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A Sentiment Analysis Model for Aspect-Based Sentiment Analysis using Biaffine Attention and Sentiment Knowledge Enhancement

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Abstract. Sentiment analysis aims to uncover the sentiment polarity of various targets in text. However, existing models predominantly rely on syntactic structures or sequential information, making it challenging to effectively capture the deep dependencies and complex emotional interactions between multi word aspect and opinion terms. This limitation hampers the accurate modeling of semantic relationships among sentiment triplets—aspect terms, opinion terms, and sentiment polarity. Furthermore, current models often overlook the potential of external sentiment knowledge, which results in suboptimal performance when dealing with complex semantic dependencies and multi-word sentiment relationships. To address these challenges, we propose a novel Aspect-based Sentiment Analysis Model (SEBM) that leverages biaffine attention and sentiment knowledge enhancement to improve performance. First, we introduce a biaffine attention mechanism to model the intricate semantic and emotional dependencies between multi-word terms, enabling more precise capture of emotional interactions and semantic relationships. Second, we integrate external sentiment knowledge from the SenticNet lexicon to optimize the syntactic dependency graph, thereby enhancing the emotional dependencies between the context and aspect terms. This approach compensates for the limitations of existing models in sentiment information modeling. We validate the proposed method on three publicly available datasets: Restaurant, Laptop, and Twitter. The experimental results show that while the accuracy slightly decreased on the Restaurant dataset, SEBM achieved improvements of 2.0% and 1.18% in accuracy on the Laptop and Twitter datasets, respectively. Moreover, SEBM outperformed the baseline model SSEGCN in Macro-F1 scores, with improvements of 0.69%, 2.78%, and 1.01% on the three datasets.

Keywords: Sentiment analysis, Biaffine Attention Mechanism, External affective knowledge, SenticNet

1 Introduction

Aspect-Based Sentiment Analysis (ABSA) is a core task in Natural Language Processing (NLP), aiming to identify and analyze the polarity of sentiments expressed toward specific aspects within text.[1] Unlike traditional sentiment analysis, which focuses on assessing the overall sentiment of a sentence, ABSA performs fine-grained analysis by detecting aspect terms and determining their corresponding sentiment polarities. This granularity offers valuable insights for business decision-making, marketing strategies, and customer feedback evaluation. For example, as illustrated in **Fig. 1**, in the sentence “The battery life of this phone is amazing, but the camera quality is terrible”, the aspect terms “battery life” and “camera quality” are associated with positive and negative sentiments, respectively. Leveraging big data technologies, ABSA can uncover precise sentiment trends from large-scale text corpora.

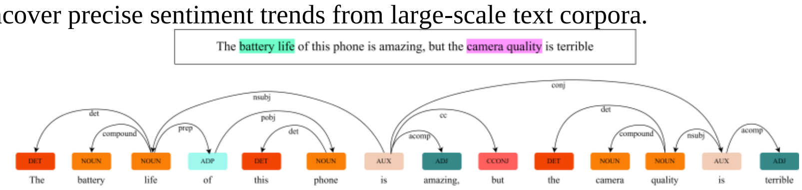

Fig. 1. Example sentence with dependency tree.

The core of the ABSA task lies in extracting aspect-specific features and establishing dependencies with opinion terms. Traditional models like CNNs and RNNs[1] are effective at capturing local semantics and long-range dependencies, while pre-trained models such as BERT significantly enhance sentence-level understanding through bidirectional encoding. Recent approaches combine dependency trees with Graph Convolutional Networks (GCNs) to model the relationships between aspect terms and their context[2-6], yet often neglect external knowledge and struggle with complex sentiment interactions involving multi-word terms. To address these issues, we propose the SEBM model, which integrates a biaffine attention mechanism[7] to capture intricate semantic and emotional dependencies, constructs a standard dependency graph based on the dependency tree, and enhances it using SenticNet as a sentiment knowledge base. This results in an aspect-specific, sentiment-enhanced dependency graph, which is then processed by a GCN to improve sentiment triplet modeling. In summary, this paper has the following contributions:

• We introduce a biaffine attention mechanism to model the complex semantic and emotional dependencies between multi-word terms, enabling a more accurate capture of emotional interactions and semantic relationships between terms.

• We incorporate external sentiment knowledge by leveraging SenticNet to optimize the graph construction process and capture emotional dependencies specific to aspects.

• We conduct experiments on three benchmark datasets—Laptop, Restaurant, and Twitter—demonstrating the superiority of the proposed SEBM model. Compared to existing baseline models, SEBM achieves significant improvements in sentiment polarity classification accuracy and Macro-F1 score.

2 Related Work

2.1 Development of Aspect-Based Sentiment Analysis Technology

Aspect-Based Sentiment Analysis (ABSA) has garnered considerable attention as a key subfield of Natural Language Processing (NLP) due to its ability to determine the sentiment polarity associated with specific aspects mentioned in textual data [9]. Early efforts in ABSA predominantly relied on sentiment lexicons and rule-based approaches[10] to extract features from text. The development of deep learning technologies has brought about a significant leap in the effectiveness of sentiment analysis, particularly with the use of CNN and RNN[11-15], which enable efficient sentence-level analysis through their powerful local feature learning and sequence data processing capabilities. Kim[11]proposed the TextCNN model, applying CNN to sentiment classification tasks and demonstrating their effectiveness in semantic parsing of text. Hammi et al.[16] combined CNNs and bidirectional RNN (Bi-RNN) with traditional machine learning methods to capture both local and contextual features, validating their high performance on smartphone review datasets. Swathi et al.[17]utilized bidirectional LSTM networks for sentiment analysis tasks, incorporating memory mechanisms to handle long-term dependencies and achieve more accurate predictions. Sun et al. [18] proposed a model based on LSTM and attention mechanisms, using attention matrices to learn the interactive attention between context and target, significantly improving sentiment prediction for each target in reviews.

2.2 The Application of Graph Neural Networks in ABSA

Graph Neural Networks (GNNs) have been widely adopted in NLP for their strength in modeling graph-structured data, which effectively captures complex relationships in text. As a key GNN approach, Graph Convolutional Networks (GCNs) integrate graph structures into deep learning to enhance feature representation by leveraging contextual dependencies between aspects[19]. In ABSA, GCNs iteratively update node representations by aggregating surrounding context, improving sentiment-relevant features. Li et al. [20] proposed a dual GCN that balances syntactic and semantic information using orthogonal and differential regularizers, while Hou et al.[21] introduced a graph integration method combining multiple dependency relations to improve connectivity and mitigate overfitting. Despite their success, many models still struggle with limited use of external knowledge and over-reliance on syntax or sequence structures, making it difficult to capture deep dependencies and complex sentiment interactions between aspect and opinion terms.

3 Methods

The architecture of the SEBM model proposed in this paper is illustrated in **Fig. 2**.The architecture consists of three main modules: the left part is the SenticNet-based external sentiment knowledge enhancement module, which integrates sentiment knowledge to enhance the syntactic dependency graph, optimizing the semantic and emotional associations between aspect terms and opinion terms in the text. The middle part is the biaffine module, which uses the biaffine attention mechanism to model the deep dependencies between multi-word terms, effectively capturing the complex emotional interactions between aspect terms and opinion terms. The right part fuses the dependency graph outputs from both the external sentiment knowledge enhancement module and the biaffine module with the encoded hidden vectors, and inputs them into the GCN to extract contextual features. This further strengthens the emotional semantic representation, which is ultimately used to predict the target sentiment polarity through a Softmax layer.

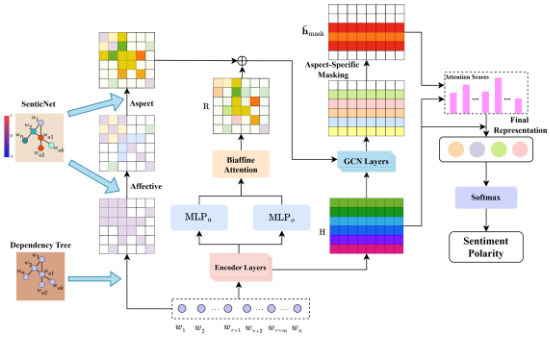

Fig. 2. SEBM Architecture Diagram.

3.1 Problem Definition

We define a sentence in SEBM as consisting n words, represented as sentence = $\{w_1,..., w_{\tau+1},w_{\tau+2},...,w_{\tau+m},w_n\}$, where w_i denotes the i-th word in the sentence, $w_{\tau+i}$ represents the i-th aspect term, and n is the length of the sentence. Aspect-based sentiment analysis (ABSA) aims to predict the sentiment polarity y ∈ {POS,NEG,NEU} corresponding to aspect terms in the sentence, where POS, NEG, and NEU denote “Positive”, “Negative”, and “Neutral” sentiments, respectively. It is important to note that an aspect can either be a single word or a phrase composed of multiple words, both of which are considered aspect terms.

3.2 Input and Encoding Layer

The contextual information of a word in a sentence re quires consideration of its relationship with other words. This hidden representation contains contextual information. BiLSTM and BERT have demonstrated their effectiveness across various tasks. In this study, we used Bi-LSTM and BERT as the sentence encoders to extract hidden con textual representations and compare the performance of these two encoders in our experiments. For an input sentence $\mathbf{X} = \{w_1,...,w_{\tau+1},w_{\tau+2},...,w_{\tau+m},w_n\}$, the sentence encoder generates hidden representation vectors $\mathbf{H} = \{h_1,..., h_{\tau+1},h_{\tau+2},...,h_{\tau+m},h_n\}$ represents the hidden vector of the contextual word w_i, and $h_{\tau+i} \in Rm$ represents the hidden vector of the aspect term $w_{\tau+i}$. Here m denotes the dimensionality of the vector. The computation is defined as shown in (1):

$$h_i = \text{Encoder}(w_i, \zeta) \tag{1}$$

where ζ represents the parameters of the encoder model. Considering the need to detect the sentiment of specific aspects, we focus on the emotional representation of the context. Therefore, for BERT-based models, we use the input format "[CLS] sentence [SEP] aspect [SEP]" to better capture the sentiment related to each aspect in the context.

3.3 Biaffine Attention Module

Traditional sentiment analysis models often struggle to capture deep dependencies between multi-word aspect terms (AT) and opinion terms (OT), limiting performance. To address this, we propose a method incorporating a biaffine attention mechanism that models complex relationships between multi-word ATs and OTs, improving dependency parsing and information flow. The module first uses two MLPs to extract semantic features for ATs and OTs, which are then input into the biaffine mechanism to compute their interactions, as defined in equations (2)–(5).

$$h_i^a = \text{MLP}_a(h_i) \tag{2}$$

$$h_j^o = \text{MLP}_o(h_j) \tag{3}$$

$$s_{i,j} = h_i^{aT} \mathbf{W}_1 h_j^o + \mathbf{W}_2 (h_i^a \oplus h_j^o) + b \tag{4}$$

$$\mathbf{R} = \text{Biaffine}(\text{MLP}_a(\mathbf{H}), \text{MLP}_o(\mathbf{H})) \tag{5}$$

Equation (5) serves as a summary of (2) to (4), where h_i^a and h_j^o represent the feature representations of aspect terms and opinion terms extracted by the MLP network, respectively. $\mathbf{W}_1$ and $\mathbf{W}_2$ are weight matrices, b denotes the bias term, and $s_{i,j}$ represents the relationship score between words w_i and w_j .Using the above equations, an adjacency matrix $R \in \mathbb{R}^{n \times n}$ is constructed to model the relationships between words.

3.4 Graph construction based on dependency tree

The interdependence of words within a sentence, as discussed in[3][4], we use the Spacy tool to construct a convolutional network graph based on the dependency tree of the input sentences. Subsequently, an adjacency matrix $C_{i,j} \in \mathbb{R}^{n \times n}$ is constructed based on the dependency tree, as defined in (6):

$$C_{i,j} = \begin{cases} score, & \text{if } w_i, w_j \text{ contains dependency} \\ 1, & i = j \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

The score depends on various factors, such as the sentiment of the words w_i and w_j their dependency relationship, and whether they are aspect terms. The derivation of score will be detailed in the following sections. To retain the information of the nodes themselves, we set the main diagonal of the adjacency matrix to 1. Note that the graph constructed in this paper is undirected, i.e., $C_{i,j} = C_{j,i}$, as we believe directed graphs may result in the loss of some dependency information.

To fully leverage the sentiment information between contextual words and target words, we further incorporate the sentiment scores from SenticNet[8] to enhance the representation of the adjacency matrix, as shown in (7):

$$S_{i,j} = \begin{cases} \text{SenticNet}(w_i) + 1, & \text{if } |\text{SenticNet}(w_i)| > |\text{SenticNet}(w_j)| \\ \text{SenticNet}(w_j) + 1, & \text{if } |\text{SenticNet}(w_i)| \le |\text{SenticNet}(w_j)| \end{cases} \quad (7)$$

The sentiment score of $SenticNet(w_i)$ ranges from [-1, 1], representing the sentiment polarity of the word w_i in the SenticNet lexicon. Specifically, when the score is close to -1, it indicates a strong negative sentiment; when the score is close to +1, it indicates a prominent positive sentiment; and a score of 0 represents a neutral sentiment or indicates that the word does not exist in the SenticNet lexicon.

In the dependency relationship modeling, to more precisely capture the sentiment relevance within a sentence, we select $Source_{i,j}$ as the larger of the sentiment scores of words w_i and w_j in the SenticNet lexicon. This is because, in modeling the dependency between two words, words with stronger sentiment tend to have a more dominant role in the relationship, thus more accurately reflecting the sentiment transmission characteristics of the sentence.

Aspect-based sentiment analysis models based on GCN can effectively capture the dependencies between words by utilizing syntactic dependency trees. However, they typically overlook the focus on the given aspect. Therefore, in this study, we further enhance the emotional dependency relationship between contextual words and aspect terms, as shown in (8):

$$Z_{i,j} = \begin{cases} 1, & \text{if } w_i \text{ or } w_j \text{ is a aspect word} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

After the above calculations, the improved sentence adjacency matrix can be obtained, as shown in (9):

$$A_{i,j} = C_{i,j} * (S_{i,j} + Z_{i,j}) \quad (9)$$

$C_{i,j}$ is the dependency arc weight between words *i* and *j*, $S_{i,j}$ is the sentiment score matrix, and $Z_{i,j}$ is the aspect word representation matrix weight distribution. $Z_{i,j}$ mainly emphasizes the importance of aspect words, when the word *i* or *j* is aspect words or the word *i* is a positive emotion word, the result of $(S_{i,j} + Z_{i,j})$ will increase, and the final weight result $A_{i,j}$ will also increase relative to the edge weight associated with non-aspect words. This formula integrates syntactic structure information, lexical emotion information and aspect word information, and combines SenticNet sentiment score as a regulator with $Z_{i,j}$ to make the results pay more attention to aspect terms.

3.5 Graph Convolutional Network Optimized by SenticNet and Dual-Affine Mechanism

After obtaining the optimized graph adjacency matrix, we fuse it with the score matrix derived from the biaffine module discussed in Section III.D, and then feed the fused result into the GCN layer for further processing. The GCN layer performs multi-layer convolution operations to progressively extract node features from the graph. In this paper, we adopt a two-layer GCN module to capture the syntactic features of the sentence. The features of each node are updated based on the hidden representations of its neighboring nodes, and normalization is applied to the feature values before the non-linear transformation. This process is defined as follows:

$$\mathbf{V} = \mathbf{A} + \mathbf{R} \tag{10}$$

$$\tilde{\mathbf{V}}_i = \mathbf{V}_i / (\mathbf{D}_i + 1) \tag{11}$$

$$h_i^l = \mathrm{relu}(\tilde{\mathbf{V}}_i h_i^{l-1} \mathbf{W}^l + b^l) \tag{12}$$

Where $\mathbf{A}$ represents the optimized graph adjacency matrix, $\mathbf{R}$ denotes the score matrix obtained through the biaffine module, $\mathbf{D}_i = \sum_{j=1}^{n} V_{i,j}$ represents the degree of $\mathbf{V}_i$, $\mathbf{W}^l$ and b^l are the weight and bias terms for the linear transformation, respectively, Additionally. h_i^{l-1} refers to the hidden representation derived from the preceding layer of the GCN.

3.6 Specific aspects of sentiment expression

To further enhance the importance of aspect terms and reduce the noise interference f rom unrelated terms, we mask the output vectors of non-aspect terms by setting them to zero, while preserving the representations of aspect terms. The specific operation is shown in (13):

$$\bar{h}_i^l = 0, \ \ 1 \le t < \tau + 1, \tau + m < t \le n + a \tag{13}$$

$\overline{h}_i^l$ is the representation of the i-th word obtained from the final output of the GCN layer, τ is the starting index of the aspect term in the sentence, and m is the length of the aspect term. Thus, we obtain the specific aspect mask representation as shown below:

$$h_{mask}^L = \{0, \ldots, h_{\tau+1}^L, \ldots, h_{\tau+m}^L, \ldots, 0\} \tag{14}$$

Inspired by the work in [3], after obtaining the final text representation through the GCN, we employ a retrieval-based attention mechanism to extract key features from the sentiment words in the context, based on the specific aspect terms. The calculation process is shown in (15) and (16):

$$\beta_t = \sum\nolimits_{i=1}^{n} h_t^{cT} \tilde{h}_i = \sum\nolimits_{i=\tau+1}^{\tau+m} h_t^{cT} \tilde{h}_i \tag{15}$$

$$\alpha_t = \frac{\exp(\beta_t)}{\sum\nolimits_{i=1}^{n} \exp(\beta_i)} \tag{16}$$

here, we employ a retrieval-based attention mechanism to capture the sentiment information and semantic relevance between context words and aspect terms. Furthermore, we enhance the importance of aspect terms by applying a masking operation to specific aspects. Consequently, the final computation of the input vector is as follows:

$$r = \sum_{i=1}^{n} \alpha_i h_i^0 \tag{17}$$

3.7 Mechanism

The feature representation r, derived from the GCN-based feature extraction module, is subsequently passed through a fully connected layer followed by a Softmax layer to generate the corresponding probability distribution $y \in \mathbb{R}^{d_p}$.

$$y = \text{softmax}(\mathbf{W}_s r + b_s) \tag{18}$$

where, d_p represents the number of sentiment polarities, while $\mathbf{W}_s$ and b_s are trainable parameters. The proposed model is trained using the gradient descent algorithm, with the optimization objective defined as minimizing the cross-entropy loss combined with L2 regularization. The loss function is expressed as:

$$\mathrm{L} = -\sum_{i=1}^{\mathrm{k}} \sum_{j=1}^{d_p} y_i^j \log \hat{y}_i^j + \lambda \|\Theta\|^2 \tag{19}$$

here, k denotes the total number of training samples, and d_p represents the number of sentiment categories. y_i^j is the actual sentiment distribution, while $\hat{y}_i^j$ refers to the predicted probability for the j-th category of the i-th sample. Θ includes all trainable parameters, and λ is the regularization factor that helps prevent overfitting by controlling model complexity.

4 Experiments

4.1 Experimental setting

To validate SEBM's effectiveness, we evaluated the model on three aspect-based sentiment analysis datasets: the Restaurant and Laptop review datasets from SemEval-2014 Task 4 [22], and the Twitter dataset of short texts from social media [23]. Each dataset is split into training and test sets, with three sentiment categories: Positive, Negative, and Neutral. For sentence encoding, we used Bi-LSTM and BERT. The GCN layer count was set to 2 based on experimental optimization. The BERT-base-uncased model was used with hidden dimensions of 768 for BERT and 300 for GCN. The model was trained with the AdamW optimizer [24], a learning rate of 0.001, and L2 regularization of 0.00001. Dropout (rate = 0.5) was applied to prevent overfitting. All experiments were conducted on an NVIDIA RTX 4090 GPU (24GB) for efficient computation.

4.2 Evaluation Metrics

To comprehensively evaluate the model's performance in the aspect-level sentiment analysis task, two commonly used evaluation metrics were adopted in this study: *Accuracy* and *Macro−F1*.

The *Accuracy* measures the overall correctness of the model across all samples, i.e., the proportion of correctly predicted samples out of the total samples. *Macro − F1* is the harmonic mean of Precision and Recall. By taking the macro average of F1-scores across all categories, it effectively balances the impact of class imbalance. Specifically, Precision measures how many of the predicted samples for a certain category truly belong to that category, reflecting the model's predictive reliability. Recall measures the proportion of actual samples belonging to a certain category that are successfully identified by the model, reflecting the model's coverage ability. The formulas for these metrics are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{20}$$

$$P = \frac{TP}{TP + FP} \tag{21}$$

$$R = \frac{TP}{TP + FN} \tag{22}$$

$$Macro-F1=\frac{1}{C}\sum_{c=1}^{C}\frac{2\times P_c\times R_c}{P_c+R_c} \tag{23}$$

In these metrics, *TP* refers to the number of samples correctly predicted as the positive class, *TN* refers to the number of samples correctly predicted as the negative class, *FP* refers to the number of samples incorrectly predicted as a positive class when they belong to the negative class, and *FN* refers to the number of samples incorrectly predicted as a negative class when they belong to the positive class.

4.3 Baseline Comparisons

To comprehensively evaluate the performance of the proposed model, we conducted comparative experiments with several baseline models used in ABSA tasks. The detailed descriptions of these models are as follows:

• ASGCN [25]: The approach commbines the GCN and dependency tree to leverage syntactical information and word dependencies.

• DGEDT [26]: The approach introduces a structure combines flat representations and graph-based representations, improving aspect-based sentiment classfication performance.

• SenticGCN [8]: The model enhances sentence dependency graphs by integrating affective knowledge from SenticNet, improving aspect-based sentiment analysis.

• DualGCN [27]: By using the SynGCN module to alleviate dependency parsing errors and the SemGCN module with self-attention to capture semantic correlations.

• KHGCN [28]: The model constructs heterogeneous graphs to fuse word feature associations, utilizing GCN and knowledge graph to improve aspect-based sentiment analysis performance.

• SSEGCN [29]: Proposes an aspect-aware attention mechanism for learning semantic information and integrates semantic and syntactic features using GCN.

• SBRS [36]: Proposes a span-level bidirectional retention scheme with two pathways—one for aspect-opinion pair extraction at multiple scales, and another for bidirectional recursion and parallel computation—enhancing context, semantic, and relational representation learning for improved triplet extraction.

• PT-GCN [37]: Converts the relation table into a graph and applies a triple-channel GCN with prompt-based attention to capture rich relational information for improved triplet extraction.

• BERT4GCN [30]: Integrates grammatical sequential features from BERT's intermediate layers and syntactic knowledge from dependency graphs, enhancing the GCN for improved aspect-based sentiment classification performance.

• R-GAT+BERT [31]: Utilizes an aspect-specific dependency tree along with a Relation Graph Attention Net work (R-GAT) for encoding, effectively improving sentiment analysis performance.

• DGEDT+BERT [32]: This approach enhances the DGEDT model by incorporating BERT.

• AIEN+BERT [33]: Combines Adaptive Interactive Emotion Network (AIEN) with BERT to dynamically adjust the propagation of sentiment information, excelling in multi-aspect sentiment analysis tasks.

• T-GCN+BERT [34]: Differentiates relationships in the graph by introducing dependency types and employs multi-layer attention mechanisms to distinguish edges (relationships), achieving state-of-the-art performance across several datasets.

• SSEGCN+BERT [29]: This approach enhances the SSEGCN model by incorporating BERT.

• DualGCN+BERT [20]: This approach enhances the Dual-GCN model by incorporating BERT.

• SGGCN+BERT [35]: The model customizes hidden vectors and improves representations by incorporating gate vectors and word importance scores from dependency trees, achieving significant performance improvements in ABSA.

4.4 Comparative Experiments

To validate the effectiveness of the SEBM model, we compared it with various existing models, and the experimental results are shown in Table 2. As shown in the table, the SEBM model achieves the best performance on the Laptop dataset compared to other GCN-based methods (such as KHGCN and DualGCN), and outperforms most state-of-the-art models on the Rest14 and Twitter datasets. By incorporating sentiment knowledge into the syntactic dependency graph, we effectively improved the modeling of multi-word sentiment relationships and deep semantic dependencies. The experimental results indicate that the undirected graph structure combined with external sentiment knowledge provides a more balanced and comprehensive representation of the dependencies between words. Notably, compared to SenticGCN, which also integrates external sentiment knowledge into GCN, SEBM achieves superior performance. This improvement validates the effectiveness of our proposed biaffine attention mechanism, which accurately models the complex semantic and emotional dependencies between multi-word aspect and opinion terms. Furthermore, we observe that BERT-based models significantly outperform most ABSA models. When combined with the BERT encoder, our SEBM+BERT model outperforms state-of-the-art BERT-based models on all datasets, demonstrating that learning more syntactic and semantic knowledge enhances the performance of aspect-based sentiment analysis.

Table 1. Comparison of model evaluation on metrics across the three datasets.

Methods	Rest14(%)		Laptop(%)		Twitter(%)	
	Accuracy	F1	Accuracy	F1	Accuracy	F1
ASGCN	80.77	72.02	75.55	71.05	72.15	70.40
DGEDT	83.90	75.10	76.80	72.30	74.80	73.40
Sentic GCN	84.03	75.38	77.90	74.71	-	-
DualGCN	84.27	78.08	78.48	74.74	75.92	74.29
KHGCN	**85.42**	68.90	80.87	77.90	**76.66**	75.15
SSEGCN	84.72	77.51	79.43	76.49	76.51	**75.32**
SBRS	-	59.79	-	**72.68**	-	-
PT-GCN	-	74.88	-	**62.04**	-	-
Our SEBM	84.68	**79.05**	**81.33**	**78.74**	76.18	74.89
BERT4GCN	84.75	77.11	77.49	73.01	74.73	73.76
R-GAT+Bert	86.60	81.35	78.21	74.07	76.15	74.88
DGEDTBERT	86.30	80.00	79.80	75.60	77.90	75.40
AIENBERT	86.96	81.82	79.01	74.98	74.98	73.15
TGCN+BERT	86.16	79.95	80.88	77.03	76.5	75.25
SSEGCNBERT	**87.31**	81.09	80.01	77.96	77.40	76.02
Dual+BERT	87.13	81.16	81.80	78.10	77.40	76.02
SGGCNBERT	87.20	**82.50**	82.80	80.20	-	-
SEBM+BERT	86.80	81.78	**83.01**	**80.74**	**78.85**	**77.03**

In the Table 1, it can be seen that the accuracy of the model in this paper on the Restaurant dataset has slightly decreased. The main reason is that the introduced knowledge graph lacks effective coverage in the catering scenario. In the feature fusion mechanism of this paper, the fusion mode of semantics, syntax and knowledge has low adaptability on the Restaurant dataset, and the introduced noise affects the model judgment.

4.5 Ablation Experiments

To analyze the impact of each module in the SEBM model on sentiment analysis performance, we conducted ablation experiments, and the results are shown in Table 3. First, we removed three key modules—SenticNet external sentiment knowledge, biaffine attention, and aspect-specific sentiment representation(*w/o s+b+a*)—which prevented the model from leveraging any external sentiment knowledge and capturing complex multi-word sentiment dependencies and semantic interactions, leading to a noticeable performance drop.

Next, we separately removed the SenticNet external sentiment knowledge module (*w/o s*), biaffine attention module (*w/o b*), and aspect-specific sentiment representation module (*w/o a*) to observe the impact of each module on the SEBM model. After removing the SenticNet external sentiment knowledge module, the model exhibited performance degradation across all datasets. On the Rest14 dataset, accuracy decreased by 1.54%, and the Macro-F1 score dropped by 0.95%; on the Laptop dataset, accuracy decreased by 2.00%, and the Macro-F1 score dropped by 2.62%; and on the Twitter dataset, accuracy decreased by 1.27%, and the Macro-F1 score dropped by 1.44%. This result indicates that the sentiment knowledge provided by SenticNet significantly enhances the model's ability to model sentiment dependencies. SenticNet supplies additional sentiment information, effectively filling in the sentiment correlations in the syntactic dependency graph, thereby improving sentiment analysis accuracy. Therefore, removing this module results in the loss of crucial sentiment context, leading to a performance decline.

Removing the biaffine attention module caused accuracy to drop by1.07%, 1.27%, and 1.48% on the Rest14, Laptop, and Twitter datasets, respectively, while the Macro-F1 scores decreased by 0.30%, 1.93%, and 0.95%. This indicates that the biaffine attention module effectively models multi-word sentiment dependencies and complex sentiment interactions. By learning the intricate semantic and emotional interactions between words, it captures fine-grained sentiment information. When this module was removed, the model lost its ability to capture complex emotional interactions between words, leading to a drop in performance.

Furthermore, removing the aspect-specific sentiment representation module also impacted model performance, leading to decreased accuracy. This suggests that incorporating aspect information into the graph helps the model better focus on the key parts of the sentence, thus improving overall performance.

Table 2. Ablation study of the model('s' represents sentiment external sentiment knowledge module, 'a' represents aspect-specific sentiment representation module , 'b' represents biaffine attention module. Best results are highlighted in bold)

Methods	Rest14(%)		Laptop(%)		Twitter(%)	
	Accuracy	F1	Accuracy	F1	Accuracy	F1
SEBMw/o s+a+b	84.89	80.47	80.62	77.61	77.10	75.14
SEBM w/o s	85.32	80.83	81.01	78.12	77.31	75.59
SEBM w/o b	85.79	81.48	81.74	78.81	77.10	76.08
SEBM w/o a	86.07	81.62	82.11	79.05	77.43	76.26
SEBM	**86.86**	**81.78**	**83.01**	**80.74**	**78.85**	**77.03**

4.6 The impact of the number of GCN layers on model performance

To assess the impact of GCN depth on model performance, we experimented with 1 to 6 layers. Results (**Fig. 3**) show that performance improves initially and peaks at 2 layers, then declines with deeper networks. A 2-layer GCN strikes the best balance, effectively capturing relevant context without introducing excessive noise or complexity. This indicates that local context around aspect terms is most critical for sentiment prediction.

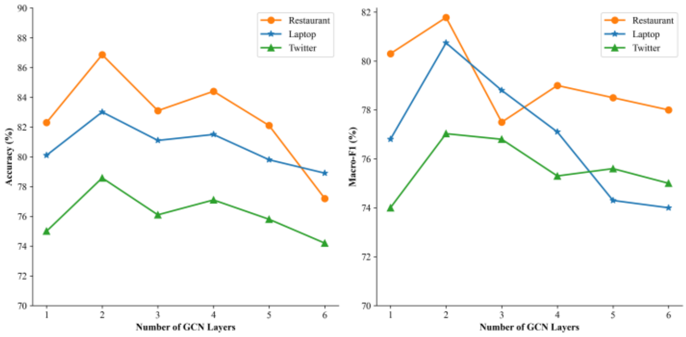

Fig. 3. Effect of GCN layer number on Accuracy and Macro-F1.

4.7 Case Study and Visualizations

To evaluate SEBM's ability to extract key sentiment words for specific aspects, we conducted a case study on representative samples (Table 4). SEBM outperformed baselines in predicting sentiment for multi-aspect sentences (e.g., Sentence 2), multi-word aspect terms (e.g., Sentence 3), single sentiments (Sentence 1), and neutral expressions (Sentence 4). These results highlight SEBM's superior performance in handling complex sentiment dependencies, thanks to its biaffine mechanism and integration of sentiment knowledge.

Table 3. Case Study. Sentiment classification results of typical instances learned by SEBM and comparison models (ASGCN and SSEGCN), with green, light purple, and blue representing positive, negative, and neutral sentiments, respectively.

Sentences	Label	ASGCN	SSEGCN	SEBM
1.The customer service at the restaurant was exceptional.	P	P	P	P
2.The movie's plot was engaging, and the soundtrack perfectly complemented the scenes.	(P,P)	(P,O)	(P,P)	(P,P)
3.The battery life of this phone is amazing, but the camera quality is terrible.	(P,N)	(P,P)	(O,N)	(P,N)
4.The meeting went as planned, with no significant issues or surprises.	O	P	O	O

5 Conclusion

This paper proposes the SEBM model, based on a biaffine mechanism and sentiment knowledge enhancement. Specifically, the model first introduces a biaffine attention mechanism to precisely model the semantic dependencies and sentiment interactions between multi-word aspect and opinion terms, capturing their latent deep connections. Then, by integrating the external sentiment knowledge base SenticNet, the syntactic dependency graph is enhanced to compensate for the limitations of purely syntactic information in sentiment semantic modeling, highlighting sentiment features related to aspect terms. This dual enhancement of semantics and sentiment allows the model to more comprehensively capture complex semantic dependencies and sentiment relationships, providing more accurate feature representations. Experimental results demonstrate that, compared to all other models, the SEBM model significantly outperforms others in sentiment polarity classification across three benchmark datasets, further confirming the effectiveness of the model's design.

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