactic structure, extracting syntactic relationships from the dependency tree often leads to poor outcomes. It is because the dependency tree relies on the syntactic rules of the sentence, which can be inaccurate when the structure is complex or ambiguous. Furthermore, syntactic dependency trees face challenges when modeling sentences with multiple aspects, as the intertwining of aspects can lead to ambiguous dependency relations and reduce analytical accuracy. Therefore, relying solely on traditional syntactic dependency trees may be insufficient to capture comprehensive syntactic and semantic information when dealing with these complex sentences.

To address the aforementioned challenges, we propose a novel Bilateral Synergistic Aggregation Network (BSAN) that integrates semantics and syntax for aspect-based sentiment analysis. The model focuses on capturing aspect-related sentiment features through the bilateral extraction of syntactic structures and semantic correlations. First of all, word embeddings are derived from the BERT pre-trained model. Then, the Syntactic Distillation Module (SDM) and the Semantic Optimization Module (SOM) are used to extract syntactic structures and semantic information, respectively. In the SDM, a SynVGC layer is used to encode the graph view of the dependency tree, while a Transformer layer processes its sequence view, effectively extracting explicit syntactic features from the sentence and enhancing aspect representation. By tightly coupling these two layers, the syntactic information from the dependency tree is fully distilled. In the SOM, SemGCN encodes AMR, which serves as a novel semantic structure, to capture the semantic information between the context and specific aspects. Finally, the Graph Cognitive Fusion Module (GCFM) is employed to integrate information between syntax and semantics, ensuring that the final feature representation contains both syntactic and semantic information. It enhances the aspect sentiment features of the sentence while effectively avoiding the information loss commonly observed in traditional architectures. The main contributions of this paper can be summarized as follows:

- We propose a Bilateral Synergistic Aggregation Network (BSAN) that integrates semantics and syntax for aspect-based sentiment analysis, improving the capacity to capture sentiment features bilaterally.
- The Syntactic Distillation Module (SDM) employs a SynVGC layer and a Transformer layer to encode the dependency tree from graph-based and sequence-based views, effectively capturing syntactic dependencies within a sentence. At the same time, AMR is introduced and encoded by using a Semantic Optimization Module (SOM), where the Graph Convolutional Network (GCN) performs multiple convolutional layers over the self-attention matrix to capture semantic relationships between words.
- By enhancing the interaction between syntactic and semantic information, the integrated GCFM significantly improves the model's ability to capture fine-grained sentiment features.
- Extensive experimental results on four public benchmark datasets demonstrate the effectiveness of the proposed model.

2 Related work

2.1 Attention-based methods

The attention mechanism focuses on significant information and captures semantic relationships between the context and specific aspects, which has led to its widespread adoption in ABSA tasks. Wang et al. [21] proposed an attention-based Long Short-Term Memory (LSTM) network that integrates aspect information into the attention mechanism, allowing aspects to guide the computation of attention weights. Ma et al. [22] designed an interactive attention network that employs two attention mechanisms to jointly generate representations for the context and target. Wang et al. [23] developed a segmented attention-based LSTM model for modeling the dependency relationship between sentiment expressions and targets. In the study of Wang et al. [24], sentence-level and word-level textual information was integrated through a hierarchical aspect-specific attention network. Tan et al. [25] adopted a multi-label classification model with a dual attention mechanism to identify conflicting opinions. Xu et al. [26] proposed a method that employs multiple attention mechanisms to effectively capture fine-grained interactions between context and aspects, while also modeling long-distance sentiment relations within a sentence. These attention-based methods have improved ABSA model performance to some extent, but they are easily affected by irrelevant contextual noise or syntactically mismatched opinion terms, which limits the accurate assignment of attention weights.

2.2 Syntax-based methods

In recent years, the use of GCNs and Graph Attention Networks to learn from syntactic dependency trees and acquire syntactic knowledge has been widely recognized in the academic community. He et al. [27] suggested incorporating syntactic knowledge into the attention mechanism and introduced a method for target representation to enhance the computation of attention weights. Sun et al. [28] designed a convolutional dependency tree model aimed at transmitting contextual and syntactic information from opinion words to aspect words, thereby addressing the long-distance dependency problem between opinions and aspects. In an effort to alleviate the influence of contextually irrelevant words lacking strong syntactic ties to the aspect, Phan and Ogunbona [29] introduced the concept of syntactic relative distance. Zhu et al. [30] utilized global and local dependency-guided GCN to more comprehensively process textual structural information. A type-aware GCN was constructed by Tian et al. [31], with the aim of differentiating various relationships in the dependency tree based on relation types. Yuan et al. [32] incorporated dependency type knowledge into Graph Attention Networks to distinguish additional syntactic dependency relationships. These methods explicitly utilized the syntactic information contained in the syntactic dependency tree. However, they neglect the extra semantic relations among words.

2.3 Syntax- and semantic-based methods

A number of studies have successfully integrated semantic relevance and syntactic structure to derive more comprehensive information in the past few years. Du et al. [33] proposed a bidirectional edge-enhanced GCN for the effective utilization of syntactic structure and semantic information. Li et al. [34] integrated syntactic and semantic information through a complementary GCN, thereby enhancing the ability to capture semantic relevance. Pang et al. [35] employed the self-attention mechanism and dependency trees to generate semantic and syntactic information. Zhang et al. [36] employed an aspect-aware attention mechanism and syntactic mask matrix to integrate syntactic and semantic information. Yi et al. [37] combined context-guided attention and syntactic enhancement with linguistic features to improve the performance of ABSA. Guan et al. [38] applied contrastive learning methods by leveraging perturbation masks and self-attention weights to construct syntactic and semantic graphs, respectively. However, as a form of syntactic structure representation, dependency trees often face potential mismatches when used to extract semantic information. Due to the complexity and differences between syntactic and semantic structures, syntactic parsing and semantic interpretation can be inconsistent.

2.4 Other methods

In recent years, Wang et al. [40] introduced Soft Momentum Contrastive Learning (SoftMCL) for fine-grained sentiment-aware pretraining, which enables the model to retain and leverage a broader range of negation cues. SoftMCL operates at both the sentence and word levels, enhancing the model's ability to learn sentiment information. With the rapid advancement of large language models, Zheng et al. [41] employed them as scorers for ABSA to estimate the likelihood of outputs conditioned on given inputs and candidate examples, which were used as prompts. Based on the ranking scores, they labeled training examples as positive or negative. The use of large language models significantly improves generation efficiency without incurring additional computational costs or training difficulties. Zhong et al. [39] compared ChatGPT with fine-tuned BERT-based models and conducted an in-depth analysis of its comprehension and generation capabilities, laying a foundation for its future application in the ABSA domain.

In summary, we design an SDM to encode the dependency tree for extracting the syntactic structure of sentences. Simultaneously, AMR is introduced into the SOM to enhance the semantic relationships between words. Finally, by utilizing GCEM to facilitate the interaction of the information obtained from these two modules, we enrich the emotional features of the aspects and improve the accuracy of the sentiment classification task. The summary of references in this section is presented in Table 1.

3 Methodology

3.1 Overview

As shown in Fig. 2, the BSAN model is divided into five main modules: Sentence Embedding, SDM, SOM, GCFM, and Sentiment Classifier. First, we use BERT as the encoder for the given sentence to extract hidden contextual representations within the sentence. Then, two different modules are used to extract the syntactic and semantic information from the sentence separately. Finally, the two types of information interact dynamically to obtain a feature-rich global representation. Additionally, SOM with graph attention is used to encode the AMR, combining the hidden contextual representations with the AMR as input to extract the semantic representation for the given aspect. To obtain a more informative feature representation, GCFM dynamically integrates syntactic and semantic representations to extract relevant emotional dependencies relevant to specific aspects. The flowchart of the BSAN model is shown in Fig. 3.

3.2 Task definition

For the ABSA task, given a sentence-aspect pair (s, a), the goal is to predict the sentiment polarity $p \in (0, \quad 1, \quad 2)$ of a specific aspect A=$\{a_1, a_2, \cdots a_n\}$ within the sentence $S = \{w_1, w_2, \cdots, w_m\}$. Where m represents the number of words, n represents the number of aspects, and 0, 1, 2 correspond to positive, neutral, and negative sentiments, respectively. Additionally, an aspect can be a single word or a phrase consisting of multiple words.

3.3 Sentence embedding

BERT is a pre-trained masked Transformer-based language model. Several studies have demonstrated that BERT can significantly improve sentiment classification performance. Therefore, the BSAN model uses BERT to perform contextual encoding of the input information, generating low-dimensional word embeddings. The sequence "[CLS] s [SEP] a [SEP]" is fed into BERT to generate context embeddings H = $H = [h_1, h_2, ..., h_n]$, which serve as aspect-related hidden representations. Where $h_n \in \mathbb{R}^{d_e}$, and d_e represent the dimensionality of the BERT hidden states.

Table 1 Summary of references in related work

Category	Method	Author	Publication Date	Description
Att.	Attention-based LSTM for aspect-level sentiment classification [21]	He et al.	2016	Wang et al. proposed an attention-based Long Short-Term Memory (LSTM) network that integrates aspect information into the attention mechanism, allowing aspects to guide the computation of attention weights.
	Interactive attention networks for aspect-level sentiment classification [22]	Ma et al.	2017	Ma et al. designed an interactive attention network that employs two attention mechanisms to jointly generate representations for the context and target.
	Learning latent opinions for aspect-level sentiment classification [23]	Wang et al.	2018	Wang et al. developed a segmented attention-based LSTM model for modeling the dependency relationship between sentiment expressions and targets.
	Aspect sentiment classification with both word-level and clause-level attention networks [24]	Wang et al.	2018	In the study of Wang et al., sentence-level and word-level textual information was integrated through a hierarchical aspect-specific attention network.
	Recognizing conflict opinions in aspect-level sentiment classification with dual attention networks [25]	Tan et al.	2019	Tan et al. adopted a multi-label classification model with a dual attention mechanism to identify conflicting opinions.
	Aspect-based sentiment classification with multi-attention network [26]	Xu et al.	2020	Xu et al. proposed a method that employs multiple attention mechanisms to effectively capture fine- grained interactions between context and aspects, while also modeling long-distance sentiment relations within a sentence.
Syn.	Effective attention networks for aspect-level sentiment classification [27]	He et al.	2018	He et al. suggested incorporating syntactic knowledge into the attention mechanism and introduced a method for target representation to enhance the computation of attention weights.
	Aspect-level sentiment analysis via convolution over dependency tree [28]	Sun et al.	2019	Sun et al. designed a convolutional dependency tree model aimed at transmitting contextual and syntactic information from opinion words to aspect words, thereby addressing the long-distance dependency problem between opinions and aspects.
	Modelling context and syntactical features for aspect-based sentiment analysis [29]	Phan et al.	2020	In an effort to alleviate the influence of contextually irrelevant words lacking strong syntactic ties to the aspect, Phan and Ogunbona introduced the concept of syntactic relative distance.
	Gl-gcn: Global and local dependency guided graph convolutional networks for aspect-based sentiment classification [30]	Zhu et al.	2021	Zhu et al. utilized global and local dependency-guided GCN to more comprehensively process textual structural information.
	Aspect-based sentiment analysis with type-aware graph convolutional networks and layer ensemble [31]	Tian et al.	2021	A type-aware GCN was constructed by Tian et al., with the aim of differentiating various relationships in the dependency tree based on relation types.
	Effective attention networks for aspect-level sentiment classification [32]	Yuan et al.	2022	Yuan et al. incorporated dependency type knowledge into Graph Attention Networks to distinguish additional syntactic dependency relationships.
Syn. and Att.	Bidirectional edge-enhanced graph convolutional networks for aspectbased sentiment classification [33]	Du et al.	2021	Du et al. proposed a bidirectional edge-enhanced GCN for the effective utilization of syntactic structure and semantic information.
	Dual graph convolutional networks for aspect-based sentiment analysis [34]	Li et al.	2021	Li et al. integrated syntactic and semantic information through a complementary GCN, thereby enhancing the ability to capture semantic relevance.
	Dynamic and multi-channel graph convolutional networks for aspect-based sentiment analysis [35]	Pang et al.	2021	Pang et al. employed the self-attention mechanism and dependency trees to generate semantic and syntactic information.
	Ssegcn: Syntactic and semantic enhanced graph convolutional network for aspect-based sentiment analysis [36]	Zhang et al.	2022	Zhang et al. employed an aspect-aware attention mechanism and syntactic mask matrix to integrate syntactic and semantic information.
	Enhanced syntactic and semantic graph convolutional network with contrastive learning for aspect-based sentiment analysis [38]	Guan et al.	2023	Guan et al. applied contrastive learning methods by leveraging perturbation masks and self-attention weights to construct syntactic and semantic graphs, respectively.
	Context-guided and syntactic augmented dual graph convolutional network for aspectbased sentiment analysis [37]	Yi et al.	2024	Yi et al. combined context-guided attention and syntactic enhancement with linguistic features to improve the performance of ABSA.

Table 1 (continued)

Category	Method	Author	Publication Date	Description
Others	Can chatgpt understand too? a comparative study on chatgpt and fine-tuned bert [39]	Zhong et al.	2023	Zhong et al. compared ChatGPT with fine-tuned BERT-based models and conducted an in-depth analysis of its comprehension and generation capabilities, laying a foundation for its future application in the ABSA domain.
	Softmcl: Soft momentum contrastive learning for fine-grained sentiment-aware pre-training [40]	Wang et al.	2024	Wang et al. introduced Soft Momentum Contrastive Learning (SoftMCL) for fine-grained sentiment-aware pretraining, which enables the model to retain and leverage a broader range of negation cues.
	Instruction tuning with retrieval-based examples ranking for aspectbased sentiment analysis [41]	Zheng et al.	2024	Zheng et al. employed them as scorers for ABSA to estimate the likelihood of outputs conditioned on given inputs and candidate examples, which were used as prompts.

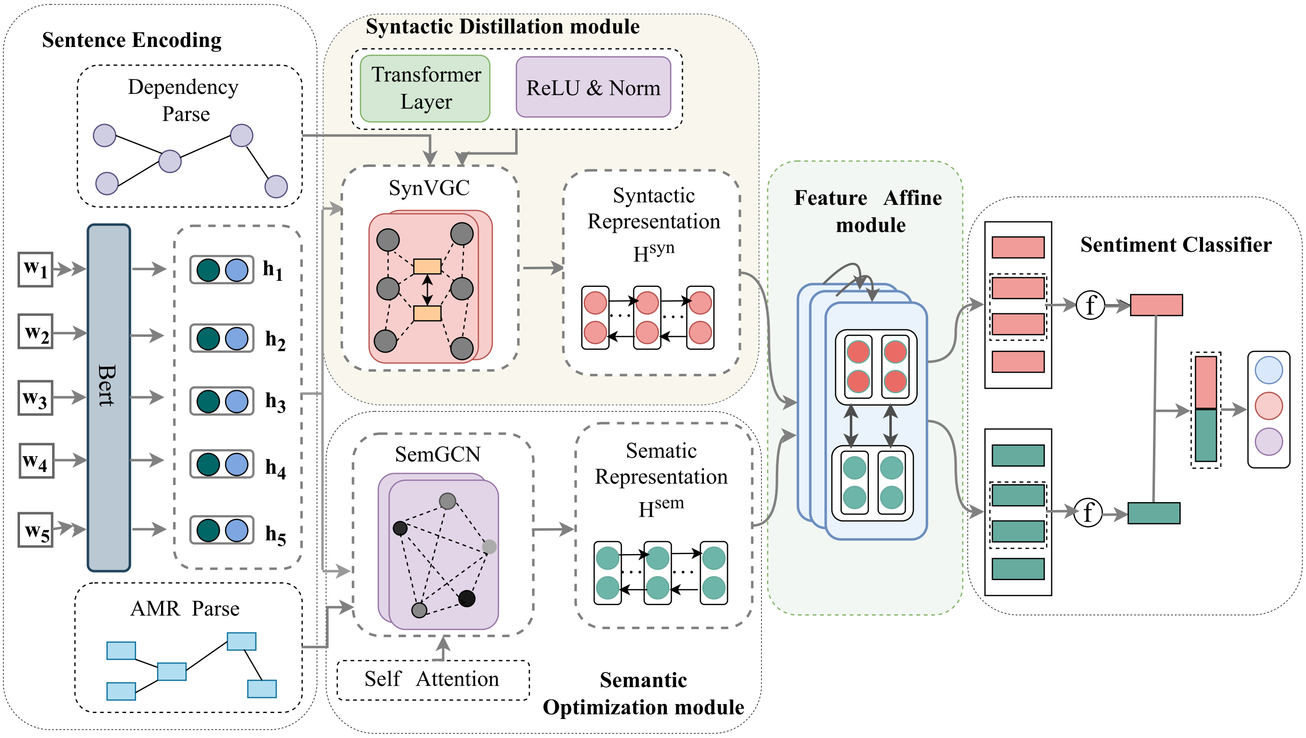


Fig. 2 Overall architecture of BSAN

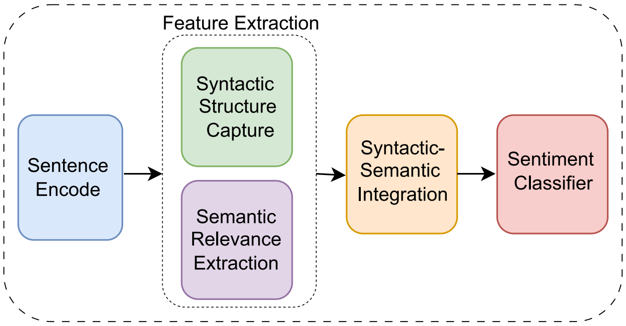


Fig. 3 Model Flowchart of BSAN

3.4 SDM

To extract dependency information from the syntactic dependency tree, we design a SDM, which is primarily composed of three components: a Transformer layer, an intermediate layer, and a Syntax View Graph Convolution (SynVGC) layer. SDM integrates the contextual hidden representations with the dependency tree structure as input, and encodes them from both graph-based and sequence-based views to more effectively capture syntactic dependencies within the sentence. These two complementary views work in synergy, significantly enhancing the module's ability to extract syntactic dependencies, particularly when dealing with syntactically complex or ambiguous sentences. As shown in Fig. 4, the SynVGC layer is composed of three parts: the message constructor, aggregator, and updater (i.e., MLP).

Compared with traditional GCNs, the SynVGC layer in SDM explicitly incorporates edge-type embeddings and integrates them with neighboring node features during the message construction phase, enabling the module to effectively capture syntactic information from dependency relations. At the same time, a masking mechanism is applied to filter out redundant edge features, ensuring that effective information is transmitted only between word pairs with actual dependency relations, thereby effectively suppressing the interference of noisy edges. Specifically, if there is no edge relationship between nodes i and j, then $m_{ij} = 0$. It ensures that noise information does not affect the updates of the node/edge representations in the next layer. Moreover, SynVGC adopts a message passing mechanism designed for dense graphs, jointly utilizing node and edge features for message construction. A multi-layer perceptron (MLP) is further applied to flexibly update the features. Notably, SynVGC can be generalized to the GNN framework to handle graphs with edge features and dense adjacency matrices.

The adjacency matrix with edge types is represented as $B \in R^{n\times n}$, and the d-dimensional node feature representation is denoted as $D \in R^{n\times d}$. Before message passing, a mask matrix is generated based on B, and D is unfolded along rows and columns into $D_{\mathrm{row}} \in R^{n\times n\times d}$ and $D_{\mathrm{col}} \in R^{n\times n\times d}$, respectively.

In terms of message passing mechanism, the construction process is shown in (1) and (2).

$$X = embedding_e(B) \tag{1}$$

$$Y = mask(D_{row} + X) \tag{2}$$

where $\mathrm{X} \in \mathbb{R}^{n\times n\times d}$ represents the edge embeddings, and $\mathrm{Y} \in \mathbb{R}^{n\times n\times d}$ represents the corresponding constructed messages for the edges. After applying a 0-1 mask matrix, any non-edge feature vectors in Y are ensured to be zero-padded. The summary is shown in (3) and (4).

$$\widehat{\boldsymbol{Y}} = f_w\left(\sum_{j=1}^{n} Y_j\right) \tag{3}$$

$$\hat{X} = f_x(X + D_{row} + D_{col}) \tag{4}$$

where $\hat{\mathrm{Y}} \in \mathbb{R}^{n\times d}$ and $\hat{X} \in \mathbb{R}^{n\times n\times d}$ represent the aggregation results for nodes and edges, respectively, while f_w and f_x are update functions similar to MLP.

The primary function of the Transformer layer is to process the input sequence data by employing an attention mechanism that globally attends to all words within the same instance. Additionally, an intermediate layer has been designed between graph data processing and sequence data processing to enable compatibility and adaptation between these two layers, allowing for their effective integration. The formulas for the aforementioned steps are shown in (5), (6), (7) and (8).

$$G^l = \mathrm{Syn}VGC^{(l)}(H^{l-1}, B) \tag{5}$$

$$\widehat{\boldsymbol{H}}^l = ReLU\left(LayerNorm^{(l)}(\boldsymbol{G}^l)\right) \tag{6}$$

$$\hat{G}^l = TransformerLayer^{(l)}(\widehat{H}^l) \tag{7}$$

$$H^l = \hat{G}^l + H^{l-1} \tag{8}$$

where H^{l-1} and $H^l \in \mathbb{R}^{n\times d}$ represent the intermediate representations of the (l-1)-th and l-th blocks of words (complete L partition), while G^l and $\hat{G}^l \in \mathbb{R}^{n\times d}$ denote the outputs from the graph convolution layer and the Transformer layer in the l-th block. $\widehat{H}^l \in \mathbb{R}^{n\times d}$ represents the output of the intermediate layer, which is followed by LayerNorm and ReLU. The syntactic representation H_{syn} is obtained through SDM. It is important to note that for aspect

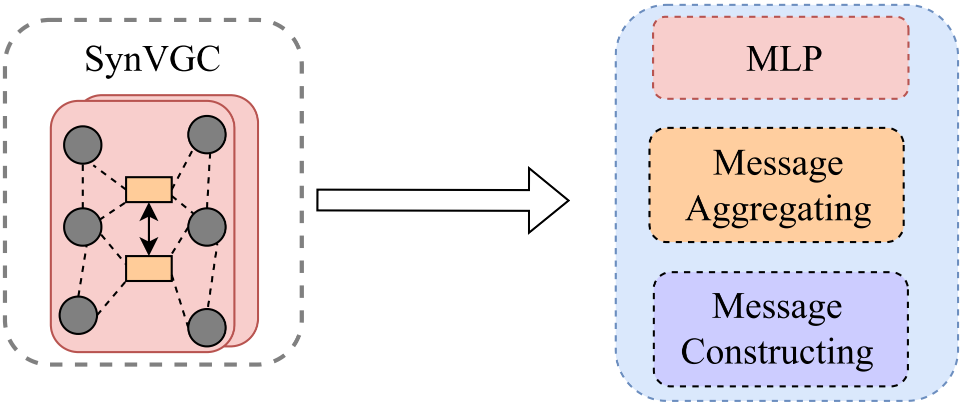


Fig. 4 The overall architecture of SynVGC

nodes, we use the notation $\{h_{a_1}^{\text{syn}}, h_{a_2}^{\text{syn}}, \ldots, h_{a_n}^{\text{syn}}\}$ to denote their hidden representations.

3.5 SOM

To capture the corresponding semantics, we introduce a novel structured representation and apply SOM to extract relevant information from it. GCN [18, 30, 36], which is widely utilized for processing graph-structured data, is regarded as a variant of graph neural networks. It encodes graph information by performing convolution operations on connected nodes, enabling information to propagate through multiple layers of GCN and effectively capturing the data represented by each node in the graph. Therefore, SOM employs GCN in conjunction with a self-attention mechanism to construct a word-level self-adjacency matrix, which can be regarded as a weighted undirected graph representing the semantic associations between words. Since it does not rely on syntactic information, SemGCN demonstrates greater flexibility in handling the semantic relationships between words.

AMR is a structured semantic representation [42] that represents the semantics of a sentence as a directed, rooted, acyclic graph with annotations on the nodes and edges. First, we utilize the existing SPRING parser [43] to extract high-quality AMR outputs from the input sentences. Subsequently, we select the LEAMR aligner [44] to align the AMR. Based on the alignment, we reconstruct the AMR relationships between words in the sentence, resulting in a transformed AMR with words as nodes.

The self-attention mechanism [45] computes the attention scores between words in a parallel manner. In the SOM, a self-attention mechanism is employed to compute the attention score matrix $A_{\text{sem}} \in R^{(n\times n)}$. Subsequently, we utilize the attention score matrix A_{sem} as the adjacency matrix for the SOM, as shown in (9).

$$A_{sem} = softmax(\frac{QW^Q \times (KW^K)^{\mathrm{T}}}{\sqrt{d}}) \tag{9}$$

where matrices Q and K represent the graphical representations from the previous layer of the SemGCN module, while W^Q and W^K are learnable weight matrices, and d denotes the dimensionality of the input node features. The semantic representation H_{sem} is obtained through SOM. Additionally, we use the notation $\{h_{a_1}^{\text{sem}}, h_{a_2}^{\text{sem}}, \ldots, h_{a_n}^{\text{sem}}\}$ to represent the hidden representations of all aspect nodes.

3.6 GCFM

To facilitate deep interaction between syntactic and semantic information and achieve synergistic fusion of multiple feature types, we design the GCFM module to enrich the emotional representation of sentences. Conventional feature fusion methods often perform only simple concatenation or weighted averaging at the vector level, making it difficult to fully capture the potential mapping relationships between syntactic and semantic features. In contrast, the GCFM introduces a biaffine mutual attention mechanism to effectively promote the interaction of correlated features between the two types of information, thereby obtaining a representation that integrates both syntactic and semantic information. The GCFM feeds syntactic and semantic features into two independent affine transformation layers, learning the mapping relationships between the two feature spaces through parameter matrices. On one hand, the mapping from syntax to semantics enables the model to extract dependency patterns from syntactic structures that are informative for sentiment prediction. On the other hand, the mapping from semantics to syntax allows the model to leverage contextual semantic information to guide the weighting of syntactic features in a reverse manner, strengthening structural components that are highly correlated with sentiment orientation. Building on it, the biaffine mutual attention mechanism computes a bidirectional attention score matrix between the two types of features, dynamically capturing the most complementary interactive components between them, thereby enhancing the effectiveness and discriminative power of the final fused representation. The detailed implementation of the GCFM is shown in (10) and (11).

$$h'_{\text{syn}} = \text{softmax}(H_{\text{syn}} W_1 (h_{\text{sem}})^T) H_{\text{sem}} \tag{10}$$

$$h'_{\text{sem}} = \text{softmax}(H_{\text{sem}} W_2 (h_{\text{syn}})^T) H_{\text{syn}} \tag{11}$$

where W_1 and W_2 are both learnable parameters.

Subsequently, we apply average pooling to obtain the syntactic representation h_a^{syn} and the semantic representation h_a^{sem} for specific aspects, which can be expressed as show in (12), (13) and (14).

$$h_a^{\text{syn}} = f\left(h_{a_1}^{\text{syn}}, h_{a_2}^{\text{syn}}, \ldots, h_{a_n}^{\text{syn}}\right) \tag{12}$$

$$h_a^{\text{sem}} = f\left(h_{a_1}^{\text{sem}}, h_{a_2}^{\text{sem}}, \ldots, h_{a_n}^{\text{sem}}\right) \tag{13}$$

$$x = [h_a^{\text{syn}}, h_a^{\text{sem}}] \tag{14}$$

where f$(\cdot)$ is the average pooling function applied to the representations of aspect nodes.

Finally, the feature x is put into a bidirectional Long Short-Term Memory (BiLSTM) network, and the outputs from both directions are summed element-wise to obtain the fused hidden representation H, as shown in (15) and (16).

$$(\overleftarrow{H}, \overrightarrow{H}) = BiLSTM(x) \tag{15}$$

$$H = \overleftarrow{H} + \overrightarrow{H} \tag{16}$$

3.7 Sentiment classifier

The obtained representation H is fed into a linear layer, followed by the application of the softmax function to generate a sentiment probability distribution p, as shown in (17).

$$p(r) = \mathrm{softmax}(W_p H + b_p) \tag{17}$$

where W_p and b_p are the learnable weights and biases, respectively.

We adopt the standard cross-entropy loss as the objective function, which can be expressed as shown in (18).

$$L_{CE} = -\sum_{(s,a)\in\mathcal{D}} \sum_{c\in\mathcal{C}} y_a^c \log p^c(r). \tag{18}$$

where y represents the true sentiment polarity, D contains all sentence-aspect pairs, and C encompasses all sentiment polarities.

4 Experiment

4.1 Implementation details

In the data preprocessing stage, we employ SPRING as the parser to generate the AMR of input sentences and use LEAMR as the AMR alignment tool to establish the correspondence between AMR and their source sentences. Meanwhile, the dependency structures of input sentences are obtained using the existing LAL-Parser. In our experiments, BSAN uses the pre-trained model of the BERT-base-uncased version as the sentence encoder, with a maximum sequence length of 100. Adam is used as the optimizer for the model to perform optimization and training, with a learning rate set to 0.002. In all experiments, the batch size of the model is set to 16, with the hidden layer dimension set to 768. Finally, accuracy and the Macro-F1 score are used as two metrics to evaluate the model's performance in terms of quality. The code can be available at https://github.com/Meaciy/Mycode.

4.2 Datasets

We conducte experiments on four public benchmark datasets from different domains. The Laptop and Restaurant datasets are from SemEval 2014 Task 4 [46], focusing on electronics and restaurant services, respectively. Twitter [47] is a collection of social media data, while MAMS [48] is a large-scale dataset consisting exclusively of multi-aspect sentences. Each sentence in the dataset has been annotated as positive, neutral, or negative. In the Restaurant, Laptop, and Twitter datasets, each sentence contains at least one aspect and its corresponding sentiment polarity. In contrast, each sentence in MAMS contains at least two aspects with differing sentiment polarities. The sample distribution for each dataset is presented in Table 2.

4.3 Baseline

To comprehensively evaluate the performance of the BSAN model, we compare it with state-of-the-art baseline models. The latest benchmark model is briefly described as follows:

Attention-based methods:

- RAM [49] employs a multi-head attention mechanism to extract long-distance sentiment features from sentences, thereby enhancing sensitivity to irrelevant information.
- TNet [50] obtains word representations from the bidirectional RNN layer and then utilizes the CNN layer to extract target-specific word representations while preserving the initial contextual information.
- MGAN [51] employs a multi-granularity attention network to facilitate interactions between words and between aspects, thereby exploring additional useful information within sentences.
- BERT [52] encodes the input "[CLS] sentence [SEP] aspect [SEP]" using a bidirectional Transformer encoder.
- AEN [53] employs an attention encoder to model the relationship between the target and context, while utilizing label smoothing regularization to address the issue of unreliable labels.

Table 2 Statistics of the four benchmark datasets.

Dataset	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
Restaurant	2164	728	637	169	807	196
Laptop	994	341	464	169	870	128
Twitter	1561	173	3127	346	1560	173
MAMS	3380	400	5042	607	2764	329

Syntax-based methods:

- ASGCN [54] constructs a Graph Convolutional Network (GCN) based on the dependency tree of a sentence to extract syntactic information and word dependency relations.
- T-GCN [31] explicitly uses dependency relations to differentiate various types of relationships in sentences, learning syntactic structures through perceptual graphs.
- R-GAT [55] designs an aspect-oriented dependency tree framework and employs a relational graph attention encoding structure.
- DulGCN [34] extracts semantic information and syntactic structures from sentences simultaneously through a dual-channel architecture with differential and orthogonal regularization terms.

- IDGNN [56] utilizes a dual graph neural network to separately obtain syntactic information and semantic relevance, while incorporating dependency labels to enhance aspect representations and applying orthogonal regularization to strengthen semantic associations.IASD-ML [57] comprehensively integrates word dependency relations and commonsense path information from ConceptNet to construct a commonsense aware graph network, thereby enhancing the emotional association between modal words and sentiment words.
- SVCCL-GCN [58] integrates a variational autoencoder with unsupervised contrastive learning to enhance its ability to learn comprehensive semantic and sentiment representations across words.
- MambaForGCN [59] encodes the dependency structure and semantic information of input sentences, and introduces an adaptive feature representation mechanism to strengthen long-range dependencies between aspect terms and opinion words.

Others:

- KDual-GraphSAGE [60] integrates semantic and syntactic information, incorporates external sentiment knowledge, and leverages n-gram syntactic features to fully exploit the learning potential of the fused representations.
- TF-BERT [61] proposes a table-filling method to ensure the consistency of span-level multi-word opinion expressions, thereby enhancing the emotional intensity of specific aspects.
- GCNet [62] establishes a collaborative learning network that utilizes global semantic information to guide the encoding of contextual information, effectively integrating global features and syntactic representations.

4.4 Experimental results

We compare the BSAN model with several benchmark models across four publicly available benchmark datasets. Extensive research has demonstrated that the BSAN model outperforms most benchmark models, with the overall performance of all models presented in Table 3. We use accuracy and macro-average F1 scores as evaluation metrics. The experimental results indicate that methods based on syntactic structures significantly outperform those relying

Table 3 Overall performance of the different methods on the four benchmark datasets. Acc stands for accuracy and F1 stands for Macro - F1 score. Best results are in bold face and second best underlined

Catgory	Model	Restraurant		Laptop		Twitter		MAMS	
		Acc	F1	Acc	F1	Acc	F1	Acc	F1
Att.	RAM [49]	80.23	70.80	74.49	71.35	69.36	67.30	–	–
	TNet [50]	80.69	71.72	76.54	71.75	74.90	73.60	–	–
	MGAN [51]	81.25	71.94	75.39	72.47	72.54	70.81	–	–
	BERT [52]	85.62	78.28	77.58	72.38	75.28	74.11	82.82	81.90
	AEN [53]	83.12	73.76	79.93	76.31	74.71	73.13	–	–
dep.	ASGCN [54]	80.77	72.02	75.55	71.05	72.15	70.40	–	–
	T-GCN [31]	86.16	79.95	80.88	77.03	76.45	75.25	83.68	83.07
	R-GAT [55]	86.60	81.35	78.21	74.07	76.15	74.88	83.16	82.42
	DulGCN [34]	87.13	81.16	81.80	78.10	77.40	76.02	–	–
	IDGNN [56]	87.25	81.16	81.12	77.73	76.72	75.92	84.57	83.42
	IASD-ML [57]	87.07	81.84	82.04	78.28	–	–	**85.19**	84.14
	SVCCL-GCN [58]	86.34	80.16	81.35	77.76	74.28	72.68	–	–
	MambaForGCN [59]	86.68	80.86	81.80	**78.59**	77.67	76.88		
Others.	KDual-GraphSAGE [60]	87.14	78.65	79.69	75.18	74.40	73.23	–	–
	TF-BERT [61]	87.08	81.14	81.17	78.46	76.70	75.90	–	–
	GCNet [62]	87.08	81.35	80.79	77.61	77.55	76.59	–	–
Ours	BSAN	**88.11**	**83.50**	**82.12**	78.44	**78.14**	**77.40**	84.98	**84.44**

on attention mechanisms (e.g., RAM, MGAN and AEN), highlighting the importance of syntactic dependencies in sentiment classification tasks. Specifically, syntactic information can reveal the structural relationships between words within a sentence, such as modification relations and coordination relations, which are particularly crucial for capturing sentiment tendencies. In contrast, traditional attention mechanisms primarily rely on contextual correlations to assign weights, making them susceptible to interference from long-range dependencies or non-critical information, thereby reducing the accuracy of sentiment classification. Similarly, among methods based on syntactic structures, those that do not utilize semantic information (e.g., T-GCN, R-GAT) perform significantly worse than those that do (e.g., DulGCN, IDGNN and MambaForGCN). Although syntactic structures can provide grammatical dependency constraints, the lack of semantic understanding when handling implicit sentiment, negations, intensifiers, or complex modifiers may prevent the model from accurately capturing sentiment intensity. Therefore, integrating semantic information into syntactic graphs can enhance the model's ability to perceive global sentiment features of a sentence, thereby improving classification performance. Compared to methods that simultaneously consider both semantic information and syntactic structures, BSAN is more competitive. It is attributed to BSAN's capability to learn more comprehensive sentiment information through effective interaction between semantics and syntax, thereby enhancing the representation of aspect-related information and optimizing sentiment classification performance.

4.5 Ablation study

To determine the significance of different components within the BSAN model, we conduct ablation experiments on four benchmark datasets, with the results presented in Table 4. It can be observed that the removal of the SDM leads to a decline in performance, indicating that establishing dependencies between sentences through syntactic knowledge is beneficial in reducing noise introduced by the attention mechanism, thereby enhancing the extraction of aspect-related sentiments. Omitting the Transformer layer results in coarser aspect representations, as the model loses its capability to capture global, sequence-level semantic dependencies. It also diminishes the model's ability to accurately interpret contextual modifiers, ultimately lowering the accuracy of aspect-level sentiment classification. Similarly, the removal of the SOM significantly degrades performance, indicating that additional semantic relevance can compensate for the deficiencies in syntactic information within incomplete syntactic structures, thereby achieving a richer representation of information. It is evident that semantic relevance is crucial for interpreting sentences with unclear syntactic structures or syntactic parsing errors. Removing the SynVGC layer would prevent the model from fully leveraging dependency-structure information, which not only reduces its ability to capture long-range dependencies but also leads to incomplete extraction of aspect-related features. Furthermore, the absence of the GCFM indicates that the integration of syntactic and semantic information through ensemble learning is beneficial for enhancing sentiment classification performance. Additionally, the removal of AMR reduces the semantic correlations within sentences, thereby decreasing the model's predictive capability in sentiment analysis. In summary, each component of our BSAN model plays a crucial role in achieving optimal performance.

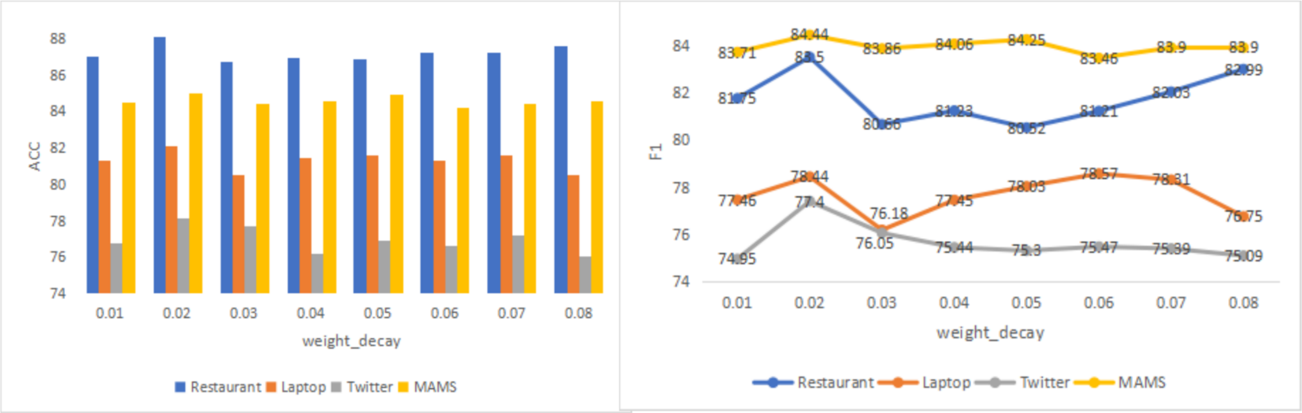
We conduct experiments comparing GCFM with simple concatenation and weighted fusion methods, as shown in Table 5. Compared to GCFM, both simple concatenation and weighted fusion exhibit a noticeable decline in accuracy and F1 scores across all datasets. It indicate that simple concatenation is insufficient for modeling the dependencies between syntactic and semantic features, as it treats both feature types independently and fails to capture their mutual influence. Consequently, the model struggles to distinguish the relative importance and complementarity of different features, which can lead to suboptimal aspect-level sentiment representations. Although weighted fusion assigns different weights to syntactic and semantic features, it still lacks an explicit interaction modeling mechanism, making it difficult to capture the structural constraints that syntax imposes on semantic expression or the reverse influence of semantics on syntactic selection. As a result, fused features may contain redundant or irrelevant information, limiting

Table 4 Experimental results of the ablation study. Best results are in bold face. Acc stands for accuracy and F1 stands for Macro - F1 score

Model	Restraurant		Laptop		Twitter		MANS	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1
BSAN w/o SOM	86.51	81.27	81.01	77.36	76.81	75.15	83.86	83.27
BSAN w/o Transformer Layer	86.60	81.06	80.54	77.43	77.40	75.73	84.23	83.49
BSAN w/o SDM	87.40	82.12	79.91	76.26	75.92	74.57	84.01	83.34
BSAN w/o SynVGC Layer	86.60	80.54	79.75	75.80	76.66	75.17	84.23	83.51
BSAN w/o GCFM	87.13	81.72	80.22	77.01	76.66	75.09	84.23	83.76
BSAN w/o AMR	86.06	80.31	81.49	77.91	76.51	75.54	82.78	82.19
BSAN	**88.11**	**83.50**	**82.12**	**78.44**	**78.14**	**77.40**	**84.98**	**84.44**

Table 5 Results of ablation experiments on GCFM and simple concatenation and weighted fusion. Best results are in bold face. Acc stands for accuracy and F1 stands for Macro - F1 score

Module	Restraurant		Laptop		Twitter		MANS	
	Acc	F1	Acc	F1	Acc	F1	Acc	F1
GCFM	**88.11**	**83.50**	**82.12**	**78.44**	**78.14**	**77.40**	**84.98**	**84.44**
simple concatenation	87.13	81.72	80.22	77.01	76.66	75.09	84.23	83.76
weighted fusion	87.22	80.90	78.64	74.27	76.07	75.23	84.61	83.92



A

B

Fig. 5 The impact of the weight_decay of the proposed BSAN. Accuracy and Macro-F1 scores based on different values of weight_decay are reported

the model's discriminative capacity. In contrast, GCFM introduces a bimodal interaction mechanism that enables syntactic and semantic features to achieve dynamic coupling and information sharing within the graph structure, effectively enhancing the model's feature discriminability and robustness while reducing interference from redundant features. By explicitly modeling syntax–semantic dependencies, GCFM ensures that the final representations capture both the structural constraints and semantic nuances essential for accurate aspect-level sentiment classification.

4.6 Impact of weight_decay

This experiment aims to evaluate the effect of the hyperparameter weight_decay. Specifically, to select appropriate hyperparameters, we adopt a systematic hyperparameter search strategy to identify optimal values within a predefined search space. We adjust the weight_decay value from 0.01 to 0.08 to assess the performance of the BSAN model across four datasets. As shown in Fig. 5, the BSAN model achieves the best performance across all datasets when the weight_decay value is set to 0.02. Therefore, we set weight_decay to 0.02 in all experiments. As the value of weight_decay increases, the accuracy and F1 scores across the four datasets show a significant decline. It occurs because when the value of weight_decay is too high, the model selectively focuses on irrelevant contextual information in the sentence, making it difficult to capture certain emotional information related to specific aspects. To address the issue that the value of weight_decay significantly affects the performance of the BSAN model, techniques such as the AdamW optimizer or difficulty-aware dynamic regularization strategies can be introduced, which help automatically adjust the regularization strength during training, thereby reducing reliance on a single hyperparameter such as weight_decay.

4.7 Impact of AMR

At present, the majority of baseline methods utilize attention mechanisms to directly extract semantic information from dependency trees, subsequently predicting sentiment polarity. The objective of the BSAN model is to enhance the accuracy of sentiment classification. It is achieved by first constructing the AMR and then extracting semantic information from it, thereby improving the quality of semantic representation. To analyze the impact of the presence or absence of the AMR structure in the BSAN model, comparative experiments are conducted across four datasets, with the results presented in Fig. 6. Clearly, the accuracy and F1 score achieve with the use of AMR are significantly higher than those obtained without it. It can be concluded that the AMR enhances the semantic relevance within sentences. More accurate semantic representations can be extracted from the AMR, thereby enhancing the model's predictive capability regarding sentiment aspects and significantly improving its performance.

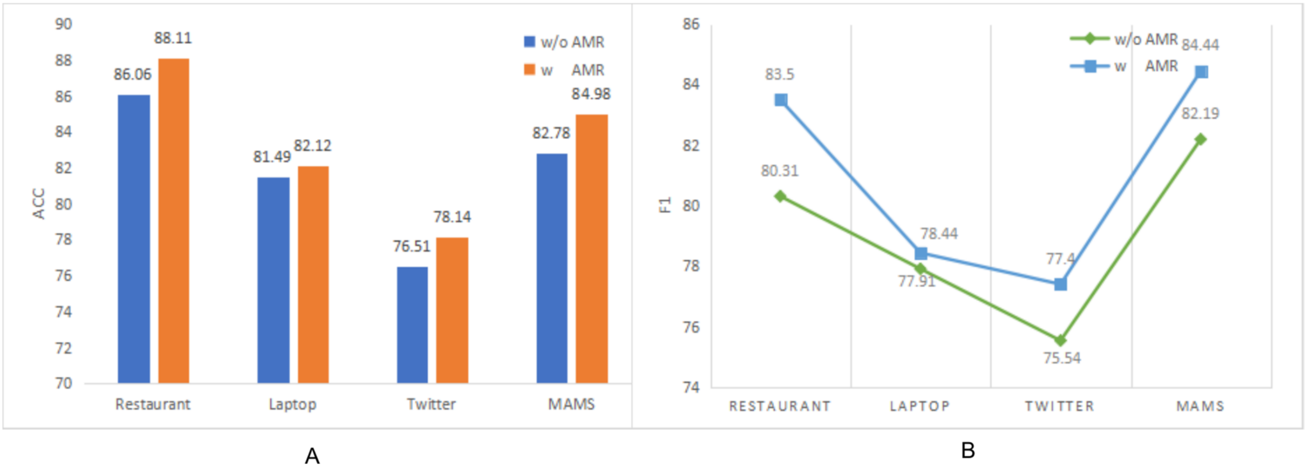


Fig. 6 The impact of AMR of the proposed BSAN. Accuracy and Macro-F1 scores based on the presence or absence of AMR are reported

Table 6 Comparison of the computational efficiency of SSEGCN, APARN, and BSAN across multiple dimensions

Model	Number of parameters	Forward pass time	Evaluating efficiency	Resource utilization	Throughput	ACC	F1
SSEGCN [36]	110.21M	1.35×10^{-3}s	1.51s	4.56 GB	739 samples/s	87.31	81.09
APARN [63]	178.85M	8.85×10^{-3}s	9.90s	21.1 GB	113 samples/s	87.76	82.44
BSAN	182.69M	3.18×10^{-3}s	3.56s	10.6 GB	314 samples/s	88.11	83.50

4.8 Computational efficiency analysis

When dealing with large-scale datasets, computational efficiency is a critical consideration for practical applications. Table 6 presents the computational efficiency comparison of the three models (SSEGCN, APARN, and BSAN) across multiple dimensions. It can be observed that SSEGCN is the most lightweight model in terms of parameter scale and resource consumption, with only 110.21M parameters and 4.56 GB of memory usage. It achieves the shortest forward propagation time, the highest evaluation efficiency, and a throughput of 739 samples/s, demonstrating excellent computational speed and resource utilization. However, its accuracy is relatively lower. In contrast, after incorporating a more complex relational attention mechanism, APARN's parameter count increases to 178.85M, memory usage rises to 21.1 GB, evaluation time reaches 9.90 s, and throughput decreases to 113 samples/s, resulting in a significantly higher computational cost. Despite having a slightly higher parameter count than APARN, BSAN achieves superior performance through an efficient bidirectional synergistic aggregation mechanism, while maintaining relatively low resource consumption and short evaluation time. Overall, SSEGCN offers high efficiency but limited accuracy, APARN provides higher accuracy at the cost of greater resource consumption, and BSAN achieves an optimal balance between efficiency and performance.

4.9 Case study

To validate the ability of the BSAN model to capture syntactic and semantic information within sentences, we conduct a case analysis using both the SSEGCN model and the BSAN model across several example sentences, as shown in Table 7. In the first sentence, which is structurally simple, the syntactic relationships and semantic information enable an accurate determination that the sentiment polarity of both "size" and "weight" is positive. In the second sentence, the aspect terms easily establish a connection with "not", resulting in the ineffectiveness of the SSEGCN model. In the third example, the SSEGCN model fails due to a lack of clear opinion information. Furthermore, the fourth example demonstrates that the SSEGCN model struggles to effectively handle sentences with multiple aspects. It is noteworthy that the final case indicates that the BSAN model still exhibits limitations when handling sentences with complex semantic structures or implicit emotional expressions. This phenomenon mainly arises from the model's constraints in deep semantic modeling and long-range dependency capture. When a sentence contains multiple subordinate structures, metaphorical expressions, or sentiment reversals, the attention mechanism of the model struggles to accurately focus on the key semantic components, leading to incomplete or inaccurate sentiment representations. Future research could integrate knowledge enhancement and semantic pre-training techniques to improve the model's semantic representation

Table 7 Case studies of our BSAN model compared with the SSEGCN baselines. The notations P , N and O represent positive, negative and neutral sentiment, respectively

#	Sentence	Gold	SSEGCN	BSAN
1	Its size is ideal and the weight is acceptable . Aspect:{size,weight}	(P, P)	$(P_{\checkmark}, P_{\checkmark})$	$P_{\checkmark}, P_{\checkmark})$
2	I have not tried the one with retina display ... maybe in the future. Aspect:{retina display }	(O)	$(N_{\times})$	$(O_{\checkmark})$
3	Chatting with acer support , i was advised the problem was corrupted operating system files . Aspect:{ acer support,operating system files }	(O, O)	$(O_{\checkmark}, N_{\times})$	$(O_{\checkmark}, O_{\checkmark})$
4	I use it mostly for content creation (audio , video , photo editing) and its reliable . Aspect:{content creation,audio,video,photo editing }	(P, P, P, P)	$(P_{\checkmark}, N_{\times}, N_{\times}, N_{\times})$	$(P_{\checkmark}, P_{\checkmark}, P_{\checkmark}, P_{\checkmark})$
5	Usb3 peripherals are noticably less expensive than the thunderbolt ones . Aspect:{Usb3 peripherals,thunderbolt }	(P, N)	$(O_{\times}, O_{\times})$	$(P_{\checkmark}, O_{\times})$

capability, and optimize the focus and stability of the attention distribution through learnable attention guidance or regularization mechanisms, thereby further enhancing the model's robustness and interpretability in complex semantic scenarios.

4.10 Visualization

Considering the importance of modeling semantic relationships between words, we visualize the attention scores of each word in the SOM self-attention mechanism, as shown in Fig. 7. By calculating the correlations between words in a sentence, the self-attention mechanism enables the BSAN model to capture features that are distant from aspect terms but mutually dependent. This approach filters out redundant information and enhances the accuracy of semantic expression. It effectively addresses the challenge of capturing key semantic information when opinion words and aspect terms are not adjacent in the syntactic structure.

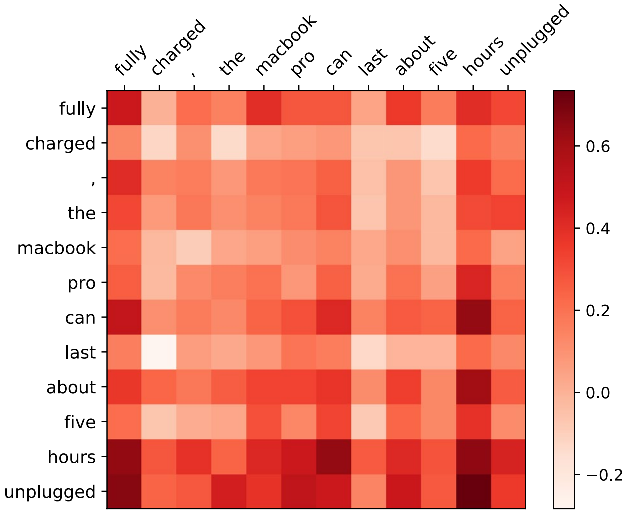


Fig. 7 Example of Attention Score Visualization

5 Conclusion

In this paper, we propose a BSAN model that integrates syntactic structures and semantic information to enhance aspect-based sentiment analysis. Specifically, we obtain word embedding representations through the BERT pre-trained model. Then, a SDM is designed to learn aspect-related syntactic dependencies from the dependency tree. Additionally, the SOM introduces AMR and utilizes a GCN to encode the self-attention matrix for extracting semantic associations within AMR. Finally, the GCFM integrates semantic information with global syntactic information to obtain the final feature representation of the model. A large amount of experimental results demonstrate that the model proposed in this paper achieves commendable performance across four benchmark datasets. In future work, we will further explore deeper semantic representations to enhance the model's ability to capture implicit emotional information in datasets containing out-of-vocabulary words and colloquial expressions. Meanwhile, we plan to evaluate the model's generalization capability and application potential across different tasks. For example, in addition to incorporating external knowledge to enhance sentiment classification performance, we will also evaluate the model's performance on unseen datasets and extend its application to related tasks such as intent recognition, sentiment triplet extraction, and reading comprehension. In addition, we will investigate several potential strategies to improve attention scores, including multi-head fusion, learnable scaling factors, gated modulation mechanisms, and attention regularization methods, to further enhance the model's ability to capture critical information.

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Data Availability Data will be made available on request.

Declarations

Conflicts of Interest All authors disclosed no relevant relationships.

Ethics approval Not applicable.

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