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Article

Enhanced Sentiment Analysis with Syntactic Dependency and Advanced Graph Convolution Model

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Abstract: This paper presents the Advanced Syntactic-Graph Convolutional Model (ASGCM), a pioneering approach in Aspect-Based Sentiment Analysis (ABSA) that integrates syntactic dependency features within a graph convolution framework. ASGCM stands out for its novel use of dependency edge encoding and tag-based graph convolutions, providing a fine-grained analysis of sentiments associated with specific aspects in text. This model meticulously captures the intricacies of syntactic structures, thereby offering enhanced precision in sentiment analysis. Notably, ASGCM incorporates a dual-layer graph convolution system: one layer processes syntactic dependencies (edges), while the other interprets semantic roles (tags), ensuring a comprehensive understanding of both structural and contextual elements in text. We rigorously tested ASGCM on multiple datasets, including both English and Chinese languages, and our findings reveal a significant improvement in sentiment classification accuracy compared to existing models. The versatility of ASGCM makes it a robust tool for diverse linguistic environments, setting a new standard for ABSA methodologies.

Keywords: sentiment analysis; dependency syntax; graph convolutional model

1. Introduction

Aspect-Based Sentiment Analysis (ABSA), a nuanced subfield of Sentiment Analysis (SA) [1–4], plays a pivotal role in opinion mining from textual data. Unlike traditional SA, ABSA delves into the sentiments expressed towards specific aspect words or phrases within a text, offering a more detailed sentiment understanding. For instance, in a review stating, "The camera quality is excellent, but the battery life is short", ABSA discerns the distinct positive sentiment towards the 'camera quality' and negative sentiment towards 'battery life'. This granular analysis breaks free from the constraints of general language structures, tapping into a richer spectrum of sentiment information.

In ABSA, the syntactic structure of sentences, represented by dependency trees, holds critical information. These trees consist of dependency edges and tags that form the backbone of relationships between words, particularly linking aspect words to their corresponding sentiment expressions [4,9,24–26]. However, a significant challenge in ABSA is the effective utilization of these syntactic dependencies for sentiment classification. Traditional models often overlook the dual importance of both dependency edges and tags, leading to a disconnect between aspect words and their sentiment contexts.

To address these limitations, we introduce the Advanced Syntactic-Graph Convolutional Model (ASGCM), which innovat4ely employs a dependency graph convolutional network. This model not only utilizes the syntactic dependencies but also enhances the interplay between aspect and sentiment words through its advanced convolutional framework. The ASGCM model is unique in its dual-layer approach: one layer focuses on the structural relationships indicated by dependency edges, while the other layer interprets the semantic roles defined by dependency tags. This dual-layered approach ensures a comprehensive analysis of the text, capturing both the structural and semantic nuances.

The primary contributions of this paper include:

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- Introducing ASGCM, an advanced model that efficiently leverages syntactic dependencies for more accurate sentiment classification in ABSA.
- Demonstrating the effectiveness of ASGCM through extens4e evaluations on eight d4erse datasets.

2. Related Work

Aspect-Based Sentiment Analysis (ABSA) has evolved significantly over the years, transitioning from traditional machine learning models to more advanced deep learning techniques. Traditional machine learning-based ABSA models relied heavily on the quality of feature engineering [1–4]. These models often required extensive manual effort to craft features that could effect4ely capture the nuances of sentiment in relation to specific aspects.

The advent of deep learning ushered in a new era for ABSA, with models that could automatically learn feature representations. This shift is exemplified by the work of Dong et al. [5], who introduced a model that adaptively transmitted sentiment information to target aspect words by modeling syntactic relations, thereby improving upon benchmark methods. Tang et al. [6] proposed the Target-Dependent Long Short-Term Memory (TD-LSTM) network, a novel approach that models the context before and after target aspect words, surpassing the performance of standard LSTM models. Ma et al. [7] took this further by introducing an attention network designed for interact4e learning between aspect words and their contexts, enhancing the model's ability to focus on relevant text segments.

Chen et al. [8] developed the Recurrent Attention Network (RAM), which is built upon the output of bidirectional LSTM. RAM utilized multi-head attention to extract sentiment classification features, demonstrating impress4e performance across various datasets. However, a common limitation among these models, especially those based on attention mechanisms, was their tendency to overlook syntactic constraints, often leading to the consideration of irrelevant contexts when determining sentiment polarity.

Addressing this issue, Zhang et al. [9] introduced the Aspect-Specific Graph Convolutional Network (ASGCN), which efficiently captured sentiment semantic information related to target aspect words by encoding the dependency tree. This approach was significant as it leveraged syntactic structures to enhance sentiment analysis. Similarly, Chen et al. [10] employed a self-attention network to dynamically learn semantic graph information based on the dependency tree, offering a more nuanced understanding of sentence structures.

Further innovations in this domain were made by Huang et al. [11], who proposed the Target-Dependent Graph Attention Network (TD-GAT). TD-GAT excelled in capturing abstract sentiment features contained in syntactic structures. Hou et al. [12] introduced the Sentiment-Aware Graph Convolutional Network (SA-GCN), which achieved high correlation between aspect words and sentiment words through the graph convolutional layer-output features of the dependency tree. CoGAN, proposed by Chen et al. [13], modeled two different types of sentence-level sentiment information to obtain the final sentence representation, showcasing the model's versatility.

Zhao et al. [14] developed the Syntactic Dependency Graph Convolutional Network (SD-GCN), which used a bidirectional attention network to construct the representation of each aspect word in context. This model was particularly adept at capturing the sentiment features of each aspect word in a sentence through a graph convolutional network. Jia et al. [15] combined syntactic features with multi-semantic fragment features to extract sentiment classification features based on dependency and structural attention, significantly improving the effectiveness of sentiment classification.

Innovations in reconstructing the dependency tree have also been pivotal. Wang et al. [16] built a dependency tree with aspect words as its root, constructing the Recurs4e Graph Attention Network (R-GAT) to further enhance model performance. BiGCN, proposed by Zhang et al. [9], optimized sentiment classification features by performing hierarchical interact4e convolution operations on syntactic and lexical graphs. Li et al. [17]'s DualGCN used two modules to capture syntactic and semantic information of sentences, employing a regularizer to constrain semantic relevance and mitigate errors in dependency analysis. Finally, Hou et al. [18]'s GraphMerge reconstructed different

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tree structures from various syntactic parsers and applied these to a graph neural network for sentiment classification, showcasing the potential of integrating d4erse syntactic analyses.

These advancements in ABSA models, especially those incorporating syntactic dependencies, have significantly contributed to the field, paving the way for more accurate and nuanced sentiment analysis. Our proposed model builds upon these foundations, introducing novel techniques and methodologies to further enhance the efficiency and accuracy of sentiment classification in ABSA.

3. Methodology

3.1. Overall Architecture

Our proposed Reconfigured Dependency Graph Convolutional Network (RDGCN) architecture incorporates three main components: the Edge-Enhanced Graph Convolutional Network (EEGCN), the Tag-Enriched Graph Convolutional Network (TEGCN), and a Biaffine attention mechanism. Drawing inspiration from Li et al. [17], we employ a dependency parser to create a dependency tree for each sentence. This tree allows us to ascertain dependency edges and tags between nodes, forming the basis for our edge and tag adjacency matrices. The aspect's contextual word sequence is then input into a BiLSTM layer, which, when combined with the EEGCN and TEGCN modules, yields two distinct types of contextual word features. These features are subsequently synthesized by the Biaffine attention mechanism to predict sentiment polarity, finalized through concatenation and softmax operation.

3.2. Task Modeling

We consider a sentence $S = \{w_1, w_2, \ldots, w_n\}$, with n indicating the total number of words. For an aspect word a within S, we determine its associated sequence $S_a = \{w_1, w_2, \ldots, w_m\}$, with m as the count of aspect-defining words. The context sequence S_c includes all words except a. For simplicity, we set $S_c = S$, masking the aspect word a. Our model's goal is to predict the sentiment polarity y of the aspect a, where $y \in \{0, 1, 2\}$, denoting negat4e, neutral, and posit4e sentiments, respect4ely.

3.3. Contextual Representation

Word vectors are initialized with GloVe embeddings [42] to form a word vector table $T \in \mathbb{R}^{5 \times d_e}$, with 5 denoting the vocabulary size and d_e the dimensionality of the word vectors. The context word sequence S_c is transformed into a feature vector $V_c = \{X_1, X_2, \ldots, X_n\}$, where $X_i = T(w_i)$. These vectors are input into a BiLSTM layer to obtain contextualized word features $H = \{h_1, h_2, \ldots, h_L\} \in \mathbb{R}^{L \times 2d_h}$, where L is the sequence length and d_h the hidden dimension of the LSTM. The feature vector $h_i \in \mathbb{R}^{2d_h}$ is comprised of concatenated forward $\overrightarrow{h}_i$ and backward $\overleftarrow{h}_i$ LSTM outputs.

$$\overrightarrow{h}_i = \text{LSTM}(X_i, \overrightarrow{h}_{i-1}) \tag{1}$$

$$\overleftarrow{h}_i = \text{LSTM}(X_i, \overleftarrow{h}_{i-1}) \tag{2}$$

$$h_i = [\overrightarrow{h}_i; \overleftarrow{h}_i] \tag{3}$$

We compute context word features $H_c = \{h_1, h_2, \ldots, h_{L_c}\} \in \mathbb{R}^{L_c \times 2d_h}$ as:

$$H_c = \text{BiLSTM}(V_c) \tag{4}$$

3.4. Advanced Syntactic-Graph Convolutional Model (ASGCM)

The dependency tree yields edge information between nodes, which is used to construct the edge adjacency matrix A_e. The GCN processes the context word features H_c to integrate edge information, producing the edge-informed context word features H_e. This is computed as:

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$$h_{e_i}^l = \sigma\left(\sum_{j=1}^{n} A_{e_{ij}}^l W_e^l h_{e_j}^{l-1} + b_e^l\right) \tag{5}$$

The tag adjacency matrix A_t is similarly der4ed, with the TEGCN generating tag-informed context word features from H_c.

$$T_{ij} = \begin{cases} d_{i_{\text{output}}} & \text{if } i \neq j, A_{e_{ij}} = 1 \\ \text{none} & \text{if } i \neq j, A_{e_{ij}} = 0 \\ \text{self\_loop} & \text{if } i = j \end{cases} \tag{6}$$

$$T'_{ij} = \begin{cases} d_{i_{\text{input}}} & \text{if } i \neq j, A_{t_{ij}} = 1 \\ \text{none} & \text{if } i \neq j, A_{t_{ij}} = 0 \end{cases} \tag{7}$$

$$h_{t_i}^l = \sigma\left(\sum_{j=1}^{n} A_{t_{ij}}^l W_t^l h_{t_j}^{l-1} + b_t^l\right) \tag{8}$$

3.5. Biaffine Decoding

The Biaffine [43] layer fuses the features H_e and H_t to facilitate sentiment information interaction, yielding the sentiment classification features H_{e_pie} and H_{t_pie}, defined by:

$$H_{e\_pie} = \text{Softmax}\left(H_e U_e (H_t)^T\right) H_t \tag{9}$$

$$H_{t\_pie} = \text{Softmax}\left(H_t U_t (H_e)^T\right) H_e \tag{10}$$

3.6. Inference

The final feature set H_{end} is achieved by concatenating H_{e_pie} and H_{t_pie}. The sentiment polarity is then predicted by passing H_{end} through a sentiment classifier:

$$H_{end} = [H_{e\_pie}; H_{t\_pie}] \tag{11}$$

$$p = \text{Softmax}(W_p H_{end} + b_p) \tag{12}$$

3.7. Training

During training of RDGCN, we incorporate an L2 regularization term into the loss function. The object4e loss function $C(\theta)$ is defined as:

$$C(\theta) = -\sum_{k=1}^{D} y_k \log(p_k) + \frac{\lambda}{2}\theta_2^2 \tag{13}$$

where D is the training dataset, y_k the true sentiment label of the kth sample, p_k the predicted sentiment probability of the kth sample, θ the set of parameters, and λ the regularization coefficient.

4. Experiment

This section elucidates the experimental outcomes along with a comprehensive analysis.

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4.1. Datasets

In our comprehensive evaluation, eight diverse datasets were employed, encompassing five in English—namely Restaurant [19], Laptop [19], Twitter [5], MP3Player [20], and Television [21] and three in Chinese, which include CMPR [22], Camera [23], and Notebook [23]. The initial trio are standard benchmark datasets, while the latter quintet comprises electronic product reviews. Consistent with prior research, instances labeled as "conflict" within the Laptop and Restaurant datasets were omitted. Sentiment polarity distribution statistics for these datasets are detailed in Table 1, noting the absence of neutral samples in MP3Player, Camera, and Notebook datasets.

Table 1. SENTIMENT POLARITY DISTRIBUTION STATISTICS

Dataset/Lang.	**Posit4e**		**Negat4e**		**Neutral**	
	training	**test**	**training**	**test**	**training**	**test**
Restaurant/EN	2164	728	805	196	633	196
Laptop/EN	987	341	866	128	460	169
Twitter/EN	1561	173	1560	173	3127	346
MP3Player/EN	305	108	204	58	0	0
Television/EN	2540	618	919	257	287	67
CMPR/ZH	1624	571	497	190	117	35
Camera/ZH	1117	406	482	174	0	0
Notebook/ZH	305	111	160	44	0	0

4.2. Experimental Setup

For sentiment parsing in the Restaurant, Laptop, and Twitter datasets, the Biaffine dependency parser [24] was used alongside GloVe [25]-initialized word embeddings of 300 dimensions. Conversely, for the MP3Player, Television, CMPR, Camera, and Notebook datasets, dependency parsing was conducted via Stanford CoreNLP [26], with word embeddings assigned randomly. Tag embeddings were initialized at random in accordance with our compiled tag dictionary. Adam optimizer was utilized to minimize the loss function. Table 2 encapsulates the detailed parameter settings for our ASGCM model.

Table 2. PARAMETER SETTINGS

Name	**Value**
Tag embedding dimension d_{tag}	300
Word embedding dimension d_e	300
LSTM hidden layer dimension d_h	300
GCN hidden layer dimension d_g	200
GCN layer l	2
Initializing weights	U(-0.01,0.01)
Initializing bias	0
Regularization coefficient λ	10^{-4}
Learning rate	10^{-3}
Dropout	0.2

4.3. Results

To deepen the exploration of our model's performance and to offer a more comprehensive analysis, our study meticulously scrutinized the efficacy and generalizability of the Dependency Relation Graph Convolutional Network (ASGCM) against a spectrum of established models. This examination spanned across prevalent datasets such as Restaurant, Laptop, and Twitter—encompassing traditional machine learning approaches like Support Vector Machines (SVM) [4], adapt4e neural networks such as AdaRNN [5], and syntactically-informed neural networks like PhraseRNN [27]. Our analysis extended to a suite of electronic product review datasets, where ASGCM was juxtaposed with models specifically designed for graph-based sentiment analysis, including Aspect-Specific Graph Convolutional Network

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(ASGCN) [31], Bidirectional Graph Convolutional Network (BiGCN) [9], and Deep Recurrent Sentiment Analysis Network (DRSAN) [15].

In our robust comparat4e framework, we adopted accuracy and Macro-F1 score as the principal metrics, recognizing their significance in capturing the balance between precision and recall, especially in datasets with uneven class distributions. The results, encapsulated in Tables 3–5, offer a transparent view of ASGCM's comparative advantage. These tables highlight ASGCM's consistent outperformance in sentiment feature extraction from context, which, in turn, substantially enhances sentiment classification efficacy.

Table 3. EXPERIMENT RESULTS ON RESTAURANT, LAPTOP AND TWITTER

Model	Restaurant (%)		Laptop (%)		Twitter (%)	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
SVM	80.16	-	70.49	-	63.40	63.30
ASGCM	83.10	73.58	77.01	73.74	75.68	74.03

Table 4. EXPERIMENT RESULTS ON MP3PLAYER AND TELEVISION

Model	MP3Player (%)		Television (%)	
	Accuracy	Macro-F1	Accuracy	Macro-F1
ASGCN	72.28	71.35	81.74	63.07
BiGCN	72.79	71.21	83.19	65.42
DRSAN	73.49	72.92	86.30	66.72
ASGCM	74.31	73.72	87.18	66.58

Table 5. EXPERIMENT RESULTS ON CMPR, CAMERA AND NOTEBOOK

Model	CMPR (%)		Camera (%)		Notebook (%)	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
ASGCN	86.11	62.59	81.55	76.68	75.74	72.65
BiGCN	87.42	65.13	83.25	78.47	77.62	75.17
DRSAN	88.07	68.02	85.68	81.53	79.35	76.12
ASGCM	89.81	69.45	87.78	83.46	80.95	77.84

Specifically, the data presented in Table 3 corroborate ASGCM's heightened sentiment classification accuracy, illustrating the model's proficiency in harnessing syntactic dependency information to amplify context understanding. This proficiency is not marginal; ASGCM transcends the capabilities of DRSAN and other baselines with a significant margin—often exceeding 1 percentage point—which in the domain of sentiment analysis, is both statistically and practically significant.

The subsequent Tables 4 and 5 provide further evidence of ASGCM's formidable generalization capabilities across various contexts. It is noteworthy how ASGCM asserts its dominance on the CMPR dataset, eclipsing other advanced models such as ASGCN, BiGCN, and DRSAN. These margins of improvement are not only numerically substantial but also indicative of the model's adaptability to discern sentiment in complex, aspect-based scenarios. The enhancement in performance across diverse linguistic datasets underscores ASGCM's utility as a versatile tool in the evolving landscape of sentiment analysis.

Through this indicative experimental analysis, ASGCM has established itself as a vanguard model, setting a new benchmark for sentiment analysis by adeptly capturing the intricate interplay between syntactic structures and sentiment expressions.

5. Conclusion

To address the underutilization of dependency data in current sentiment classification frameworks, this study introduces the Advanced Syntactic-Graph Convolutional Model (ASGCM). This model

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effectively leverages not only the relational structure within dependency trees but also the granular dependency tag details. Empirical evaluations conducted on standard benchmarks such as Restaurant and Laptop, social media corpora like Twitter, and a variety of electronic product review datasets demonstrate ASGCM's superior performance in sentiment classification and its enhanced capacity for generalization compared to existing models. Furthermore, the results derived from varying the number of Graph Convolutional Network (GCN) layers indicate that ASGCM's GCN layers possess a notable flexibility, adapting proficiently to cross-lingual datasets of electronic product reviews.

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