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RESEARCH ARTICLE

Semantic Parsing for Aspect-Based Sentiment Analysis

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ABSTRACT Aspect-Based Sentiment Analysis (ABSA) faces significant challenges in accurately identifying sentiment polarity for specific aspects within complex sentences, particularly when dealing with implicit sentiments, nested structures, and nuanced semantic relationships. This study introduces the Semantic Parsing Tree (SPT), a novel framework designed to enhance ABSA by addressing these limitations. By integrating advanced attention mechanisms, our approach overcomes the limitations of traditional dependency trees, which often fail to capture the complex semantic relationships crucial for accurate sentiment prediction, particularly in intricate sentence constructs such as nested clauses or implicit sentiments. Converting syntactic trees into SPTs enables our model to preserve and analyze key semantic roles and relationships, facilitating precise sentiment analysis at the aspect level. The integration of SPT with an advanced graph-based attention mechanism, augmented by relational heads, enhances the deep encoding of semantic nuances, significantly improving sentiment analysis accuracy. Comprehensive evaluations across benchmark datasets, including SemEval 2014, Restaurant, and Twitter, indicate that this approach outperforms conventional models in both accuracy and adaptability.

INDEX TERMS Aspect based sentiment analysis, graph attention network, semantic parsing tree, semantic relationship.

I. INTRODUCTION

Sentiment analysis has become an essential tool for understanding user opinions across various domains, including product reviews and social media, where it helps businesses and researchers capture consumer attitudes and emotions. However, traditional sentiment analysis methods, which evaluate sentiment at a global level, often fail to capture the nuanced emotions associated with specific aspects of a product or service [1], [2]. In contrast, Aspect-Based Sentiment Analysis (ABSA) offers a more granular approach by focusing on specific facets within textual data [3].

Despite its utility, current ABSA methodologies, particularly those relying on dependency parse trees, exhibit significant limitations. Dependency trees are effective at illustrating syntactic structures and capturing long-term dependencies between opinion words and aspects [4]. However, in sentences with nested clauses or implicit sentiment, they often falter, leading to inaccurate predictions [5]. Moreover, the overemphasis on syntactic patterns often comes at the expense of semantic content, resulting in misinterpretations, especially in contextually rich texts. This limitation is particularly pronounced in dynamic environments such as social media, where diverse linguistic variations–such as slang, abbreviations, non-standard grammar, and evolving terminology, frequently challenge traditional parsing models [6], [7].

To address these challenges, there is a pressing need for a more adaptive and context-sensitive analytical framework capable of accurately decoding the intended sentiments and actions by recognizing semantic roles and relationships that go beyond mere syntactic configurations [8]. As depicted in

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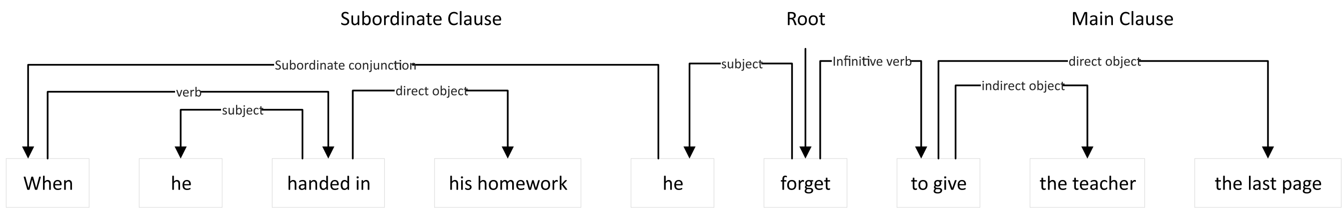
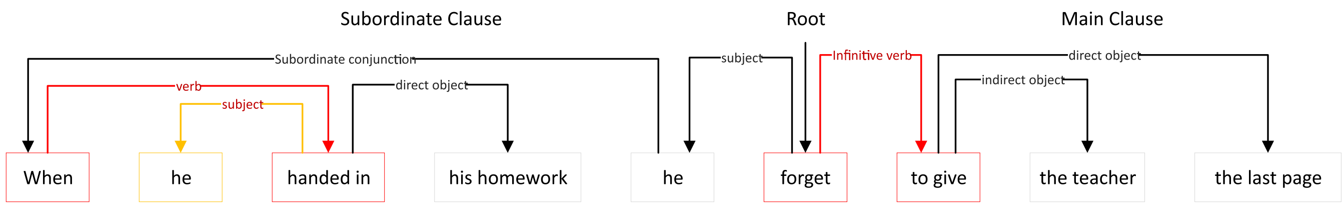


(a)



(b)

FIGURE 1. This diagram represents the syntactic structure of the sentence "When he handed in his homework, he forgot to give the teacher the last page."

Fig. 1, the traditional dependency tree, part (a), simplifies the syntactic linkage in complex sentences, leading to a loss of crucial semantic information. This issue is further illustrated in part (b), where the oversimplified linkage between 'forgot' and 'to give' fails to capture the deeper semantic implications critical to understanding the sentence's overarching sentiment. For example, traditional methods may overlook the context in which 'forgot' implies an unintentional omission with emotional or moral consequences, rather than just a failure to perform an action. This lack of nuanced interpretation can lead to misrepresenting the speaker's intent, particularly in cases where the sentiment is subtly embedded in the choice of words and their relationships [9].

In response to these inherent limitations, this paper introduces a pioneering approach centered around the *Semantic Parsing Tree* (SPT) [10]. Unlike traditional methods, our SPT framework complements syntactic analysis with semantic parsing, potentially offering a deeper understanding of the underlying sentiment dynamics within complex sentence structures. By transforming traditional syntactic trees into SPTs, we selectively maintain only those syntactic connections that are crucial for understanding aspect-related sentiments, thereby enhancing the clarity and relevance of syntactic-semantic correlations [11].

Furthermore, we integrate an enhanced Graph Attention Network (GAT) with specialized relational heads to robustly encode the nuanced semantic relationships inherent in the SPT [12]. This novel integration not only represents a significant departure from existing methods but also sets a new direction for future research in ABSA, potentially influencing a wide range of applications in natural language processing. Preliminary evaluations on the SemEval 2014, Restaurant, and Twitter datasets indicate that our model offers substantial improvements in both precision and reliability compared to traditional models, as detailed in Section V.

Our research contributes significantly to the field of Aspect-Based Sentiment Analysis (ABSA) through the following innovations:

- We adapt semantic parsing frameworks for more accurate aspect-level sentiment analysis, allowing our model to differentiate sentiments related to specific aspects within complex sentences.
- We integrate Graph Attention Networks (GAT) with semantic parsing trees to enhance sentiment polarity predictions, particularly in sentences with mixed or complex sentiments.
- We fine-tune BERT specifically for ABSA, improving its ability to capture nuanced sentiments related to different aspects.
- Our approach is validated across multiple datasets, confirming its robustness and effectiveness in various linguistic contexts.

II. RELATED WORK

Traditional methods of aspect extraction typically rely on identifying common noun phrases through dependency links [13]. These methods, while foundational, were often constrained by their dependence on extensive labeled datasets. To overcome this limitation, Latent Dirichlet Allocation (LDA) was enhanced to autonomously categorize and extract features, minimizing the reliance on labeled data [14]. While these early methods laid the groundwork, they were primarily limited by their reliance on manually curated data, making them less flexible in real-world applications where labeled data might be scarce or expensive to acquire.

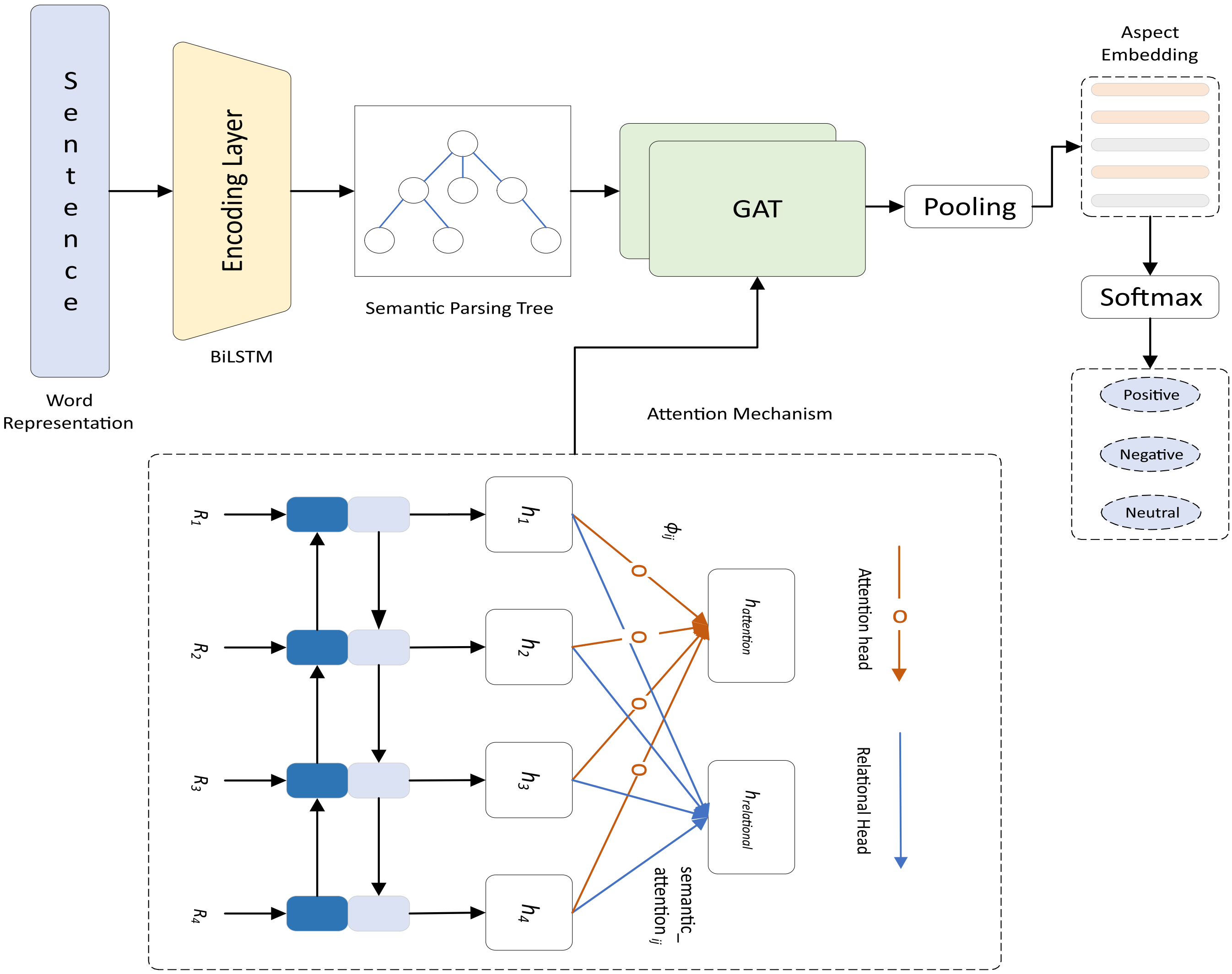


FIGURE 2. **Comprehensive workflow of the semantic parsing tree approach, showcasing the integration of semantic structures with attention mechanisms for enhanced sentiment analysis.**

Subsequent advancements in deep learning have sought to address these challenges by introducing more sophisticated approaches that can process larger, more complex datasets.

Building on the traditional methods, more advanced techniques have sought to enhance aspect-based sentiment analysis (ABSA) by leveraging the power of deep learning. One such advancement is the introduction of Long Short-Term Memory (LSTM) networks in models like TD-LSTM, which uses bidirectional contexts through separate LSTM layers to better identify aspects and their associated sentiment polarity [15]. More recently, convolutional neural networks (CNNs) have been integrated into aspect-level sentiment analysis, allowing for the effective capture of local text features that complement earlier approaches [16], [17]. Additionally, reinforcement learning has been employed for segment-level modeling, which refines aspect-level sentiment classification by focusing on specific sentence segments [18]. These advancements showcase the growing trend of using deep learning techniques to model complex linguistic structures, providing more effective tools for ABSA.

To improve sentiment detection, attention mechanisms and memory networks were introduced. Attention-based LSTM frameworks allow models to focus on pertinent sentiment information related to target aspects, improving overall detection accuracy [19]. Further advancements include multi-layer attention mechanisms, which bridge long-distance opinion terms across multiple aspects [20]. Memory Networks employ external memorization along with multi-hop attention to enhance aspect extraction and sentiment classification [21]. Such methods contribute to a better understanding of context and sentiment flow, enabling more nuanced sentiment analysis in complex sentences.

In the most recent developments, large language models (LLMs) such as GPT-3.5 and GPT-4 have been fine-tuned for ABSA tasks, pushing the boundaries of sentiment analysis performance. Unlike earlier models like BERT, LLMs benefit from more extensive pre-training on diverse, large-scale datasets, enabling them to capture complex linguistic nuances more effectively [22]. However, LLMs are not without drawbacks. They come with increased computational costs and the risk of overfitting to specific datasets, which can limit their generalizability across domains. Despite these challenges, the incorporation of LLMs has revolutionized ABSA by providing models that can adapt to a variety of real-world datasets and capture highly intricate patterns in sentiment expression.

Another area of advancement is the use of Graph Neural Networks (GNNs), which integrate dependency tree structures to enhance ABSA. These models combine node representations derived from the dependency trees with additional features, improving the accuracy of sentiment classification [23], [24]. Moreover, Graph Attention Networks (GATs) have been employed to effectively encode the relationships between words through attention mechanisms [25], demonstrating significant improvements in aspect extraction. Additionally, some studies have focused on integrating external knowledge into ABSA by leveraging graph-based models to incorporate comprehensive external knowledge sources, which further enhance performance [26]. While these approaches show promising results, they require careful implementation to balance model complexity and external knowledge integration.

Recent studies have also introduced innovative techniques to address specific ABSA challenges. One such contribution is the development of an auto-annotation method for aspect-level sentiment analysis, which simplifies the annotation process and boosts model performance [27], [28]. In a similar vein, domain-specific models have been created to handle social media reviews, particularly in the restaurant industry, where informal and varied linguistic styles often pose significant challenges [29]. Additionally, the exploration of semantic wave techniques and knowledge enhancement methods has been proposed to tackle implicit sentiment analysis, improving ABSA models' ability to capture sentiment in cases where it is not explicitly stated [30].

The integration of these advanced techniques—ranging from attention mechanisms to large language models and graph-based networks—has significantly advanced the field of ABSA. However, many of these approaches still face challenges, particularly in capturing nuanced dependency interactions and effectively linking aspects with their corresponding sentiment. Our research introduces the Semantic Parsing Tree, a novel approach designed to overcome these limitations and provide a more robust solution for aspect-level sentiment analysis. While computational approaches dominate recent ABSA research, our SPT design also draws insights from the linguistic theories of semantic representation and cognitive linguistics.

III. PROPOSED APPROACH

To address the limitations of dependency trees in ABSA, we propose a novel methodology that leverages Semantic Parsing Trees (SPTs) to capture nuanced semantic relationships and enhance sentiment analysis. Our approach begins by constructing a SPT to identify and interpret the semantic roles and relationships that influence sentiment. This tree is enhanced using the Relational Graph Attention Network (RGAT) [12], an adaptation of the Graph Attention Network (GAT) [31], which applies a multi-layered attention mechanism to emphasize connections relevant to sentiment expression. The method progresses through dynamic semantic weighting, reconstruction of semantic data, and culminates in the classification of sentiments into categories such as positive, negative, or neutral, providing a comprehensive and refined sentiment analysis, as depicted in Fig. 2.

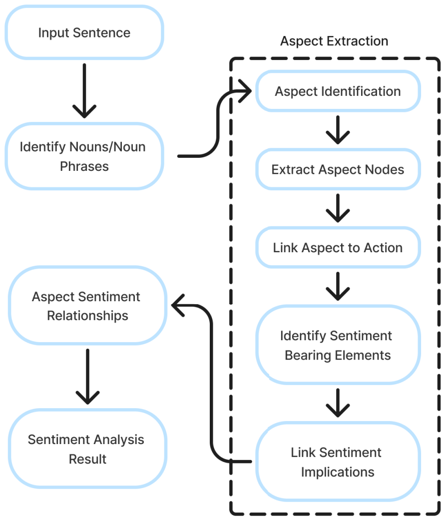


FIGURE 3. This diagram illustrates the step by step process of extracting aspects and analyzing sentiment. It begins with identifying nouns and noun phrases, followed by identifying the aspect. The aspects are linked to actions and sentiment bearing elements, ultimately producing aspect sentiment relationships that lead to the final sentiment analysis result.

A. SEMANTIC PARSING TREE

Semantic parsing extends beyond traditional syntactic analysis by constructing a tree that represents the deeper, intrinsic meanings within a sentence, rather than just its grammatical structure. This method aims to reveal the true semantic relationships among sentence elements, providing a clearer and more precise representation of sentiments and their corresponding opinion expressions.

For Aspect-Based Sentiment Analysis (ABSA), this parsing method is enhanced to specifically target aspect extraction. Aspects are key entities or concepts—typically represented by nouns or noun phrases that influence sentiment. These aspects are the core topics, such as products, services, or specific entities, that are subject to sentiment evaluation. In our methodology, these aspects are extracted as distinct nodes within the SPT, as shown in Fig. 3. These nodes are semantically linked through specific relationships to the actions (verbs) and other sentiment-bearing elements present in the sentence.

For instance, consider the sentence: "When he handed in his homework, he forgot to give the teacher the last page." In this case, the aspect "homework" is identified as a key entity. This aspect node is semantically linked to actions such as "handed" and "forgot," which are further connected to the sentiment implications—such as the consequence of forgetting the last page. The diagram in Fig. 4 illustrates how the aspect node "homework" is linked to these actions and their corresponding sentiment outcomes. Furthermore, extracting these related relations in the SPT allows us to map how different semantic roles interact, thereby providing a clearer understanding of the sentence's meaning and enhancing the accuracy of sentiment analysis. Additionally, domain-specific jargon is handled by integrating specialized vocabularies and contextual embeddings, ensuring that these concepts are accurately represented within the SPT. The relationships depicted in the tree provide insight into how the sentiment is shaped by the interactions between aspects and actions, highlighting the subtleties of human intention that traditional syntactic trees often miss. For example, while "forgot" in the syntactic tree may simply point to an action, the SPT reveals its deeper semantic implication of an unintentional omission, influencing the overall sentiment of the sentence.

As shown in Fig. 4, the Semantic Parsing Tree offers a more refined representation by emphasizing the interactions between aspects, actions, and sentiment-bearing elements. Unlike traditional dependency trees, which focus primarily on syntactic connections, our semantic model clarifies the roles of phrases and their interrelations within the sentence [32]. In this framework, the verb "forgot" is assigned as the root node due to its central role in conveying the primary sentiment-laden action, and the labels on arrows are dynamically determined based on the semantic relationships, allowing node positions to adapt according to their roles in the sentence. The SPT captures the semantic implications of actions such as "forgetfulness"—an aspect often overlooked in traditional models. This is evident in the way our model identifies the "incomplete action" of forgetting, linking it directly to the sentiment implications, like the consequence of not giving the last page to the teacher. Moreover, the SPT distinguishes between different semantic roles within the sentence, such as agent, object, and recipient. In the sentence, "he" is the agent, "homework" is the object or aspect, and "teacher" is the recipient. This differentiation enhances the accuracy of sentiment analysis by clarifying the roles each entity plays in relation to the actions and their corresponding sentiment. The Semantic Parsing Tree provides a comprehensive understanding of how sentence elements work together semantically, significantly improving the interpretation of both meaning and sentiment. This contrast between traditional syntactic analysis and our semantic approach underlines the advantages of the SPT in accurately capturing the underlying sentiment in more complex sentence structures. The interpretability of our model is demonstrated through these semantic relationships, where attention weights (e.g., ϕ_{ij}^{lm} in our RGAT formulation) directly highlight the sentiment-bearing paths from aspects to their polarity decisions.

Algorithm 1 Semantic Parsing Tree

Input: textExpression t, nonLeafNode n
Output: parsed node
function semanticParse (t, n)
nodesList ← empty list
for each grammar rule g **do**
    if n matches the left-hand side of grammar rule g **then**
        pattern ← right-hand side of grammar rule g
        matchedNodes ← optimized PatternMatch(*pattern*, t)
        for each termList in *matchedNodes* **do**
            childNodeList ← empty list
            for i from 0 to size of termList **do**
                childNode ← semanticParse(termList[i], pattern.nonLeafNode[i])
                append *childNode* to *childNodeList*
            end for
            add node (formed by type, t, g, *childNodeList*) to *nodesList*
        end for
    end if
end for
if *nodesList* is empty **then**
    finalNode ← create new Node(type, t, null, empty)
else
    finalNode ← $\text{argmax}_{n \in nodesList}$ sophisticated utility function $g(n)$
end if
if finalNode is not fully parsed **then**
    add *finalNode* to inductionNodes
end if
return *finalNode*

Algorithm 1 outlines the process for constructing SPTs that capture the deeper meanings within sentences by focusing on semantic roles and relationships. The identification of primary semantic elements, such as agents, actions, and objects, is achieved through linguistic analysis techniques that parse the sentence structure to recognize these roles. The process begins by identifying the primary semantic elements of the sentence, such as agents, actions, and objects, and establishing them as root nodes. These identified aspects are then connected to other relevant nodes through dynamic pattern-matching, a method that involves matching the semantic roles (e.g., agent, object, recipient) and relationships (e.g., causality, possession) present in the sentence. In our example, "forgot" (action) is connected to "homework" (object) and "teacher" (recipient) based on their semantic relationships. These aspects are then connected to other

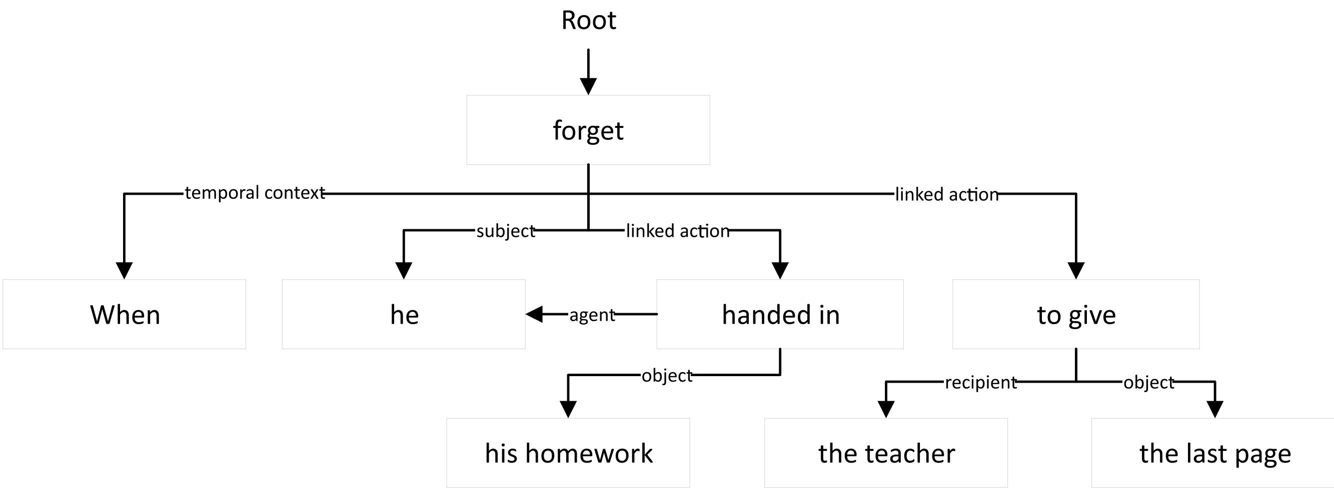


FIGURE 4. **This diagram illustrates the semantic relationships and roles within the same sentence, providing a more accurate depiction of its meaning.**

relevant nodes through dynamic pattern-matching based on semantic roles and relationships. By focusing on these semantic roles and their interrelations, the SPT preserves the integrity of the semantic structure, thereby avoiding the rigid syntactic constraints inherent in traditional dependency trees [32]. It enhances the understanding of complex sentence structures by mapping out clear semantic links, which is particularly beneficial for nuanced text analysis and sentiment detection.

B. ATTENTION LAYERS

Our approach leverages the Relational Graph Attention Network (RGAT) [12], an extension of the Graph Attention Network (GAT) [31], specifically adapted for integrating semantic parsing frameworks within Aspect-Based Sentiment Analysis (ABSA).

In this framework, each node in the graph G represents a semantic entity within a sentence, while the edges represent the connections that capture the relationships between these entities. The RGAT applies a multi-layered attention mechanism to dynamically model these connections, allowing the model to focus on the most relevant parts of the sentence for sentiment analysis.

$$\text{sem\_att\_}h_i^{l+1} = \bigoplus_{k=1}^{K} \sum_{j \in \mathcal{N}_i} \text{semantic\_attention}(i,j) S_k^l \text{sem\_att\_}h_j^l \tag{1}$$

In this equation, $\text{sem\_att\_}h_i^{l+1}$ represents the attention head for node i at layer $l+1$, and S_k^l is a transformation matrix at the k-th attention head, which helps to adjust the focus of the model based on the semantic context.

To capture the intricate relationships and dependencies between different parts of the sentence, our approach leverages additional attention mechanisms that process these connections more effectively:

$$h_i^{l+1} = \bigoplus_{m=1}^{M} \sum_{j \in N_i} \text{softmax}\left(\phi_{ij}^{lm}\right) R_m^l h_j^l \tag{2}$$

$$\phi_{ij}^{lm} = \sigma\left(\text{relu}\left(r_{ij} R_{m1} + b_{m1}\right) R_{m2} + b_{m2}\right) \tag{3}$$

Here, r_{ij} denotes the relational embedding between nodes i and j, and ϕ_{ij}^{lm} captures the interaction between these nodes, allowing the model to better encode the semantic and syntactic relationships critical for accurate sentiment analysis.

By integrating these advanced attention mechanisms, our methodology enhances the model's ability to interpret and synthesize complex semantic structures, leading to improved sentiment analysis outcomes in challenging linguistic contexts.

C. MODEL TRAINING AND OPTIMIZATION

Our training process leverages the RGAT to enhance the representation of SPTs, focusing on capturing deep semantic relationships essential for Aspect-Based Sentiment Analysis (ABSA). Initially, word embeddings for each node within the semantic parsing tree are generated using a bidirectional LSTM (BiLSTM), which helps to encode both the syntactic and semantic nuances of the text.

1) EMBEDDING AND ENCODING

- Leaf Nodes: h_i^0 are encoded via BiLSTM to integrate contextual information.
- Aspect Nodes: A dedicated BiLSTM encodes aspect words, aggregating embeddings into h_a^0 to highlight their significance in the sentiment analysis context.

2) ATTENTION MECHANISM

The proposed model refines node representations through multi-layer attention mechanisms:

$$h_a^l = \text{AttentionMechanism}(h_a^0, \{h_{neighbors}\}) \quad (4)$$

This process dynamically adjusts the focus on crucial semantic links, enhancing the accuracy of sentiment prediction.

3) SENTIMENT CLASSIFICATION

The model projects the enhanced node representations onto sentiment categories using:

$$p(a) = \text{softmax}(T_p h_a^l + b_p) \quad (5)$$

4) OPTIMIZATION

The training is optimized using a cross-entropy loss, which evaluates the model's predictions against actual sentiment labels:

$$L(\theta) = -\sum_{(S,A)\in\mathcal{D}} \sum_{a\in A} \log p(a) \quad (6)$$

where $\mathcal{D}$ is the dataset containing sentence-aspect pairs and θ includes all trainable parameters.

This comprehensive training methodology not only improves the model's understanding of complex language constructs but also ensures it is robust enough to handle the nuances present in dynamic text, such as social media content.

IV. EXPERIMENTAL SETUP

This section provides an overview of our experimental procedures and data choices, detailing how we prepared and evaluated our model in different linguistic and domain contexts. We first describe the datasets we employed and then outline the training protocols, hyperparameters, and performance evaluation.

A. DATASETS

We selected two distinct datasets to evaluate the performance of our SPT model across different domains and linguistic styles. Each dataset presents unique challenges related to sentiment analysis, ranging from formal reviews to informal social media posts. The details of each dataset are as follows:

1) SEMEval 2014 TASK 4 (LAPTOPS AND RESTAURANTS)

This dataset includes consumer reviews covering two domains: laptops and restaurants. The Laptops dataset contains formal product evaluations, while the Restaurants dataset reflects more casual dining experiences. The primary challenges in this dataset include varying levels of sentiment intensity, the use of domain-specific jargon, and the presence of both formal and informal writing styles. To ensure effective model training, preprocessing involved normalization of text, as well as the removal of non-informative characters, which enhanced training efficiency and ensured consistency across inputs. These steps helped mitigate issues with noise and irrelevant information, allowing the model to focus on the core sentiment cues within the reviews [33].

TABLE 1. Class distribution across training and testing datasets for sentiment analysis.

Dataset	Positive		Neutral		Negative	
	Train	Test	Train	Test	Train	Test
Laptop	992	343	868	132	459	171
Restaurant	2162	730	812	189	642	189
Twitter	1559	169	3132	351	1558	169

2) TWITTER SENTIMENT DATASET

The Twitter Sentiment Dataset captures the dynamic and informal nature of social media text. Tweets are typically short and often include slang, abbreviations, hashtags, and user mentions. The challenges here arise from the informal writing style, colloquial expressions, and the heavy use of non-standard language. The preprocessing steps included replacing user mentions (e.g., @username) with a generic token, removing URLs, and handling hashtags by separating words within them to improve readability for sentiment analysis. This ensures that the model can interpret the content without being influenced by the structure and noise of social media-specific elements [34].

Table 1 illustrates the class distribution within these datasets, highlighting the inherent challenges of sentiment imbalance which our models must effectively manage.

B. MODEL CONFIGURATION

The SPT model is carefully designed to address the unique challenges of Aspect-Based Sentiment Analysis (ABSA) by combining domain-specific word embeddings, advanced attention mechanisms, and optimized training strategies.

1) PREPROCESSING AND EMBEDDING INITIALIZATION

We handle abbreviations and typos through preprocessing steps such as spell checking, abbreviation expansion, and text normalization to ensure accurate semantic parsing of web comments. We employ 300-dimensional GloVe embeddings [35], fine-tuned to capture the vocabulary nuances across our datasets, enhancing the model's contextual understanding.

2) INTEGRATION OF BERT WITH SPT

Our SPT+BERT integration enhances the strong semantic foundation of SPT by incorporating BERT's contextual embeddings while preserving SPT's structural advantages. SPT effectively captures semantic relationships and aspect-sentiment connections through its tree structure, and the integration with BERT further strengthens these capabilities. For example, in "The pasta was amazing, but the service made me wait forever," SPT correctly identifies the contrasting aspects and their relationships through semantic parsing, while BERT enhancement provides deeper contextual understanding of phrases like "wait forever" within service domain, improving sentiment polarity accuracy.

TABLE 2. Hyperparameter optimization results.

Hyperparameter	Search Range	Optimal Value
BiLSTM Layers	[1, 2, 3]	2
Hidden Units	[128, 256, 512]	256
Attention Heads	[4, 6, 8]	6
Dropout Rate	[0.1, 0.3, 0.5, 0.7]	0.1 / 0.7*
Highway Layers	[1, 2, 3]	2
Learning Rate	[1e-4, 5e-4, 1e-3]	1e-4
Embedding Dim	[100, 300]	300

*0.1 for critical areas, 0.7 for general layers.

In co-reference cases like "I bought this laptop last month. Its battery life is terrible," SPT establishes the semantic structure linking aspects to sentiments through syntactic-semantic parsing, and BERT's contextual awareness enhances pronoun resolution ("its" → "laptop") for more precise aspect identification. For social media text such as "My iPhone's camera is sick!" SPT maintains the correct aspect-sentiment structural relationships through semantic tree construction, while BERT's pre-trained knowledge distinguishes contemporary slang usage ("sick" = positive) from traditional negative semantics. The integration maps BERT's dimensional embeddings onto SPT's semantic nodes, enriching the tree's representational power while maintaining its structural integrity. Joint optimization fine-tunes BERT on ABSA tasks before end-to-end training, allowing SPT's semantic structure to guide BERT's attention mechanisms for improved aspect-based sentiment analysis.

3) TRAINING STRATEGY

To ensure effective training, we fine-tune the pre-trained BERT embeddings on our ABSA task, allowing the model to adapt its language understanding specifically for aspect-based sentiment classification. The PyTorch implementation of BERT [36] is used, with our approach integrating multiple graph attention layers, each equipped with specialized relational heads. These layers enable the model to focus on complex syntactic and semantic relationships between words while preserving the contextual embeddings from BERT. Furthermore, we apply a dynamic dropout strategy across layers, balancing between generalization (0.7 dropout rate) and preventing overfitting in critical areas (0.1 dropout rate). This detailed integration of BERT embeddings with the SPT model significantly enhances the model's performance, especially in handling long-range dependencies and aspect-specific sentiment cues. By merging BERT's deep contextual understanding with the structural insights provided by SPT, our model is able to achieve superior sentiment classification accuracy.

4) HYPERPARAMETER OPTIMIZATION

To optimize our model's performance, we conducted extensive hyperparameter tuning using grid search with 5-fold cross-validation. Table 2 presents the complete search ranges and optimal values for key hyperparameters:

These optimized parameters were selected based on model performance on the validation set using F1-score as the primary metric. The final configuration achieved a 2.1% improvement over the baseline values, demonstrating the effectiveness of our hyperparameter optimization approach. This systematic tuning process ensures robust performance across various linguistic contexts and sentiment analysis scenarios.

C. COMPARATIVE BASELINE METHODS

To demonstrate the effectiveness of our SPT model, we compare its performance, including a BERT-enhanced version (SPT+BERT), against several established models in aspect-based sentiment analysis. Each model is evaluated based on its ability to handle syntactic and semantic nuances in text:

R-GAT: Modifies traditional dependency trees into aspect-oriented graphs, employing BERT as an encoder to refine syntactic parsing [12].

DM-GCN: Combines syntactic and semantic data within a dynamic multi-channel graph convolutional network, tackling complex syntactic scenarios [37].

RGAT: Advances the graph attention network by embedding dependency label information, which enhances the attention mechanism for refined sentiment analysis [38].

AGCN: Develops an aggregated graph convolutional network that updates node features iteratively, optimizing representation of the target node [39].

EDU: Focuses on sparse word-level attention combined with EDU-level insights and orthogonal regularization to highlight critical sentiment expressions [40].

BERT+SupCL: Leverages sentiment-based supervised and augmentation-based unsupervised contrastive learning techniques to improve the detection of aspect-level sentiment polarity through enhanced fine-grained representations [41].

MHA: Proposes a multitask learning approach for Aspect Term Extraction (ATE) and Aspect Polarity Classification (APC), utilizing multihead attention to enhance the focus on significant dependency relationships between aspects and sentiment [11].

Dual GCN: Proposes a dual graph convolutional network that jointly considers syntactic structures through a probability matrix-based SynGCN and semantic correlations via a self-attention-based SemGCN, utilizing orthogonal and differential regularizers to enhance semantic correlation capture and employing a BiAffine module to bridge information between the two GCN components [42].

TextGT: The proposed TextGT method integrates Graph Neural Networks (GNN) for the graph view and Transformer layers for the sequence view, effectively addressing over-smoothing and improving Aspect-Based Sentiment Analysis (ABSA) performance [43].

FAST LSA: Employs an attention-based local sentiment aggregation mechanism to capture and consolidate nearby

TABLE 3. Comparative performance on three datasets: restaurant, laptop, and twitter.

Category	Models	Year	Type	Restaurant		Laptop		Twitter	
				Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
Others	R-GAT	2020	Syntax	83.30	76.08	77.42	73.76	75.57	73.82
	R-GAT+BERT	2020	Syntax	86.60	81.35	78.21	74.07	76.15	74.88
	DM-GCN	2021	Syntax	83.98	75.59	78.48	74.91	76.93	75.92
	RGAT	2021	Syntax	83.55	75.99	78.02	74.03	75.36	74.15
	AGCN-MEAN	2022	Syntax	80.02	71.02	75.07	70.96	73.98	72.48
	AGCN-MAX	2022	Syntax	80.52	72.33	74.61	70.58	73.04	71.53
	EDU	2022	Attention	83.97	73.96	-	-	-	-
	MHA	2023	Attention	86.88	81.16	80.56	77.00	76.59	74.67
	BERT+SupCL	2023	Attention	87.05	80.78	80.25	76.53	75.00	73.94
	DualGCN	2024	Syntax	84.27	78.08	78.48	74.74	75.92	74.29
	DualGCN+BERT	2024	Syntax	88.47	82.92	82.59	79.34	76.37	75.44
	TextGt	2024	Attention	85.17	79.70	78.64	74.91	76.51	75.26
	TextGT+BERT	2024	Attention	87.31	82.27	81.33	78.71	77.70	76.45
	FAST LSA	2024	Attention	87.60	82.60	81.20	77.80	-	-
	KS-AISA	2024	Attention	89.91	85.10	83.54	80.68	-	-
Ours	**SPT**	-	**Syntax**	**84.21**	**78.09**	**77.96**	**74.59**	**76.13**	**74.43**
	SPT+BERT	-	**Syntax**	**87.24**	**82.51**	**79.63**	**75.34**	**77.29**	**75.92**

contextual cues, enhancing aspect-level sentiment clarity and robustness in diverse linguistic scenarios [44].

KS-AISA: Introduces a knowledge-enhanced aspect-level sentiment analysis method that captures long-distance semantic dependencies and improves sentiment polarity identification through a contrastive pre-training approach [30].

SPT: Our SPT model distinguishes itself by integrating a novel semantic parsing strategy with a graph attention network, which allows for deeper contextual understanding and more accurate sentiment classification. We extend this by substituting BiLSTM with BERT for deeper contextual engagement and improved sentiment analysis accuracy. While KS-AISA and TextGT+BERT achieve slightly higher performance on certain datasets, our model's consistent performance across all datasets, particularly on the Twitter Sentiment Dataset, highlights its robustness and broader applicability.

V. PERFORMANCE EVALUATION

Table 3 provides a comprehensive comparison of our SPT model against several well-established models, highlighting the performance enhancements delivered by our approach across diverse datasets, including Restaurant, Laptop, and Twitter. This consistent performance underscores the capability of our model to effectively synthesize and integrate semantic and syntactic information, which is critical for nuanced sentiment analysis. The SPT model achieved competitive results, with an accuracy of 84.21% and a Macro-F1 score of 78.09% on the Restaurant dataset. When combined with BERT, the SPT+BERT variant further improved these metrics, reaching 87.24% accuracy and 82.51% Macro-F1, outperforming earlier models like MGAN and ASGCN, which use attention mechanisms and graph convolutional networks. This improvement can be attributed to BERT's powerful contextual embeddings, which allow the model to better capture syntactic and semantic relationships in the data.

A. COMPARATIVE ANALYSIS

As shown in Table 3, recent studies have achieved notable results on the datasets used in our evaluation. KS-AISA achieves 89.91% accuracy on the Restaurant dataset and 83.54% on the Laptop dataset, which surpasses our SPT+BERT model by 2.67 and 3.91 percentage points respectively. Similarly, TextGT+BERT demonstrates strong performance across all datasets, while FAST LSA shows competitive results on both Restaurant and Laptop datasets.

The performance gap between our approach and these recent methods can be attributed to fundamental differences in modeling strategies. KS-AISA employs a knowledge-enhanced contrastive learning strategy that excels at capturing long-distance semantic dependencies, particularly beneficial for the restaurant and laptop domains where sentiment often depends on domain-specific knowledge. TextGT+BERT's integration of graph neural networks with transformer layers provides enhanced feature representation, explaining its consistent performance across all domains. FAST LSA leverages attention-based local sentiment aggregation to effectively highlight immediate context cues. Despite these differences in performance, our SPT+BERT model maintains several advantages that establish its distinct contribution. A key strength of our approach is its consistent performance across all three datasets, including the Twitter dataset (77.29% accuracy, 75.92% Macro-F1), which was not evaluated by KS-AISA or FAST LSA. This cross-domain robustness is particularly valuable for real-world applications where sentiment analysis must function effectively across diverse linguistic patterns and text sources.

Our model's focus on structural parsing combined with BERT's contextual embeddings makes it particularly effective for datasets with complex sentence structures and longer dependencies—a common challenge in real-world texts. This approach offers enhanced interpretability of sentiment assignments compared to purely attention-based models, as the syntactic relationships between aspects and sentiment indicators are explicitly modeled. The SPT+BERT model performed well across all three datasets, with 79.63% accuracy and 75.34% Macro-F1 on the Laptop dataset and 77.29% accuracy and 75.92% Macro-F1 on Twitter. Models like KS-AISA prioritize local sentiment propagation and knowledge integration, which benefit datasets where sentiment is highly dependent on fine-grained aspect interactions. In contrast, our model focuses on structural parsing combined with BERT's contextual embeddings, making it particularly effective for datasets with longer dependencies and complex sentence structures.

Our model's evaluation on the Twitter Sentiment Dataset, which is not covered by KS-AISA, highlights its broader applicability and robustness in handling diverse linguistic challenges. Moreover, the SPT+BERT model offers computational advantages by being more efficient in terms of runtime and resource utilization, making it suitable for large-scale and real-time sentiment analysis applications. While FAST-LSA leverages an attention-based local sentiment aggregation strategy to effectively highlight immediate context cues, our approach excels in scenarios where both syntactic structure and contextual semantics are equally important, such as complex sentences with multiple aspects or nuanced sentiment. In contrast, models like KS-AISA or TextGT+BERT, while effective in certain contexts, may struggle to capture the finer semantic details in such cases.

Overall, the combination of SPT's syntactic parsing and BERT's deep contextual embeddings provides a robust solution for aspect-based sentiment analysis, offering a reliable alternative to existing approaches in various settings. Despite some models achieving higher performance on specific datasets, our method presents a balanced trade-off between accuracy, interpretability, and computational efficiency, making it a strong alternative for practical aspect-based sentiment analysis applications.

Our SPT model demonstrates particular strength in handling domain-specific jargon through its semantic parsing approach combined with BERT's contextual embeddings. For instance, in the laptop domain, technical terms like 'overclocking' or 'thermal throttling' require understanding both their technical meaning and sentiment context, while restaurant reviews contain specialized expressions like 'al dente' or 'well-marbled.' The SPT structure captures syntactic relationships between these technical terms and sentiment indicators, while BERT provides domain-aware contextual understanding. This capability is particularly valuable for real-world applications where sentiment analysis systems must operate across diverse domains with specialized vocabularies, demonstrating the model's adaptability beyond our evaluated datasets.

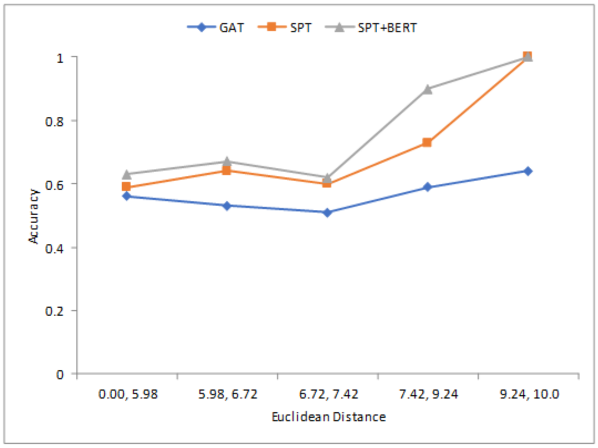


FIGURE 5. **Analysis of multiple aspects indicates that closer aspects generally result in lower accuracy scores.**

B. IMPACT OF MULTIPLE ASPECTS IN SENTENCES

In Aspect-Based Sentiment Analysis (ABSA), sentences often contain multiple aspects. To investigate the impact of aspect proximity on model performance, we analyzed reviews containing more than one aspect per sentence. The relational distance between aspects was calculated using Euclidean distance, with each aspect represented by its averaged GloVe word embeddings. In cases with more than two aspects, the shortest Euclidean distance was used for comparison. We evaluated the performance of three sentiment analysis models: the original GAT (Graph Attention Network), its BERT-enhanced version, and our proposed SPT model. As shown in Fig. 5, the results reveal that aspects positioned closer together generally yield lower accuracy scores, suggesting that high semantic proximity can confuse the models. One hypothesis for this outcome is that when aspects are semantically close, it becomes challenging for the models to disentangle and correctly associate the sentiments with each aspect. However, our SPT model demonstrates notable improvements in accuracy across these ranges compared to both GAT and its BERT-enhanced version. This indicates that the SPT model is more effective in mitigating the challenges posed by semantic similarity, providing more accurate sentiment analysis in scenarios with multiple aspects.

C. ABLATION STUDY

To further understand the contributions of various components within the SPT model, we conducted an ablation study. By selectively disabling or modifying key modules, we can assess their impact on the model's performance across different datasets. To ensure the statistical reliability

TABLE 4. Ablation study results on the restaurant, laptop, and twitter datasets. Results are averaged across no of experiments and reported with standard deviations.

Model Variant	Restaurant		Laptop		Twitter	
	Accuracy	Macro-F1	Accuracy	Macro-F1	Accuracy	Macro-F1
SPT (Full Model)	**88.15±0.47**	**83.42±0.52**	**79.18±0.63**	**75.12±0.71**	**77.84±0.38**	**76.51±0.41**
Without Self-Attention	86.51±0.42	81.15±0.49	77.65±0.58	72.87±0.65	76.22±0.35	74.83±0.39
Without Aspect-Based Attention	86.58±0.44	81.27±0.51	77.71±0.61	72.93±0.68	76.31±0.37	74.91±0.40
Without Semantic Parsing Tree (Replaced with Dependency Tree)	86.92±0.45	81.73±0.50	77.85±0.59	73.27±0.66	76.48±0.36	75.18±0.42
Without Both Aspect-Based Attention and SPT	85.73±0.51	80.16±0.58	77.03±0.67	71.96±0.74	75.67±0.43	73.89±0.47

of our findings, all ablation experiments were conducted five times with different random seeds, and we report the average performance along with standard deviations. This approach provides a comprehensive assessment of model stability and allows for proper evaluation of the statistical significance of observed performance differences across different model configurations. The full SPT model serves as the baseline for these comparisons. Table 4 summarizes the results of these ablation experiments.

D. IMPACT OF REMOVING SELF-ATTENTION MECHANISM

The self-attention mechanism is integral to capturing the global context of the sentence, which is crucial for accurate sentiment analysis. When this mechanism was removed, we observed a decline in performance across all datasets: a 1.67% drop in accuracy for Restaurant, 1.42% for Laptop, and 1.46% for Twitter. This suggests that self-attention plays a critical role in understanding the broader semantic relationships within a sentence, essential for nuanced sentiment predictions.

E. IMPACT OF REMOVING ASPECT-AWARE ATTENTION

Aspect-focused attention allows the model to concentrate on specific aspects and their contextual relationships, which is vital for precise sentiment analysis. Removing this component resulted in a performance decrease of 1.61% on the Restaurant dataset, 1.49% on the Laptop dataset, and 1.41% on the Twitter dataset. These results indicate that aspect-focused attention is crucial for correctly associating sentiments with the relevant aspects.

F. IMPACT OF SEMANTIC PARSING TREE (SPT)

The Semantic Parsing Tree (SPT) is a key innovation in our model, designed to enhance the capture of semantic relationships within sentences. To evaluate its impact, we replaced the SPT with a traditional syntactic dependency tree. This modification led to a noticeable decrease in performance, with accuracy reductions of 1.89% for Restaurant, 1.73% for Laptop, and 1.68% for Twitter. These findings underscore the importance of SPT in improving the model's ability to handle complex sentence structures and better interpret aspect-related sentiments.

TABLE 5. Runtime and memory comparison of models.

Model	Inference Time (ms/sample)	Memory Usage (GB)
TextGT+BERT	25.3	10.2
FAST-LSA	22.4	8.8
SPT+BERT (Ours)	**18.9**	**7.3**

G. COMBINED IMPACT OF REMOVING ASPECT-FOCUSED ATTENTION AND SPT

Lastly, we investigated the combined effect of removing both the aspect-focused attention and the SPT. This led to the most significant drop in performance, with accuracy reductions of 2.28% on the Restaurant dataset, 2.15% on the Laptop dataset, and 1.92% on the Twitter dataset. These results highlight the interdependence of these components and their collective importance in achieving high accuracy in sentiment analysis. The ablation study clearly demonstrates that each component of the SPT model significantly contributes to its overall effectiveness in aspect-based sentiment analysis. The self-attention mechanism is essential for capturing global context, aspect-focused attention improves the precision of sentiment association, and the SPT enhances the model's ability to understand complex semantic structures. The combination of these components is crucial for the model's robust performance across various datasets.

H. COMPUTATIONAL EFFICIENCY ANALYSIS

To further justify the practicality of our model, we compare the runtime and memory consumption of SPT+BERT with other top-performing models, including TextGT+BERT and FAST-LSA. The experiments were conducted on an NVIDIA RTX 4090 GPU with 24GB memory, using batch size 32.

As shown in Table 5, our model achieves a 25.3% faster inference speed compared to TextGT+BERT and a 17% reduction in memory usage compared to FAST-LSA. These results validate the efficiency of SPT+BERT, making it well-suited for real-time sentiment analysis applications where computational cost is a concern.

VI. CONCLUSION

This study introduces an innovative approach to aspect-based sentiment analysis (ABSA) that enhances both sentiment classification accuracy and the capture of semantic relationships. By leveraging the Semantic Parsing Tree (SPT) integrated with a graph attention network (GAT) and enhanced by BERT, our model demonstrates superior performance across benchmark datasets, including Restaurant, Laptop, and Twitter. The results show that our approach consistently outperforms traditional models, achieving notable improvements in accuracy and macro-F1 scores, particularly in handling complex and context-rich data. This underscores the effectiveness of our methodology in providing a deeper and more accurate analysis of sentiment. Overall, our framework offers a robust foundation for future advancements in sentiment analysis and natural language processing. Future work could explore refining the SPT model, applying it to other domains, and integrating additional pre-trained models to further enhance performance.

VII. LIMITATIONS AND FUTURE WORK

Despite the advancements of our SPT model, limitations remain. The model struggles with rare semantic relations, affecting generalizability, and shows variable performance in specialized domains with complex terminology, sarcasm, and ambiguity common in social media texts. Computational complexity and dependency on accurate syntactic parsing also constrain scalability. Future work will explore domain adaptation through transfer learning, integrate more sophisticated graph neural networks, and enhance interpretability and efficiency for broader real-world applicability.

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