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BIDIRECTIONAL SEMANTIC AND HIERARCHICAL SYNTACTIC SENTIMENT CLASSIFICATION BASED ON GCN

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Abstract: In order to solve the problems of insufficient coordination between global semantics and local syntactic features and noise interference of dependency parsing in aspect sentiment classification tasks, this paper proposes a bidirectional semantic enhancement and hierarchical syntactic analysis model based on graph convolutional network (GCN). The model effectively integrates semantic enhancement GCN and syntactic enhancement GCN for feature interaction to accurately model the complex hierarchical relationship between aspect words and sentiment words. In semantic modeling, self-attention and perceptual aspect attention (ASA) are integrated to extract deep semantic information through the attention fusion mechanism (GAFM). In terms of syntactic feature extraction, the syntactic distance mask matrix is introduced to measure semantic association, and the syntactic modeling is optimized in combination with the dependency relationship. In terms of structural optimization, the hierarchical phrase structure is adopted to fuse the syntactic dependency matrix with the phrase matrix to significantly reduce the noise of dependency tree parsing. Experimental results show that the model performs well on multiple datasets, with consistently improved accuracy and stability. Ablation experiments and visualization analysis further verify the effectiveness of each module, proving that the combination of bidirectional semantic enhancement and hierarchical syntactic analysis helps substantially improve the performance of aspect sentiment classification.
Keywords: Graph convolutional network; Semantic enhancement; Syntactic enhancement; Feature interaction; Aspect sentiment classification

1 INTRODUCTION

Aspect-based Sentiment Analysis (ABSA) aims to identify the sentiment tendencies of different aspects in text and is a key task in sentiment analysis. Traditional methods mainly focus on overall sentiment analysis, which is difficult to meet the needs of accurate identification. Therefore, ABSA improves the precision of sentiment analysis by modeling the association between sentiment polarity and specific aspects.

Current research mainly focuses on the self-attention mechanism and the graph convolutional network (GCN) based on the dependency tree to model the dependency relationship between aspect words and context. However, the self-attention mechanism may cause semantic feature loss when capturing the association between aspect words and context, while the dependency tree may introduce noise due to parsing errors or irregular text structure, weakening the model's discriminative ability.

In response to the above challenges, this chapter proposes a bidirectional semantic and hierarchical syntactic aspect sentiment classification model (SEAFM-GCN) based on GCN. The model improves the feature representation ability and enhances the accuracy and robustness of sentiment classification by integrating semantic information and syntactic information. In terms of semantic enhancement, we first use BiLSTM to extract context representation, and then combine self-attention and perceptual attention to calculate attention weights, which are then fused with the syntactic mask matrix to generate the adjacency matrix of GCN input to extract global semantics and local syntactic features. In terms of syntactic enhancement, we introduce a hierarchical phrase structure to explore the phrase collocation relationship within the sentence, and optimize the syntactic feature representation by screening out irrelevant dependency edges. Finally, we interactively fuse the extracted features to improve the classification ability of sentiment polarity.

2 RELATED WORK

GCN has outstanding performance in text syntactic modeling. Zhou et al[1]. introduced common sense knowledge to optimize the representation of aspect terms. Qi et al[2]. used weight matrices to enhance syntactic relations. Chen et al[3]. proposed D-GCN, combining dependency encoding to optimize aspect word extraction. Zhang et al[4]. first introduced syntactic dependency in GCN to improve the sentiment classification effect. Nguyen et al[5]. strengthened the connection between aspect words and sentiment words through dependency trees. Gu et al[6]. proposed MFSGC to optimize the adjacency matrix, remove irrelevant information, and strengthen dependencies.

The current study combines self-attention with GCN, integrates semantic and syntactic features, promotes the development of aspect sentiment classification, and provides theoretical support for this study.

3 MODLE CONSTRUCTION

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The SEAFM-GCN model framework is shown in Figure 1, which consists of five parts: input module, attention fusion module, semantic enhanced graph convolution module, syntactic enhanced graph convolution module, feature interaction module and classification module.

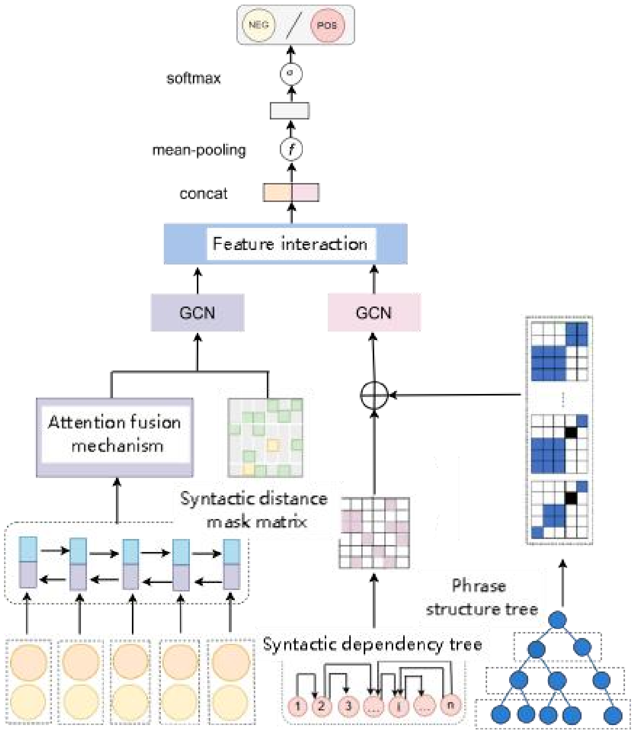

Figure 1 SEAFM-GCN Model Framework

3.1 Input Module

The input module consists of two parts: the embedding layer and the encoding layer.
(1) Embedding layer
Currently, models with relatively good results widely use pre-trained language models as the basis. For the sake of comparison, this model uses the BERT pre-trained language model as part of the word embedding. Considering that the task of performing aspect-level sentiment analysis on the course review text is to adjust the sentence format to [CLS]+sentence+[SEP] +aspect+[SEP] before sending it to BERT.
(2) Encoding layer
In the encoding layer, BiLSTM is used to encode the word vector sequence X to generate a hidden vector that integrates context information. The word vector sequence generated by the embedding layer is input into the BiLSTM, and is processed according to the encoding order from front to back and from back to front, so that two different hidden vectors are generated at the output of the two LSTMs, which can be expressed as and. Finally, the final hidden vector is obtained by concatenating the vector and the vector. This paper uses the vector and the vector as the output of the encoding layer, mainly because these two vectors can capture richer feature information. The specific formulas are shown in Equations 1 to 3.

$$\overrightarrow{h}_t = \mathrm{LSTM}\left(x_t, \overrightarrow{h}_{t-1}\right) \tag{1}$$

$$\overleftarrow{h}\mathrm{t} = \mathrm{LSTM}\left(x_t, \overleftarrow{h}_{t-1}\right) \tag{2}$$

$$h_t = \left[\overrightarrow{h}_t, \overleftarrow{t}_t\right] \tag{3}$$

Among them, represents the word vector at time t, represents the output of the LSTM from left to right at time t, represents the output of the LSTM from right to left at time t, and represents the output from the BiLSTM at time.

3.2 Attention Fusion Module

This chapter proposes a Global-Aware Fusion Mechanism (GAFM) to extract global and aspect-related semantic features efficiently. GAFM combines a Self-Attention Mechanism (SA) and an Aspect-Sensitive Attention Mechanism (ASA). Additionally, a syntactic distance mask matrix serves as an adjacency matrix, enhancing the SEAFM-GCN model's ability to capture semantic and syntactic distance features.

3.2.1 Self-Attention Mechanism (SA)

In this study, the hidden state output of the encoding layer is represented as , and the self-attention mechanism is employed to extract global semantic feature information. After three linear transformation operations, the Q, K, and V matrices are obtained. The self-attention score matrix for the text data $A_{\mathrm{Self}} = \{h_1^S, h_2^S, \cdots, h_n^S\}$ can be computed using Equation 4, as shown below.

$$A_{Self} = \frac{h^i W^q \times (h^i W^k)^T}{\sqrt{d^i}} h^i W^v \quad (4)$$

Among them,W^q、$W^k$and$W^v$are parameter matrices that can be adaptively optimized during the training process of the SEAFM-GCN model to improve prediction accuracy. represents the feature dimension of the input vector, playing a crucial role in the model's performance.

3.2.2 Aspect-Sensitive Attention Mechanism(ASA)

In the Aspect-Sensitive Attention Mechanism, the output vectors from the encoding layer are multiplied by the aspect mask matrix to extract the vectors corresponding to the aspect terms,represented by a∈R1×d,where d denotes the dimension of the hidden layer. The detailed calculation process is shown in Equation 5.

$$a = mean\ (mask \times h^i) \quad (5)$$

In the formula, the mean function represents average pooling. The final feature representation is generated by replicating a n times.

The obtained representation is fed into the ASA layer to capture aspect-related semantic features. The aspect-sensitive attention score matrix is computed using Equation 6.

$$A_{ASA} = tanh\ \left((h^a W^a) \times \left(h^i W^k\right)^T + b^a\right) \quad (6)$$

$tanh$ represents the activation function, h^i denotes the output of the encoding layer, W^a and W^k are the weight matrices, and b^a is the bias term.

Finally, according to Equation 7, the global semantic information is fused with the aspect-specific semantic information to generate the final attention score matrix. In the equation, α is the scaling factor.

$$A^{Att} = softmax\ (A_{Self} + \alpha A_{ASA}) \quad (7)$$

3.2.3 Syntactic Mask Matrix

First, the syntactic mask matrix is applied to mask each fully connected graph. The syntactic dependency tree is treated as an undirected graph, where nodes represent tokens and the distance between nodes is defined by a function. The shortest path distance between nodes is denoted as DD, as shown in Equation 8.

$$D(i,j) = mind(v_i, v_j) \quad (8)$$

3.3 Semantic Enhanced Graph Convolutional Module

As shown in Equation 9, The model performs graph convolution on the fused attention mask matrix.

$$h_i^l = \sigma\left(\sum_{j=1}^{n} A_{ij} W^l h_j^{l-1} + b^l\right) \quad (9)$$

Here, σ is the nonlinear function,W^l is the weight matrix, b^l is the bias term.

3.4 Syntactically Enhanced Graph Convolutional Module

As shown in Equation 10.This paper uses the Stanford Dependency Parser developed by Stanford University to automatically parse syntactic structures. This tool extracts part-of-speech information and their dependency relations, providing detailed syntactic analysis support for text understanding. In contrast, phrase structure trees focus on representing the hierarchical structure and phrase-level relationships of the text. Their construction relies on phrase structure analysis, where each node corresponds to a specific phrase, and the phrases at each level cover all the words in the sentence, capturing richer syntactic features. The proposed method uses the Stanford Constituency Parser to generate phrase structure trees, revealing the hierarchical structure and lexical organization within a sentence. By segmenting the hierarchical nodes in the phrase structure tree, each node corresponds to a phrase, providing detailed syntactic information that supports subsequent sentiment analysis and enhances the model's understanding of sentence semantics.

$$P_{i,j}^l = \begin{cases} 1 & if\ w_i, w_j in\ same\ phrase\ of\ \{h_p^l\} \\ 0 & otherwise \end{cases} \quad (10)$$

Here, h_p^l represents the vector representation of each phrase at layer.L denotes the number of layers in the phrase set, and p refers to the number of phrases at that layer.

Relying only on syntactic dependency trees may result in incomplete word relationship modeling, affecting sentiment classification. To address this, we combine phrase structure tree information to improve contextual modeling and enhance sentiment classification accuracy, as shown in Equation 11.

$$D_{i,j} = \begin{cases} 1 & \text{if i=j o r}w_i, w_j \text{ dependency tree} \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

As shown in Equation 12.By merging the phrase and syntactic dependency matrices, the adjacency matrix captures both phrase-level and sentence-level syntactic features{PD^1， PD^2， $\ldots$, PD^l},and is used as the input to the GCN.

$$h_{Di}^{(l)} = \rho\left(\sum_{j=1}^{n} PD_{ij} W^{(l)} h_j^{(l-1)} + b^{(l)}\right) \quad (12)$$

3.5 Feature Interaction Module and Classification Module

3.5.1 Feature fusion layer

The feature fusion extraction module performs deep interaction and fusion of the semantic feature matrix and syntactic feature matrix, fully integrating information to overcome the limitations of a single feature. This reduces the impact of information redundancy on model performance and improves the accuracy of sentiment polarity classification. After the interaction, the module concatenates the two types of features to construct the final feature representation, as shown in equation (13).

$$H^{AB} = \mathrm{concat}(H^{Sem}, \; H^{Syn}) \tag{13}$$

3.5.2 Sentiment output layer

The final feature vector is obtained through average pooling, and then the input is passed to the sentiment classification module, which uses a function for sentiment polarity classification. The calculation formulas are shown in equations 14 and 15.

$$H = \mathrm{Average\ Pooling}(H^{AB}) \tag{14}$$

$$Y = \mathrm{softmax}(W^{T}H + b) \tag{15}$$

4 EXPERIMENTS AND RESULTS ANALYSIS

4.1 Experimental data and evaluation indicators

The experiments in this chapter are conducted based on the dataset constructed in Chapter 3. The relevant data and statistical information have been thoroughly explained in the previous section and will not be repeated here.

For evaluation metrics, this study follows the evaluation methods used in previous related works, employing Precision (P) and Recall (R) to calculate the F1-score, which measures the model's classification performance (as detailed in Section 6 of Chapter 2). The F1-score, as the harmonic mean of precision and recall, approaches 1 when the model achieves better classification performance.

4.2 Experimental parameter settings

The SEAFM-GCN model utilizes the bert-base-chinese version of the BERT model, with a word embedding dimension of 768 and a part-of-speech (POS) embedding dimension of 100. The specific experimental hyperparameter settings are shown in Table 1. The loss function employed is the cross-entropy loss function.

Table 1 Experimental Parameter Settings

Parameter	Value
BERT Embedding Dimension	768
POS Embedding Dimension	100
Optimizer	BertAdam
Batch Size	8
Number of GCN Layers	2
GCN Dropout	0.1
Dropout Rate	0.3
Learning Rate	2×10^{-5}
Number of Attention Heads	5
Epochs	20

4.3 Comparative Experiments on Different Models

To evaluate the performance of the SEAFM-GCN model on aspect-level sentiment analysis of MOOC course reviews, this study selected the following baseline models for comparative experiments on the constructed aspect-level MOOC review dataset. The experimental results are shown in Table 2.

AOA: Utilizes multiple attention layers to model the interaction between aspects and sentences, effectively preserving aspect-specific sentiment features.

MGAN[7]: Introduces multi-granularity attention to better capture word-level interactions between aspects and sentences.

ASGCN: Combines syntactic dependency trees and graph convolutional networks (GCN), leveraging attention mechanisms to adjust feature weights for classification.

BERT-SPC[8]: Leverages the BERT pre-trained model to extract contextual information, followed by pooling word vectors to optimize classification performance.

AEN-BERT[9]: Employs the BERT model and an attention-based encoder to model the relationship between context and aspect terms.

R-GAT+BERT[10]: Transforms the dependency tree into a star graph with edges defined by minimal distance and dependency types, incorporating relational GAT with attention-based aggregation.

SSEGCN+BERT[11]: Uses a syntactic mask matrix obtained via a distance-based mask mechanism and incorporates attention mechanisms with GCN to enhance the representation of nodes related to aspect-specific sentiment features.

SEAFM-GCN: Proposes a model that integrates bidirectional semantics with hierarchical syntax through a graph convolutional network.

Table 2 Comparison of Results on MOOC Aspect-Level Datasets (%)

	MOOC1		MOOC2	
Method	Accuracy	F1	Accuracy	F1
AOA	83.25	69.15	82.62	68.82
MGAN	82.64	74.32	82.45	74.17
ASGCN	83.76	75.48	83.64	75.26
BERT-SPC	92.38	83.05	92.02	82.43
AEN-BERT	94.47	85.73	93.73	84.68
R-CAT+BERT	94.61	85.91	94.24	84.88
SSEGCN+BERT	95.05	86.62	94.65	85.74
SEAFM-GCN	**96.47**	**87.89**	**95.22**	**86.48**

Table 2 presents the experimental results of the proposed SEAFM-GCN model compared with baseline models, showing superior performance on both MOOC1 and MOOC2 datasets. The first three models, lacking BERT embeddings, demonstrated limited performance. However, ASGCN, incorporating GCN with syntactic information, achieved relatively good results. Models utilizing BERT significantly improved performance due to pre-trained contextual knowledge. Compared with R-CAT+BERT, the proposed model improved F1 scores by 1.98 and 1.6 points on MOOC1 and MOOC2, respectively, attributed to the integration of hybrid attention and syntactic information, enhancing context-aspect interaction. While SSEGCN+BERT considered syntactic distances in attention computation, it underutilized local context relevant to aspect terms, resulting in lower F1 scores than SEAFM-GCN.

Overall, SEAFM-GCN effectively integrates structural and semantic information from local to global levels, outperforming other models and validating the fusion of syntax and semantics in aspect-level sentiment classification.

4.4 Feature Ablation Experiment

This section analyzes the impact of key modules within the SEAFM-GCN model by conducting extensive ablation experiments. The experimental results were recorded by averaging multiple runs, as shown in Table 3. In the table, “w/o” indicates the removal of a specific module, with the best results highlighted in bold.

Without Phrase Structure Tree (SEAFM-GCN w/o phrase): Retains only the traditional syntactic dependency matrix.

Without Syntactic Distance Mask Matrix (SEAFM-GCN w/o SDMM): Uses only the attention score matrix as the semantic feature map.

Without Aspect-Sensitive Attention (SEAFM-GCN w/o ASA): Replaces the aspect-sensitive attention matrix with a self-attention score matrix as the adjacency matrix, combined with the syntactic distance mask matrix.

Without Self-Attention (SEAFM-GCN w/o SA): Uses only the aspect-sensitive attention score matrix as the adjacency matrix, combined with the syntactic distance mask matrix.

Table 3 Ablation Study Results on MOOC Review Datasets (%)

	MOOC1		MOOC2	
Method	Accuracy	F1	Accuracy	F1
SEAFM-GCN	96.47	87.89	95.22	86.48
w/o phrase	92.18	86.77	91.23	86.12
w/o SDMM	94.43	86.48	92.46	85.89
w/o ASA	95.45	85.64	94.57	84.53
w/o SA	93.42	84.71	93.18	83.22

Conclusions from Ablation Study Results:

(1) Removing the phrase structure tree module led to performance degradation, highlighting the importance of phrase adjacency matrix integration for reducing parsing errors.

(2) The ASA layer improves feature extraction by optimizing noise in the self-attention mechanism. Removing the syntactic distance mask matrix caused a drop in F1 scores by 1.41% and 0.59%, showing its role in enhancing structural information extraction.

(3) Deleting the ASA layer reduced classification performance, demonstrating its contribution to aspect-specific feature extraction. Without ASA, self-attention alone loses aspect-related information, especially with multiple aspects of different sentiments.

(4) Removing the self-attention layer decreased classification accuracy, confirming its importance in extracting global semantic features. The impact was more significant than removing the ASA module, indicating that self-attention benefits final sentiment classification.

4.5 Visualization Analysis

This experiment first verifies the impact of the number of GCN layers on model performance to optimize the model structure and guide subsequent experimental design. Specifically, experiments were conducted with GCN layers ranging from 1 to 5, and the performance at each layer count was evaluated. The results are shown in Table 4, presenting the F1 scores of the SEAFM-GCN model for different GCN layer counts. Additionally, Figure 2 further visualizes the trend of how varying the number of GCN layers affects the model's F1 score on the two datasets. The experiment shows that increasing the number of GCN layers moderately improves the model's performance, but too many layers may lead to a plateau or overfitting.

Table 4 F1 Values of SEAFM-GCN Model at Different GCN Layer Numbers

Number of GCN Layers	1	2	3	4	5
MOOC1	86.23	**87.89**	86.42	87.28	86.16
MOOC2	85.51	**86.48**	85.79	86.35	85.34

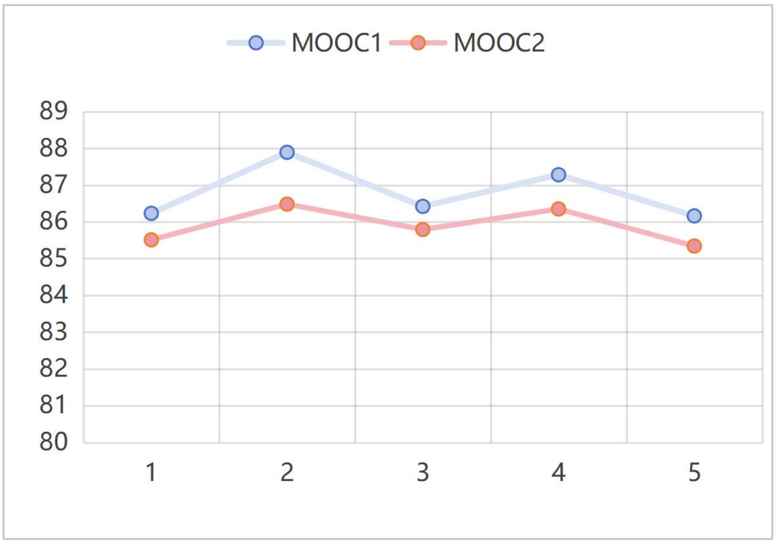

Figure 2 The Impact of GCN Layers on F1 Values

From Figure 2, it can be observed that the number of GCN layers significantly impacts the model's performance on both the MOOC1 and MOOC2 datasets. On the MOOC1 dataset, the best performance (87.89) was achieved with 2 GCN layers, while performance slightly declined with other layer configurations, suggesting that 2 layers of GCN are most effective in balancing information extraction and noise control. The results for the MOOC2 dataset were similar, with 2 GCN layers also yielding the best performance (86.48), although the performance fluctuation was smaller, likely due to the simpler or more robust nature of the dataset. In both datasets, the model's F1 value reached its maximum with 2 layers, indicating that 2 layers should be considered the optimal choice for the number of GCN layers.

5 CONCLUSION

This chapter presents a bidirectional semantic and hierarchical syntactic aspect sentiment classification model (SEAFM-GCN) based on Graph Convolutional Networks (GCN). The model first designs a perception-based aspect attention mechanism to learn aspect-related semantic information, which is then combined with a self-attention mechanism to form a fused attention mechanism. Next, by integrating phrase structure and syntactic dependency structures, it enhances syntactic feature representation, addressing the noise issue in traditional syntactic dependency analysis. Finally, Graph Convolutional Networks are used to further optimize the syntactic features. Experimental results demonstrate that the model achieves significant performance improvement on the MOOC review dataset, validating the effectiveness of the attention mechanism and syntactic enhancement strategy.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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