SDGCN : Span Dual-Channel Graph Convolutional Networks for Aspect Sentiment Triplet Extraction

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***Abstract*—Aspect Sentiment Triplet Extraction (ASTE) identifies terms of aspect, terms of opinion, and sentiments in text. Early approaches to the ASTE task, used token-level models, were prone to errors during decoding, affecting accuracy. Span-level models address this by capturing interactions between aspect and opinion spans. But encounters challenges due to sentence encoding methods that primarily rely on contextual data without utilizing syntactic and semantic information. This limitation lead to an inaccurate interpretation of complex sentiment interactions.This study proposes a span-based model that combines syntactic encoding through dependency parsing and graph convolutional networks, along with semantic encoding using multi-head attention and graph convolutional networks. Experimental results on four public datasets show the model achieves a precision of 74.9%, recall of 67.12%, and F1 score of 71.7%, providing an average improvement of 3% over span-based methods in aspect sentiment triplet extraction.**

***Index Terms*—Aspect Sentiment Triplet Extraction, Multi-head Attention, Graph Convolutional Networks**

I. Introduction

Aspect-based Sentiment Analysis (ABSA) [1] focusing on understanding opinions tied to specific aspects of products or services. Within ABSA, Aspect Sentiment Classification and Extraction (ASCE) plays a significant role in predicting sentiment polarity for given aspect targets, such as Fig 1. "Service". However, assuming the aspect target is always available is often impractical [2] [3] [4]. To address this, Aspect Target Extraction (ATE) has been developed to identify specific aspect terms from text [5] [6] [7], while Opinion Target Extraction (OTE) expands on this by extracting broader opinion terms and determining the sentiment associated with them [8].

Another essential task in ABSA, known as Aspect-Opinion Pair Extraction (AOPE), aims to extract terms that connect aspects with opinions, creating a detailed profile of products or services through aspect-opinion pairings [9] [10] [11]. Recently, Extracting Aspect Sentiment Triplets (ASTE) has emerged as a new subtask in ABSA, providing a more comprehensive view of sentiment by identifying aspect, opinion,

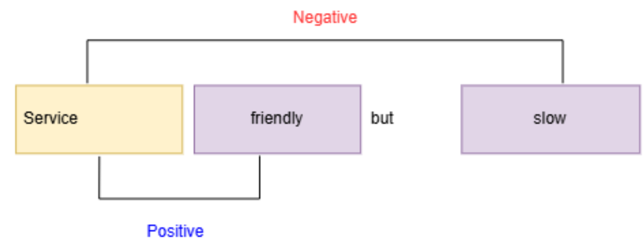

Fig. 1. Typical of ASTE

and sentiment as triplets. For instance, an ASTE task might extract triplets such as Fig 1. ("Service" "friendly" Negative) and ("Service" "slow" Negative), offering deeper sentiment insight than aspect-opinion pairs alone.

Early approaches to the ASTE task [12] [13] [14] relied on sequential token-level techniques, treating the task as a sequence tagging problem. However, these methods face limitations, as their sequential token-level models are susceptible to cascading errors during decoding, which affects the precision of triplet extraction. In response, span-level model aimed at improving ASTE by capturing interactions between spans of aspect terms (ATs) and opinion terms (OTs) that share tokens [15]. This approach involves generating all possible spans as input, which has shown promising results, but still encounters challenges, especially in sentence encoding.

Current sentence encoding in ASTE models primarily rely on the sequential order of words to form embeddings for each span. This approach treats each span as a linear sequence, focusing on the words' positions relative to one another without fully capturing deeper linguistic structures. As a result, this method often overlooks essential syntactic structures, such as dependency relationships between words, which provide valuable clues about grammatical roles and hierarchical rela-

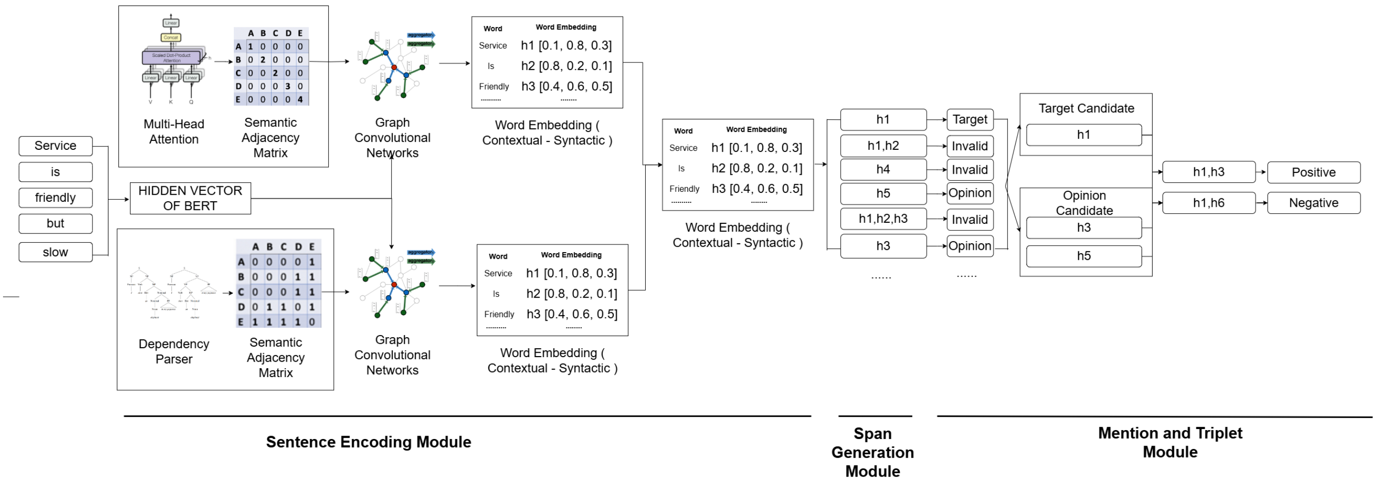

Fig. 2. SDGCN Architecture

tionships in a sentence. Additionally, relying solely on word order limits the model's ability to capture semantic relationships that can span across non-adjacent words or phrases. For example, certain aspect-opinion relationships are not expressed in a simple, linear manner but are instead connected through complex dependencies. By not incorporating syntactic and semantic correlations [16], current sentence encoding may lack the nuanced understanding necessary to accurately identify and interpret complex sentiment interactions in text, potentially leading to incomplete or inaccurate triplet extractions.

To address these challenges, proposed Span Dual-Channel Graph Convolutional Networks (SDGCN), designed to improve ASTE. Our model leverages both syntactic and semantic information to create comprehensive sentence representation. This allows the model to generate consistent sentiment predictions across spans. Experimental results across four public datasets demonstrate that our model has better performs than current baselines, highlighting its effectiveness in extracting sentiment triplets more accurately and robustly.

II. Related Works

The span-based approach was introduced to overcome the limitations of sequential models by better capturing long-range dependencies between aspect and opinion terms [15]. improved ASTE by using word spans as input features, increasing extraction accuracy. However, many of these models focus on either syntactic or semantic information, limiting their performance.

To address this, the SDGCN was proposed. It uses both syntactic and semantic channels to provide a richer sentence representation, capturing both sentence structure and meaning. This approach improves on previous methods. SDGCN has shown better performance on various datasets, with improved precision, recall, and F1 scores, marking a significant advancement in ABSA by effectively tackling challenges related to sentence structures and dependencies [17].

III. Methodology

The overall modules shown in Fig 2. In this section, we start by outlining the triplet extraction problem. Then, we provided a detailed introduction to the modules of SDGCN.

A. Task Definition

The task focuses on extracting sentiment triplets from a given text, denoted as W, which is a sequence of n words. Within this sequence, each possible span is represented as $\{(i, j)\}$, where i and j indicate the start and end positions of the span, respectively. The maximum allowable span length is constrained to L_{max}. Each extracted triplet is composed of three components: Terms of Target, Terms of Opinion, and Sentiment (Positive, Negative and Invalid).

B. Sentence Encoding Module

In this section, the methodology for encoding sentence with dual-channel GCN divided into three primary module: contextual encoding with BERT, syntactic encoding with GCN (syntacticGCN), semantic encoding with GCN (SemanticGCN), concenate syntactic-semantic.

*1) **Contextual Encoding with BERT**:* BERT [18] is one of the pre-trained language models, used to acquire the contextualized embedding. Each word is processed through BERT, generating a hidden state vector for each. When a word is tokenized into multiple sub-word units, we apply mean pooling to combine these sub-word vectors into a single representation, capturing the complete meaning of the word. The BERT representations are defined as $H_{\text{BERT}} = \{h_1, h_2, \ldots, h_n\}$.

*2) **Syntactic Encoding with GCN (syntacticGCN)**:* The syntacticGCN module employs syntactic encoding for graph-based learning, utilizing an adjacency matrix derived from a dependency parser. This matrix encodes relationships between words by reflecting their syntactic dependencies within the sentence, generated using the Spacy dependency parser.

SyntacticGCN taking the hidden state vectors, $H_{\text{BERT}} = \{h_1, h_2, \ldots, h_n\}$, generated by BERT for node representation

TABLE I
DATASET STATISTIC

Dataset	Train				Validation				Test			
	#TOTAL	#POS(+)	#NEG(-)	#INV(x)	#TOTAL	#POS(+)	#NEG(-)	#INV(X)	#TOTAL	#POS(+)	#NEG(-)	#INV(X)
14-Rest	906	817	517	126	219	169	141	36	328	364	116	63
15-Rest	605	783	205	25	148	185	53	11	322	317	143	25
16-Rest	857	1015	329	50	210	252	76	11	326	407	78	29
14-Lapt	1266	1692	480	166	310	404	119	54	492	773	155	66

each word in the text. These vectors serve as the initial representations of the nodes in the syntactic graph. Next, constructed an adjacency matrix $A_{\text{syn}}(i, j)$ of size $n \times n$ that represents the syntactic relationships between words i and word j in the sentence. The matrix is created using the syntactic dependencies.

Using the adjacency matrix A_{syn} and the hidden state vectors H_{BERT}, we update the node representations in the graph through the GCN layer [19]. This is done by applying the Eq. 1 to update the node i's representation at the l layer.

$$H_{\text{i}}^{l} = \sigma\left(A_{\text{ij}} H_{\text{j}}^{l-1} W_{\text{l}} + b_{\text{l}}\right) \tag{1}$$

After several iterations of GCN, we obtain the final node representations H_{i} that incorporate both the original contextual information from BERT and the syntactic relationships between words. The result of all vectors is given by the formula $H_{\text{SYNTACTIC}} = \{h_1, h_2, \ldots, h_n\}$.

*3) **Semantic Encoding with GCN (SemanticGCN)**:* SemanticGCN module aims to capture semantic relationships between words in addition to syntactic information. This module generates an attention matrix as the adjacency matrix, which contrasts with the syntactic approach of SyntaticGCN.

SemanticGCN uses multi-head attention [20] to generate an attention matrix A. In multi-head attention, each attention head computes with a separate attention score matrix A_i with the Eq.2.

$$A_i = \text{softmax}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right) \tag{2}$$

After computing the attention scores for each head, the results are concatenated and passed through an output weight matrix W_O :

$$A = \text{concat}(A_1, A_2, \ldots, A_h) W_O$$

This produces a combined attention matrix A that captures the semantic relationships between words in a text. Attention matrix A is then used as the adjacency matrix in a GCN layer along with H_{BERT}, where the node representations are updated by aggregating information from their semantically related words. The update rule using Eq. 1

After several iterations of GCN, we obtain the final node representations H_{i} that include both contextual information and semantic, enabling the model to effectivelty capture the meaning of words in the sentence and their relationships.The result of all vectors is given by the formula $H_{\text{SEMANTIC}} = \{h_1, h_2, \ldots, h_n\}$.

*4) **Concenate syntactic-semantic**:* To integrate both syntactic and semantic information into a unified representation, we employ a concatenation approach, merging the output vectors from the semantic and syntactic channels along the feature dimension. Formally, given $H \in \mathbb{R}^{n \times d}$. Where n denotes the number of nodes (e.g., tokens or aspects) and d represents the dimensionality of each feature vector, we concatenate these matrices along the last dimension to produce a combined feature representation $H_{\text{combined}} \in \mathbb{R}^{n \times 2d}$. This concatenated representation, H_{combined}, effectively integrates both channels, enabling the model to leverage syntactic dependencies alongside semantic relationships.

C. Span Generation Module

Defined the span representation for H_{combined} s_{ij} as follows:

$$s_{ij} = [h_i; h_j; f_{\text{width}}(i, j)]$$

where $f_{\text{width}}(i, j)$ refers to a trainable embedding representing the span's width, defined as $j - i + 1$. To compute this value, the representations of the beginning token, ending token, and span width are concatenated. Additionally, to create the concatenation of the start token, end token, and span width representations, max-pooling or mean-pooling is applied to all token embeddings within the range from position$i$ to j, with the goal of summarizing the information from all tokens in the span into a single representation.

D. Mention and Triplet Module

Mention Module leverages a dual-channel span pruning strategy to identify target and opinion spans prediction. It utilizes the ATE and OTE tasks to guide the pruning process. Each span is predicted as either a target, opinion, or invalid using a softmax function based on its score. To reduce computational complexity, two separate pools are formed for target and opinion spans, selecting candidates based on the predicted mention scores.

After pruning, the top nz spans are selected for each pool, with n being the sentence length and z a threshold parameter. The model is trained in a fully integrated manner, benefiting from the supervision provided by the ATE and OTE tasks.

Target-opinion pairs are created by concatenating the target and opinion candidate representations, along with a distance feature that captures the relative position of the spans. Then, the pair is input into a neural network to determine the sentiment corresponding with it.

An "Invalid" sentiment label indicates that no valid sentiment relationship exists between the target and opinion pair. This approach effectively extracts valid aspect-sentiment triplets for sentiment analysis.

E. Training

The learning goal is designed to reduce the combined negative log-likelihood from both the mention and triplet modules. This objective involves calculating the log-likelihood of the predicted mention type for each span, as well as the sentiment relation between pairs of target and opinion spans. Predicted mention types are compared to their gold-standard labels, and predicted sentiment relations are matched with the gold-standard sentiment for each target-opinion pair. The set of spans, S, includes all possible spans, with S_t and S_o representing filtered sets of target and opinion spans, respectively. As a performance evaluation procedure across various approaches, three metrics are used: precision, recall, and F1 score.

IV. Result and Discussion

A. Dataset

SDGCN using four datasets [21], three of which are from restaurant reviews and one from laptop reviews. These datasets are refined versions from the SemEval Challenge [22], where opinion terms have been explicitly extracted to better support aspect-based sentiment analysis tasks [23]. Detailed statistics for each dataset, such as the total number of terms and sentiment labels, are presented in TABLE I, providing a comprehensive breakdown of the data distribution.

Unlike conventional approaches, no pre-processing was applied to the datasets in this study. This decision was made to allow the model to learn the inherent meaning of the data in its entirety, avoiding potential loss of contextual and semantic information during pre-processing. This approach aligns with prior models, which similarly refrained from pre-processing to focus on end-to-end learning of raw data.

The selection of these datasets was also based on their widespread use in previous studies, ensuring comparability with existing models and benchmarks. By utilizing the same datasets as prior research, this study aims to provide a fair evaluation of the proposed model's performance while contributing to the ongoing development of aspect-based sentiment analysis methodologies.

B. Baseline

our model compare with SPAN-ASTE [15], which serves as our baseline. SPAN-ASTE has been established as a leading model in the field, consistently outperforming other models in aspect sentiment triplet extraction tasks, making it a reliable choice for comparison.

To enhance its functionality for our study, we modify SPAN-ASTE by incorporating both semantic and syntactic information. This modification aims to capture more comprehensive contextual dependencies within the spans, which can lead to more accurate and insightful extraction of triplet relationships. By enriching the span-based model with semantic and syntactic information, we hope to address potential limitations and improve upon the already high standards set by SPAN-ASTE.

Our approach ensures a fair and competitive baseline that aligns with our goal to create a more context-aware and linguistically robust model for this task.

C. Comparison Result

Comparison between our models and SPAN-ASTE shown in TABLE II. SDGCN outperforms SPAN-ASTE across all datasets and evaluation metrics, achieving an average performance improvement of up to 3%. This consistent advantage highlights SDGCN's robustness and efficiency in aspect sentiment triplet extraction tasks, validating the impact of its enriched design. SDGCN's integration of semantic and syntactic information provides a deeper understanding of contextual relationships, contributing to an accuracy improvement over SPAN-ASTE by capturing nuances in sentence structure that the baseline may miss; this also enhances precision by reducing false positives and correctly filtering out irrelevant triplets—especially valuable in applications requiring high precision, where SDGCN's additional contextual layers help clarify complex or overlapping sentiments; the syntactic layer in SDGCN further broadens recall, enabling it to identify a more comprehensive set of valid triplets even in linguistically complex sentences, leading to a more thorough extraction; finally, the balance of precision and recall in SDGCN yields an increase in F1 score across datasets, reflecting its consistent ability to maintain both accuracy and completeness in triplet extraction, unlike SPAN-ASTE, which struggles to sustain this balance in datasets with diverse sentence structures and sentiment expressions.

D. Ablation Study

1) ***SyntacticGCN and SemanticGCN****:* The results presented in TABLE II demonstrate that incorporating either syntactic or semantic representations into SPAN-ASTE independently leads to improvements across all metrics. Specifically, the addition of syntactic information yields higher performance compared to the inclusion of semantic information alone. This suggests that the syntactic representation enhances the model's understanding of sentence structure more effectively. However, when both SyntacticGCN and SemanticGCN are combined, further improvements are observed. The integration of both representations offers a deeper understanding of the text, enabling the model to better capture aspect-sentiment relationships. These findings highlight the effectiveness of combining syntactic and semantic information to achieve higher accuracy and F1 scores, demonstrating that each type of representation contributes uniquely to the model's performance. Therefore, this study explores the synergy between both syntactic and semantic layers to enhance the overall results.

The combined use of both SyntacticGCN and SemanticGCN with SPAN-ASTE yields the highest overall performance, with a peak F1 score of 74. alongside improved recall and precision.

TABLE II
COMPARISON RESULT

Model	14-Rest			14-Lap			15-Rest			16-Rest		
	Pr	**Rc**	**F1**	**Pr**	**Rc**	**F1**	**Pr**	**Rc**	**F1**	**Pr**	**Rc**	**F1**
Span-ASTE	72.82	63.56	67.99	64.09	60.44	62.38	69.78	66.93	68.33	69.80	72.18	72.56
SDGCN	75.07	65.22	**69.2**	68.23	64.9	**63.97**	74.9	68.16	**71.7**	72.34	73.50	**74.76**
SDGCN (-Syntactic)	74.67	64.5	68.3	67.34	64.29	63.28	74.18	67.6	70.89	71.32	73.04	73.63
SDGCN (-Semantic)	72.81	63.95	68.0	65.44	63.32	62.45	73.1	67.12	70.28	69.9	72.48	73.08

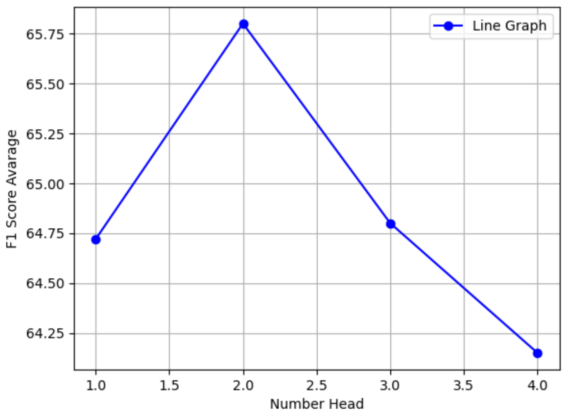

Fig. 3. Examination of impact from Head Number - 14-Lapt

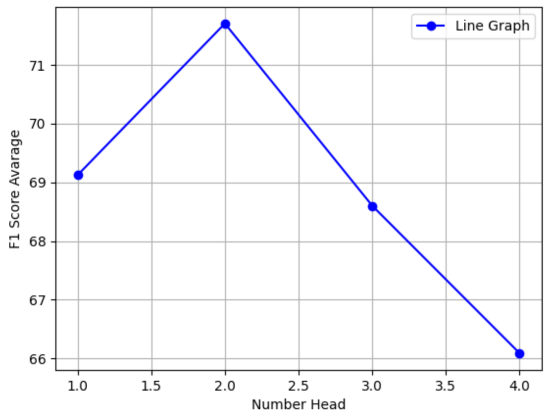

Fig. 4. Examination of impact from Head Number - 15-Rest

This integration effectively balances the precision from syntactic relationships with the broad context provided by semantic understanding. The combined model achieves the best results across all metrics, highlighting the complementary strengths of syntactic and semantic information in enhancing aspect-sentiment triplet extraction, resulting in a more comprehensive and balanced model performance.

*2) **Head Number of Multi-Head Attention**:* We tested 1 to 4 heads mechanism using the Lap14 (Fig 3) to observe the effect of the number of heads on the model's accuracy. and the Res15 dataset (Fig 4). Results showing that using 2 heads achieves the highest accuracy compared to 3 and 4 heads. While the Lap14 dataset shows no significant performance change, the Res15 dataset demonstrates a substantial drop in accuracy as the number of heads expands from 2 to 3 and 4, suggesting that expanding heads from 2 in the Res15 dataset degrades performance, possibly due to overfitting, redundancy, or suboptimal interactions between heads, and thus the optimal number of heads for this model is 2, as both datasets perform better with 2 heads, with Lap14 showing no significant impact from additional heads and Res15 showing a clear reduction in accuracy with more than 2 heads.

V. CONCLUSION

This study presents a span-based model that integrates syntactic encoding via dependency parsing and graph convolutional networks, alongside semantic encoding through multi-head attention and graph convolutional networks, to improve Aspect Sentiment Triplet Extraction (ASTE). The model addresses the limitations of prior approaches that relied heavily on contextual sentence encoding, leading to inaccurate interpretations of complex sentiment interactions. Experimental results demonstrate the model's effectiveness, achieving notable improvements in precision, recall, and F1 score across four public datasets.

However, the approach still faces certain limitations. While the integration of syntactic and semantic encodings improves accuracy, the reliance on dependency parsing may introduce errors in cases of noisy or grammatically incorrect text. Additionally, the computational complexity of combining multi-head attention with graph convolutional networks can pose challenges for scaling the model to larger datasets or real-time applications.

Future work could focus on optimizing the computational efficiency of the model and exploring techniques to enhance robustness against noisy or informal text. Incorporating pre-trained language models fine-tuned for sentiment tasks and developing adaptive methods for handling domain-specific nuances could further improve the performance and applicability of ASTE models.

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